

RESEARCH REPORT

How Might Investing in Private Equity Funds Affect Retirement Savings Accounts?

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Acknowledgments

This report was funded by the American Investment Council. We are grateful to them and to all our funders, who make it possible for Urban to advance its mission.

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Introduction

Until recently, managers of 401(k) retirement plans were reluctant to include private equity (PE) in their investment options because of concern they would violate the Employee Retirement Income Security Act (ERISA) of 1974. That may change after the US Department of Labor (DOL) clarified in a June 2020 letter that PE funds could be offered as part of multiasset class vehicles such as target-date funds.¹ Removing the barrier between retirement savings plans and PE funds could have far-reaching consequences for both retirement savings plans and the PE industry. Millions of participants in retirement savings plans could allocate part of their portfolios to an asset class with different characteristics than public stocks and bonds, which are traditional investment vehicles for 401(k) plans. The PE industry would see an influx of money seeking new investments and high returns. It is unclear how these changes might play out.

In this report, we examine the potential consequences of including PE funds in retirement savings portfolios. We are primarily interested in the effects on retirement savings and how those changes might be distributed across demographic groups. To fully understand this issue, we also need to understand the PE industry and its future. PE funds have outperformed the public stock market, on average, but that pattern may not continue in the future, especially as retirement savings flow into PE funds. To address these questions, we combine a literature review approach with microsimulation modeling. We rely on the existing literature to understand the evolution of the PE industry, its relation to public stock markets, and its potential future trajectory. Based on this review, we construct a model of returns to PE, and use it in conjunction with DYNASIM, Urban Institute's dynamic microsimulation model, to simulate investment returns, accumulation of retirement savings, and retirement income. We selected 16 scenarios of plausible PE return characteristics and simulated outcomes under each.

We analyze projected outcomes through 2075. This kind of long-term analysis depends on many unknowns and it is impossible to simulate all of them. Instead, we make some simplifying assumptions. Based on guidance from the DOL (2020), we assume that target-date funds would invest no more than 15 percent of total managed assets in PE. We assume they would make this shift gradually by increasing their exposure to PE funds by one percentage point each year until they reach the maximum. We also make an implicit assumption that target-date funds would manage their assets to keep the asset liquidity, from the perspective of the investors, the same as it was without any PE investments.

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Our results show that adding limited PE funds to retirement savings funds would most likely raise the average rate of return and increase average retirement savings account balances. These gains occur because PE funds offer potentially higher returns than public stocks, on average, and because PE adds diversification to savings portfolios. Even under our most pessimistic assumptions, adding PE to the mix of investments can be beneficial. The average outcomes were less favorable than under the baseline in only two of simulated scenarios. It would take time for any changes in returns to accumulate, so these effects on retirement savings would be negligible over the next decade, as target-date funds gradually add PE to their portfolios. At the end of our analysis period, the most optimistic scenario produces retirement accounts that are on average about 7 percent higher than under the baseline. We also show that the distribution of the policy effects is quite wide. Some savers do substantially better than the average, and others do substantially worse. Even under the most optimistic scenario, some retirees may receive lower cumulative returns. And under the most pessimistic scenario, some retirees may receive higher cumulative returns.

Background

Retirement Savings Accounts

Retirement savings accounts, which allow workers to set aside pretax earnings, are an important component of the US retirement system. Most US workers with these accounts participate in employer-sponsored retirement savings plans, which include 401(k) plans in the for-profit sector, 403(b) and 457 plans in the nonprofit and public sectors, and the Thrift Savings Plan provided to federal government employees. Most defined contribution (DC) plans sponsored by nongovernment entities are covered by ERISA, which sets minimum standards for information disclosure, fiduciary responsibility, and conflict resolution, among other things. Investment options available to participants usually include a mix of stock and bond mutual funds.

In 2019, about 43 percent of workers ages 25 to 64 participated in an employer-sponsored retirement savings plan (Munnell and Chen 2020), which managed \$8.9 trillion assets (Investment Company Institute 2020). Employees often roll over their savings into an Individual Retirement Account (IRA) when they retire or change jobs. Assets in these accounts totaled an additional \$11 trillion in 2019. Asset allocation is the responsibility of individual savers, who typically maximize returns with stock-heavy portfolios at younger ages, and then gradually lower their risk exposure as they approach retirement by reducing the share of stocks they hold. However, this portfolio management requires a level of financial literacy that many participants lack, often resulting in suboptimal asset allocation decisions (Elton et al. 2015).

A growing share of retirement savings plan participants have their asset allocation managed by target-date funds, which provide a predetermined portfolio allocation path. This equity glide path allows target-date funds to play the role of financial advisor by decreasing the equity-to-bonds ratio as participants approach retirement and regularly rebalancing portfolios. These funds have grown dramatically. Between 2000 and 2019, assets held by target-date funds increased from \$6 billion to \$1.4 trillion (Mitchell and Utkus 2012; Shoven and Walton 2020). Although target-date funds have reduced management complexity, they did not protect investors from significant losses during the 2008 and 2020 recessions (GAO 2011; Shoven and Walton 2020).

Private Equity

Another dramatic recent change in US capital markets is a shift from public to private equity over the last couple of decades. Although the capitalization of public companies still far exceeds the amount of assets managed by PE funds,² this gap is shrinking as the number of publicly listed companies decreases and the value of PE assets grows. Between 1997 and 2016, the number of US firms listed on US exchanges dropped by more than half, from 7,509 to 3,618 (Doidge et al. 2018). Globally, PE market capitalization doubled between 2000 and 2018, and the net asset value of one segment of the PE industry—buyout funds—increased sevenfold over the period (Bain and Company 2020).

Investments in PE are usually made through PE funds, which research and identify investment opportunities. Professionals actively manage the firms in a fund's portfolio with the goal of increasing the firms' value. An investment cycle, which typically lasts 10 years, starts with investment commitments by external investors (i.e., limited partners) and usually ends with the sale of the acquired holdings and the distribution of proceeds to investors. The two main types of PE funds differ by the type of firms in which they invest: buyout funds typically acquire established firms, and venture capital (VC) funds invest in early-stage businesses.

Both types of funds received an influx of capital during the 1990s, following a period of excellent performances that attracted many large institutional investors. The number of potential investors also increased after a series of rule changes³ loosened restrictions on raising private capital and trading private securities (De Fontenay 2016; Ewens and Farre-Mensa 2019). This growth, in turn, made private equity an attractive alternative to public stock markets. Additionally, raising capital from public exchanges is becoming less attractive as firms' investment needs change. The disclosure requirements and accounting rules that govern public equity markets may be ill-suited for financing research and development and other increasingly necessary intangible investments (Doidge et al. 2018).

From an investor's perspective, privately held firms and publicly listed firms differ primarily in terms of liquidity and the availability of public information about the firms. Because public stocks can be sold any time on stock exchanges, they are highly liquid. The exchanges also generate a share price, a key piece of information for valuing a company. In addition, regulations require publicly traded companies to disclose detailed information on their business activities, financial condition, and governance. By contrast, privately owned companies must disclose much less information, and their value is more opaque because of the absence of a market. A long investment cycle and the absence of a market make PE more difficult to trade and therefore less liquid than publicly traded stocks.

Economists believe that, because of the risk stemming from limited liquidity and information, investors require higher returns from PE than from public equities. Fund managers, with their specialized expertise and hands-on approach to investing, so far have delivered this risk premium. Despite the challenges in measuring PE returns, which arise from the absence of a market, the literature suggests that PE funds have outperformed public stocks over the past three decades (Ang et al. 2018; Brown and Kaplan 2019; Ilmanen, Chandra, and McQuinn 2019, 2020; Kaplan and Sensoy 2014). Another potential benefit of including PE funds in a portfolio is that it can reduce the overall risk of losses through diversification. Measurement issues again prevent a precise quantification, but researchers appear to agree that PE returns include a component that is uncorrelated with the overall market, a key to risk reduction. In addition, because of the attrition of small companies from stock exchanges, PE funds have increasingly become an alternative way of investing in that segment of the capital market.

The influx of capital from retirement savings accounts will accelerate the growth in the PE industry, which would likely continue even without regulatory changes that facilitate investments from retirement savings (Bain and Company 2020; Mauboussin and Callahan 2020; Henry et al. 2020). As assets under the management of PE funds grow, the gap between their average rate of return and the average rate of return to public stocks will continue shrinking (Bain and Company 2020; Mauboussin and Callahan 2020; Mauboussin and Callahan 2020).

Measuring Asset Performance

The two main aspects of asset performance are rate of return and risk, most commonly reported as the mean rate of return and the standard deviation of those returns. The rate of return to an asset priced P_t at time t and P_{t+1} at time t+1 is P_{t+1}/P_t -1. When prices are available in regular intervals, as they are for publicly traded equity, a time series of rates of returns can easily be constructed and used to calculate the mean and standard deviation. This is not the case for PE funds, which are generally not traded in public markets. Even for PE funds that are traded in secondary markets, trades occur at irregular intervals and do not always reflect the fund's value, especially soon after a fund's inception or close to its liquidation date (Boyer et al. 2018). Therefore, the first challenge in evaluating the performance of PE funds is estimating their rates of return.

Researchers have developed several ways to address this problem. One is based on net asset value, the value of a PE fund reported quarterly by the fund manager. Although it provides a measure of a fund's value at regular time intervals, these self-reported estimates tend to include some measurement error because managers may overestimate fund performance and smooth estimates over time. Some analysts have addressed this measurement error by unsmoothing the estimates (Rudin et al. 2019) or supplementing them with other data (Brown, Ghysels, and Gredil 2019). Another common method for estimating PE fund returns uses cash flows to and from the fund to calculate a measure of annualized rates of returns. When the cash flows are between the fund and the investors (i.e., limited partners), the resulting rate of return is net of management fees. In contrast, when the cash flows are between the fund and the investors of trading investments in PE funds to create PE indices similar to those constructed for public stocks. However, these markets were developed in the early 2000s and they provide data for only a relatively short period.

A common way to estimate an annual rate of return from cash flows is based on the condition that the present value of all investments in a PE fund must equal the present value of all distributions the fund pays out to investors if these cash flows are discounted at the fund's annual rate of return. The rate of return for which this condition is satisfied is called the *internal rate of return (IRR)*. A few other measures, which are defined in terms of the ratio of total distributions to total investments, differ mainly in how they account for the timing of cash flows. The *multiple of invested capital*, which does not take time into account, is the ratio of the sum of all distributions and residuals to the sum of all investments. The so called *modified internal rate of return* is calculated as the geometric average of the

ratio of the forward value of distributions to the present value of investment, both discounted at some interest rate (Franzoni et al. 2012). Another ratio of distributions to investment, designed to compare the fund's performance to the market's performance, is *public market equivalent (PME)*, which compares the return of private equity investments to comparable investments in the S&P 500 stock index (Kaplan and Schoar 2005).

PME has become widely adopted among researchers as a way to compare returns to a PE fund with returns to public stocks. A PME of 1.20, for example, indicates that, at the end of the fund's life, investors ended up with 20 percent higher returns than what they would have collected if they had invested in the stock market index. Using this measure, Harris et al. (2014) found that buyout funds have consistently outperformed the market by about 3 percent on average annually,⁴ while VC funds outperformed the market in the 1990s but underperformed since then. The authors obtained their main result by using returns to the S&P 500 to estimate PME, but they report similar results with small cap indices, implying that excess returns to PE funds are not driven by an overrepresentation of small firms in these funds' portfolios. Robinson and Sensoy (2016) found similar results.

Although the measures described above provide information about a fund's returns to investment, they do not contain any information about risk. With fund-level data, the calculated value is averaged over the fund's lifetime, which means that only one value per fund is obtained. Consequently, a measure of volatility, such as standard deviation, can only be calculated for a group of funds based on their type, vintage, or industry. However, this volatility measure does not account for systemic market risk and the correlation between that risk and PE risk. That relationship is vitally important to investors.

Capital Asset Pricing Model

In general, investors view PE as an alternative investment that can help them improve their investment strategy. Their objective, to maximize returns and minimize risk, is achieved by diversifying investments across various assets. The resulting expected rate of return to a portfolio of assets is simply a weighted average of individual asset returns. Asset risks, however, combine nonlinearly and the resulting risk depends not only on the risk of each asset in the portfolio but also on the correlation of returns among the assets: the lower the correlation, the lower the resulting portfolio risk. This is why assets cannot be evaluated in isolation; they must be evaluated in the context of other available assets.

The main optimization problem an investor faces is to find the mix of assets that maximizes returns and minimizes risk. A group of assets can be combined in different proportions to generate different rates of return. Given a sufficiently large group of assets with randomly distributed returns, a given rate of return can be obtained in various ways. In general, a combination of assets exists that minimizes the total risk for a given rate of return. The set of all such points represents the *efficient frontier* in the risk-returns space. When all available assets are risky, optimizing investors will choose a point on that frontier, with their exact location determined by their risk preference.

When a risk-free asset is also available for borrowing and lending, there is one optimal point on the frontier that maximizes the so-called *Sharpe Ratio*—the ratio of expected returns in excess of the risk-free rate to the standard deviation of those returns. Assuming that all investors have the same information about the assets and the market is in an equilibrium, all investors, regardless of risk preference, would invest in the same portfolio of risky assets that maximizes the Sharpe Ratio. An individual investor's risk tolerance would determine how much they invest in risky assets and how much in risk-free assets. More risk-averse investors would provide risk-free loans as part of their portfolios, while those who tolerate more risk might borrow funds at the risk-free rate and use them to increase their portfolio of risky assets.⁵

In an equilibrium, the optimal portfolio includes all stocks available in the market, and its expected rate of return in excess of the risk-free rate of return represents the *market risk premium*. Any stock in that portfolio derives its risk premium solely from its correlation with the market risk premium. But an asset that is not traded on the market, such as PE, can have other sources of excess returns. In general, an individual asset's rate of return, R_i , in excess of the risk-free rate, R_f , can be decomposed into two components. The component that represents the asset's excess return arising from its correlation with the market is proportional to the market risk premium. The factor of proportionality beta (β) depends on this correlation and the ratio of the standard deviations of the asset and market returns.⁶ The other component of the asset's excess return, alpha (α), represents the excess return that is uncorrelated with the market:

$$R_i - R_f = \alpha_i + \beta_i (R_m - R_f)$$

where R_m is the market rate of return.

This, in essence, is the capital asset pricing model (CAPM) that provides important insights about asset valuation, but it is also a tool for evaluating asset performance. Perold (2004) provides a useful example that illustrates the importance of evaluating asset performance in the context of market risk. The example assumes that market and risk-free rates of return are 15 and 5 percent, respectively, and the standard deviation of market returns is 20 percent. It also assumes that the two hypothetical funds being evaluated, A and B, have rates of returns of 12 and 18 percent and standard deviations of 40 and 30 percent, respectively. Based solely on the funds' returns and standard deviations, fund B appears to be a more attractive investment because it produces higher returns at a lower risk. However, if we also knew that the betas for fund A and fund B equal 0 and 1.5, we would reach the opposite conclusion. Using the above expression to calculate the implied alphas for the two funds, we obtain 7 percent for fund A and -2 percent for fund B. When funds' returns are adjusted for their exposure to market risk, fund A outperforms the market and fund B underperforms it.

For any publicly traded stock, which is part of the market portfolio, alpha is expected to be 0. If not, investors could improve their investment strategy by investing more in stocks with positive alpha and less in those with negative alpha, which, in turn would cause stock prices to adjust and bring all alphas to 0. Consequently, the excess return for any public stock comes solely from its correlation with the overall market risk.

For an asset that is not publicly traded, such as a PE fund, alpha could differ from 0 for several reasons. Skilled fund managers could deploy active investment strategies that outperform the market and create a positive alpha. Or investors may demand returns in excess of market returns because PE investments are less liquid, in which case alpha would reflect the *illiquidity premium*. Finally, the asset could be exposed to risks that are correlated to specific market factors, such as a risk premium on small versus large firms, or low- versus high-valued firms. Richer models that include these factors, like the one developed by Fama and French (1993) and expanded by Pástor and Stambaugh (2003), provide more insight into the sources of excess returns.

Beta measures the sensitivity of an asset's return to variation in market returns, but this sensitivity varies with leverage. Given two otherwise equal assets that differ only in the amount of leverage, the more-leveraged asset will have a higher beta than the less-leveraged asset. One could create a portfolio with an arbitrary value of beta by mixing the risk-free asset and the market portfolio, which have betas of 0 and 1, respectively. Investing a fraction *x* of one's total investment in the market portfolio and remaining (1-x) in the risk-free asset would yield a portfolio with beta equal to *x*. On the other hand, taking a risk-free loan and investing it, in addition to one's own funds, at a ratio of *x*:1 in the market portfolio would result in a portfolio with a beta equal to 1+x.

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Estimates of CAPM for PE Funds

We reviewed the literature on PE funds to select parameters for our simulation model. Because the simulation model is CAPM, we focused on studies that estimated that model and reported values for alpha and beta. We also reviewed some studies that did not estimate CAPM but whose findings could inform our modeling decisions. Because our ultimate goal is to project future returns, we use recent estimates and focus on studies published within the last 10 years. We found seven studies that satisfy these criteria.

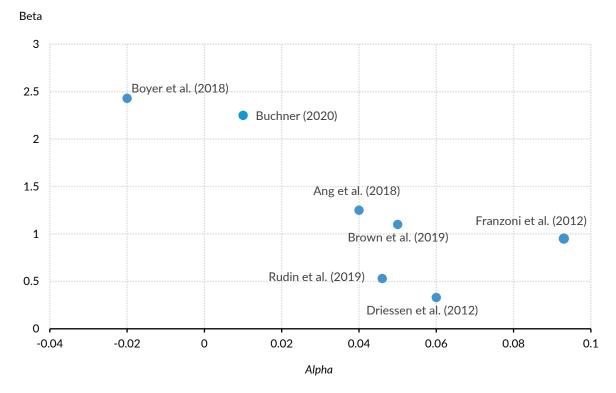
Estimates of alpha and beta for PE funds vary widely. For buyout funds, net-of-fees estimates of alpha range from -2 percent (Boyer et al. 2018) to more than 9 percent (Franzoni et al. 2012). Buchner (2020) estimated a gross-of-fees alpha of 7 percent but believes that accounting for fees would reduce it to 1 percent. Driessen et al. (2012) estimated an alpha of 0.49 on a monthly basis, which is equivalent to almost 6 percent annually, but their estimate was not statistically different from 0 at the 90 percent significance level. Moreover, Driessen et al. (2012) used Venture Economics data, which Stucke (2011) found contains some inaccurate information. Brown and Kaplan (2019) and Rudin et al. (2019) estimated alphas close to 5 percent but did not report standard errors.

Estimates of beta in the reviewed studies vary from 0.33 to 2.43. However, the beta for buyout funds is unlikely to be very low because buyout funds tend to have a high debt-to-equity ratio. Buchner (2020) shows that beta may be 2.5 times higher in a PE fund with a 3:1 debt-to-equity ratio— which is typical for buyout funds (Axelson et al. 2013)—than in an equivalent public stock with a 1:3 debt-to-equity ratio, which is typical for publicly traded stocks. For example, the PE fund must have an unleveraged beta less than 0.4 for its leveraged beta to be less than 1. To have a leveraged beta of 0.33, as estimated by Driessen et al. (2012), the unleveraged beta would have to be only 0.13. We believe that estimates of beta greater than 1 are more likely to represent the true relationship between excess returns to PE and the market risk premium.

Plotting these estimates reveals the expected negative correlation between alpha and beta (figure 1). In the simple CAPM model there are two sources of excess returns: the market risk premium and returns uncorrelated with the market. A high beta indicates that the former is large and therefore the latter is likely to be smaller for a given amount of excess returns. The opposite is true when beta is low. The negative correlation between alpha and beta was also observed by Frazzini and Pedersen (2014) for PE funds in their sample.

FIGURE 1

Estimates of Alpha and Beta in the CAPM Model for Buyout Funds

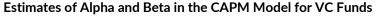


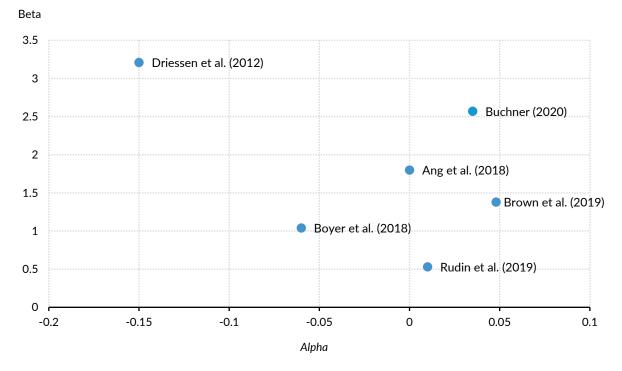
Notes: The estimate of alpha by Driessen et al. (2012) is not statistically different from 0 at the 90-percent level; it was estimated on a monthly basis and converted to an annual rate by multiplying it by 12. The authors used data from Venture Economics, which was found to be problematic. Rudin et al. (2019) and Brown, Ghysels, and Gredil (2019) do not provide standard errors for their estimates of alpha and beta.

Harris et al. (2014) and Robinson and Sensoy (2016) do not estimate beta, but they test the sensitivity of their PME estimates to their assumption of beta. The standard PME that uses returns of the S&P 500 index to discount PE fund cash flows implies a beta of 1. The multiple of invested capital, which does no discounting, implies a beta of 0. They also constructed a PME with a beta of 1.5 by using returns of the S&P 500 index, multiplied by 1.5 as a discount factor. Both studies conclude that the value of PME is very sensitive to beta for values of beta less than 1, while PME is fairly stable for beta values between 1 and 1.5. The authors interpret this result as suggestive of a true beta greater than 1.

The ranges of estimated alphas and betas are even wider for VC funds than for buyout funds. Estimated values of alpha range from -15 percent to 4.8 percent and estimates of beta range from 0.5 to 3.2 (figure 2). In almost all studies that estimated CAPM for both VC and buyout funds, VC funds have a lower alpha and a higher beta than buyout funds. For example, Ang et al. (2018) estimated values of 4 percent and 1.25 for alpha and beta in buyout funds, and 0 percent and 1.8 in VC funds. Only Buchner (2020) obtained a higher alpha for VC funds than for buyout funds, and Boyer et al. (2018) obtained a lower beta for VC funds than for buyout funds.

FIGURE 2





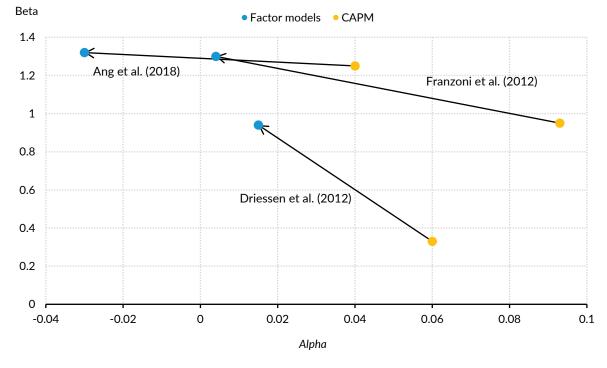
Notes: The value of alpha by Driessen et al. (2012) was estimated on a monthly basis and converted to an annual rate by multiplying it by 12.

Another important piece of information about the sources of excess returns to PE funds can be gleaned from multifactor models, which, in addition to the market risk premium, include premiums on small stocks and stocks with high book-to-market ratio. In addition, Pástor and Stambaugh (2003) proposed a measure of liquidity as another factor that could help explain PE returns. While it has been hypothesized that part of the unexplained excess returns on PE is a premium on a lower liquidity of PE assets, the liquidity factor represents changes in liquidity over time that are common to PE and publicly traded stocks, rather than the illiquidity premium that is unique to PE. These three additional factors can be constructed from returns to public stocks and used as explanatory variables in a model of returns to PE. The estimated beta coefficients associated with those factors reflect the correlation between PE returns and those factors. The product of a factor and the associated beta represents the size of the risk premium arising from that factor.

According to the literature, these additional factors are a significant source of returns to PE. When they are added to the basic CAPM equation for buyout PE in the three studies that estimated this expanded model, the estimated alpha decreased substantially while the beta associated with the market risk premium increased (figure 3). The decrease in alpha caused by adding the factors is quite dramatic: alpha decreases from 9 to 0 percent in Franzoni et al. (2012), from 4 to -3 percent in Ang et al. (2018), and from 6 to 1.5 percent in Driessen et al. (2012), although both estimates are statistically indistinguishable from 0.

FIGURE 3





Notes: The estimates of alpha by Driessen et al. (2012) are not statistically different from 0 at the 90-percent level; they were estimated on a monthly basis and converted to an annual rate by multiplying them by 12.

Methods

The goal of this study is to examine how diversifying retirement savings by allowing DC participants to invest in PE funds might affect account balances and, consequently, the distribution of retirement income. Using Urban's Dynamic Simulation of Income Model, DYNASIM, we simulate retirement savings and income under a scenario that allows DC investors to invest in PE funds and compare those outcomes to retirement savings and income simulated under the baseline scenario that does not allow PE funds in DC accounts. We also assess the impact of PE investment options by individual characteristics, including birth year, race and ethnicity, educational attainment, and lifetime earnings. These simulations require assumptions about future investment returns, the speed at which plan assets would shift into PE funds, and the speed at which PE as an asset class would grow to meet the increase in demand. Because of the uncertainty surrounding these assumptions, we simulate outcomes under multiple scenarios that vary simulation parameters across the most likely range of values of alpha, beta, and the maximum share of DC assets invested in PE funds.

DYNASIM

The DYNASIM microsimulation model, which was designed to analyze the long-run distributional consequences of retirement and aging issues, starts with a representative sample of US individuals and families from 2006⁷ and ages them year by year, simulating key demographic, economic, and health events through 2093. The model projects that, each year, some people in the sample get married, have a child, or find a job, for example, and other people become divorced or widowed, stop working, begin collecting Social Security, become disabled, or die. These transitions are based on probabilities generated by carefully calibrated equations estimated from nationally representative household survey data. The equations account for differences by sex, education, earnings, and other characteristics in the likelihood of various experiences. Other equations in DYNASIM project annual earnings, savings, and home values. The model uses program rules—combined with projections of lifetime earnings, disability status, and household income and wealth—to project Social Security retirement and disability benefits and Medicaid coverage. DYNASIM also includes detailed federal and state income tax calculators, allowing it to project incomes net of taxes. For consistency with Social Security's projections about system's finances, we generally follow the Social Security and Medicare trustees' demographic and economic assumptions (Trustees 2020).

DYNASIM projects retirement accounts based on annual contributions to investment accounts and accumulated investment returns. Investment experience varies for each individual because the model sets rates of return stochastically, using historical means and standard deviations, and allocates portfolios based on an assigned individual-specific risk tolerance.⁸ In the baseline, DYNASIM allocates investments to two asset classes: stocks and bonds. The share of retirement account assets invested in stocks varies by age and risk tolerance, with highly risk-tolerant and younger individuals investing more in stocks than less risk-tolerant and older individuals. DYNASIM assigns some DC participants to invest in target-date funds, and the stock and bond portfolio mix for these investors is determined by their assigned fund. The model rebalances investment portfolios annually to preserve the target mix of stocks and bonds.⁹ DYNASIM assumes that the share of DC participants investing in target-date funds grows over time. When workers who participate in a DC plan retire, we assume they roll their savings over to an IRA and start withdrawing money to supplement their retirement income.

DYNASIM simulates annual stock and bond returns by drawing a random number for each person from a normal distribution characterized by the mean and standard deviation. We use historical rates of returns through 2020 and past average returns to project future returns. Stock returns are drawn from a normal distribution with a mean of 9.0 percent (6.5 percent real) and standard deviation of 17.3 percent (table 1). Bonds in the DC plans are a 60-to-40 mix of corporate and government bonds whose returns are drawn from a normal distribution with a mean of 5.3 percent (3.2 percent real for corporate bonds and 2.4 percent real for government bonds) and standard deviation of 2.1 percent. Our risk-free rate of return is based on historical interest rates for the three-month Treasury bill and future projections for this rate made by the Congressional Budget Office. We assume that all funds in DC plans charge the same 1.0 percent management fee. We recognize that these future returns differ from current markets returns. For example, the risk-free rate is currently close to zero. DYNASIM models returns over many decades, however, and the future returns reflect our assumptions about the long-term values of these parameters.

TABLE 1

DYNASIM Assumptions about Future Investment Returns and Inflation

Asset class	Mean	Standard Deviation
Annual returns by asset class		
Stocks	0.091	0.173
Bond portfolio	0.053	0.021
Government bond	0.048	0.021
Corporate bond	0.056	0.021
Risk-free asset	0.024	0.0
Annual inflation rate	0.024	NA

Notes: Projections are based on historical rates of returns (Trustees 2020; Ibbotson 2019). The bond portfolio consists of 60 percent corporate bonds and 40 percent government bonds. NA = not applicable.

Modeling Returns to Private Equity

To simulate PE investment, we introduce a third asset class whose returns and volatility emulate the returns and volatility of the PE funds that might become available to DC investors. We use the CAPM to simulate returns to PE funds. Denoting returns to PE by R_{PE} , returns to risk-free assets by R_f , returns to the stock market by R_m , the unexplained component of excess returns to PE by α_{PE} , the measure of systemic risk of PE by β_{PE} , and a random term drawn from a normal distribution by ε , the formula for simulating returns to PE is:

$$R_{PE} - R_f = \alpha_{PE} + \beta_{PE} (R_m - R_f) + \varepsilon$$

In the CAPM literature, the risk-free asset is commonly represented by one-month Treasury bills, whose current rate of return is close to 0. We project that, over the long run, returns to this asset will equal the rate of inflation.

Selecting the values of alpha, beta, and the standard deviation for simulations of private equity returns is one of the most consequential assumptions in this study. Because our model simulates PE funds over several decades, our parameter selection must account for future economic trends and anticipate the economic consequences of increasing PE fund investments. Given this uncertainty, our strategy is to simulate outcomes under a range of plausible values for each parameter. We selected our parameter values by reviewing the literature on PE returns, examining historical trends in those returns, and assessing how economic and regulatory factors might affect future trends.

Our review of the literature revealed a wide range of estimates for PE returns. To select parameter values, we performed both a qualitative analysis of estimation methods used by the authors and a quantitative analysis of the results. The study by Ang et al. (2018) ranked highest in the qualitative sense. The authors deployed the most compelling estimation methodology; the sample they used for the analysis is fairly recent (1994 to 2015) and representative of the most likely composition of PE investments that will be made by DC funds; and their estimates are robust and consistent with theory. Coincidentally, the estimates made by these authors are also excellent candidates in a quantitative sense. For example, looking just at the subset of private equity funds that focus on buyout funds (for which more empirical work is available), we see that their estimates of alpha and beta are close to the mean and median of all the estimates for buyout funds we reviewed. Their estimates of alpha and beta are 4 percent and 1.25 respectively. By comparison, the mean estimates of alpha and beta for this type of funds in the seven studies we reviewed are 4 percent and 1.26, and the median estimates are 4.6 percent and 1.1. Consequently, we chose the estimates from Ang et al. (2018) as the starting point for our parameter assumptions.

In the next step, we considered the likely composition of PE funds in which DC participants would invest, likely future trends in returns to PE, and likely effects of an increase in the demand for PE. The best indication of how DC fund managers might allocate their investments in PE funds is the current PE allocation in pension funds. The Preqin dataset used by Ang et al. (2018) provides a glimpse into these strategies. The dataset, which was compiled from information obtained through Freedom of Information Act requests, shows that between 1994 and 2008 US pension funds invested in 423 buyout funds and 453 VC funds. We see no reason why DC investors would adopt a substantially different strategy. Especially in light of a likely increase in the demand for PE assets, with a large volume of capital competing for limited investment opportunities, it is unlikely that DC funds will limit their investments to only one class of PE assets. Instead, DC investors, like their counterparts in pension funds, will almost certainly invest in both buyout and VC funds.¹⁰

To understand how PE fund returns might evolve, we examined recent trends in those returns. The growth of the PE industry over the last two decades has been accompanied by a decrease in the average returns to buyout PE funds. Between 2000 and 2020, the net asset value of global buyout funds increased seven-fold, while their returns, as measured by the 10-year annualized IRR, decreased by six percentage points (Bain and Company 2020). Robinson and Sensoy (2016) report similar results for both buyout and VC funds. This downward trend in returns is most likely caused by a growing demand for PE assets, which raises their price and makes high returns more difficult. Bain and Company (2020) note that the performance of PE funds in the top quartile of the returns distribution has remained steady. While this stability indicates the existence of elite PE funds that can perform consistently at the highest level, decreasing average returns indicate that returns to additional capital may be diminishing.

A large influx of retirement savings would increase demand for PE assets and raise their price, making high returns even more challenging to achieve. By the end of 2019, the combined assets under management in DC and IRAs approached \$20 trillion.¹¹ Assuming that only target-date funds, which currently hold about \$1.4 trillion in assets,¹² invest in PE funds, we estimate that capital investments in PE would increase \$70 billion if only 5 percent of target-date-fund assets invested in PE and \$140 billion if 10 percent of target-date funds invested.¹³ In 2019, investor commitments to US PE funds, including both buyout and VC, totaled about \$315 billion, a small fraction of the total \$1.4 trillion of assets under management (Mauboussin and Callahan, 2018). The PE industry would have to grow fast to accommodate this influx of capital, likely accelerating a decrease in the average rate of return to PE.

To summarize, there is no indication that returns to PE will increase. Based on recent historical trends and a likely increase in demand for PE assets, average returns to PE are likely to decrease in the

future. We expect that target-date funds will invest in both buyout and VC funds. Based on these expectations and estimates by Ang et al. (2018), we selected four values of alpha and two values of beta and the associated standard deviation. In addition, we selected two values for the maximum share of a target-date fund that may be invested in PE. Combining these parameter values yields 16 simulation scenarios (table 2).

Scenario	Alpha	Beta	Standard deviation	Maximum PE share
1	-0.01	1.25	0.280	0.075
2	-0.01	1.50	0.315	0.075
3	-0.01	1.25	0.280	0.150
4	-0.01	1.50	0.315	0.150
5	0	1.25	0.280	0.075
6	0	1.50	0.315	0.075
7	0	1.25	0.280	0.150
8	0	1.50	0.315	0.150
9	0.01	1.25	0.280	0.075
10	0.01	1.50	0.315	0.075
11	0.01	1.25	0.280	0.150
12	0.01	1.50	0.315	0.150
13	0.02	1.25	0.280	0.075
14	0.02	1.50	0.315	0.075
15	0.02	1.25	0.280	0.150
16	0.02	1.50	0.315	0.150

TABLE 2 Assumed Values of the PE Model Parameters in Our Simulation Scenarios

Source: Authors' calculations.

Notes: The standard deviation represents the total standard deviation for PE returns. The standard deviation of the random term in the CAPM model is calculated by subtracting the squared product of the PE beta and stock's standard deviation from the squared PE standard deviation and taking the square root of that value.

The highest value of alpha we selected, 2 percent, is Ang et al. (2018)'s estimate of the current average rate of return on PE funds, based on a dataset that included both buyout and VC funds. Retaining the current rate of return is, in our opinion, the most optimistic scenario for the future of PE. This does not mean that the performance of PE funds would not change. Rather, to retain today's level of returns in the face of future headwinds PE funds would have to improve their performance. More likely, in our opinion, is that the average returns to PE will continue to decline, dragging alpha down with it. The main question, then, concerns the magnitude and pace of that decline. We selected four values of alpha to represent the likely range of scenarios. We assigned the highest likelihood to the long-term alpha settling between the values of 0.0 and 1.0. Aside from a small illiquidity premium, it is unlikely that PE as an asset class can maintain a large advantage over public stock in the very long run. In a less likely but plausible scenario, in which both headwinds materialize, alpha would fall to -1.0, indicating that PE would underperform relative to the stock market. Despite a negative alpha, PE may

still be an attractive option for portfolio diversification, especially considering that its beta is greater than 1.0.

Based on the values estimated in the reviewed literature, we selected two values of beta, 1.25 and 1.50, that are likely to cover the range of plausible future values. We selected the standard deviation for PE returns as the mean of the standard deviations for buyout and VC funds estimated by Ang et al. (2018). We used this standard deviation in combination with a 1.25 beta to calculate the standard deviation of the idiosyncratic random term in the simulation model, which we used in all simulation scenarios. Because the estimates of alpha and beta are made on after-fee cash flows, our model that uses these values simulates net-of-fee returns to PE. Finally, we selected two values for the maximum share of PE in target-date funds, 7.5 percent and 15 percent. The higher value is based on DOL (2020, footnote 8), which suggests that investors' exposure to PE be limited to a certain percentage, citing the US Securities and Exchange Commission rule that includes a 15 percent limit on illiquid investments. To understand the sensitivity of our results to this assumption, we also simulated scenarios in which the maximum share invested in PE is 7.5 percent.

Target-Date Funds

One of the challenges in modeling PE assets is the treatment of liquidity, which differentiates PE from assets that are currently available to DC investors. The illiquidity of PE raises concerns about investors' short-term ability to move their funds into other assets or withdraw them as needed. Recognizing these concerns, DOL (2020) suggests that if PE funds are added to a DC portfolio, they must be treated differently from other assets. While the letter does not specify conditions for adding PE to a DC plan, it suggests some restrictions that might be necessary for the plan to remain compliant with ERISA. In addition to limiting exposure to PE funds, the letter assumes that PE funds would be offered only as part of a multi-asset class vehicle, such as a target-date fund, and that such a vehicle would be professionally managed. This restriction would all but guarantee that, with respect to liquidity, PE funds would appear to investors as equivalent to traditional assets. We conduct our simulations under this assumption. We make PE funds available only through target-date funds.

Target-date funds are defined by their glide paths, which specify the shares of stocks and bonds investors hold in their portfolio at each age. As investors age, glide paths typically reduce the share of stocks in their portfolios and increase the share of bonds. DYNASIM simulates 42 target-date funds, each with a distinct glide path (figure 4). Diversifying a fund by investing in PE requires a new glide path that defines shares of stocks, bonds, and PE funds. We determine the PE share based on the initial allocation to stocks and bonds. We assume that funds that hold less than 10 percent of their portfolio in stocks do not invest in PE and those that hold 90 or more percent in stocks invest the maximum share in PE. For funds with initial stock holdings between 10 and 90 percent, we calculate the PE share by linear interpolation.

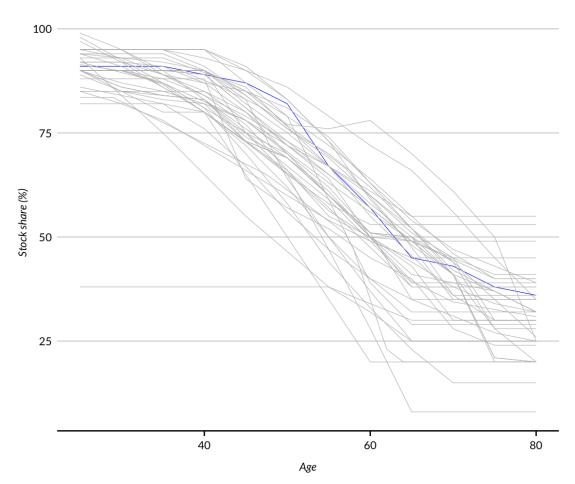


FIGURE 4

Share of Stocks by Age in Target-Date Funds Simulated by DYNASIM

Source: Morningstar (2012).

Note: Each line represents one target-date fund, showing the share of stocks in an investor's portfolio by age. Remaining funds are invested in bonds. The blue line represents the fund we used in our hypothetical simulations of a single target-date fund.

Once the PE share is determined, our model must rebalance stocks and bonds within the targetdate fund. We were not able to find specific information on this process in the literature, so we considered three portfolio-allocation approaches that a fund manager might adopt when adding PE to a portfolio. The *alpha-based* approach focuses on returns and sets the mix of stocks and bonds so that the portfolio's expected return after adding PE equals the initial portfolio's expected return plus the PE fund's alpha weighted by the PE share. The other two approaches focus on risk. The *beta-based* approach allocates stocks and bonds in such a way that the portfolio's beta remains the same as before the addition of PE. The *sigma-based* approach holds the portfolio's variance constant.

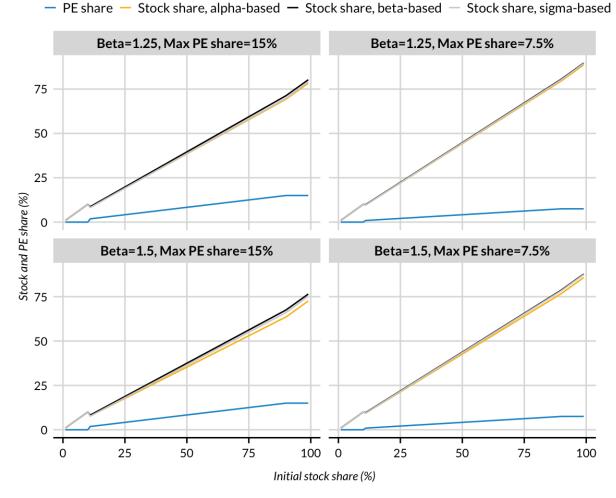
Using these three methods, we calculated, for any given initial shares of stocks and bonds, the shares of stocks and bonds after adding PE funds to the portfolio. We repeated these calculations for all four combinations of the two beta values and two values of the maximum PE share (figure 5). Although the calculation method does not matter much, the beta-based method results in the highest stock share and the alpha-based method results in the lowest stock share. We opted to use the middle-of-the-road sigma-based approach in our simulations. Considering that target-date-fund managers design their glide paths based on risk, they likely would adopt a risk-focused approach to rebalancing rather than one focused on returns. Moreover, of the two risk-focused approaches we considered, the sigma-based approach can be implemented more accurately than the beta-based approach because we assume a zero-beta for bonds, which almost certainly would underestimate the total portfolio risk.

Because PE carries a greater risk than stocks, investing a given share of a portfolio in PE requires divesting a larger share from stocks and increasing the share of bonds to maintain the portfolio's overall variance. For example, if the beta is 1.25, the maximum PE share is 15 percent, and the portfolio initially held 40 percent stocks and 60 percent bonds, our behavioral assumptions imply that the portfolio manager would invest 6.7 percent of the fund's assets in PE, reduce the stocks share to 30.8 percent, and increase the bonds share to 62.5 percent.

FIGURE 5

Rebalancing Strategies when Investing in PE Funds

For three values of the PE share



Source: Authors' calculations.

Notes: Values are plotted for two maximum values of PE shares, 7.5 and 15 percent, and two values of beta, 1.25 and 1.50. A fund invests in PE only if it initially holds at least 10 percent of its funds in stocks. The share of PE is set at the maximum value for funds that initially held at least 90 percent of their funds in shocks. The alpha-based method adjusts stock shares so that the portfolio's expected return changes by alpha, the beta-based method adjusts the stock share to keep the portfolio beta fixed, and the sigma-based method holds the portfolio variance constant.

Results

Our main results come from DYNASIM, which simulates people with realistic earnings histories and savings patterns. These simulations include many factors that affect savings behavior and produce results that represent the best and most realistic projections of actual savings. However, these factors introduce some noise that can blur some patterns that may be of interest. To show clearly the patterns caused by the choice of model parameters, we first show simulations of a hypothetical saver. The example is unrealistic, but it allows us to see the effects of investment in PE more clearly by isolating them from other factors such as differences in savings rates, withdrawals, glide paths, etc. We then report results from our DYNASIM simulations.

Simulations of a Target-Date Fund

We report simulations of investment returns in a target-date fund that holds stocks and bonds and compare them with simulated returns in the same fund when it includes PE in its portfolio. We first simulate one-year investment returns at age 50 under the 16 different scenarios. Then we simulate cumulative savings over a career from ages 30 to 65. In each case, we draw 100,000 random samples for each age.

Table 3 shows simulated returns to a target-date fund that, for 50-year-old investors, holds 82 percent of its portfolio in stocks and 18 percent in a mix of corporate and government bonds. After investing in PE, the portfolio differs across the various scenarios. When the maximum PE share is 7.5 percent, this fund would allocate 6.8 percent of its assets to PE; when the maximum is 15 percent, the PE allocation would reach 13.7 percent. The allocation to stocks and bonds depends on beta. With the PE share at 6.8 percent, the stock share is 73.1 percent for the low beta and 71.4 percent for the high beta. When the PE share is 13.7 percent, the stock share is 63.6 percent for the low beta and 60.2 percent for the high beta. The rest of the portfolio is invested in bonds. We calculated the mean and standard deviation of these returns, as well as of the difference between each scenario and the baseline.

TABLE 3

Simulated Returns to a Target-Date Fund with and without PE

						Differe	nce Relativ	e to the
	Mo	del Parar	neters	Annual	Returns		Baseline	
			Maximum				Mean	
Scenario	Alpha	Beta	PE share	Mean	SD	Mean	(%)	SD
1	-0.01	1.25	0.075	0.0734	0.1415	-0.0005	-0.7368	0.0122
2	-0.01	1.50	0.075	0.0737	0.1415	-0.0002	-0.2946	0.0122
3	-0.01	1.25	0.150	0.0726	0.1415	-0.0013	-1.7935	0.0244
4	-0.01	1.50	0.150	0.0733	0.1415	-0.0007	-0.9127	0.0244
5	0.00	1.25	0.075	0.0741	0.1415	0.0001	0.1871	0.0122
6	0.00	1.50	0.075	0.0744	0.1415	0.0005	0.6293	0.0122
7	0.00	1.25	0.150	0.0740	0.1415	0.0000	0.0544	0.0244
8	0.00	1.50	0.150	0.0747	0.1415	0.0007	0.9352	0.0244
9	0.01	1.25	0.075	0.0748	0.1415	0.0008	1.1110	0.0122
10	0.01	1.50	0.075	0.0751	0.1415	0.0011	1.5532	0.0122
11	0.01	1.25	0.150	0.0754	0.1415	0.0014	1.9022	0.0244
12	0.01	1.50	0.150	0.0760	0.1415	0.0021	2.7830	0.0244
13	0.02	1.25	0.075	0.0755	0.1415	0.0015	2.0350	0.0122
14	0.02	1.50	0.075	0.0758	0.1415	0.0018	2.4771	0.0122
15	0.02	1.25	0.150	0.0767	0.1415	0.0028	3.7500	0.0244
16	0.02	1.50	0.150	0.0774	0.1415	0.0034	4.6308	0.0244

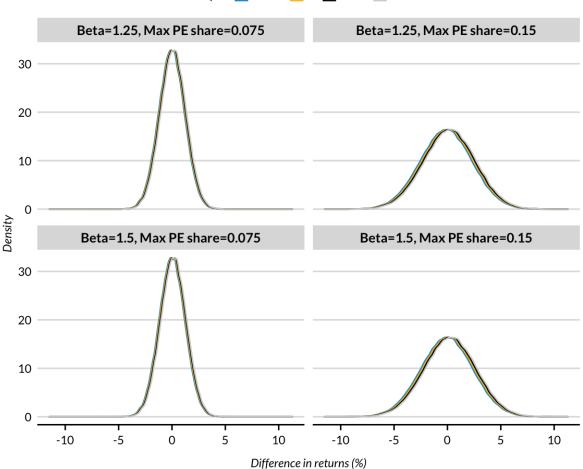
Source: Authors' calculations.

Notes: Returns were simulated at age 50, when the fund holds 82 percent of its assets in stocks and 18 percent in bonds. Under the baseline, the returns have a mean of 7.4 percent and standard deviation of 0.1415. The actual PE share is 6.8 percent in scenarios with the maximum PE share of 7.5 percent and 13.7 percent in scenarios with the maximum of 15 percent. The stock share ranges from 60.2 percent in scenarios with a high beta and high max PE share to 73.1 percent in scenarios with a low beta and low maximum PE share. The risk-free rate of return is 2.4 percent. For each scenario, 100,000 samples were randomly drawn.

The average annual returns to the baseline fund that contains only stocks and bonds was 0.074 with a standard deviation of 0.1415 (not shown in the table). As expected, alpha is the main determinant of average returns to the fund. Diversifying investments to include PE increased average returns under scenarios that assumed a non-negative alpha, with gains ranging from 0.05 percent under scenario 7 to 4.6 percent under scenario 16. Average returns increased even with alpha equal to 0 because of the diversification provided by PE investments. The losses in the case of negative alpha ranged from 0.29 percent under scenario 2 to 1.79 percent under scenario 3. The second most important determinant of average gains is the PE share, which in one case dominates the effect of alpha. Scenario 12 with an alpha of 0.01 and PE share of 15 percent generated higher gains relative to the baseline than scenario 14 with an alpha of 0.02 and PE share of 7.5 percent. Both scenarios have a beta of 1.5. Finally, the average gains also grow with beta for fixed values of alpha and PE share.

FIGURE 6

Distribution of the Difference in Simulated Annual Returns in a Target-Date Fund that Invests in PE *Relative to investment returns in target-date funds that exclude PE*



Alpha 🔲 -0.01 🗌 0 🔲 0.01 🗌 0.02

Source: Authors' calculations.

Notes: Returns were simulated at age 50, when the fund holds 82 percent of its assets in stocks and 18 percent in bonds. Under the baseline, the returns have a mean of 7.4 percent and standard deviation of 0.1415. The actual PE share is 6.8 percent in scenarios with the maximum PE share of 7.5 percent and 13.7 percent in scenarios with the maximum of 15 percent. The stock share ranges from 60.2 percent in scenarios with a high beta and high max PE share to 73.1 percent in scenarios with a low beta and low maximum PE share. The risk-free rate of return is 2.4 percent. For each scenario, 100,000 samples were randomly drawn.

The standard deviation of the fund's returns did not change after PE was added to the mix because our allocation strategy assumption holds the standard deviation constant. Figure 6 shows the distribution of gains under each scenario relative to the baseline. A relatively wide spread shows that even in cases in which investors were on average better off by investing in the fund with PE, individual returns can sometimes be lower when investments include PE than when they do not. To see how these differences in returns play out over longer, career-length periods, we also simulated savings in an unrealistic but illustrative example of a hypothetical target-date-fund investor who saved \$1 per year between ages 30 and 65 (table 4). As in the previous example, the target-date fund under the baseline invests only in stocks and bonds. At age 30, 91 percent of the portfolio is invested in stocks and 9 percent in bonds. This ratio gradually changes to 45 percent in stocks and 55 percent in bonds by age 65. Among the 100,000 simulated savers, the mean cumulative savings at age 65 were \$124.15 and their standard deviation was \$91.5. When PE is added to the mix, the fund starts at younger ages with the maximum share of PE–7.5 percent or 15 percent—and falls by half at age 65 to 3.75 percent or 7.5 percent. The associated shares of stocks vary between 67 percent and 81 percent at age 30, and between 33 percent and 40 percent at age 65. The mean savings at age 65 varied between \$120.12 in scenario 3 and \$136.59 in scenario 16. Relative to the baseline, this ranged between a mean loss of 3.2 percent (scenario 3) to a mean gain of 10.0 percent (scenario 16). For each assumed value of alpha, however, individual outcomes vary widely around the mean savings difference (figure 7).

TABLE 4

	Mo	del Paramo	eters		Balance at e 65	Differe	nce Relativ Baseline	e to the
			Max PE	Mean		Mean	Mean	
Scenario	Alpha	Beta	share	(\$)	SD (\$)	(\$)	(%)	SD (\$)
1	-0.01	1.25	0.075	122.52	90.38	-1.64	-1.32	8.58
2	-0.01	1.50	0.075	123.60	91.07	-0.55	-0.44	8.56
3	-0.01	1.25	0.150	120.12	88.72	-4.03	-3.24	17.14
4	-0.01	1.50	0.150	122.26	90.07	-1.89	-1.52	17.13
5	0.00	1.25	0.075	124.81	91.85	0.66	0.53	8.57
6	0.00	1.50	0.075	125.92	92.55	1.76	1.42	8.67
7	0.00	1.25	0.150	124.68	91.62	0.52	0.42	17.18
8	0.00	1.50	0.150	126.88	93.01	2.73	2.20	17.40
9	0.01	1.25	0.075	127.15	93.34	3.00	2.41	8.82
10	0.01	1.50	0.075	128.27	94.05	4.12	3.32	9.04
11	0.01	1.25	0.150	129.38	94.61	5.23	4.21	17.72
12	0.01	1.50	0.150	131.66	96.05	7.50	6.04	18.19
13	0.02	1.25	0.075	129.52	94.85	5.37	4.32	9.32
14	0.02	1.50	0.075	130.66	95.58	6.51	5.24	9.65
15	0.02	1.25	0.150	134.24	97.71	10.08	8.12	18.79
16	0.02	1.50	0.150	136.59	99.20	12.44	10.02	19.48

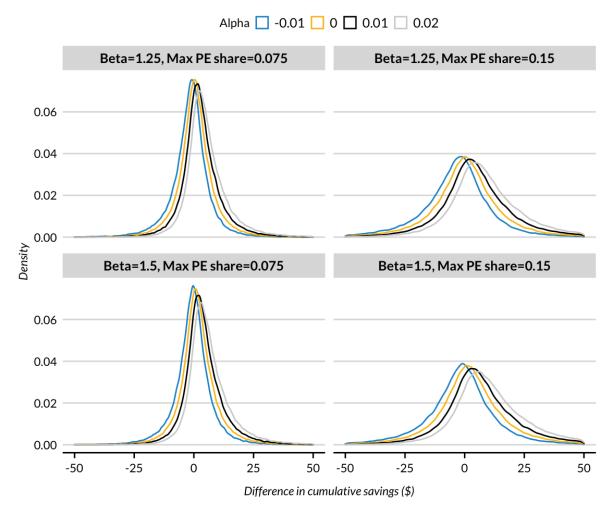
Simulated Savings in a Target-Date Fund with and without PE

Source: Authors' calculations.

Notes: Simulated 401(k) participant invested \$1 per year in a target-date fund between ages 30 and 65. Under the baseline, at age 30, the fund holds 91 percent of its assets in stocks and 9 percent in bonds. This ratio changes to 45 percent in stocks and 55 percent in bonds by age 65. Under scenarios that include PE, the fund starts at younger ages with 7.5 percent or 15 percent of PE and falls by half at age 65 to 3.75 percent or 7.5 percent. The associated shares of stocks vary between 67 percent and 81 percent at age 30, and between 33 percent and 40 percent at age 65. The risk-free rate of return equals 2.4 percent, the rate of inflation. For each scenario, 100,000 samples were randomly drawn.

FIGURE 7

Distribution of the Difference in Simulated Savings in a Target-Date Fund with and without PE For investors who save \$1 per year from ages 30 to 65



Source: Authors' calculations.

Notes: Simulated investors invested \$1 per year in a target-date fund between ages 30 and 65. At age 30, the fund holds 91 percent in stocks and 9 percent in bonds. After investing 10 percent in PE, the stock share is 76.5 percent and the bond share is 13.5 percent. At each subsequent age, the portfolio is rebalanced according to the fund's glide path. The last contribution is at age 65, at which the no-PE fund contains 45 percent stocks and 55 percent bonds, and the fund with PE contains 30.5 percent stocks, 10 percent PE, and 59.5 percent bonds. Risk-free rate of return is 2.4 percent, the rate of inflation. For each scenario, 100,000 samples were randomly drawn.

DYNASIM Simulations

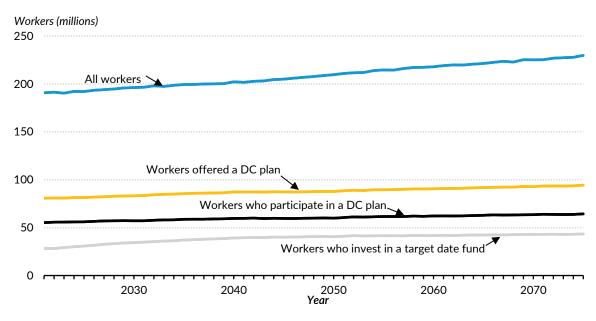
Our DYNASIM simulations show outcomes for a nationally representative sample of workers rather than hypothetical cases. We first consider baseline projections of the aggregate number of people who invest in DC plans and the amount of assets they hold, and show how they evolve over the simulation period. We also report the demographic composition of people with DC plans and those who invest in target-date funds. We then report simulated outcomes under different scenarios in which target-date funds invest in PE and show how they differ from the baseline. We report most outcomes as percentage differences relative to the baseline. We report contribution amounts and account balances in inflation-adjusted 2020 dollars. Our projection period runs through 2075.

We project that by the end of 2021, the economy will recover sufficiently to bring the total number of workers to 191 million, above the prepandemic level. Absent any major shocks, the labor force is projected to reach 230 million by 2075, the end of our projection period (figure 8). The fraction of workers who are offered a retirement savings plan by their employer recently has been about 43 percent, and we project it to remain at that level in the long run. Among the workers who are offered a DC plan, about two-thirds decide to participants, bringing the number of participants to 55 million in 2021 and 64 million in 2075. Among participants, about half were investing in target-date funds in 2021. We project that this share will gradually increase to about 65 percent in 2040 and remain at that level throughout the analysis period. The rising share of target-date fund participants reflects an increase in the number of plans that offer target-date funds and the rising use of target-date funds as the default investment fund (Investment Company Institute 2020; Shoven and Walton 2020).

Narrowing our focus to workers ages 25 to 69, who are most likely to participate in a DC plan, we project that this age group will include 156 million workers in 2022, when DC funds will start investing in PE under our simulated scenarios (table 5). We project that employers will offer DC plans to 52 percent of workers in this age range, and about two-thirds of these workers will accept the offer and contribute to their plan. The average size of the projected employer plus worker contribution is about \$8,400 in 2020 inflation-adjusted dollars, although contributions are significantly higher for some workers and significantly lower for others.¹⁴ The participation rate is highest among white workers, who are most likely to receive a retirement plan offer from an employer and most likely to participate when a plan is available. Projected plan offer and participation rates are lowest for Hispanic workers.

FIGURE 8





Source: DYNASIM4 ID981.

Educational attainment is an even stronger predictor of having access to and participating in an employer-sponsored DC plan. About 63 percent of college graduates are offered a plan, compared with only 24 percent of those without high school diploma. Among college graduates who are offered a plan, 77 percent opt to participate, resulting in an unconditional participation rate of about 50 percent. Among those without a high school diploma, however, the acceptance rate is about one-half of the college graduates' rate, resulting in a 9 percent unconditional participation rate. Younger workers are more likely than older workers to be offered a DC plan, but the participation rate peaks for workers in their early 50s. The average contribution increases with age and plateaus at about \$11,000 at ages 55 to 69.

TABLE 5

		Percentage of Workers with DC Plans		Annual DC Contributions (\$2020)		
	Number of workers (millions)	Offered	Participate	Mean	Standard deviation	
All	155.7	51.9	34.8	8,425	8,860	
Race and Hispanic origin				,	,	
White non-Hispanic	96.2	55.8	38.6	9,211	9,270	
Black non-Hispanic	18.2	50.0	31.1	5,732	6,859	
Hispanic	28.0	39.4	23.2	5,953	7,036	
Other	13.3	52.8	36.1	8,842	8,683	
Education						
No high school diploma	11.1	23.8	9.3	4,094	5,835	
High school graduate	40.6	42.3	23.2	5,523	6,523	
Some college	45.0	52.8	33.6	6,924	7,617	
College graduate	59.0	63.2	48.4	10,321	9,719	
Age						
25-29	20.5	56.7	33.8	3,923	4,874	
30-34	21.7	53.3	32.8	6,139	6,975	
35-39	20.1	52.3	34.5	7,619	7,733	
40-44	19.0	50.4	34.2	8,452	8,060	
45-49	16.9	52.8	36.9	8,621	7,904	
50-54	17.7	53.5	38.8	10,117	9,956	
55-59	16.9	49.8	36.6	11,357	10,732	
60-64	14.5	48.9	33.9	11,343	10,360	
65-69	8.4	43.7	28.7	11,221	10,513	

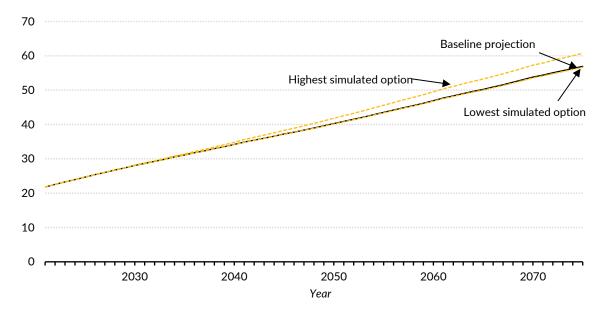
Demographic Composition of Workers and DC Plan Participants, and their DC Contributions in 2022

Source: DYNASIM4 ID981.

Notes: The table is limited to workers ages 25 to 69. The mean and standard deviation of annual contributions to DC plans are calculated for the subset of workers who participate in a DC plan. DC contributions include both the employer and worker contribution.

Under the baseline, total DC savings, which include the DC assets of active contributors and the assets of retirees that were rolled over into IRAs, are projected to grow at an average real annual rate of 1.76 percent, increasing from \$22.6 trillion in 2022 to about \$57 trillion in 2075 (figure 9). Under simulated alternatives, in which DC funds invest in PE, the assets would most likely grow at a higher rate than under the baseline, although two of the scenarios with a negative alpha had a marginally slower growth rate. All other scenarios generated higher rates of asset growth, with scenario 16 producing the highest average growth rate of 1.89 percent and a total balance of \$61 trillion in 2075.

FIGURE 9



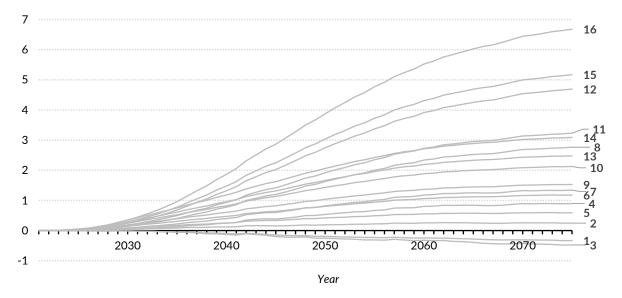
Total Assets in Retirement Savings Accounts, Baseline and the Simulated Range, 2021–75 *Trillions of constant 2020 dollars*

Source: DYNASIM4 ID981.

Notes: Total assets in retirement savings accounts including 401(k) and IRA. The solid black line represents the baseline, and the two dashed yellow lines represent the range of simulated outcomes. The asset values are reported in inflation-adjusted 2020 dollars.

Figure 10 shows percentage changes in asset values under simulated scenarios relative to the baseline. In 2075, the end of the analysis period, the changes range from -0.5 percent (scenario 3) to 6.7 percent (scenario 16).

FIGURE 10



Percent Change in Simulated Retirement Savings Relative to the Baseline, 2021–75 By scenario

Source: DYNASIM4 ID981.

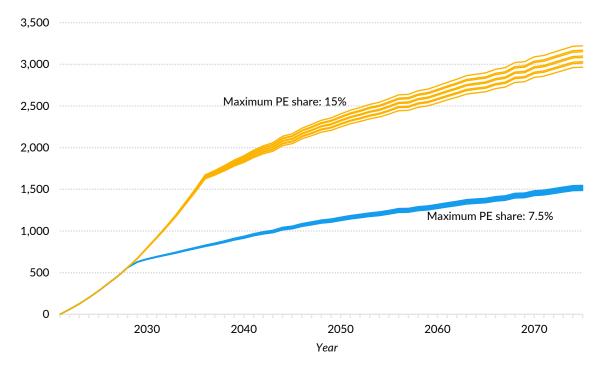
Notes: Percent change in total assets in retirement savings accounts between scenarios that include PE funds and the baseline. Table 4 shows parameter values for the 16 scenarios. Endpoint labels indicate the scenario number.

These results show a likely range of future outcomes, driven largely by our assumptions about returns to PE assets and their correlation with stock market returns. A scenario with a higher value of alpha or beta produces higher returns than a scenario with a lower value of alpha or beta, assuming all other parameters are the same. By contrast, the effect of the maximum share that a target-date fund can hold in PE is not monotonic. When alpha is positive, a higher maximum share of PE increases asset growth, but when alpha is negative, a higher value of this parameter can reduce asset growth.

The two values of the maximum PE allocations that we used in the simulations—7.5 and 15 percent—create a bimodal distribution of the PE assets held by DC plans (figure 11). In the first year of the policy, the total value of PE assets in retirement savings funds is about \$60 billion.¹⁵ Because we assume that target-date funds gradually increase their PE share by 1 percentage point annually until they reach the maximum, the value of PE assets in retirement savings plans does not vary much across scenarios over the first seven years of the policy; PE assets in those plans reach \$560 billion in 2028, which is more than a quarter of the total assets that PE funds had under management in 2019. In 2029, the PE asset values bifurcate into two distinct groups. In 2075, PE asset values reach around \$1.5 trillion in 2020 price-adjusted dollars when PE is capped at 7.5 percent of target-date fund holdings and about double that amount when the cap is set at 15 percent.

FIGURE 11

DC Assets Invested in PE Funds by Scenario, 2021-75 Billions of constant 2020 dollars



Source: DYNASIM4 ID981.

Notes: Each line represents total PE assets under 1 of the 16 simulated scenarios. Yellow lines show scenarios with PE share capped at 15 percent. Blue lines show scenarios with PE share capped at 7.5 percent. Table 4 shows parameter values for the 16 scenarios.

To better understand how these changes would affect retirement income, we look at retirement savings and individual incomes at age 65—the age at which many workers have retired or are near retirement—across five 10-year birth cohorts. The oldest cohort that could invest in PE, people born between 1961 and 1970, includes late baby boomers and early Gen Xers who will turn 65 between 2026 and 2035. The youngest cohort we consider includes Gen Zers born between 2001 and 2010 who will turn 65 between 2066 and 2075.

According to our assumptions, only people who choose to hold their retirement savings in a target-date fund could invest in PE. At age 65, a quarter of people born between 1961 and 1970 are projected to have ever held their retirement savings in a target-date fund that invested in PE (table 6). This share will increase steadily across subsequent cohorts, reaching 59 percent for those born between 2001 and 2010. Because this cumulative measure includes anyone who invested in a target-

date fund at some point, it may exceed the percentage of workers projected to participate in a DC plan at a point in time.

TABLE 6

Share of Adults Who Held Retirement Savings in a Target-Date Fund by Age 65

By demographic characteristics

	1961-1970	1971-1980	1981-1990	1991-2000	2001-2010
All	25.5	40.1	54.3	57.8	58.8
Race and ethnicity					
White non-Hispanic	29.3	46.0	60.3	63.2	65.5
Black non-Hispanic	20.8	38.6	52.6	56.1	57.4
Hispanic	14.9	24.3	40.2	48.2	47.9
Other	24.4	40.2	54.3	58.4	59.7
Education					
No high school diploma	7.1	14.6	25.3	29.3	28.3
High school graduate	18.1	31.2	45.5	52.4	53.5
Some college	27.3	45.0	58.7	62.0	62.6
College graduate	37.7	51.4	64.5	67.1	68.1
Shared lifetime earnings quinti	le				
Bottom quintile	7.5	15.1	25.0	31.1	32.1
2nd quintile	16.0	31.7	47.4	53.3	54.4
Middle quintile	25.5	43.7	60.2	63.2	63.3
4th quintile	34.4	51.8	67.6	68.4	69.4
Top quintile	44.0	58.1	71.2	73.4	74.7

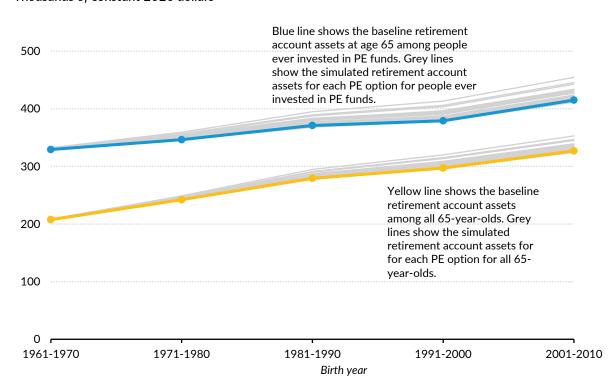
Source: DYNASIM4 ID981.

Notes: Couples split earnings in years they are married in the shared lifetime earnings measure and includes earnings from age 20 to 70.

Race, education, and income differences in the likelihood of investing in PE are similar to differences in DC plan participation, and they diminish over time. Among people born between 1961 and 1970, white people are 40 percent more likely to have invested in PE than Black people and twice as likely as Hispanic people. For people born between 2001 and 2010, however, white people are projected to be only 13 percent more likely than Black people to have held some retirement savings in PE and 31 percent more likely than Hispanic people. The same pattern holds for educational attainment and lifetime earnings differences. People with higher level of educational attainment and higher lifetime earnings are more likely to have retirement accounts assets at age 65 and to have ever invested in PE, but these differences decrease over time as people in later cohorts have more years to save in PE funds and more firms include target-date fund options in their DC plans.

Those who invested in target-date funds had significantly higher retirement account balances than the general population under the baseline, but this difference shrinks as more people invest in targetdate funds (figure 12). People born between 1961 and 1970 who invested in target-date funds averaged \$329,000 in retirement savings at age 65, which was more than 50 percent higher than the general population, including people with no retirement accounts. Simulated changes in asset allocation had little effect on the savings of this cohort. Average savings grew for subsequent cohorts, reaching \$415,000 for target-date-fund investors and \$327,000 for the general population for the 2001 to 2010 cohort in 2020 price-adjusted dollars. Similar to the aggregate assets, the simulated changes in asset allocation increased average retirement account balances at age 65 under 14 scenarios and decreased them under 2 scenarios (figure 12).

FIGURE 12



Average Retirement Account Balance at Age 65 by Scenario, Birth Year, and TDF Status Thousands of constant 2020 dollars

Source: DYNASIM4 ID981.

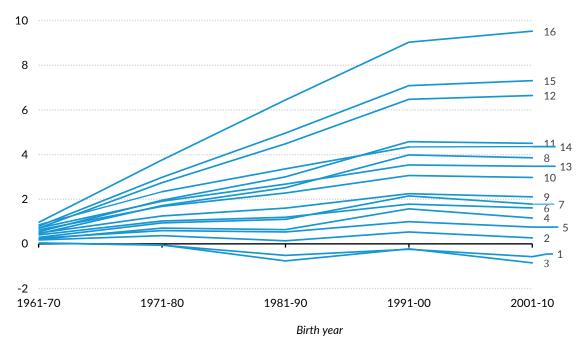
Notes: The average retirement savings account at 65 for those who ever invested in target-date funds in blue and for all in yellow. Grey lines represent outcomes in simulated scenarios. Table 4 shows the parameter values for the 16 scenarios.

Among people born between 2001 and 2010 who ever invested in a PE fund, the average change in retirement account assets at age 65 ranged from a 0.9 percent loss (scenario 3) to a 9.5 percent gain (scenario 16) (figure 13). Access to PE investments would increase average retirement accounts by 3.9 percent under scenario 8, which assumes sets alpha at 0, beta at 1.5, and maximum PE share at 15 percent. The gains and losses are smaller in earlier cohorts who have fewer years ever invested in PE

funds than later cohorts. Average percentage gains are higher for simulations with higher assumed alpha (scenarios 13 to 16) than simulations with lower alpha (scenarios 1 to 4), but scenario 11 with alpha of 1 percent generates a higher percentage gain than scenario 14 with alpha of 2 percent because scenario 11 has a higher share of assets invested in PE (15 percent maximum) than scenario 14 (7.5 percent maximum).

FIGURE 13

Percent Change in Retirement Account Assets at Age 65 among People Ever Invested in PE By birth year and scenario



Source: DYNASIM4 ID981.

Notes: The figure is limited to people ever invested in PE funds by age 65. Table 4 shows the parameter values for the 16 scenarios.

Among 65-year-olds born between 2001 and 2010 who ever invested in a target-date fund, average retirement account assets at age 65 is about \$415,100 in 2020 price-adjusted dollars, but average retirement savings varies markedly by lifetime earnings. The bottom 20 percent of lifetime earners are projected to accumulate only \$48,300 at age 65, the middle 20 percent earners accumulate \$246,800, and the top 20 percent accumulate \$889,300 on average in 2020 price-adjusted dollars (table 7). Values by race, ethnicity, and educational attainment reflect underlying differences in projected lifetime earnings of these subgroups. White people save more on average

than Black and Hispanic people. Higher educated people save more on average than lower educated people (appendix table A1).

TABLE 7

Average Retirement Account Assets and Change in Average Assets at Age 65 among People who Ever Invested in a Target-Date Fund by Shared Lifetime Earnings Quintile and Scenario Adults born between 2001 and 2010 (thousands of 2020 price-adjusted dollars)

			Shareu Lifeume Earnings Quintile							
Scenario	All	Bottom qui	ntile Second o	quintile Middle d	quintile Fourth q	uintile Top quintile				
Baseline	415.1	48.3	136	.3 246	5.8 446	.8 889.3				
_			Change compare	ed with the baseline	e (\$ thousands)					
1 -	-2.4	-0.5	-0.9	-1.3	-3.0	-4.6				
2	1.1	0.1	0.5	0.9	0.8	2.6				
3	-3.5	-0.8	-1.2	-1.8	-4.7	-6.7				
4	4.8	0.4	2.1	3.2	4.1	10.7				
5	3.1	0.4	1.2	2.1	2.9	6.8				
6	6.7	0.9	2.6	4.3	6.7	14.1				
7	7.4	0.9	3.1	4.8	6.9	16.0				
8	16.0 📕	2.2	6.4	10.1	15.9	34.0				
9	8.7	1.3	3.5	5.6	8.8	18.4				
10	12.3	1.9	4.8	7.8	12.6	25.9				
11	18.7	2.6	7.6	11.8	18.8	39.4				
12	27.6	4.0	11.0	17.2	28.2	58.0				
13	14.4	2.2	5.6	9.1	14.8	30.2				
14	18.1	2.8	7.0	11.4	18.7	37.8				
15	30.3	4.5	12.1	19.0	31.1	63.6				
16	39.5	5.8	15.6	24.6	40.9	82.9				

Shared Lifetime Earnings Quintile

Source: DYNASIM4 ID981.

Notes: The table includes all people born between 2001 and 2010 at age 65 who ever invested in target-date funds. Couples split earnings in years they are married in the shared lifetime earnings measure and includes earnings from age 20 to 70. Table 4 shows the parameter values for the 16 scenarios.

Expanding target-date fund portfolios to include PE would increase average retirement account savings at age 65 in all but two scenarios (scenarios 1 and 3). The change in average projected retirement account savings in 2020 price-adjusted dollars ranges from a \$3,500 decline (scenario 3) to a \$39,500 increase (scenario 16) overall, but changes are larger for higher lifetime earners than for lower lifetime earners. High lifetime earners are more likely to work more years, receive a DC plan offer, contribute to an offered plan, and make large contributions than low lifetime earners. High earners also are less likely to cash out their accounts or borrow from them before retirement than low lifetime earners, allowing high earners to amass greater savings. Under the most optimistic scenario (scenario 16), average projected retirement savings increases by \$5,800 for the bottom quintile earners and by \$82,900 for top quintile earners with PE investments. Under the most pessimistic

scenario (scenario 3), average projected retirement savings falls by \$800 for bottom quintile earners and by \$6,700 for top quintile earners. Appendix table A1 shows changes by race, ethnicity, and educational attainment.

The change in retirement savings from adding PE to target-date fund portfolios in percentage terms is more evenly distributed by lifetime earnings quintile than dollar changes (table 8). In percentage terms, the bottom quintile lifetime earners are both the biggest winners and biggest losers from including PE in target-date fund portfolios, gaining 12.1 percent in scenario 16 and losing 1.7 percent in scenario 3. Scenarios with high alpha (scenarios 13 to 16) generate higher average gains than scenarios with low alpha (scenarios 1 to 4). Scenario 16, which generates the largest gains, has the highest alpha (2 percent), highest maximum allocation to PE (15 percent), and the highest beta (1.5). Scenario 3, which generates the largest losses, has the smallest alpha (-1 percent), highest maximum allocation to PE (15 percent), and smallest beta (1.2). Appendix table A2 shows percent changes by race, ethnicity, and educational attainment.

TABLE 8

Percent Change in Average Retirement Account Assets at Age 65 by Shared Lifetime Earnings Quintile and Scenario

Adul	ts l	born l	between	2001	and	2010	who	ever	invested	in	a target-d	ate fu	nd
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		Shared Lifetime Earnings Quintile										
Scenario	All	Bottom quintile	Second quintile	Middle quintile	Fourth quintile	Top quintile						
		Percen	Percent change compared with the baseline									
1	-0.6	-1.0	-0.6	-0.5	-0.7	-0.5						
2	0.3	0.1	0.4	0.3	0.2	0.3						
3	-0.9	-1.7	-0.9	-0.7	-1.1	-0.8						
4	1.2	0.8	1.5 📜	1.3	0.9	1.2						
5	0.8	0.8	0.9	0.9	0.6	0.8 🛔						
6	1.6	1.9	1.9	1.7 📜	1.5 📘	1.6 📘						
7	1.8 📕	1.9	2.3 📜	1.9	1.5 📘	1.8 📘						
8	3.9	4.5	4.7	4.1	3.6	3.8						
9	2.1	2.7	2.5	2.3	2.0	2.1						
10	3.0 📃	3.8	3.5 📃	3.2	2.8	2.9						
11	4.5	5.5	5.6	4.8	4.2	4.4						
12	6.6	8.2	8.1	7.0	6.3	6.5						
13	3.5	4.6	4.1	3.7	3.3 📩	3.4						
14	4.4	5.7	5.2	4.6	4.2	4.3						
15	7.3	9.2	8.9	7.7	7.0	7.2						
16	9.5	12.1	11.5	10.0	9.2	9.3						

Source: DYNASIM4 ID981.

Notes: The table includes all people born between 2001 and 2010 at age 65 who ever invested in target-date funds. Couples split earnings in years they are married in the shared lifetime earnings measure and includes earnings from age 20 to 70. Table 4 shows the parameter values for the 16 scenarios.

We project that extending PE investments to retirement accounts would change retirement account assets for about half (51 percent) of people born between 2001 and 2010. The other half either never invested in PE or reached age 65 with no retirement account assets. Among those invested in PE, each simulated scenario leaves some people worse off than they were under the baseline, even if the scenario is more favorable than the baseline on average, because PE returns have a relatively wide distribution. In the most optimistic scenario (scenario 16), 77 percent of affected investors accumulate more by investing in PE, but 23 percent accumulate less (table 9). Under the most pessimistic scenario (scenario 3) 45 percent accumulate more, and 55 percent accumulate less. The greater the share invested in PE, the greater the percentage gains and losses in retirement account holdings. For example, among scenarios 1 through 4 with alpha equal to -1 percent, scenarios 3 and 4, which invest up to 15 percent of retirement account assets in PE, have larger percentage gains and losses than scenarios 1 and 2, which invest up to 7.5 percent of retirement accounts in PE. Similarly, among scenarios 13 through 16 with alpha equal to 2 percent, scenarios 15 and 16, which invest up to 15 percent of retirement accounts in PE, have larger percentage gains and losses in retirement account than scenarios 13 and 14, which invest up to 7.5 percent of retirement accounts in PE. The size of beta has a smaller impact on retirement account assets than the share invested in PE or the value of alpha.

TABLE 9

Distribution of the Change in Average Retirement Account Assets at Age 65 by Scenario

Percent Change in Retirement Account Assets 3 to 0% More than 10 to 3% 0 to 3% 3 to 10% More than 10% lower 10% higher Scenario lower lower higher higher

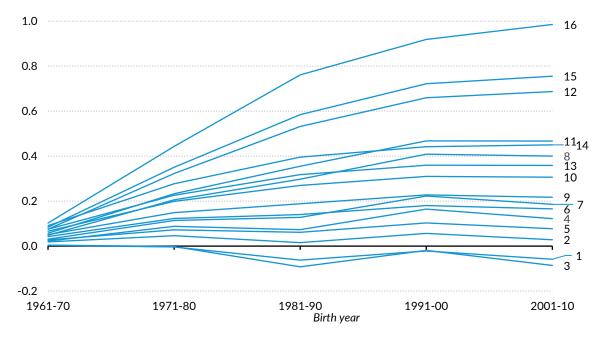
Adults born between 2001 and 2010 who experience a change in retirement account balances

Source: DYNASIM4 ID981.

Notes: The table includes all people born between 2001 and 2010 at age 65 with a change in retirement account assets. Table 4 shows the parameter values for the 16 scenarios.

We also simulated income at age 65 to understand the potential impact of opening PE investments to retirement savings plans. Simulated income consists of earnings, Social Security, Supplemental Security Income, DB pension income, and partnership and S-corporation income. In addition, we include the income that a person could generate by annuitizing 80 percent of their financial assets, which includes retirement savings. It is a measure of potential income that is not affected by different rates of withdrawals from retirement accounts. Because the retirement account annuity is the only part of income affected by allocations to PE, income changes across the simulated scenarios are fairly small (figure 14). Projected average income at age 65 for people born between 2001 and 2010, the cohort most affected by the simulated changes in asset allocation, would increase by no more than 1 percent under the most favorable scenario (scenario 16) and decrease by one-tenth of 1 percent under the least favorable scenario (scenario 3).

FIGURE 14



Percent Change in Per Capita Income Relative to the Baseline by Scenario and Birth Year People age 65 who have invested in target-date funds

Source: DYNASIM4 ID981.

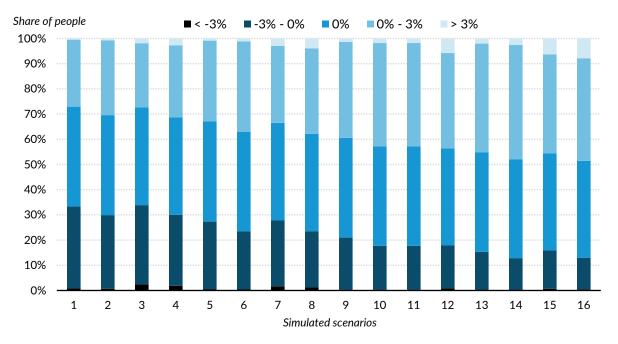
Notes: The figure is limited to 65-year-olds ever invested in target-date funds. Income includes earnings, Social Security, SSI, DB pension income, annuitized retirement accounts and other financial assets, and partnership and S-corporation income. Couples split incomes and benefits. Table 4 shows parameter values for the 16 scenarios. Endpoint labels indicate the scenario number.

Finally, we show that each simulated scenario makes some people worse off than they were under the baseline, even if the scenario is more favorable than the baseline on average. Because we split the incomes of married couples, a change in retirement account assets of one family member affects retirement incomes of both people in the couple. Although we project that PE investments will change retirement account balances at age 65 for 51 percent of people born between 2001 and 2010, 60 percent will experience a change in retirement income. As with changes in retirement account assets, expanding PE investments can leave people better off on average while a subset of people are left worse off, because returns to PE have a relatively wide distribution. Figure 15 shows that even under the most favorable scenario (scenario 16), more than 10 percent of 65-year-olds born between 2001 and 2010 would have lower incomes than under the baseline. This share increases to one-third under the least favorable scenario (scenario 3). On the other hand, the share of winners is never higher than 50 percent; under the least favorable scenario, it is about 28 percent. The percent change in retirement incomes are generally smaller than the percent change in retirement accounts assets.

FIGURE 15

Distribution of Gains and Losses in Income Relative to the Baseline

People age 65 born between 2001 and 2010



Source: DYNASIM4 ID981.

Notes: The figure includes all 65-year-olds born between 2001 and 2010. Income includes earnings, Social Security, SSI, DB pension income, annuitized retirement accounts and other financial assets, and partnership and S-corporation income. Couples split incomes and benefits. Table 4 shows parameter values for the 16 scenarios.

Although allowing retirement account investments to include PE funds generates losses for some investors, those losses tend to be small. Because retirement account ownership is more prevalent among people with higher earnings than those with lower earnings, few of those who experience losses reach age 65 with retirement incomes below poverty. We project that adding PE to retirement account assets has no impact on age 65 poverty (or near poverty) rates, even under our most pessimistic scenario. Similarly, the increase in average retirement account returns from investing in PE does not generate sufficient additional retirement income to lift any retirees out of poverty.

Conclusion

Although PE funds have increased rapidly in recent decades and have outperformed the public stock market, PE funds are not generally available to participants in qualified DC retirement plans. However, the share of retirement assets held in PE could surge following recent DOL guidance clarifying the conditions under which plan sponsors could offer PE investment options. This DOL guidance could substantially increase PE investments in retirement accounts. This development could significantly affect retirement account balances and the financial security of future retirees.

In this report, we simulate how the availability of PE investment options might affect retirement account balances and future retirement outcomes. Outcomes depend crucially upon our assumptions about how PE returns will compare to returns for publicly traded stocks and bonds and the maximum share of assets that a target-date fund could hold in PE. Our simulations quantify PE fund returns in excess of the risk-free return by alpha, the portion of the excess return that is uncorrelated with overall market returns, and beta, which captures the correlation between PE fund returns and market returns. Because of the uncertainty surrounding future returns and how much target-date fund managers would choose to invest in PE, we simulated 16 different scenarios that assumed different values of alpha (-1 percent, 0, 1 percent, and 2 percent), beta (1.25 and 1.50), and the maximum PE share (7.5 percent and 15.0 percent). Our assumed values for alpha and beta came from a careful review of recent empirical studies.

Our simulations show that the availability of a PE investment option in DC retirement plans would increase average account balances under 14 of our 16 scenarios. We focus on outcomes for people born between 2001 and 2010, most of whom have just entered or will soon enter the labor force and would be able to invest their workplace retirement savings in PE for their entire careers. For this cohort, the scenario that adopted the most favorable assumptions for PE (2.0 percent alpha, 1.5 beta, and maximum PE share of 15 percent) would increase average account balances at age 65 by \$39,500 (in 2020 inflation-adjusted dollars), or 9.5 percent, relative to the baseline that excludes PE investments from retirement plan accounts. The scenario with the least favorable assumptions for PE (-1.0 alpha, 1.25 beta, and maximum PE share of 15 percent) would reduce average account balances at age 65 by \$3,500, or 0.9 percent relative to the baseline. A scenario with more neutral assumptions (1.0 percent alpha, 1.5 beta, and maximum PE share of 15 percent) would increase average accounts balances at age 65 by \$27,600, or 6.6 percent.

Because higher earners are more likely to have retirement account assets than lower earners, higher earners see bigger dollar changes in accumulated savings from investing in PE. Expanding retirement account investments to include PE has no impact on aged poverty. Few people in old-age poverty have retirement account assets, so they neither gain or lose from expanding retirement account investments to include PE.

Like any study that aims to project future outcomes, this one comes with many caveats. Our simulations required several assumptions that directly affect our results, especially regarding future rates of returns to various asset classes. Although we took care to consult the relevant literature and choose what we believe are reasonable values, other choices would generate different outcomes.

Appendix A

TABLE A.1

Average Retirement Account Assets and Asset Changes at Age 65 among People Ever Invested in a Target-Date Fund by Race, Ethnicity, Education, and Scenario

Adults born between 2001 and 2010 (thousands of 2020 price-adjusted dollars)

Scenario	White non- Hispanic	Black non- Hispanic	Hispanic	Less than h school	igh High scho graduat		College ge graduate
Baseline	474.6	311.1	314.4	67.9	241.9		588.1
			ands)				
1	-2.3	-3.8	-2.1	0.0	-1.6	-1.5	-3.7
2	1.7	-1.3	0.6	0.6	0.5	1.8	1.1
3	-3.2	-7.1	-3.4	-0.1	-2.4	-1.8	-5.8
4	6.4	-1.1	3.1	1.6	2.5	6.0	5.7
5	4.0	0.3	2.1	0.9	1.7	3.6	3.8
6	8.1	3.0	4.9	1.5	3.8	6.9	8.7 📕
7	9.3	1.0	5.0	1.9	4.2	8.4	9.1
8	19.2 📕	7.2	11.6 📕	3.4	9.2	16.5 📕	21.0
9	10.4 📕	4.5	6.5	1.8	5.1	8.8	11.5
10	14.5 📕	7.2	9.3	2.4	7.2	12.2	16.4 📕
11	22.3 📃	9.5	13.6 📕	3.9	11.0	18.9	24.6
12	32.5	15.8	20.5 🔳	5.4	16.2	27.2	36.8
13	16.9 📕	8.8	10.8	2.7	8.5	14.1	19.3
14	21.1	11.5	13.7	3.3	10.7	17.5	24.3
15	35.6	18.1 📕	22.7	5.8	18.1	29.7	40.5
16	46.2	24.7	29.7	7.4	23.4	38.3	53.2

Source: DYNASIM4 ID981.

Notes: The table includes all people born between 2001 and 2010 at age 65 who ever invested in target-date funds. Couples split earnings in years they are married in the shared lifetime earnings measure and includes earnings from age 20 to 70. Table 4 shows the parameter values for the 16 scenarios.

TABLE A.2

Percent Change in Average Retirement Account Assets at Age 65 among People Ever Invested in a Target-Date Fund by Race, Ethnicity, Education, and Scenario

Adults born between 2001 and 2010

Scenario	White non- Hispanic	Black non- Hispanic	Hispanic	Less than high school	High school graduate	Some college	College graduate					
Scenario	riispanie	riispanie			0	Joine conege	graduate					
		Percent change compared with the baseline										
1	-0.5 🖡	-1.2	-0.7 🖡	0.0	-0.7 [-0.4	-0.6 🖡					
2	0.4	-0.4	0.2	0.8	0.2	0.5	0.2					
3	-0.7 [-2.3	-1.1 🕻	-0.1	-1.0	-0.5	-1.0					
4	1.3	-0.4	1.0	2.3 📘	1.0	1.6 📜	1.0					
5	0.8	0.1	0.7	1.3	0.7	1.0	0.7					
6	1.7	0.9	1.5 📘	2.2	1.6 📜	1.9 📜	1.5 📘					
7	2.0	0.3	1.6	2.7 📕	1.7 📜	2.3	1.5					
8	4.0 💻	2.3 📕	3.7 💻	5.0	3.8 💻	4.5	3.6 💻					
9	2.2 📕	1.5 📘	2.1 📘	2.6 📃	2.1	2.4 📜	2.0 📜					
10	3.1 💻	2.3 📕	2.9 📜	3.5 💻	3.0 📜	3.3 📜	2.8 📜					
11	4.7	3.0 📃	4.3 💻	5.8	4.5	5.2	4.2					
12	6.8	5.1 💻	6.5	8.0	6.7	7.5	6.3					
13	3.6 💻	2.8 📃	3.4 📜	4.0	3.5 📜	3.9 📜	3.3 💻					
14	4.4 💻	3.7 📜	4.3 💻	4.9	4.4 📃	4.8 📜	4.1					
15	7.5	5.8	7.2	8.6	7.5	8.2	6.9					
16	9.7	7.9	9.5	10.9	9.7	10.5	9.0					

Source: DYNASIM4 ID981.

Notes: The table includes all people born between 2001 and 2010 at age 65 who ever invested in target-date funds. Couples split earnings in years they are married in the shared lifetime earnings measure and includes earnings from age 20 to 70. Table 4 shows the parameter values for the 16 scenarios.

Notes

- ¹ "Information Letter 06-03-2020," US Department of Labor, June 3, 2020, https://www.dol.gov/agencies/ebsa/about-ebsa/our-activities/resource-center/information-letters/06-03-2020#footnotes.
- ² At the end of 2019, the capitalization of the US public equities was \$38 trillion and private equity funds had \$1.9 trillion of assets under management including "dry powder," money that was committed but not drawn (Mauboussin and Callahan, 2020).
- ³ In 1982, Regulation D created an exception from securities registration for accredited investors. In 1990, Rule 144A allowed trade of restricted securities. In 1996, a change to section 3(c)(7) of the Investment Company Act lifted the 100-investor cap for private investment funds. In 2012, the JOBS Act loosened eligibility requirements on individual investors and increased the threshold for the number of shareholders that requires companies to go public from 500 to 2000.
- ⁴ Based on the authors' estimates of PME in the range of 1.20 to 1.27. Taking into account the cost of illiquidity and different discounting rates for management fees, Sorensen, Wang, and Yang (2014) calculate a theoretical break-even PME of 1.30 for investors in PE funds.
- ⁵ See Perold (2004) for an overview.
- ⁶ An expression for beta can be written as $\beta = \rho \sigma_a / \sigma_m$ where ρ is the correlation factor between the asset and market and σ_a and σ_m are the standard deviations of the asset and market returns, respectively.
- ⁷ The DYNASIM sample is based primarily on the 2004 and 2008 panels of the Survey of Income and Program Participation, but many other datasets were used to impute information that is not available in that survey, such as employment histories.
- ⁸ DYNASIM calibrates the distribution of risk tolerance to match the distribution found in the Survey of Consumer Finances.
- ⁹ For more information about DYNASIM, see Favreault, Smith, and Johnson (2019).
- ¹⁰ As noted by the DOL (2020, footnote 9), investment managers need to satisfy certain regulatory requirements to qualify for inclusion in target date funds. Buyout funds are more likely to satisfy those requirements than VC funds, although many large VC funds recently have met those requirements. We expect more VC funds would elect to satisfy those requirements if target date funds became potential investors.
- ¹¹ Investment Company Institute (2020).
- ¹² Investment Company Institute (2020).
- ¹³ Our assumption about the maximum PE share for target date funds, which is based on a suggestion from Department of Labor (DOL 2020), applies to funds that are far from their target date and hold a large share of their portfolio in stocks. The funds that are closer to their target date will generally invest a lower share in PE.
- ¹⁴ Worker and employer contributions are subject to annual contribution limits that include age 50 and older catch-up contribution amounts.
- ¹⁵ The simulated annual growth in PE assets due to investments from retirement savings accounts is a little higher than the \$50 billion that Henry et al. (2020) project.

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