No Portfolio is an Island

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Abstract

No man is an island,
Entire of itself,
Every man is a piece of the continent,
A part of the main.

John Donne, 1624

Financial assets such as stocks and bonds are only one component of an investor's total economic worth. Other assets, such as human capital, real estate, and pensions (e.g., Social Security retirement benefits) often represent a significant portion of an investor's total wealth. These assets, however, are frequently ignored by practitioners when building portfolios, despite the fact that they share common risks with financial assets. This paper provides evidence that industry-specific human capital, region-specific housing wealth, and pensions have statistically significant exposures to different asset classes and risk factors. Through a series of portfolio optimizations we determine that the optimal allocation for an investor's financial assets varies materially for different compositions of total wealth. These findings suggest that narrowly focused portfolio optimization routines that ignore human capital and outside wealth are insufficient, and that a holistic definition of wealth is necessary to build truly efficient portfolios.

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When building portfolios, investors tend to focus on the risk characteristics of the opportunity set of investible financial assets and fail to consider the risks associated with other assets they effectively "own," such as human capital, real estate, and pensions. In many cases, the value of these overlooked assets may exceed the value of the individual's financial (i.e., liquid) wealth. For example, Becker (1993) estimates the value of human capital to be at least four times as large as the value of stocks, bonds, housing, and all other assets combined. Heaton and Lucas (2000) estimate that human capital is 48% of household wealth, while financial assets represent only 6.8%.

There is a growing body of research that incorporates the unique risks associated with human capital into the asset allocation decision (i.e., how much to invest in stocks or bonds), but a relatively limited body of research that accounts for the different dimensions of wealth and explores how the characteristics of outside wealth impact optimal portfolio choice. While the majority of research on the subject relied on complex utility-based consumption models, this paper uses a familiar single-period portfolio optimization routine.

We find that the optimal allocation for an investor's financial assets varies materially for different compositions of total wealth. The absolute differences in the optimal asset weights exceed 20% generally and are especially notable for younger individuals with higher levels of human capital. The total wealth framework approach introduced in this paper can help financial planners build more efficient portfolios for their individual clients, as well as help plan sponsors who are interested in implementing a more "custom" custom target-date solution for their participants.

Different Dimensions of Wealth

The original work by Markowitz (1952) provided the framework for portfolio optimization and serves as the foundation for the approach taken in this paper. Most investment professionals focus entirely on the risk and return characteristics of the opportunity set of investible financial assets, such cash, bonds, and stocks, when constructing a portfolio and ignore the other assets "owned" by the investor. These other assets have unique risk factors, often referred to as background risks, that can vary materially. Ignoring these other assets when optimizing a portfolio, therefore, may create an allocation that is efficient for the financial assets, but may not be the most efficient allocation from a total wealth perspective.

The body of research on intertemporal portfolio theory has expanded considerably since Merton's (1969, 1971a, 1971b) seminal studies, both in academic (see Cochrane (2013) for a recent example) and practitioner journals (see Wallmeier and Zainhofer (2006), Ibbotson, Milvesky, Chen, and Zhu (2007). These studies commonly provide insight for investors in terms of how they should allocate assets over their lifetimes with a focus on nontradeable asses like human capital. The models used in the studies are generally complex, and have been relatively ignored in practice (see Cochrane (2013) for a review of recent academic research on the subject). This study uses a more straightforward framework to incorporate the varying risky assets held by an investor that should be easier for investment professionals to implement.

Cochrane (2007) contends that the optimal portfolio for an investor with non-tradeable income should deviate from the market portfolio to the extent that he or she is different from everyone else. In particular, he emphasizes two potential sources of deviation from the market portfolio for a given level of risk aversion: the relative weight of human capital and other outside wealth as a percentage of total wealth and the difference in the riskiness of the investor's human capital and other outside wealth to that of the average investor. This deep insight is central to the objective of this paper, which is to describe the characteristics of the outside wealth empirically and to make inferences about the optimal portfolio choice given the unique characteristics of an investor's non-tradable income (e.g., industry-specific human capital).

While the focus for this paper is that of an individual (i.e., a household), the concept of total wealth optimization can be extended to different types of investors, since financial wealth is generally just one part of an investor's total wealth. One example of a potential extension of the total wealth framework would be for a charitable endowment, given the unique risks some charities face by financing their operations through a combination of both donations and endowment earnings. Ideally, the charity should consider the covariances between expected changes in donations and the expected returns of investible asset classes when determining the asset allocation of the endowment to create a more diversified revenue stream. Taking a holistic perspective of risk, and adjusting the financial assets accordingly, should lead to a more efficient total wealth allocation for each investor regardless of investor type.

The focus of this piece is on systematic risks, not unsystematic (i.e., idiosyncratic) risks. Idiosyncratic risks vary by investor and by asset, and are far more difficult to identify, quantify, and incorporate into a portfolio optimization routine than systematic risk factors. Unlike idiosyncratic security risk, which can be diversified away by holding a diversified mix of securities in a portfolio, there are limited options available to mitigate the idiosyncratic risks associated with different types of household assets, such as human capital. While there are some forms of insurance available that can serve as a quasi-hedge (e.g., unemployment insurance, disability insurance, and life insurance for human capital), these risks are highly personalized and beyond the scope of the general model introduced in this paper.

Financial Assets

Financial assets, or financial capital, are the most easily observable and are generally the most liquid portion of household wealth, and therefore tend to receive the majority of the attention when building a portfolio. The relative weight of financial assets as part of an investor's total wealth varies by investor type and age. Younger individuals tend to have little financial wealth, but tend to accumulate financial wealth over their working careers through savings, which is then spent down during retirement. Financial assets are usually the largest when retirement first commences.

Since financial capital is the part of an investor's wealth that can be traded most easily, financial assets serve as a "completion portfolio" and are optimized based on the goal of minimizing the variance in inflation-adjusted change in the total wealth of an investor. The opportunity set of investible financial assets are included in Table 1, along with their respective index proxies, returns, and standard deviations over the test period, which is from the second quarter of 1993 to first quarter of 2013, for a total of 80 quarters. The analysis begins in the second quarter of 1993 since that is the first quarter the change in the value of human capital can be estimated given the required industry-specific bond yield data, which will be discussed further in the next section.

Thirteen different individual asset classes are included in the analysis: one cash asset class (Cash), five bond asset classes (US Intermediate-term Bond, US Long-term Bond, US TIPS, US High Yield Bond, and NonUS Bond), five equity asset classes (US Large Growth, US Large Value, US Small Growth, US Small Value, and NonUS equity), and two alternative asset classes (REITs and Commodities). The opportunity set is intentionally selected to reflect asset classes that are commonly used by investment professionals when building portfolios for clients.

While inflation is listed in Table 1, it is not considered an investible asset for the analysis. Inflation is included because it plays an important role in the optimization routine, and is therefore included for informational purposes. While the analysis is based on quarterly data, the annualized figures are included in Table 1 for informational purposes as well.

Table 1: Asset Classes, Proxies, and Historical Returns and Standard Deviations: Q2 1993–Q1 2013

			Quarterly		Annualized	
Asset Class	**Index Proxy**	**Name**	**Return**	**Std Dev**	**Return**	**Std Dev**
Cash	Barclays US Treasury Bills	Cash	0.76%	0.53%	3.07%	1.06%
US Intermediate-term Bond	Barclays US Govt/Credit Interm	IntBd	1.40%	1.68%	5.71%	3.37%
US Long-term Bond	Barclays US Govt/Credit Long	LgBd	2.05%	4.37%	8.46%	8.75%
US TIPS	Barclays US Treasury US TIPS	TIPS	1.75%	2.28%	7.20%	4.55%
US High Yield Bond	IA Barclays US HY Corporate Bonds	HiYld	2.07%	4.91%	8.55%	9.81%
NonUS Bond	Barclays Gbl Agg Ex USD	nUSBd	1.54%	4.39%	6.31%	8.79%
US Large Growth	Russell 1000 Growth	LarGro	2.35%	9.77%	9.72%	19.53%
US Large Value	Russell 1000 Value	LarVal	2.58%	8.33%	10.73%	16.66%
US Small Growth	Russell 2000 Growth	SmGro	2.46%	12.33%	10.19%	24.67%
US Small Value	Russell 2000 Value	SmVal	2.95%	9.64%	12.34%	19.28%
NonUS Equity	MSCI EAFE GR	nUSEq	2.15%	9.43%	8.87%	18.86%
Commodities	DJ UBS Commodity	Comm	1.63%	8.27%	6.68%	16.54%
Real Estate (REITs)	FTSE NAREIT All REITs	REITs	2.96%	9.88%	12.36%	19.76%
Inflation	IA SBBI US Inflation	n/a	0.61%	0.87%	2.46%	1.73%

The nominal returns for the asset classes were relatively high over the historical period used for the analysis, especially for cash and fixed income when compared to yields available today. For example, the average annual return on cash was approximately 3.07% over the test period, which is considerably higher than the yield available on 1 month Treasury bills, which was approximately .1% as of January 2014.

The weights to the 13 asset classes are determined using a nonlinear optimization routine where the goal is to minimize the variance in inflation-adjusted change of the total wealth of an investor. For the optimization only the weights to the financial assets are adjusted, i.e., all other types of wealth are considered nontradeable. It is also assumed that it is not possible to perfectly hedge the risk of the other asset classes (e.g., using some form of insurance) or the covariance of the other assets with each other. Therefore, this optimization routine seeks to determine the additional potential diversification benefits that can be obtained by incorporating the unique risk factors associated with different assets, and their weights, from a total wealth perspective.

Three constraints are placed on the optimization to reflect common investor considerations as well as to more easily isolate the differences that result from holding different amounts and types of wealth. First, there is no shorting (i.e., all asset class weights must be positive). Second, the maximum allocation to a single asset class is 20%, this ensures the portfolio must have nonzero weights to at least five classes. Third, the return of the financial assets (i.e., portfolio) must be equal to the average quarterly return of all available asset classes over the test period, which was 2.05%. The third constraint is included to ensure the resulting allocations are at least somewhat balanced across both equities and fixed income. Given these three assumptions, the return of each of the financial assets for the optimized portfolios will be identical (within four decimal places); however, the asset class weights will vary by scenario depending on the riskiness of the other assets (human capital, housing wealth, and pension wealth), and their weights, that are included in the optimization.

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[1] This approach was introduced by Jagannathan and Wang (1996), and used most recently by Eiling (2013)

Human Capital

Human capital has a variety of definitions, but can generally be thought of as the total economic value of an individual's set of skills and talents. Human capital is a unique asset, since it varies by age, health, education, occupation, industry, and experience, among other variables, and is nontradeable. These traits, in effect, create endowed exposures to certain risk factors that can be difficult to effectively hedge.

In the late 1960s, models developed by various economists such as Samuelson (1969) and Merton (1969) suggested that individuals should maintain constant portfolio weights throughout their lives. An important assumption of these models was that investors had no labor income (or human capital). Subsequent research by Wallmeier and Zainhofer (2006) and Ibbotson, Milvesky, Chen, and Zhu (2007), among others, have attempted to incorporate the bond-like nature of human capital into the equity allocation decision framework. Their research suggests that equity allocations should change over time as human capital is consumed (or depleted), taking the shape of a "glide path" that is common in target-date investments today.

Models used to estimate the value of human capital generally view earnings as a type of "dividend" from the individual's total human capital; therefore, dividend growth models can be used to estimate the total value of human capital. Under this approach, the total value of human capital (HC) at a given point in time (t), could be estimated based on the individual's wage (w), an appropriate discount rate (r), and an expected wage growth rate (g), using equation 1.

$$HC_t = \frac{W_t}{r_t - g_t} \qquad [1]$$

The return on human capital (r_{HC}) could then be estimated by comparing the change in the total value of human capital over two points in time, based on equation 2.

$$rHC_t = \frac{HC_t - HC_{t-1}}{HC_{t-1}} \qquad [2]$$

The riskiness of human capital can then be determined based on the variability of the return of human capital, or some other measure. The simplest approach to estimating the return of human capital is to assume it is equal to the changes in wages over time[1]. This approach requires the assumption that that the discount rate and wage growth rate are constant across both industries and over time, which does not hold in reality and will be explored in the next section.

Estimating Industry-Specific Human Capital

The approach used to estimate the total value of human capital, and its return (i.e., riskiness) is motived by the work of Ibbotson, Milvesky, Chen, and Zhu (2007) and noted in equation 3, where HC_t is the total human capital at time t, n is the current age of the individual, R is the expected retirement age (which is assumed to be age 65), q_{R-n} is the probability of surviving to a given age (which is based on the Society of Actuaries 2000 annuity mortality table for a unisex individual), w_t is the earnings at time t, g_t is the expected earnings growth rate at time t (which is based on historical employment growth rates from the Bureau of Labor Statistics), i_t is the expected inflation rate at time t (which is based on historical inflation expectations from

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[1] This approach was introduced by Jagannathan and Wang (1996), and used most recently by Eiling (2013)

the Cleveland Federal Reserve),and r_t is the nominal discount rate at time t (which is based off the historical yield for different Barclays Investment Grade Industry Bond indexes yields plus a term premium). Equation 3 is effectively an extension of equation 1, where the value of human capital is the mortality-weighted net present value of an individual's future expected labor income. Pension benefits are intentionally disentangled from human capital and the rationale for this decision is explored in a future section.

$$HC_t = \sum_{n}^{R} \frac{q_{R-n}\, w_t\, (1+g_t+i_t)^{R-n}}{(1+r_t)^{R-n}} \qquad [3]$$

Eiling (2013) shows that industry-specific human capital can be used to explain differences in expected returns of individual stocks, suggesting that industry affiliation has important implications on how individuals allocate their assets. Motivated by this finding, a key contribution of this study is using equation 3 to estimate the value of human capital, and its respective change over time, and the implications of these changes for optimal portfolio choice.

Historical quarterly wage data is obtained from the Bureau of Economic Analysis (BEA) for various industries for the analysis. Although wage data is available as far back as 1941 for some industries, only more recent values are used in order to match the available data for the different asset classes included the analysis, as well as to match the available data for the discount rates. An additional benefit of using more recent data is that it is likely more reflective of industry risks today. The 10 industries selected for the analyses were: construction, finance, government, healthcare, lodging, manufacturing, mining, real estate, transportation, and utilities.

The discount rate (r) used to estimate the value of human capital (in equation 3) is assumed to be the yield on the Barclays corporate bond indexes for the relevant industry. As such, we assume that the certainty with which the average worker within an industry gets paid a salary is the same as the certainty, priced into the bond market, with which the average company represented in the corporate bond index is able to meet its coupon and/or principal payments. Furthermore, this method implicitly assumes that the debt and remuneration claim have the same seniority in the firm's capital structure. Calcagno and Renneboog (2004) point out that the seniority of the debt versus remuneration claim is a complex issue and that the relative seniority of either claim cannot be generalized.

There may be idiosyncratic reasons for a firm to cease paying someone's salary (i.e. the person gets fired). However, these idiosyncratic shocks are irrelevant for the purposes of this study, which is to characterize the co-movements of financial assets and human capital which are, by definition, systematic. Despite the potential weaknesses of this approach, the theoretical justification for using the corporate bond yields to discount human capital is that the creditor and the employee in a given industry are affected by the same systematic shocks given that they are paid out of the same cash flow. Changes in corporate bond yields are observable real time. Incorporating industry-specific and time-varying shocks to the discount rates is important because doing so better reflects how the expected value of human capital would change over time.

The discount rates for industry-specific human capital are based on the yields of a respective Barclays investment grade bond index for that industry, plus a term premium. The term premium is included in an attempt to equalize the maturities among the various Barclays indexes over time, as well as to better match the expected maturity of human capital (at retirement) and the maturity of the index. Actual maturities for the 10 different indexes varied between approximately four and 18 years over the historical period, therefore, including a term premium helps normalize the differences that can be attributed to different industry exposures versus different durations.

The term premium is calculated based on the historical term premium for Treasury bonds for the respective month. The term premium is added (or subtracted) to the yield of the respective industry-specific Barclays Investment Grade bond index so that all the maturities are the same across indexes, based on the number of years until retirement. For example, if the duration of the utilities index is 10 years, yet the years until retirement are 20 years, the difference in the yield between the 20-year Treasury and 10-year Treasury would be added to the yield for the utilities index for that month. The maximum maturity is assumed to be 30 years, even if the years to retirement exceed 30 years (e.g., an individual who is 25 years old). Historical yields at various historical points in time, along with the respective proxies for select industries, are included in Table 2.

Table 2: Industry-Specific Human Capital Discount Rates for Select Months

		Month					
Industry	**Bond Proxy**	**1993-03**	**1997-03**	**2001-03**	**2005-03**	**2009-03**	**2013-03**
Construction	Barclays IG Building Materials	7.77%	7.70%	7.43%	5.57%	13.23%	4.18%
Finance	Barclays IG Banking	7.96%	7.62%	6.72%	5.30%	9.96%	3.50%
Government	Barclays Investment Grade	7.21%	7.63%	7.07%	5.58%	8.53%	3.49%
Healthcare	Barclays IG Health Care	7.15%	7.59%	7.19%	5.46%	7.12%	3.26%
Lodging	Barclays IG Lodging	8.07%	8.00%	7.93%	5.55%	13.63%	3.86%
Manufacturing	Barclays IG Div Manufacturing	7.81%	7.72%	6.74%	5.36%	7.16%	3.15%
Mining	Barclays IG Metals & Mining	8.21%	7.90%	7.29%	5.41%	9.81%	4.08%
Real Estate	Barclays IG REITs	7.77%	7.75%	7.64%	5.81%	14.46%	3.81%
Transport	Barclays IG Transport	8.18%	7.78%	7.21%	5.85%	7.75%	3.51%
Utilities	Barclays IG Utility	7.64%	7.70%	7.28%	5.50%	7.45%	3.56%

Table 2 clearly demonstrates that discount rates are neither constant across industries nor constant over time. Therefore, an approach that assumes a constant discount rate (which is common) would not accurately capture industry-specific volatility that has existed historically.

There are two components used to estimate the expected historical nominal wage growth rates: the expected wage growth rate and the expected level of general inflation. Both of these metrics are forward looking estimates at varying historical points in time (so there is implied estimation error). The expected wage growth rate is based on the projected annual growth rate in employment for various industries, with data obtained from the Bureau of Labor Statistics (BLS). The BLS has been producing projections of the labor force, industry output and employment, and occupational employment and job openings since 1966. While forecasted changes in real wages are not the same as estimated changes in employment, they are assumed to be reasonable proxies for each other[2]. This is based on the assumption as an industry grows (or shirks) wages are likely to follow suit. The BLS publishes projections biannually, and the projected growth rates used for the analysis are included in Table 3.

[2] The correlation between expected employment growth and actual future wage growth rate over the following 5 years has averaged .234 with a t statistic of 8.82. Therefore, while expected changes in employment and expected wage growth are not the same thing, a positive and statistically significant relationship clearly exists.

Table 3: Industry-Specific Human Capital Real Wage Growth Rates

	Projection Period (%)											
Industry	1992-2005	1994-2005	1996-2006	1998-2008	2000-2010	2002-2012	2004-2014	2006-2016	2008-2018	2010-2020	2012- 2022	Avg
Construction	1.8	0.9	0.9	0.9	1.2	1.4	1.1	1.0	1.7	2.9	2.6	**1.5**
Finance	1.5	0.6	1.0	1.2	1.2	1.2	1.0	1.4	0.7	1.0	0.8	**1.1**
Government	-0.4	-0.8	-0.3	-0.5	-0.6	0.0	0.2	-0.4	0.3	-1.3	-1.6	**-0.5**
Healthcare	3.0	2.7	2.9	2.6	2.5	2.8	2.7	2.4	2.3	3.0	2.6	**2.7**
Lodging	2.6	1.5	2.9	2.9	1.3	1.7	1.6	1.3	0.8	1.0	0.9	**1.7**
Manufacturing	-0.2	-0.7	-0.2	0.0	0.3	-0.1	-0.6	-1.1	-0.9	-0.1	-0.5	**-0.4**
Mining	-0.9	-2.8	-2.5	0.1	-1.1	-1.3	-0.9	-0.2	-1.6	0.4	1.4	**-0.9**
Real Estate	1.8	0.7	1.2	1.2	1.4	1.2	1.7	1.8	1.3	2.8	1.1	**1.5**
Transport	1.6	0.6	-0.3	1.5	1.7	2.0	1.1	1.1	0.9	1.9	0.7	**1.2**
Utilities	1.0	0.2	1.0	-0.4	0.5	-0.6	-0.1	-0.6	-1.1	-0.7	-1.1	**-0.2**
Average	**1.2**	**0.3**	**0.7**	**1.0**	**0.8**	**0.8**	**0.8**	**0.7**	**0.4**	**1.1**	**0.7**	**0.8**

Similar to the discount rates, which varied by industry and over time, the expected wage growth rates also vary by industry and over time. Again, this implies that an approach to estimating human capital that assumes a constant wage growth rate would not capture the actual historical differences in industry expectations that have existed historically.

The average projected real wage growth rate for the 10 industries over the historical period has been 0.8%. This value is relatively consistent with the historical difference in growth of the National Average Wage Index, as calculated by the Social Security Administration, and inflation (CPI-U), from 1952 to 2012, which has been approximately 1.0%. For the analysis the real growth rates are averaged on a weighted basis between the two respective periods to smooth out the changes over time.

Expected general inflation (i_t in equation 3) is proxied based on the historical 20-year inflation forecast for the respective quarter, with data obtained from the Cleveland Federal Reserve Bank[3]. Similar to historical bond yields, employment growth rates, and wages, expected inflation vary over the historical period. Expected 20-year inflation was approximately 3.0% at the beginning of the test period and had declined to approximately 1.8% by the end of the test period.

For each analysis that incorporates human capital, the age of the individual is assumed to be constant for the entire duration of the study, although different current ages are considered in different scenarios. A single age is used for the analysis, versus assuming an individual "ages" through time to disentangle the effects of the natural decline in the value of human capital that results from aging. Human capital will decline as a person ages or approaches retirement, holding all other variables constant. By holding the age constant, it is possible to observe the relationships between changes in human capital and changes in the returns for the other assets (both investible and noninvestible) over time, without having to worry about the implications of changes in age.

The correlations between the changes in the value of the 10 industry-specific forms of human capital and the returns of the 13 asset classes is included in Table 4 to provide the reader with some perspective as to the extent and statistical significance of the relations. The assumed age for the human capital estimates in Table 4 is 45.

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[3] http://www.clevelandfed.org/research/data/inflation_expectations/

Table 4: Correlations Between Industry-Specific Human Capital and Test Asset Classes

	Industry-Specific Human Capital									
Asset Class	**Cons**	**Fin**	**Govt**	**Health**	**Lodge**	**Manu**	**Mine**	**RE**	**Trans**	**Util**
Cash	-.023	.009	-.069	-.087	-.156	-.013	-.111	-.094	-.033	-.095
InterBond	.313***	.572***	.691***	.502***	.142	.645***	.288***	.200*	.517***	.610***
LongBnd	.306***	.588***	.696***	.522***	.168	.742***	.331***	.209*	.549***	.650***
TIPS	.317***	.155	.348***	.327***	.241**	.354***	.352***	.282**	.282**	.369***
HiYld	.569***	.340***	.359***	.260**	.666***	.079	.369***	.648***	.316***	.298***
NnUSBd	.207*	.381***	.447***	.232**	.123	.419***	.250**	.161	.331***	.267**
LarGro	.244**	.078	-.048	.084	.362***	-.137	.066	.251**	.099	-.101
LarVal	.368***	.253**	.078	.155	.388***	.008	.255**	.373***	.228**	.067
SmGro	.224**	.079	-.083	.099	.397***	-.139	.066	.263**	.099	-.091
SmVal	.335***	.208*	.034	.167	.385***	-.016	.200*	.367***	.206*	.046
NnUSEq	.347***	.266**	.081	.145	.444***	-.023	.221**	.394***	.215*	-.014
Commod	.253**	.127	.042	.039	.261**	-.036	.323***	.353***	.011	-.021
REITs	.576***	.398***	.315***	.314***	.501***	.257**	.493***	.602***	.421***	.248**

*** p < .01, ** .01 <= p < .05, * p <= .1

The correlations are statistically significant for many of the relationships, generally more so for the fixed income assets than cash, equities, or the alternative asset classes. The average absolute correlation across all asset classes is .266 with a median of .253. These values (a correlation of ~.25) correspond to p-value of approximately .02. The four asset classes with the highest absolute correlations, along with the highest degrees of statistical significance, are Intermediate-term bonds (.45 average), Long-term Bonds (.48 average), High Yield bonds (.39 average), and REITs (.41 average).

There are some notably high correlations, for example the correlation between the human capital of the real estate industry and the return on REITs is .602. This is an intuitive relationship, suggesting that changes in the value of REITs have a significant and positive relationship with the wages in the real estate industry. The obvious implication is that individuals who work in the real estate industry should likely have a lower (or no) allocation to REITs in their financial assets than individuals who work in other industries, such as manufacturing, based on the correlations in Table 4.

Understanding how portfolio weights should vary based on different asset and risk exposures is the primary goal of this paper. While there is potentially only a single efficient frontier for financial assets when ignoring other assets, this efficient frontier becomes far more dynamic (and varying) as different types of individual assets are considered across investors.

Human Capital Optimizations with Primary Asset Classes

To demonstrate how optimal portfolio allocations can vary by industry-specific human capital a series of portfolio optimizations are performed. For the optimizations in this section, human capital is assumed to be 80% of the individual's total wealth, where the only other asset would be financial wealth (i.e., the completion portfolio, which represents the remaining 20% of the individual's wealth). Assuming the individual only holds two assets is a simplifying assumption used to isolate the marginal impact of different industry-specific human capital on the optimal portfolio weights; more complex scenarios that include multiple assets will be considered in a later section. The individual is assumed to be 45 years old for all human capital calculations in this section.

The optimal portfolio allocations are included in Table 5. In addition to the industry-specific human capital optimized portfolios, the optimized portfolio that ignores total wealth is included for reference purposes and is referred to as the "non-total wealth" portfolio. The non-total wealth portfolio is determined using the same optimization procedure as the total wealth portfolios, but it ignores any other sources of wealth (e.g., human capital, housing wealth, or pension wealth) during the optimization routine.

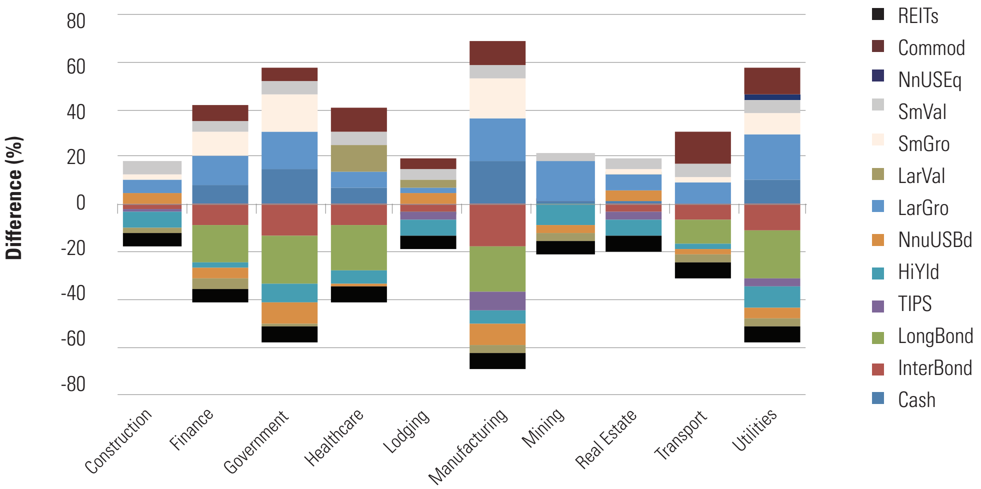
Table 5: Optimal Portfolio Allocations for Various Industries Using Primary Asset Classes

	Asset Class												
	Cash	**IntBd**	**LgBd**	**TIPS**	**HiYld**	**nUSBd**	**LarGro**	**LarVal**	**SmGro**	**SmVal**	**nUSEq**	**Comm**	**REITs**
Construction	0.0%	14.8%	20.0%	19.4%	2.1%	12.6%	7.0%	1.3%	2.7%	20.0%	0.0%	0.0%	0.0%
Finance	8.4%	8.6%	4.2%	20.0%	6.8%	3.0%	13.8%	0.0%	9.5%	20.0%	0.0%	5.8%	0.0%
Government	14.9%	4.2%	0.0%	20.0%	0.0%	0.0%	16.4%	1.8%	16.1%	20.0%	0.0%	6.5%	0.0%
Healthcare	7.1%	8.3%	0.8%	20.0%	3.8%	6.7%	8.4%	14.3%	0.0%	20.0%	0.0%	10.5%	0.0%
Lodging	0.0%	14.1%	20.0%	16.6%	2.7%	13.7%	2.6%	7.0%	0.0%	20.0%	0.0%	3.5%	0.0%
Manufacturing	17.8%	0.0%	0.0%	12.0%	3.3%	0.0%	20.0%	0.0%	16.3%	20.0%	0.0%	10.5%	0.0%
Mining	1.3%	17.2%	20.0%	20.0%	0.0%	5.4%	18.1%	0.0%	0.0%	18.0%	0.0%	0.0%	0.0%
Real Estate	1.5%	14.1%	20.0%	16.9%	1.7%	13.1%	7.2%	3.8%	1.7%	20.0%	0.0%	0.0%	0.0%
Transport	0.5%	11.0%	9.3%	20.0%	7.0%	5.9%	10.0%	0.0%	2.7%	20.0%	0.0%	13.6%	0.0%
Utilities	10.2%	5.7%	0.0%	16.5%	0.0%	3.9%	20.0%	0.0%	9.9%	20.0%	2.6%	11.2%	0.0%
Average	**6.2%**	**9.8%**	**9.4%**	**18.1%**	**2.7%**	**6.4%**	**12.4%**	**2.8%**	**5.9%**	**19.8%**	**0.3%**	**6.2%**	**0.0%**
non-Total Wealth	**0.0%**	**17.1%**	**20.0%**	**20.0%**	**8.7%**	**8.3%**	**1.2%**	**3.5%**	**0.0%**	**14.8%**	**0.0%**	**0.0%**	**6.4%**

Table 5 provides a number of interesting insights. First, REITs are the only asset class not included in any of the optimizations. This is likely due to the relatively high correlation between industry-specific human capital and REITs. Second, the allocations are relatively similar across the different industries, with the majority having higher allocations to Large Growth, Small Value, and Commodities. This suggests there are risk factors that are common to investors' human capital across different industries. Finally, the allocations for the industry-specific human capital portfolios differed materially when compared to the non-total wealth portfolios.

The differences in the allocations in the total wealth optimized portfolios and the non-total wealth optimized portfolios are easier to observe in Figure 1. In Figure 1, the asset class weights for the total wealth portfolios for each asset class are subtracted from the asset class weights for the non-total wealth portfolios. The sum of the negative differences is always equal to the sum of the positive differences, since the optimization routine includes a no-shorting constraint as well as a constraint that the total weights must equal 100%.

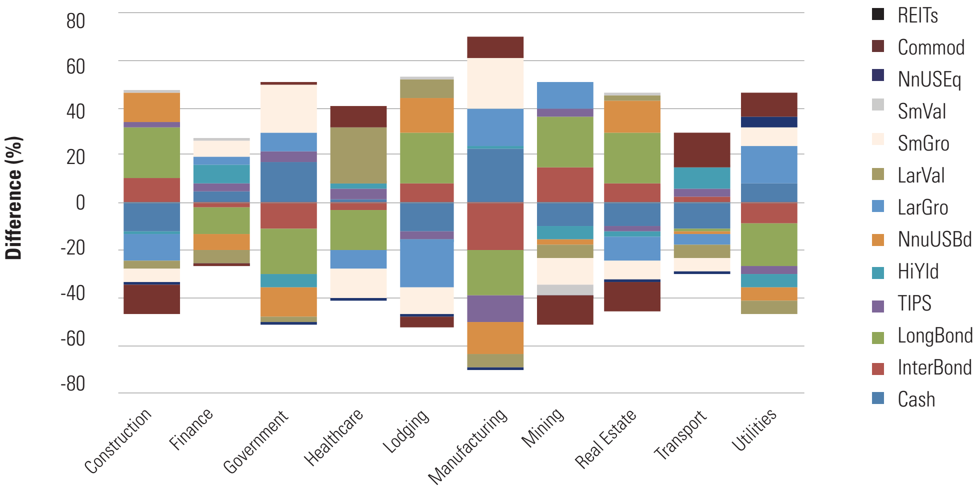
Figure 1: Allocation Differences Between Optimal Total Wealth and non-Total Wealth Portfolios



The average absolute difference between the industry-specific human capital portfolios and the non-total wealth portfolios in Figure 1 is 37.6%. This means approximately slightly more than one third of the total allocation is different when comparing the industry-specific human capital portfolios and the non-total wealth portfolio. The industry-specific human capital portfolios tend to have lower allocations to Intermediate-term Bonds and Long Bonds, and higher allocations to Large Growth and Commodities. The material differences between the non-total wealth optimization and the optimization that incorporates industry-specific human capital highlights the importance of incorporating this asset into the portfolio optimization process.

There are considerable differences among the portfolios that consider different types of industry-specific human capital. These differences are displayed in Figure 2, which is similar in sprit to Figure 1; however, instead of comparing the allocations for the industry-specific human capital portfolios against the non-total wealth optimized portfolios, the allocations are compared to the average asset class weights across the 10 different industry-specific human capital portfolios.

Figure 2: Allocation Differences Between Each Industry-Specific Human Capital Portfolio and the Average Industry-Specific Human Capital Portfolio



Not surprisingly, the average absolute difference between the industry-specific human capital optimized portfolios and the average are smaller than the differences between the industry-specific human capital optimized portfolios and the non-total wealth optimized portfolios, 23.0% and 37.6%, respectively. There are still some notable differences, though, that should be considered when developing portfolios for individuals in different industries. For example, as we might expect, the Finance portfolio (based on Finance industry-specific human capital) had a lower allocation to Large Value and the Mining portfolio had a lower allocation to Commodities, etc. Overall, Figures 1 and 2 clearly demonstrate that the true efficient portfolio is not constant across individuals when an additional asset (industry-specific human capital) is introduced.

Human Capital Optimizations with Industry Asset Classes

The majority of prior research exploring the implications of industry-specific human capital on portfolio allocations has used an investment opportunity set that is industry-based (e.g., Eiling 2013), versus the more generic asset classes used for this analysis. Along these lines, an additional analysis is performed for this section where the opportunity set is changed from the 13 generic asset classes to 12 industry portfolios obtained from Kenneth French's website[4]. The 12 industries (and names) are: Consumer NonDurables (NoDur), Consumer Durables (Durbl), Manufacturing (Manuf), Oil, Gas, and Coal Extraction and Products (Enrgy), Chemicals and Allied Products (Chems), Business Equipment (BusEq), Telecommunications (Telcm), Utilities (Utils), Wholesale, Retail, and Some Services (Shops), Healthcare, Medical Equipment, and Drugs (Hlth), Finance (Money), and Other (Other).

The same three constraints are applied to the optimization: no shorting, the maximum allocation to a single industry is 20%, and the return of the financial asset portfolio must equal the average return of the industry portfolios. The results of the optimizations, along with the respective industry non-total wealth portfolio, are included in Table 6. Similar to the general asset classes used for the primary analysis, there are varying ETFs and mutual funds that could be used to create industry-specific portfolios. Therefore, there may not be investible portfolios that are identical to 12 industry portfolios selected for the optimization, but there are likely reasonably close substitutes.

Table 6: Optimal Portfolio Allocations for Various Industries Using Industry Portfolios

	Industry Portfolio											
	NoDur	**Durbl**	**Manuf**	**Enrgy**	**Chems**	**BusEq**	**Telcm**	**Utils**	**Shops**	**Hlth**	**Money**	**Other**
Construction	19.1%	0.0%	0.0%	3.1%	10.0%	0.0%	7.8%	20.0%	20.0%	20.0%	0.0%	0.0%
Finance	20.0%	0.0%	0.0%	5.5%	16.3%	0.0%	0.0%	7.1%	20.0%	19.4%	0.0%	11.8%
Government	20.0%	0.0%	0.0%	14.1%	15.1%	0.0%	0.0%	0.0%	20.0%	13.5%	0.0%	17.3%
Healthcare	9.8%	0.0%	0.0%	20.0%	8.5%	0.0%	20.0%	11.9%	6.3%	18.0%	0.0%	5.6%
Lodging	18.6%	0.0%	0.0%	5.9%	11.6%	0.0%	13.3%	20.0%	10.6%	20.0%	0.0%	0.0%
Manufacturing	5.2%	0.0%	0.0%	16.1%	20.0%	0.5%	0.0%	0.0%	20.0%	18.4%	0.0%	19.7%
Mining	15.6%	0.0%	0.0%	0.0%	10.8%	8.9%	6.9%	9.6%	20.0%	20.0%	0.0%	8.2%
Real Estate	20.0%	0.0%	0.0%	3.6%	9.4%	0.0%	9.6%	17.5%	20.0%	20.0%	0.0%	0.0%
Transport	16.2%	0.0%	0.0%	18.9%	2.6%	0.0%	0.0%	16.8%	9.1%	20.0%	0.0%	16.4%
Utilities	13.6%	0.0%	0.0%	8.8%	20.0%	6.3%	0.0%	0.0%	15.8%	15.6%	0.0%	20.0%
Average	**15.8%**	**0.0%**	**0.0%**	**9.6%**	**12.4%**	**1.6%**	**5.8%**	**10.3%**	**16.2%**	**18.5%**	**0.0%**	**9.9%**
non-Total Wealth	**20.0%**	**0.0%**	**0.0%**	**4.4%**	**7.4%**	**0.0%**	**8.7%**	**20.0%**	**19.5%**	**20.0%**	**0.0%**	**0.0%**

The optimal portfolio allocations for the varying types of industry-specific human capital are more similar using the industry portfolios (Table 6) versus the generic asset classes (Table 5). This can potentially be attributed to the lower average absolute correlations between the industry-specific human capital and the industry portfolios, as noted in Appendix 1. The average absolute correlation for industry-specific human capital and the industry portfolios is .164, which is significantly less than the average absolute correlation for industry-specific human capital and the base asset classes, which was .266. It is worth noting, though, that the absolute correlations for industry-specific human capital are considerably higher for the fixed income asset classes versus the bond asset classes, at .328 and .186, respectively. Therefore, the fact the industry portfolios only include equities likely explains the reduced differences, since the correlations

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[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

between industry-specific human capital and the base equity asset classes and the industry portfolios are quite similar (at .186 and .164, respectively).

Similar to the previous analysis, Figure 3 includes the optimization differences versus the non-total wealth optimized portfolios and Figure 4 includes the differences versus the average industry-specific human capital optimized portfolios.

Figure 3: Allocations Differences between non-Total Wealth Optimized Portfolios and Industry-Specific Human Capital Optimized Portfolios Using Industry-Based Assets

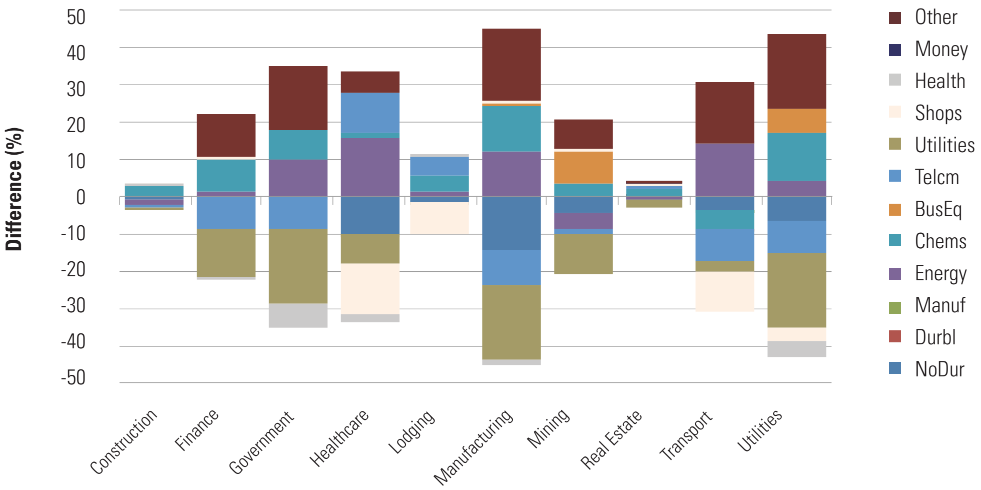
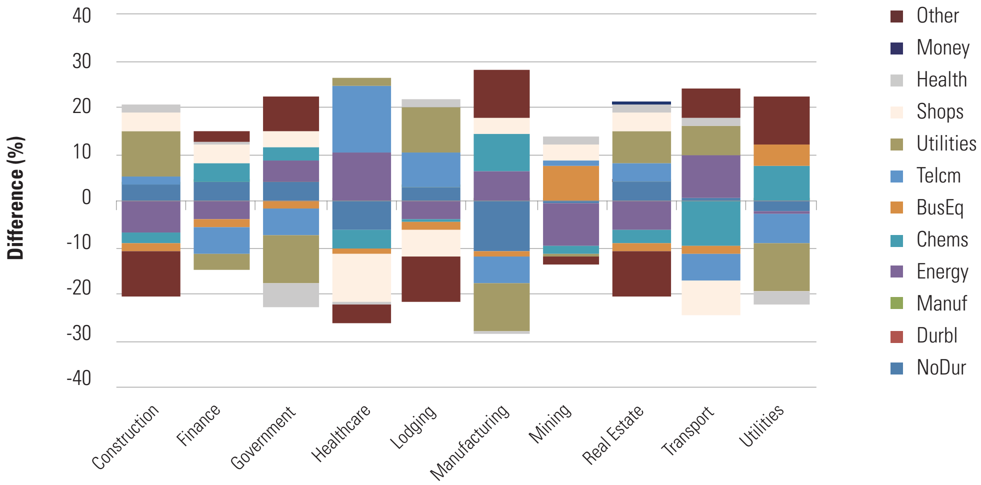


Figure 4: Allocations Differences Between Each Industry-Specific Human Capital Portfolio and the Average Industry-Specific Human Capital Portfolio Using Industry-Based Assets



The average relative difference between the non-total wealth optimized portfolio and the average industry-specific optimized portfolio were relatively similar, at 24.7% and 21.4%, respectively. There is little consistency across the differences in the industry-specific optimized portfolios when compared to the non-total wealth optimized portfolios; however there are some notable differences for some industry-specific optimized portfolios. For example, Finance, Government, Manufacturing, and Utilities all had higher weights to the Other industry portfolio and lower weights to utilities.

We do get some of the expected differences, though, when comparing the industry-specific optimized portfolios to each other. For example, the Mining portfolio had a lower allocation to Energy, the Utilities portfolio had a lower allocation to Utilities, and the Healthcare portfolio had a lower allocation to healthcare. Regardless of whether the optimization routine includes asset class proxies or industry proxies, the optimal portfolio for an individual clearly varies based on that individual's industry-specific human capital. This has important implications for investors, especially younger investors where human capital is the dominant asset from a total wealth perspective.

Pension Wealth

Pensions represent a significant asset to U.S. households, especially older households. Nine out of ten individuals age 65 and older receive Social Security benefits and the average monthly benefit is \$1,269 based on data obtained from the Social Security Administration website[5]. Also, among elderly Social Security beneficiaries, 53% of married couples and 74% of unmarried persons receive 50% or more of their income from Social Security. Defined benefit pensions also represent a material asset for many Americans; however, this relative share of wealth for defined benefit plans has been declining as they become less popular among plan sponsors.

In a previous section, we introduced a valuation model for human capital (equation 3) that did not include pension benefits (e.g., Social Security retirement benefits). Excluding Social Security retirement benefits from human capital effectively assumes they are independent. This is obviously a simplifying assumption, since pension benefits and human capital are related, especially since Social Security retirement benefits are wage-based. However, the risk factors associated with pension benefits are different than human capital, and the relation between human capital and pension benefits will vary by individuals.

Accrued pension benefits have already been earned and therefore, by definition, are less risky than future yet-to-be-earned human capital. While the amount of the pension benefit or time at which pension benefits may commence may change (reducing the present value and obviously affecting the discount rate), the riskiness associated with accrued pensions is not the same as human capital. For example, a change in wages would likely have a less material impact on the value of pension benefits for an older individual (since Social Security retirement benefits are based on the highest average 35 years of inflation-adjusted earnings) than a younger individual. Also, married individuals are entitled to Social Security benefits based entirely on the earnings record of their spouse, and therefore their pension benefits are not based on their own human capital at all.

We estimate the total value of pension wealth, which is assumed to be based entirely on Social Security retirement benefits, using equation 4. This approach is functionally very similar to equation 3, where pension wealth P_t is the mortality-weighted net present value of future expected Social Security retirement benefits (SS_t). The key difference between equation 4 (estimating the value of pension wealth) and equation 3 (estimating the value of human capital) is that equation 4 includes a risk-free rate (rf), which is assumed to be the return on long-term government bonds. Social Security retirement benefits (SS) are not assumed to commence until retirement (age 65) and the probability of being alive to receive the benefits is considered up to age 115 (D).

$$P_t = \sum_n^D \frac{q_{D-n} SS_t (1+i_t)^{D-n}}{(1+rf_t)^{D-n}} \qquad [4]$$

An alternative potential real discount rate for Social Security retirement benefits would be the yield on Treasury Inflation-Protected Securities (TIPS); however, TIPS were not created until 1997, which is after the start of the time period for this analysis. In reality, though, the discount rate for pension benefits should vary depending on the amount of time until pension benefits commence (and are to be received), as well as the type of benefits (e.g., if they are based on that worker or that

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[5] http://research.stlouisfed.org/fred2/release?rid=199

worker's spouse). Using a single discount is obviously a simplifying assumption for this analysis that may not be appropriate for all individuals or pensions.

The change in the value of Social Security retirement benefits is estimated using the same approach as the change in value of human capital, which is effectively the change in the mortality-weighted net present value of Social Security retirement benefits from one period to the next. An analysis focusing solely on pension wealth is not performed in this section, but the implications of varying levels of pension wealth as a function of total wealth is explored in the combined total wealth analysis.

Housing Wealth

Housing is a material asset for many Americans. According to the U.S. Census Bureau, homeownership in the United States was 65.3% as of third quarter of 2013 and has ranged between approximately 63% and 69% since 1965. According to summary data from the 2010 Survey of Consumer Finances, the primary residence represented 47.4% of all nonfinancial assets for a household and 29.43% of total assets. For the purposes of this analysis, housing wealth is defined as the net equity value of the home, which is the value of the home minus all outstanding loans (e.g., a mortgage or any other type of home equity loan).

A unique risk with housing wealth is leverage. Homes are generally purchased with some kind of loan, such as a mortgage, with down payments that can be as little as 5%, although a 20% down payment is more common. A 20% down payment implies a five times multiple with respect to how a change in the value of the home will affect the net equity. For example, if an individual owns a home worth $100,000 with a mortgage of $80,000, and the house increases in value by 10% (to $110,000) the return realized by the owner, based on the net equity, is 50% ($10,000/$20,000 = 20%). The amount of leverage is obviously very important for homeowners, since even slight changes in housing values can have a material impact on the net equity of a home, especially for younger investors who may to have less equity.

The region-specific housing analysis conducted in this section is similar to the industry-specific analysis conducted in the previous section where it is assumed the individual only holds two assets: financial capital and housing wealth. This is a simplifying assumption intended to isolate the implications of holding different types of region-specific housing wealth. For the analysis the relative weight of housing wealth and financial assets is assumed to be equal (i.e., both represent 50% of the individual's total wealth). The net equity is assumed to be 50% of the home value (i.e., the individual owns 50% of the home outright).

The risk associated with housing wealth is based on the change in different S&P/Case-Shiller Home Price Indexes for 10 different cities, with data obtained from the Federal Reserve Bank of St. Louis[6]. The 10 cities selected for the analysis are Atlanta, Charlotte, Cleveland, Washington DC (DC), Las Vegas, Miami, Minneapolis, Phoenix, Seattle, and San Francisco (SanFran). The term "regions" is used because the geographic region is the key distinguishing factor between the different changes in home values. While individual cities were selected to represent different regions, states or other characteristics could just have easily been used. The regions selected were intended to be broadly representative of the United States. The optimization differences between the non-total wealth optimized portfolio and region-specific housing portfolios are included in Figure 5. Figure 6 shows the optimization differences between each region-specific housing portfolio the average region-specific housing portfolio. The correlations between region-specific housing wealth and the base asset classes are included in Appendix 2.

Figure 5: Allocation Differences between non-Total Wealth Optimized Portfolio and Region-Specific Optimized Portfolios

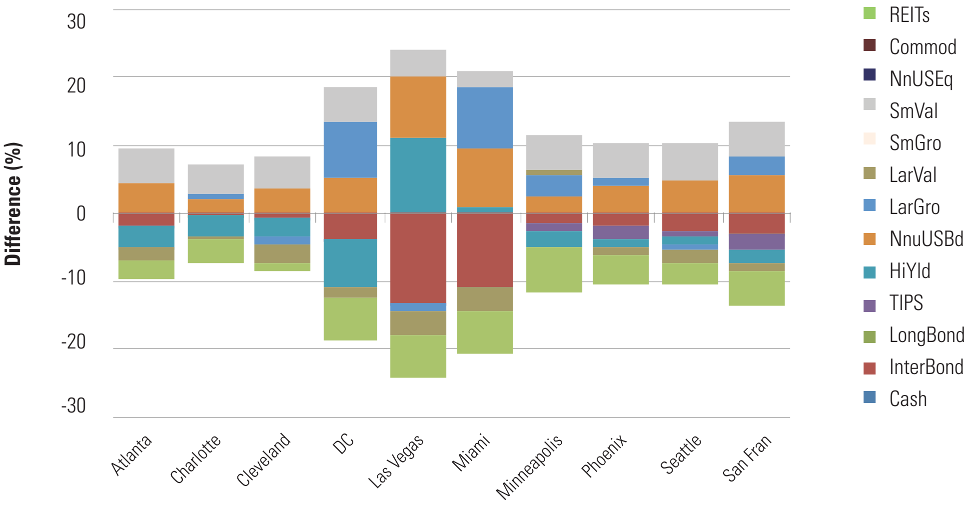
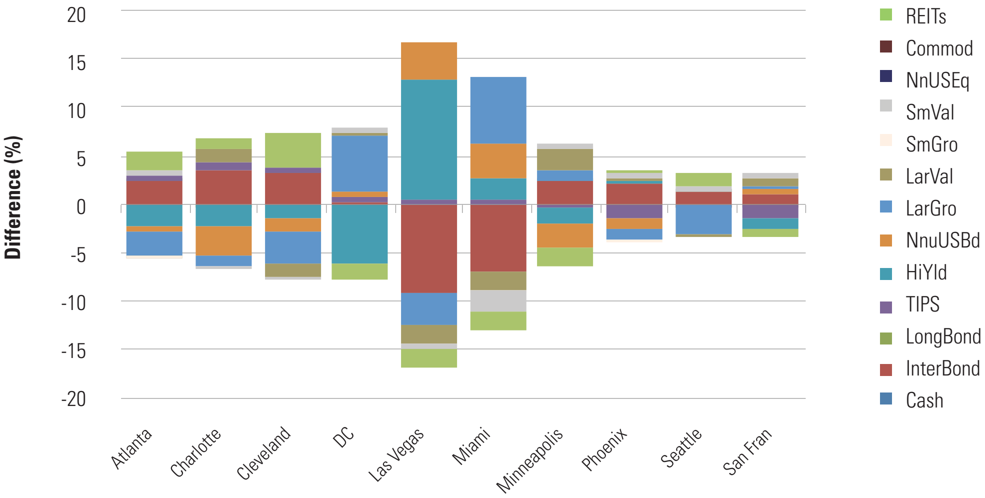


Figure 6: Allocation Differences Between Each Housing-Specific Portfolio and the Average Region-Specific Optimal Allocation



The relative differences in the allocations when considering only region-specific housing wealth are not as material as the optimizations using the generic asset classes focused on industry-specific human capital, which is why total allocations are not included. The average absolute difference between the average region-specific housing portfolio and the non-total wealth optimized portfolio is only 13.5%, and the average absolute difference between the region-specific housing portfolios and the average region-specific optimized portfolio is only 7.3%. This can likely be attributed to the fact changes in region-specific housing prices tended to have a lower average absolute correlation to the test asset classes, averaging only .170 (versus .266 for the industry-specific human capital).

The region-specific housing wealth optimization portfolios tended to have higher allocations to Small Value when compared to the non-total wealth optimized portfolio and lower allocations to REITs. There are not consistent differences among the region-specific housing allocations when compared to the average allocations across the 10 regions.

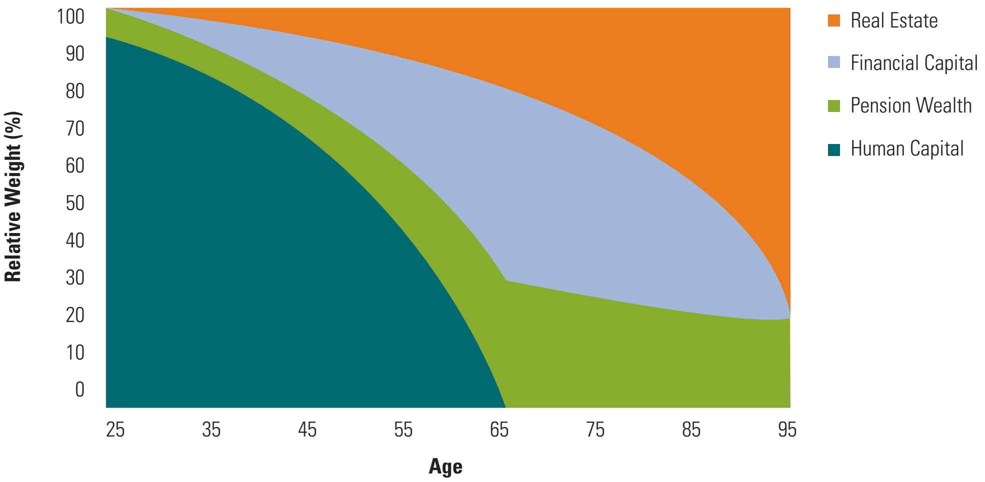
Total Wealth Analysis

Previous optimizations have demonstrated that meaningful differences can result in a portfolio optimization that includes assets beyond just financial wealth. In this section we take a more holistic perspective of wealth, by including all four types of wealth in the analysis.

When thinking about different types of wealth, it's important to understand how their relative weights are likely to vary over an individual's lifetime. To demonstrate this relationship, we create a hypothetical scenario. The hypothetical scenario begins with an individual who is 25 years old and earns $40,000 a year in after-tax income. The individual's real wage growth rate is expected to be a constant 1.0% per year, the annual savings rate is 10.0%, the discount rate is 8%, and the rate of expected inflation is 3.0%.

The hypothetical scenario assumes that the individual purchases a home at age 30 that costs $100,000. The home is purchased with a 10.0% down payment (that comes from financial capital) with the remainder financed by a 30-year mortgage at an interest rate of 5.0%. The real growth rate of the home is assumed to be 1.0%. Social Security retirement benefits are assumed to be $20,000 per year, in today's dollars, commencing at age 65, and the real discount rate for Social Security retirement benefits is 5.0%. The results of the scenario are depicted in Figure 7.

Figure 7: Hypothetical Depiction of the Relative Weight of Different Assets over an Individual's Lifetime



While Figure 7 is based on a certain set of relatively precise assumptions, certain aspects of the scenario are likely to be consistent across different individuals (i.e., households). First, human capital is likely to be the dominate asset for younger households. While the relative weight of human capital goes to 0% when the individual retires (age 65) in Figure 7, in reality, as long as an individual is willing and able to do some type of work, there would be some positive value for human capital. Second, the relative value of pensions increases as the individual ages (i.e., as the realization of the benefits comes nearer). Third, financial assets are likely to be at their largest at retirement, i.e., follow a hump-shape over an individual's lifetime. Finally, the relative value of real estate may increase during an individual's lifetime, and if housing wealth is not used to fund retirement, potentially become the dominate asset later in life.

Even at their peak, financial assets never account for more than 50% of the total wealth of the individual in Figure 7. Therefore, how can an asset allocation based entirely on less than half of a client's assets truly be optimal?

Next, we consider 10 scenarios with varying weights to the four different assets for the combined total wealth analysis. These weights are listed in Table 7. The lower number scenarios are intended to reflect potential asset weights for a younger individual (with higher relative levels of human capital), while the higher numbers reflect potential weights for an older individual (with higher relative levels of the other three assets, most notably pensions). While it would be possible to include the base assumptions required to create the different scenario asset class weights, these values are not included to avoid complexity and therefore the weights in Table 7 should be viewed as hypothetical in nature.

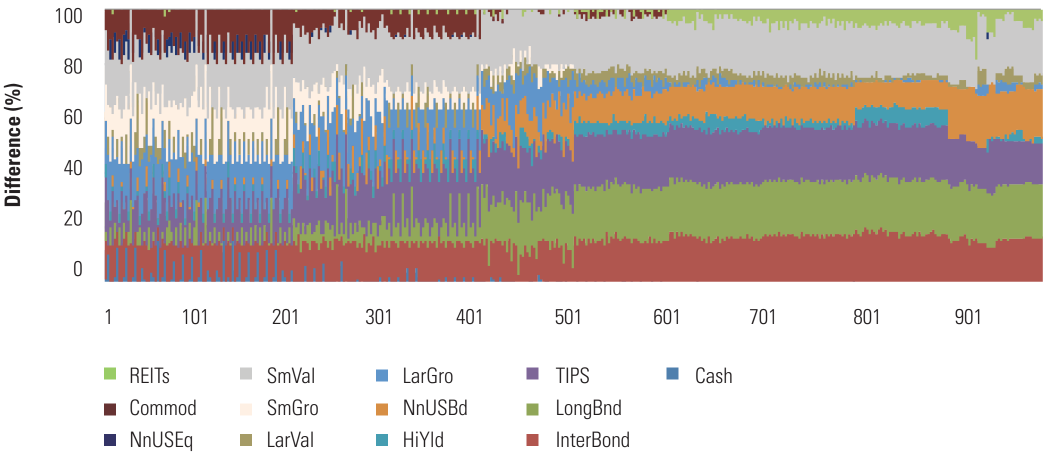
Table 7: Asset Weights by Scenarios

	Scenario Number									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Human Capital	80%	80%	60%	60%	40%	40%	20%	20%	5%	5%
Housing Wealth	5%	0%	15%	0%	30%	10%	20%	5%	15%	30%
Pension Wealth	5%	5%	10%	10%	20%	10%	30%	50%	30%	55%
Financial Capital	10%	15%	15%	30%	10%	40%	30%	25%	50%	10%
Total	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**	**100%**
Assumed Age	30	30	40	40	50	50	60	60	70	70
Housing Equity	20%	20%	40%	40%	60%	60%	80%	80%	100%	100%
Implied Leverage	5.00	5.00	2.50	2.50	1.67	1.67	1.25	1.25	1.00	1.00

For each scenario, each of the 10 different types of industry-specific human capital and the 10 different types of region-specific housing wealth are considered, which creates 100 combinations for each scenario, for a total of 1,000 total optimizations. While this approach effectively treats employment industry and state of residence as independent variables, this is unlikely to be the case in reality.

Figure 8 contains the optimal portfolio allocation weights for each of the 1,000 test simulations. In Figure 8 simulations 1 to 100 are based off scenario 1, simulations 101 to 200 are based off scenario 2, etc. The average underlying allocation by asset class for the 1,000 scenarios for the varying respective exposures is included in Appendix 3 using different methods of aggregation.

Figure 8: Asset Allocations for 1,000 Scenarios



It is obviously not possible to ascertain the individual simulation allocations in Figure 8 (which is intentional), although general trends can be observed. First, the most obvious change is that as industry-specific human capital declines (i.e., as the simulation number increases) the resulting allocations become increasingly similar. This is consistent with the past analysis, since industry-specific human capital resulted in larger changes in allocations than region-specific housing and pension wealth is determined using the same discount rate.

Second, asset classes like Long-term Bonds, TIPS, and non-U.S. bonds tend to receive higher weights as the scenario numbers increase, while the allocations to Large Growth, Small Growth, and Commodties tend to decrease. To better demonstrate the differences in the resulting total wealth optimized portfolios, the allocations for each of the 1,000 simulations is compared against the non-total wealth optimized portfolio in Figure 9 and the average optimized total wealth portfolio in Figure 10.

Figure 9: Allocation Differences between Total Wealth Portfolios and non-Total Wealth Optimized Portfolio

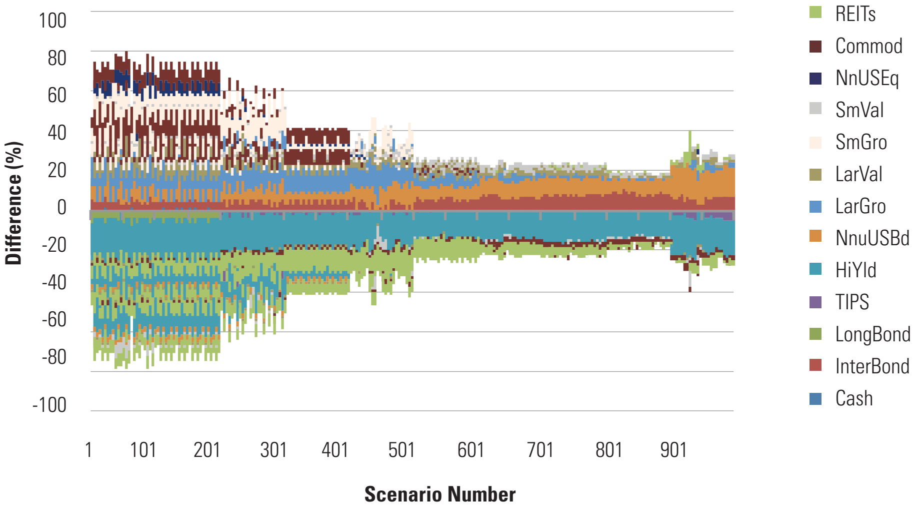
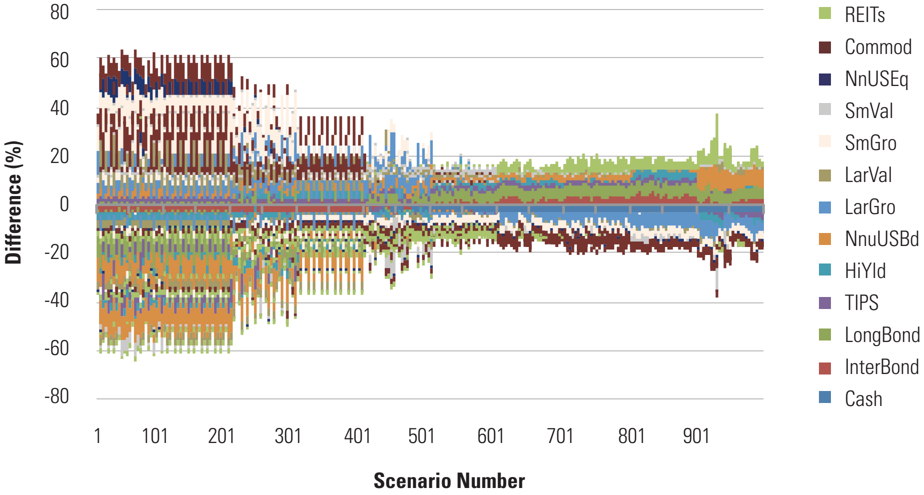


Figure 10: Allocation Differences between Optimized Total Wealth Portfolios and the Average Optimized Total Wealth Portfolio



The dispersion of the allocations is clearly more significant for younger individuals with higher levels of industry-specific human capital, with some absolute differences exceeding 75% when compared to the non-total wealth optimized portfolios. For simulations 1 to 200, based off scenarios 1 and 2, where the human capital weight is 80%, the average absolute difference versus the non-total wealth optimized portfolio is 49.9% while the average difference versus the average overall portfolio is 35.6%. Both of these represent significant differences in the allocations to different asset classes.

Across each of the simulations, when comparing the total wealth optimized portfolios to the non-total wealth optimized portfolios, there are lower allocations to Long-term Bonds and especially High Yield bonds. These reductions are offset with higher allocations primarily to Large Growth and Commodities. When comparing the total wealth optimized portfolios to each other, it is difficult to pinpoint common differences, although allocations to Long-term Bonds increase in scenarios where pensions are a significant asset (and where the individual is assumed to be older). There is a considerable amount of noise surrounding the other differences that are very scenario-specific.

How Risky is Industry-Specific Human Capital?

The results in the previous section, especially Figures 8, 9, and 10, clearly demonstrate that different types of industry-specific human capital can have a material impact on the optimal allocation for an individual's financial assets when taking a total wealth perspective. Therefore, understanding the relative risks of different types of industry-specific human capital are an important step when building a portfolio and targeting a given level of portfolio risk.

The optimization routine for this paper uses the financial assets as the "completion portfolio" to minimize the variance in real change of the total wealth of an investor, subject to three constraints. One of the three constraints was that all total wealth optimized portfolios must have the same return. This optimization model, therefore, incorporates the covariance between the different types assets (i.e., varying forms industry-specific human capital) when determining the optimal asset class weights but does not directly incorporate the varying levels of risk for the different types of assets. For example, if one type of industry-specific human capital is more risky than another, the individual with riskier human capital should potentially take less risk with his or her financial assets.

To estimate how the risk of different types of industry-specific human capital varies, we use the five-factor model introduced by Fama and French (1993). The formula is noted in equation 5, where the coefficient for B_1 would provide insight as to what extent a given type of industry-specific human capital is a "stock" or a "bond." Additional factors were considered when developing the model, such as momentum and liquidity, yet the original model introduced by Fama and French is used because including additional independent variables/factors added little, if any, benefit to the regression.

$$R_{HC} - R_f = a + B_1(R_{Mkt} - R_f) + B_2(SMB) + B_3(HML) + B_4(TERM) + B_5(DEF) + \varepsilon \qquad [5]$$

The coefficients from the regression using equation 5 for each of the 10 different types of human capital for a 45 year old are included in Table 8.

Table 8: Regression Coefficients for Five-Factor Regression for Different Types of Industry-Specific Human Capital

	Industry-Specific Human Capital									
	Cons	**Fin**	**Govt**	**Health**	**Lodge**	**Manu**	**Mine**	**RE**	**Transp**	**Util**
α	-0.51	-0.66	-0.56	-0.65	-0.40	-1.19**	0.23	-0.36	-0.71	-0.92*
β_1	0.39***	0.22**	0.05	0.29***	0.46***	0.12*	0.28***	0.40***	0.25***	0.14**
β_2	-0.06	-0.01	-0.03	0.17	0.30	0.04	-0.15	0.04	0.04	0.02
β_3	0.41***	0.30***	0.12*	0.20*	0.20	0.18**	0.38***	0.46***	0.20**	0.20***
β_4	0.43***	1.11***	0.71***	0.75***	0.40*	0.81***	0.35**	0.35*	0.61***	0.57***
β_5	0.41	1.57***	0.92***	0.11	0.36	0.40**	0.09	0.53	0.25	0.16
R^2	29%	59%	56%	33%	23%	53%	25%	25%	37%	39%

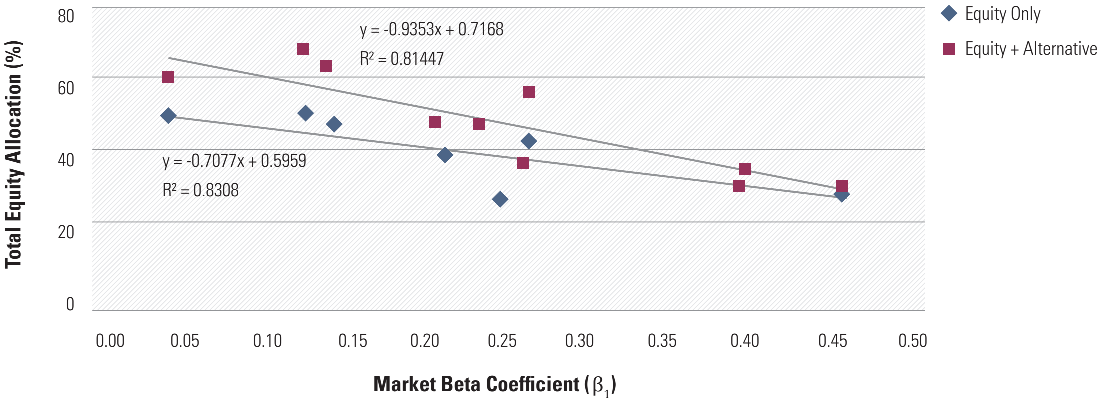
*** $p < .01$, ** $.01 <= p < .05$, * $p <= .1$

The coefficient for market risk (β_1 in Table 8) clearly varies by industry. For example, the coefficient is .05 for government industry-specific human capital, while the coefficient is .46 for lodging industry-specific human capital. This suggests lodging industry-specific human capital is, for example, more "stock-like" than government industry-specific human capital. The average coefficient is .26, which suggests human capital is approximately ~25% stock-like and ~75% bond-like.

An individual interested in incorporating these varying levels of risk into a portfolio could vary the target equity allocation for the financial assets based on the riskiness of the industry-specific human capital. For example, given the results in Table 8, holding all other variables constant, an individual working in the real estate industry should likely have a more conservative portfolio than an individual working for the government. Next, the optimization could be performed within each of the asset classes to determine the respective weights.

While the optimization routine used for this paper does not explicitly incorporate the different levels of risk for different types of industry-specific human capital, the resulting portfolios are affected. One of the optimization constraints is that the return of the portfolio be equal to the average return of all the 13 asset classes, this in effect results in a target equity allocation that is approximately 50%. However, if we run a regression on the market beta coefficients for the different types of industry-specific human capital (Table 8) on the resulting equity allocations for each of the industry-specific human capital portfolios (Table 5) there is a very strong negative relationship, depicted in Figure 11.

Figure 11: Relationship Between Market Beta Coefficients and Optimal Industry-Specific Human Capital Portfolio Allocations



The optimal allocation to equities, as well alternatives, is clearly affected by the riskiness of the industry-specific human capital, whereby industry-specific human capital that is more bond-like (e.g., government) tends to have higher equity allocations than industry-specific human capital that is more stock-like (e.g., lodging). Therefore, even though the riskiness of industry-specific human capital was not explicitly incorporated into the optimization routine, it clearly affects the optimal allocations.

Conclusions

In this piece, we explored the implications from taking a total wealth perspective to portfolio optimization. For the analysis the assets included in the optimization were extended beyond financial assets to include industry-specific human capital, region-specific housing wealth, and pension wealth. The financial assets were treated as a “completion portfolio” that is optimized to minimize the variance in inflation-adjusted change of the total wealth of an investor.

The optimal allocation for an investor’s financial assets varies materially based on different total wealth risk exposures. The absolute differences in the total wealth optimized and the non-total wealth optimized portfolios varied by simulation, but exceeded 20% for many simulations. The differences were the largest for those scenarios where human capital was the dominant asset, i.e., for younger individuals. These results suggest that there is not a single set of portfolio weights for all individuals (or investors) and that allocations should vary based on each individual’s unique assets and risks.

This research has important and practical implications for a variety of individuals and investors. Perhaps most notably, the perspective of an efficient portfolio must be gauged with respect to its risk contribution to an investor’s total wealth. For example, financial planners developing portfolios for clients should consider an investor’s holistic wealth when developing portfolios, and not focus entirely on the investor’s financial assets. Additionally, plan sponsors interested in building custom-target date portfolios should likely consider the unique industry-specific human capital, region-specific housing, and other types of risks that make their participant population unique. Finally, this methodology can be extended to other types of investors, such as charitable endowments, since each investor has risks that extend beyond the portfolio that should be considered in the optimization routine.

References

Becker, Gary S. 1993. Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education. Chicago, University of Chicago Press.

Calcagno, Riccardo and Renneboog, Luc, "Capital Structure and Managerial Compensation: The Effects of Remuneration Seniority." ECGI - Finance Working Paper No. 47/2004; CentER Working Paper No. 2000-101. Available at SSRN: http://ssrn.com/abstract=249040 or http://dx.doi.org/10.2139/ssrn.249040

Cocco, Joao F., Francisco J. Gomes, and Pascal J. Maenhout. 2005. "Consumption and portfolio choice over the life cycle." Review of Financial Studies, vol. 18, no. 2: 491–533.

Cochrane, John H. 2007. "Portfolio Theory." February 2007, http://faculty.chicagobooth.edu/john.cochrane/research/papers/portfolio_text.pdf.

Cochrane, John H. 2013. "A Mean-Variance Benchmark for Intertemporal Portfolio Theory." Journal of Finance Forthcoming

Eiling, Esther. 2013. "Industry-Specific Human Capital, Idiosyncratic Risk, and the Cross-Section of Expected Stock Returns." Journal of Finance, vol. 68, no. 1: 43–84.

Fama, Eugene F., and Kenneth R. French. 1993. "Common Risk Factors in the Returns on Stocks and Bonds." Journal of Financial Economics, vol. 33, no.1: 3–56.

Fama, Eugene F., and G. William Schwert. 1977. "Human capital and capital market equilibrium." Journal of Financial Economics, vol. 4: 115–146.

Heaton, John, and Deborah Lucas. 2000. "Portfolio Choice and Asset Prices: The Importance of Entrepreneurial Risk." Journal of Finance, vol. 55: 1163–1198.

Ibbotson, Roger, Milevsky, Moshe A., Peng Chen, and Kevin X. Zhu. 2007. Lifetime Financial Advice: Human Capital, Asset Allocation, and Insurance. Charlottesville, VA: Research Foundation of CFA Institute.

Jagannathan, Ravi, and Zhenyu Wang. 1996. "The Conditional CAPM and the Cross-section of Expected Returns." Journal of Finance, vol. 51: 3–53.

Merton, Robert C. 1969. "Lifetime Portfolio selection under uncertainty: The continuous-time case." The Review of Economics and Statistics, vol. 51, no. 3: 247–257.

Merton, Robert C., 1971a, "Optimum consumption and portfolio rules in a continuous time model." Journal of Economic Theory 3, 373–413.

Merton, Robert C., 1971b, "An intertemporal capital asset pricing model." Econometrica, vol. 41, 867–87.

Samuelson, Paul A. 1969. "Lifetime portfolio selection by dynamic stochastic programming." The Review of Economics and Statistics, vol. 51, no .3: 239–246.

Siegel, Laurence B., and M. Barton Waring. 2004. "TIPS, the dual duration, and the pension plan." Financial Analysts Journal: 52–64.

Wallmeier, Martin, and Florian Zainhofer. 2006. "How to invest over the life cycle: Insights from theory." Journal für Betriebswirtschaft, vol. 56, no. 4: 219–244.

Waring, M. Barton. 2004. “Liability-relative Investing.” The Journal of Portfolio Management, vol. 30, no. 4: 8–20.

Ziemba, William T., and John M. Mulvey. 1998. Worldwide Asset and Liability Modeling. vol. 10. Cambridge University Press.

Appendices

Appendix 1: Correlations Between Industry-Specific Human Capital and Industry Portfolios

	Industry-Specific Human Capital									
Asset Class	**Cons**	**Fin**	**Govt**	**Health**	**Lodge**	**Manu**	**Mine**	**RE**	**Trans**	**Util**
NoDur	.247**	.106	-.004	.119	.273**	-.060	-.131	.263	.109	.004
Durbl	.357***	.260**	.022	.125	.457***	-.080	.199*	.420***	.206*	-.016
Manf	.307***	.210*	-.027	.104	.404***	-.099	.178	.359***	.162	-.076
Enrgy	.175	.103	-.036	-.018	.214*	-.092	.283**	.259**	-.013	-.015
Chems	.265**	.100	-.027	.093	.289***	-.126	.157	.303***	.112	-.091
BusEq	.144	.035	-.094	.034	.330***	-.164	-.020	.161	.063	-.142
TelCm	.203*	.198*	-.032	.035	.251***	.000	.160	.183	.144	.092
Utils	.269**	.265**	.207*	.169	.291***	.150	.301***	.295***	.183	.270**
Shops	.192*	.055	-.095	.116	.311***	-.182	.001	.194*	.103	-.091
Hlth	.195*	.115*	.040	.089	.179	-.063	.031*	.190*	.102	.011
Money	.409***	.324***	.142	.200*	.426***	-.060	.253**	.432***	.279**	.063
Other	.260**	.165	-.032	.117	.372***	-.122	.137	.282**	.138	-.042

***p < .01, ** .01 < = p < .05, * p< = .1

Appendix 2: Correlations Between Region-Specific Real Estate and Primary Asset Classes

	Region-Specific Real Estate									
Asset Class	**Alt**	**Char**	**Clev**	**DC**	**LasV**	**Mia**	**Min**	**Phoe**	**Sea**	**SanF**
Cash	.195*	.094	-.266**	-.117	-.029	-.018	.099	.007	.244**	.031
InterBond	-.110	-.068	-.164	-.049	-.160	-.063	.074	-.118	-.149	-.060
LongBnd	-.165	-.069	-.194*	.008	-.091	.034	.141	.013	-.141	.003
TIPS	.000	-.037	-.014	.131	-.054	.020	.098	.009	.014	.118
HiYld	.260**	.244**	.219*	.225**	.149	.191*	.280**	.291***	.174	.297***
NnUSBd	-.094	-.020	-.128	-.057	-.077	-.050	.047	-.071	-.158	-.083
LarGro	.148	.095	-.210*	.012	.158	.074	.093	.215*	.146	.153
LarVal	.249**	. 182	.246*	.158	.307***	.256**	.203*	.352***	.245**	.296***
SmGro	.186*	.127	-.208	.088	.183	.132	.125	.209*	.133	.151
SmVal	.231**	.176	.185	.206*	.304***	-.264**	.198*	.305***	.211*	.272**
NnUSEq	.243**	.180	.261**	.194*	.261**	-.250**	.221**	.328***	.245**	.316***
Commod	.198*	.105	.245**	.188*	.213*	-.159	.149	.217*	.164	.274**
REITs	.294***	.294***	.233**	.334***	.330***	.372***	.383***	.422***	.300***	.386***

***p < .01, ** .01 < = p < .05, * p< = .1

Appendix 3: Average Allocations Across the 1,000 Scenarios

Industry-Specific Human Capital (%)

Asset Class	Cons	Fin	Govt	Health	Lodge	Manu	Mine	ReEs	Trans	Util	Avg	Std Dev
Cash	0.3	3.7	7.0	2.6	0.1	7.2	3.1	0.1	0.8	5.3	**3.0**	**2.6**
InterBond	15.6	13.0	11.3	12.4	15.9	10.9	14.9	15.6	14.7	11.4	**13.6**	**1.9**
LongBnd	18.8	12.8	12.1	13.2	19.3	10.8	17.0	19.3	14.5	12.4	**15.0**	**3.1**
TIPS	18.8	19.6	17.5	19.4	18.5	15.2	17.5	18.6	19.5	16.4	**18.1**	**1.4**
HiYld	3.0	5.2	1.9	3.6	2.3	5.0	3.0	2.3	4.3	1.4	**3.2**	**1.2**
NnUSBd	12.9	7.3	6.9	10.6	13.4	5.9	9.7	13.7	8.3	9.7	**9.8**	**2.7**
LarGro	4.5	9.1	8.4	5.3	0.9	10.4	8.5	5.2	6.6	9.7	**6.9**	**2.8**
LarVal	2.4	1.4	4.1	7.1	5.6	1.6	1.3	3.3	2.4	1.5	**3.1**	**1.9**
SmGro	1.7	4.5	6.8	0.0	0.0	7.3	4.2	0.6	1.4	6.2	**3.3**	**2.7**
SmVal	19.9	19.3	19.1	19.3	19.9	18.5	19.4	19.8	19.5	18.7	**19.4**	**0.4**
NnUSEq	0.0	0.0	0.2	0.0	0.0	1.4	0.0	0.0	0.0	1.5	**0.3**	**0.6**
Commod	0.5	2.7	2.9	4.6	1.5	3.9	0.0	0.0	6.1	3.3	**2.6**	**1.9**
REITs	1.8	1.3	1.7	1.9	2.6	1.8	1.5	1.5	1.9	2.4	**1.8**	**0.4**

Region-Specific Housing (%)

Asset Class	Alt	Char	Clev	DC	LasV	Mia	Min	Phoe	Sea	SanF	Avg	Std Dev
Cash	2.9	3.3	3.3	3.3	2.7	2.8	3.3	2.7	3.0	2.9	**3.0**	**0.2**
InterBond	13.6	13.8	13.7	13.4	13.4	13.5	13.5	13.7	13.5	13.5	**13.6**	**0.1**
LongBnd	15.2	14.8	14.9	14.8	15.4	14.9	14.6	15.2	15.1	15.2	**15.0**	**0.2**
TIPS	18.2	18.1	17.9	17.9	18.5	18.3	17.9	18.2	17.9	17.9	**18.1**	**0.2**
HiYld	2.9	2.7	3.1	2.4	4.2	3.2	3.2	3.8	3.2	3.1	**3.2**	**0.5**
NnUSBd	10.2	9.2	9.9	9.7	9.7	9.5	9.4	10.1	10.2	10.5	**9.8**	**0.4**
LarGro	6.4	6.6	5.9	8.2	6.7	8.1	7.3	6.2	6.3	7.0	**6.9**	**0.7**
LarVal	2.9	3.2	2.9	3.8	2.6	3.0	3.6	2.8	2.9	3.0	**3.1**	**0.4**
SmGro	2.9	3.4	3.3	3.4	3.3	3.4	3.2	3.2	3.3	3.4	**3.3**	**0.1**
SmVal	19.5	19.7	19.3	19.1	18.6	18.9	19.7	19.7	19.5	19.5	**19.4**	**0.4**
NnUSEq	0.3	0.3	0.4	0.3	0.3	0.3	0.4	0.3	0.3	0.3	**0.3**	**0.0**
Commod	2.6	2.9	2.7	2.5	2.3	2.5	2.6	2.5	2.7	2.2	**2.6**	**0.2**
REITs	2.3	1.9	2.8	1.9	2.3	1.4	1.1	1.7	2.1	1.5	**1.8**	**0.5**

Scenario Number

Asset Class	1	2	3	4	5	6	7	8	9	10	Avg	Std Dev
Cash	10.2	10.2	5.4	3.0	1.2	0.1	0.0	0.0	0.0	0.0	**3.0**	**4.0**
InterBond	7.4	7.2	11.1	12.8	13.2	16.1	16.8	17.5	18.2	15.6	**13.6**	**3.8**
LongBnd	5.4	5.1	10.0	12.1	18.1	19.5	20.0	20.0	20.0	20.0	**15.0**	**5.9**
TIPS	14.4	15.0	18.2	19.5	18.8	19.2	19.6	19.8	20.0	16.4	**18.1**	**2.0**
HiYld	1.5	1.4	2.5	3.8	2.5	5.6	4.7	2.9	6.0	1.2	**3.2**	**1.7**
NnUSBd	5.6	4.8	8.4	7.5	11.9	9.8	11.3	11.8	9.5	17.7	**9.8**	**3.5**
LarGro	13.1	12.6	12.3	9.7	11.0	4.8	2.2	1.2	0.4	1.5	**6.9**	**5.1**
LarVal	3.9	3.9	2.5	3.1	2.6	3.5	2.9	3.3	2.1	2.9	**3.1**	**0.6**
SmGro	10.5	10.6	6.2	2.9	2.6	0.0	0.0	0.0	0.0	0.0	**3.3**	**4.1**
SmVal	19.3	19.7	19.7	20.0	17.8	19.9	19.5	19.4	18.8	19.5	**19.4**	**0.6**
NnUSEq	1.6	1.4	0.1	0.1	0.0	0.0	0.0	0.0	0.0	0.0	**0.3**	**0.6**
Commod	7.1	8.1	3.5	5.5	0.3	1.1	0.0	0.0	0.0	0.0	**2.6**	**3.1**
REITs	0.0	0.0	0.0	0.2	0.2	0.5	3.1	4.2	5.0	5.2	**1.8**	**2.1**

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David Blanchett, CFA, is head of retirement research for the Morningstar Investment Management division, which provides investment consulting, retirement advice, and investment management operations around the world. In this role, he works closely with the division's business leaders to provide research support for the group's consulting activities and conducts client-specific research primarily in the areas of financial planning, tax planning, and annuities. He is responsible for developing new methodologies related to strategic and dynamic asset allocation, simulations based on wealth forecasting, and other investment and financial planning areas for the investment consulting group, and he also serves as chairman of the advice methodologies investment subcommittee.

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Monte Carlo is an analytical method used to simulate random returns of uncertain variables to obtain a range of possible outcomes. Such probabilistic simulation does not analyze specific security holdings, but instead analyzes the identified asset classes. The simulation generated is not a guarantee or projection of future results, but rather, a tool to identify a range of potential outcomes that could potentially be realized. The Monte Carlo simulation is hypothetical in nature and for illustrative purposes only. Results noted may vary with each use and over time.