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Abstract

With industry-specific human capital, the value of life-cycle portfolio choice varies across otherwise identical households employed in different industries. To quantify the extent of this variation, I solve a life-cycle model for households employed in 73 industries at the three-digit NAICS classification level. Applying the Method of Moments to time series of industry-specific income growth and aggregate stock returns, allows me to solve the Euler equations without specifying the distribution of these variables and to consider predictability. At 20-year horizon, the smallest and highest certainty-equivalent consumption estimates, obtained for industries associated with Hollywood and Wall Street, respectively, deviate by more than 10 percent from the median. I explain the cross-sectional variation in certainty-equivalent consumption with moments of industry-specific income growth and its cross-moments with aggregate stock returns. The first two moments of real income growth have strong explanatory power while higher-order moments and cross-moments, including correlation and newly proposed measures of business cycle variation in labor income risk, hardly matter.

JEL Classification: E21, G11, J24.

Key Words: Life-cycle portfolio choice, industry-specific human capital.

The potentially important role of human capital for optimal portfolio choice decisions of households across the life cycle is well understood from the theoretical literature: In the absence of complete markets, households optimally choose portfolios to offset their labor income risk. If human capital is relatively riskless as in the model of Cocco, Gomes and Maenhout (2005), the household bears increased stock market risk early in life when human capital is large and reduces exposure to stock market risk later in life. This timing is reversed when human capital is risky early in life because labor income and dividends are cointegrated as in Benzoni, Collin-Dufresne and Goldstein (2007). Moreover, a nonzero correlation between innovations to labor income and stock returns allows the household to hedge part of the labor income risk.[1] Business cycle variation in idiosyncratic labor income risk (Storesletten, Telmer and Yaron, 2004; Guvenen, Ozkan, and Song, 2014) leads to additional hedging demands (Lynch and Tan, 2011; Shen, 2018).

If human capital is industry-specific as emphasized in Eiling (2013), the value of life-cycle portfolio choice varies across otherwise identical households employed in different industries. This is because the moments of labor income growth and its cross-moments with aggregate stock returns are likely to vary across industries. While it is important for the individual household to understand the life-cycle portfolio choice implications of its human capital holdings, this insight is particularly relevant for occupational pension plans that are organized at the industry level in many countries. Given the power of default funds,[2] should the default asset allocation account for the industry-specific human capital of its members? If so, which properties of the industry-specific labor income process should be taken into account?[3] The

[1] See, e.g., the discussion in Viceira (2001) and Haliassos and Michaelides (2003).

[2] See Madrian and Shea (2001) and Choi, Laibson and Madrian (2004).

[3] These questions are obviously relevant for the design of target or life-cycle default funds. However,

existing literature on life-cycle portfolio choice cannot answer these questions because the labor income process does not account for industry-specific idiosyncratic risk. While Cocco et al. (2005) and Benzoni et al. (2007) investigate the impact of variations in the second moments of the labor income process on portfolio choice, these variations are only loosely linked to the human capital of a few selected industries.[4] Cocco et al. (2005) also consider the extreme case of completely ignoring the stochastic nature of labor income. It turns out that the utility loss associated with this extreme assumption is very small. However, these results need to be seen conditional on the stochastic specification of the labor income process.

In this paper, I present a systematic analysis of the impact of industry-specific human capital on the value of life-cycle portfolio choice. Like Cocco et al. (2005), I calculate the certainty-equivalent consumption (CEC) to summarize the value of life-cycle portfolio choice for each investor. I solve a life-cycle portfolio choice model for households employed in 73 different industries at the three-digit NAICS classification level and derive the cross-sectional distribution of CEC. Importantly, I leave the joint distribution of labor income growth and aggregate stock returns in each industry completely unspecified.[5] This is done by solving a sample analog of the Euler equations for consumption and portfolio choice using monthly time series of real industry-specific income growth from the Current Employment Statistics (CES) and the real return on a broad stock market index from January 1990–June 2018. I then relate the cross-sectional variation in the value of life-cyle portfolio choice to variation

Inkmann and Shi (2016) show that default asset allocations in defined contribution plans tend to take into account the age distribution of its members even if not explicitly designed as target or life-cycle funds.

[4]For example, Cocco et al. consider variations in the variance decomposition of labor income, which are calibrated to match second moments of labor income in Agriculture, Construction and Public Administration.

[5]Apart from assuming that the underlying data are ergodic and stationary as in Hansen (1982).

in the moments of the empirical distribution of labor income growth and its cross-moments with stock returns.

I propose to use higher-order cross-moments to investigate the importance of business cycle variation in industry-specific labor income risk: An industry with a low negative value of coskewness between labor income growth and aggregate stock returns is likely to exhibit high labor income growth volatility during recessions. An industry with a high positive value of cokurtosis between industry-specific labor income growth and aggregate stock returns is likely to exhibit negative skewness in labor income growth during recessions. Moreover, my framework allows me to investigate the role of predictability of labor income growth and stock returns. I solve an unconditional model without predictability and two conditional models that exploit the labor income-consumption ratio (Santos and Veronesi, 2006) and the dividend-price ratio (e.g. Campbell and Shiller, 1988) as predictor variables.

Due to the limitations of the underlying data, I consider the specific life-cycle portfolio choice problem of a household that faces labor income growth in line with the average income growth of employees in production and non-supervisory roles in its industry of occupation over an extended period of up to 20 years. Life-cycle decisions outside this period are ignored because I do not observe age-specific variation in industry-specific human capital.[6] Industry-specific human capital is the only source of idiosyncratic variation in labor income growth. This framework is certainly more appropriate for an industry-level pension fund

[6] Given the absence of age-profiles in labor income, one might question my repeated use of the "life-cycle portfolio choice" phrase. Perhaps "long-term portfolio choice" fits the investor's problem better. However, in contrast to the literature on long-term portfolio choice with consumption (e.g. Brandt, 1999, Campbell, Chan and Viceira, 2003), my model includes labor income, which is typical for life-cycle models.

that cares about its average member than for an individual household who bears additional idiosyncratic labor income risk.

Despite these limitations, I generate substantial cross-sectional variation in the value of life-cycle portfolio choice across industries from my model. The value of life-cycle portfolio choice in the "Motion picture and sound recording" industry turns out to be 10% (11%) lower than the median CEC across industries for an investment horizon of 10 (20) years and annual (biannual) rebalancing. At the positive tail of the distribution, the value of life-cycle portfolio choice in the "Securities, investments, funds and trusts" industry turns out to be 7.5% (13%) higher than the median CEC. These results, which are robust against variations in the household's conditioning information, motivate the title of this paper, the value of life-cycle portfolio choice indeed increases from Hollywood to Wall Street according to my analysis. The underlying cross-sectional variation in the moments of labor income growth and its cross-moments with stock returns is substantial as well but maybe less so than assumed in previous work. For example, the median correlation between labor income growth and stock returns across industries is -0.018, in line with figures used for the baseline model in Cocco et al. (2005), but the highest correlation is just 11% (in the "Couriers and messengers" industry), well below the assumed values of 20% and 40% used in variations from the baseline model. On the other hand, the lowest correlation is -10% (in the "Petroleum and coal products" industry) and therefore substantially lower than the median.

Given that industry-specific human capital is the only source of idiosyncratic variation across industries in my model, it is obvious that the cross-sectional variation in CEC can be explained with industry-specific moments of the labor income process. Which moments matter in terms of statistical and economic significance is less obvious. It turns out that the first and second moments of real monthly labor income growth have strong explanatory power. A one standard deviation increase in the average income growth increases CEC by about 3% (4.5%) when the investment horizon is 10 (20) years. A one standard deviation increase in the variance of labor income growth reduces CEC by 2.3% (3.3%). The impact of correlation is of an order of magnitude smaller and often not statistically significant once higher-order moments and cross-moments of labor income growth are added. Among these moments, only Kurtosis has a significant and negative impact on CEC at the 10-year horizon, although the impact is small in terms of economic relevance and disappears at the 20-year horizon.

This paper is related to previous work by Davis and Willen (2000, 2013). In Davis and Willen (2000), the authors focus on the variation in the covariance structure of labor income and asset returns due to differences in sex, education and birth cohort. In Davis and Willen (2013), the authors consider differences in the covariance structure across 10 occupations. In both cases, the covariance structure is estimated from repeated annual cross sections of the March Current Population Survey (CPS). The sample ranges from 1963-1994 in the first paper and from 1967-1994 in the second paper. While the covariance structure estimated in Davis and Willen (2000) leads to significant income hedging motives, aggregate stock returns turn out to be uncorrelated with occupation-level income innovations in Davis and Willen (2013). A welfare analysis in Davis and Willen (2000) focuses on the utility gains from trading in a tractable equilibrium life-cycle model with incomplete markets. The scope of my analysis is different. I derive the value of life-cycle portfolio choice across industries from a standard life-cycle model and relate the variation in CEC to variation in the moments of labor income growth. These moments are estimated from 342 monthly observations in my study while Davis and Willen rely on about 30 annual observations for the calculation of group-specific covariances. Asset returns and income innovations follow a joint normal distribution conditional on the information set in each period in Davis and Willen (2000), while I leave the joint distribution of asset returns and labor income growth unspecified. I also investigate higher-order moments and cross-moments and consider predictability of stock returns and labor income gowth.

My paper also relates to a large body of empirical work that uses micro data to investigate whether households are trying to offset or hedge income risk when choosing portfolios as implied by the life-cycle portfolio choice model. The conclusions from this literature are mixed: Heaton and Lucas (2000a) do not find any impact of wage volatility on the portfolio share of risky assets.[7] Guiso, Jappelli and Terlizzese (1996) report a negative impact of expected future wage volatility on the portfolio share of risky assets. Vissing-Jørgensen (2002) documents a negative impact of the volatility of nonfinancial income on the probability of stock market participation and the share of wealth invested in stocks conditional on participation, while the correlation between nonfinancial income and stock returns turns out to be insignificant. Massa and Simonov (2006) show that instead of hedging nonfinancial income risk, households tend to invest in stocks closely related to their nonfinancial income and explain this finding with familiarity. Betermier, Jansson, Parlour, and Walden (2012) show that households tend to offset increases in human capital risk due to job changes

[7] However, the authors find that households choose less risky portfolios in the presence of high and variable business income risk, another form of background risk (Heaton and Lucas, 2000b).

with reduced holdings of risky assets. The effect of human capital risk on portfolio choice becomes weaker when levels are considered instead of changes. Bonaparte, Korniotis, and Kumar (2014) find that a low correlation between income and stock market returns increases a household's propensity to participate in the stock market and the share of wealth allocated to stocks conditional on participation, even when income risk is high.

One reason for the huge variety of results reported in this literature could be the small number of annual time series observations available in typical micro datasets for the estimation of second moments of income and its correlation with stock returns. In addition, my analysis suggests that the inconclusive results of the empirical literature with respect to the hedging motive may be due to the economically small and statistically often insignificant effect of the correlation between labor income growth and stock returns on the value of life-cycle portfolio choice. Households may not engage in labor income hedging when they realize that the associated economic benefits are small. However, this argument does not explain the inconclusive result of the empirical literature with respect to labor income volatility because my results consistently suggest that substantial economic benefits can be gained from offsetting labor income risk.

The outine of this paper is as follows: Section 1 introduces the life-cycle portfolio choice model and the solution technique based on the Method of Moments. Section 2 describes the data sources and presents the empirical results. Section 3 concludes.

1. Life-Cycle Portfolio Choice

1.1. Optimization Problem

Similar to Cocco et al. (2005), the household is assumed to maximize the time-0 conditionally expected lifetime utility in consumption[8]

$$E_0 \sum_{t=0}^{T} \beta^t \frac{C_t^{1-\gamma}}{1-\gamma}, \tag{1}$$

where $\gamma > 0$ $(\gamma \neq 1)$ denotes the household's coefficient of relative risk aversion, β its subjective discount factor and T its investment horizon, by optimally choosing consumption, C_t, and the allocation to n risky assets, w_t, for $t = 0, ..., T$. Consumption is financed from cash-on-hand, X_t, which evolves according to the budget constraint

$$X_{t+1} = (X_t - C_t)\, R_{t+1}^p + L_{t+1}, \tag{2}$$

where L_{t+1} denotes the household's labor income and

$$R_{t+1}^p = R_{t+1}^f + w_t' R_{t+1}^e \tag{3}$$

the gross return on a portfolio of n risky assets with excess returns $R_{t+1}^e = R_{t+1}^e - R_{t+1}^f 1_n$ and the risk-free return, R_{t+1}^f. Unlike existing literature on life-cycle consumption and portfolio choice, I leave the stochastic processes governing the evolution of labor income and asset returns unspecified. Instead, time series data on labor income growth and asset returns

[8] Unlike Cocco et al. (2005), I ignore survival probabilities because the maximum investment horizon considered in the empirical section is 20 years.

are used below to estimate the households's optimal decisions. I assume that the household conditions on state variables, z_t, when forming expectations of future labor income and asset returns. This assumption allows for return predictability in contrast to the asummption of *iid* returns commonly employed in the life-cycle portfolio choice literature.

1.2. Dynamic Programming

The model is solved using dynamic programming. The value function is homogeneous of degree $-(1-\gamma)$ in labor income, $V_{t+1}(x_{t+1}, z_{t+1}) = L_{t+1}^{-(1-\gamma)} V_{t+1}(X_{t+1}, L_{t+1}, z_{t+1})$, where

$$x_{t+1} = \frac{X_{t+1}}{L_{t+1}} = \left(\frac{X_t}{L_t} - \frac{C_t}{L_t}\right)\frac{R_{t+1}^p}{G_{t+1}} + 1 \equiv G_{t+1}^{-1}(x_t - c_t) R_{t+1}^p + 1. \tag{4}$$

Cash-on-hand is scaled by labor income in order to rewrite the budget constraint in terms of labor income *growth,* $G_{t+1} = \frac{L_{t+1}}{L_t}$, and asset returns.[9] Differences in the joint empirical distribution of these random variables across industries will generate variation in the value of life-cycle portfolio choice in the empirical section of this paper. The Bellman equation of the problem now can be written as

$$V_t(x_t, z_t) = \max_{c_t, w_t}\left\{\frac{c_t^{1-\gamma}}{1-\gamma} + \beta E_t\left[G_{t+1}^{1-\gamma} V_{t+1}(x_{t+1}, z_{t+1})\right]\right\}. \tag{5}$$

The terminal condition of the problem is

$$V_T(x_T, z_T) = \frac{x_T^{1-\gamma}}{1-\gamma} \tag{6}$$

because the household optimally consumes all available cash-on-hand at the investment

[9] In life-cycle models that rely on a specification of the stochastic process for income (e.g. Carroll, 1996), cash-on-hand is often scaled by permanent income in order to save one state variable.

horizon T in the absence of a bequest motive, i.e. $c_T = x_T$. Using the Envelope Theorem, the Euler equations for consumption and the allocation to risky assets follow from (5) as

$$E_t\left[\beta\left(G_{t+1}\frac{c_{t+1}}{c_t}\right)^{-\gamma}\left(R^f_{t+1} + w_t' R^e_{t+1}\right) - 1\right] = 0 \tag{7}$$

$$E_t\left[\beta\left(G_{t+1}c_{t+1}\right)^{-\gamma}\left(x_t - c_t\right) R^e_{t+1}\right] = 0. \tag{8}$$

1.3. Method of Moments Estimation

The pair of Euler equations, (7) and (8), can be seen as a set of $n+1$ conditional moment restrictions of the form

$$E_t\left[\rho\left(y_{t+1}, \beta^0_t\right)\right] = E\left[\rho\left(y_{t+1}, \beta^0_t\right)|z_t\right] = 0, \tag{9}$$

where $y_{t+1} = \left(G_{t+1}, R^f_{t+1}, R^{e'}_{t+1}\right)'$ collects the involved random variables and $\beta_t = (c_t, w_t')'$ the unknown $s = n+1$ parameters to be estimated. I use a 0-superscript to indicate the true parameter vector solving the Euler eqautions. For a simpler dynamic consumption and portfolio choice problem without labor income,[10] Brandt (1999) proposes nonparametric Kernel-M estimation of β^0_t by replacing the conditional expectation in (9) with a Kernel-weighted time series average of the $s \times 1$ vector of conditional moment functions, $\rho\left(y_{t+1}, \beta_t\right)$. The author also mentions a parametric Method of Moments approach as an alternative, which I am using in this paper.[11] Like Brandt (1999), I estimate the optimal consumption

[10] Without labor income, the value function is homothetic in wealth, which considerably simplifies the estimation problem. With labor income, the Euler equations at each rebalancing time need to be solved for a grid of cash-on-hand.

[11] This approach is also used by Ghysels and Pereira (2008) for a myopic portfolio choice problem and by Inkmann and Shi (2015) for a dynamic portfolio choice problem without consumption.

and portfolio choice decisions from time series of stock returns and, in my case, labor income as the particular values of these choice variables that set the sample equivalent of the Euler equations equal to zero for given preference parameters. This application of the (Generalized) Method of Moments (Hansen, 1982) is different from Hansen and Singleton (1982), who estimate the preference parameters of a representative investor from time series of asset returns and aggregate consumption. The Method of Moments approach to solve the life-cycle model is particularly convenient for my application because it allows me to leave the joint distribution of labor income growth and asset returns unspecified. The standard approach to solve life-cycle portfolio choice problems relies on a discrete approximation of the assumed density functions governing the stochastic processes of labor income and stock returns.

The Method of Moments approach readily accomodates predictability of asset returns and labor income growth. While the potential predictability of asset returns plays a central role in the literature on dynamic portfolio choice,[12] predictability in life-cycle portfolio choice models has received much less attention.[13] This is because the age-profile of labor income already introduces horizon effects in life-cycle models, which are absent from typical models of dynamic portfolio choice. To incorporate predictability, the optimal consumption and portfolio choice decisions are parameterized as a flexible function of the state variables, z_t[14]

[12]See, e.g., Brandt (1999), Campbell and Viceira (1999) and Campbell, Chan and Viceira (2003) for dynamic portfolio choice problems involving consumptions but not labor income.

[13]Notable exceptions are Benzoni et al. (2007), Koijen, Nijman, and Werker (2010), Lynch and Tan (2011), and Michaelides and Zhang (2017).

[14]Parameterized portfolio weights are also proposed in Brandt and Santa-Clara (2006) and Brandt, Santa-Clara, and Valkanov (2009).

$$\beta_t^0 = \Theta_t^0 z_t^p, \tag{10}$$

where z_t^p is a $p \times 1$ vector of polynomial terms in the state variables, z_t. For example, if z_t includes two state variables, and a second-order polynomial is used, then $z_t^p = \begin{pmatrix} 1 & z_{1,t} & z_{2,t} & z_{1,t}^2 & z_{2,t}^2 & z_{1,t}z_{2,t} \end{pmatrix}'$ and $p = 6$. The unconditional model results from $z_t^p = 1$. It is convenient to use a vectorized version of the parameter matrix, $\theta_t^0 = vec\left(\Theta_t^0\right)$, which is a column vector with $q = (n+1)\,p$ elements. From replacing the parameterization of β_t^0 in the Euler equations, I obtain a conditional moment restriction in θ_t^0

$$E\left[\rho\left(y_{t+1}, \theta_t^0\right)|z_t\right] = 0. \tag{11}$$

A $r \times 1$ vector of unconditional moment functions, $\psi\left(y_{t+1}, z_t, \theta_t\right) = A\left(z_t\right)\rho\left(y_{t+1}, \theta_t\right)$, results from choosing an $r \times s$ matrix of state variables (or instruments), $A\left(z_t\right)$, such that

$$E\left[\psi\left(y_{t+1}, z_t, \theta_t^0\right)\right] = E\left[A\left(z_t\right)\rho\left(y_{t+1}, \theta_t^0\right)\right] = 0. \tag{12}$$

The second equality of this orthogonality condition holds by (11) and the law of iterated expectations. Given (10), a natural choice of the matrix of instruments is $A\left(z_t\right) = z_t^p \otimes I_s$, where I_s denotes an identity matrix of dimension s. This choice leads to $r = (n+1)\,p$ unconditional moment functions for $q = (n+1)\,p$ unknown parameters. Thus, the Method of Moments estimator is exactly identified, $r = q$, and θ_t^0 can be estimated for $t = 0, ..., T-1$ from a sample of observations $\{y_{s+1}, z_s : s = 1, ..., S-1\}$ by replacing the expectation operator in (12) with a time series average of the unconditional moment functions

$$\frac{1}{S-T}\sum_{s=t+1}^{S-(T-t)}\psi\left(y_{s+1},z_s,\widehat{\theta}_t\right)=0. \tag{13}$$

Table 1 shows the relationship between sample size (S) and investment horizon (T). At each rebalancing time t, the Method of Moments estimator averages over $S-T$ unconditional moment functions from $s=t+1,...,S-(T-t)$. The problem is solved backwards: At rebalancing time $t=T-1$, using the terminal condition, c_{t+1} is replaced with $c_T=x_T=G_T^{-1}\left(x_{T-1}-c_{T-1}\right)R_T^p+1$ in (7) and (8). Assuming an initial value for cash-on-hand x_{T-1}, the Euler equations are solved for the parameterization (10) of the optimal consumption and portfolio choice decision rules using the Method of Moments estimator (13) for $t=T-1$. This is repeated for an equally-spaced grid of possible cash-on-hand values, x_{T-1}. It is important to realize that I estimate the decision rule (10) for each value in the cash-on-hand grid. The parameter vector $\widehat{\theta}_t$ is saved for each grid point instead of the optimal consumption and portfolio choice decisions. All future decision rules are estimated at the time the household solves the dynamic program. When the household ages and reaches the next rebalancing time, the decision rules for each grid value of cash-on-hand are evaluated at the then observed vector of state variables and the optimal decisions of the household for the then observed value of cash-on-hand follow from a linear interpolation. In this way, I obtain the functions $c_{T-1}=f_{T-1}\left(x_{T-1}\right)$ and $w_{T-1}=g_{T-1}\left(x_{T-1}\right)$ describing the optimal decision rules of the household at $T-1$. At time $t=T-2$, c_{T-1} is replaced by $c_{T-1}=f_{T-1}\left(x_{T-1}\right)=f_{T-1}\left(G_{T-1}^{-1}\left(x_{T-2}-c_{T-2}\right)R_{T-1}^p+1\right)$ and the Euler equations are again solved by the Method of Moments for a grid of cash-on-hand, x_{T-2}, which allows me to generate the decision rules $c_{T-2}=f_{T-2}\left(x_{T-2}\right)$ and $w_{T-2}=g_{T-2}\left(x_{T-2}\right)$. The solution process is continued until period $t = 0$, in which the Euler equations only need to be solved once for a single starting value of (scaled) cash-on-hand, x_0.

1.4. Short-Sales and Borrowing Constraints

The share of wealth allocated to each risky assets in the unconditional model is restricted to fall in the unit interval. For the conditional models described below, I assume that the expected portfolio share of each risky asset falls in the unit interval.

1.5. Certainty-Equivalent Consumption

I follow Cocco et al. (2005) and compute the certainty-equivalent consumption that makes the household indifferent between receiving a stream of certain consumption, CEC, and implementing the optimal consumption and portfolio choice decisions. Starting from given initial values of (scaled) cash-on-hand, x_0, and labor income, L_0, and using the observed state variables, z_0, I obtain the optimal consumption at the initial rebalancing time, $\widehat{C}_0 = \widehat{c}_0 L_0$. Using the budget constraint and the then observed realizations of asset returns and labor income growth, G_1, I calculate (scaled) cash-on-hand at the next rebalancing time. From evaluating the saved optimal decision rules for $t = 1$ at the then observed state variables, z_1, I obtain $\widehat{C}_1 = \widehat{c}_1 L_1 = \widehat{c}_1 L_0 G_1$. The process is then iterated forward to $t = T$. Using this algorithm, I calculate the optimal consumption decisions, $\widehat{C}_{st}$, for each rebalancing time $t = 0, ..., T$ and each observation $s = 1, ..., S - T$ in my sample and estimate the household's time-0 value function $V_0 (x_0, z_0)$ as

$$\widehat{V}_0 = \frac{1}{S-T} \sum_{s=1}^{S-T} \sum_{t=0}^{T} \beta^t \frac{\widehat{C}_{st}^{1-\gamma}}{1-\gamma}. \tag{14}$$

CEC then follows from

$$\sum_{t=0}^{T} \beta^t \frac{CEC^{1-\gamma}}{1-\gamma} = \widehat{V}_0 \Leftrightarrow CEC = \left(\frac{(1-\beta)(1-\gamma)}{1-\beta^{T+1}} \widehat{V}_0 \right)^{\frac{1}{1-\gamma}}. \tag{15}$$

The following empirical analysis focuses on the distribution of CEC across households employed in different industries.

2. Empirical Analysis

2.1. Data

I consider a simple asset universe consisting of Treasury bills and an aggregate stock market index for the United States. Monthly returns on 30-day T-bill and a value-weighted return including dividends on a broad stock market index are obtained from CRSP for the period January 1990–June 2018. The data period is determined by the availability of the industry-specific labor income data described below. I solve an unconditional life-cycle model and two conditional models, in which the household conditions on predictive or state variables, for a household in each industry. Life-cycle models with predictability of asset returns use a variety of state variables: Benzoni et al. (2007) consider the log difference between aggregate labor income and dividends as a predictor for stock returns, while Lynch and Tan (2011) and Michaelides and Zhang (2017) condition on the dividend-price ratio. Koijen et al. (2010) investigate predictability of time-varying bond premia using prevailing premia as conditioning variables. I choose the labor income-consumption ratio of Santos and Veronesi

(2006) as my first state variable, which relates aggregate compensation of employees to aggregate personal consumption expenditures (W/C). Both series are seasonally adjusted and obtained from the National Income and Product Accounts (NIPA) Table 2.6 provided by the Bureau of Economic Analysis (BEA).[15] Santos and Veronesi (2006) show that W/C has strong predictive power for aggregate stock returns at horizons of 1 to 4 years. The numerator of the variable also should help predicting industry-specific labour income growth because aggregate compensation is correlated by construction with industry-specific labor income.

Like Lynch and Tan (2011) and Michaelides and Zhang (2017), I also consider the dividend-price ratio (D/P) as a (separate) predictive variable. The dividend-yield predicts cyclical variation in labor income risk in Lynch and Tan (2011). The dividend-price ratio has been widely used as a predictive variable for aggregate stock returns (e.g. in Campbell and Shiller, 1988). The present-value model of Campbell and Shiller (1988) suggests that (the log of) D/P may be particularly useful for prediciting stock returns at longer horizons. However, Santos and Veronesi (2006) document that D/P's ability to predict long-horizon stock returns was seriously diminished in the late 1990s, which simultaneously saw high returns and low dividend yields. Moreoever, Boudoukh, Richardson, and Whitelaw (2008) warn that empirical results overstate the value of D/P for long-horizon predictabilty because to some extent these results follow mechanically from the high persistence of D/P. Dividends for the CRSP broad stock market index are accumulated over 12 months at a zero rate of return

[15] This is the variable w_t^{ce}/C_t in Santos and Veronesi (2006) with the exception that I am using personal consumption expenditures instead of consumption of nondurables and services due to the 2013 revision of the NIPA data series.

and then related to the total market value of the index to obtain D/P. I also obtain monthly inflation series from CRSP to convert nominal returns and income growth figures into real ones. Table 2 contains descriptive statistics for the time series of real asset returns and state variables.

Data on industry-specific labor income is taken from the Current Employment Statistics (CES) provided by the Bureau of Labor Statistics. From CES, I obtain "average weekly earnings of production and nonsupervisory employees". CES also provides corresponding earnings series for all employees, which I am not using. There are two reasons for this choice: First, most of the earnings series for all empoyees are much shorter (often starting in 2006) than the series for production and non-supervisory employees that are available since January 1990. Second, I am assuming a household that faces labor income growth in line with the average income growth of employees in its industry of occupation over an extended period of up to 20 years. Such a stylized framework is probably not a good fit for supervisory employees on a steeper career path. CES provides all series in either raw of seasonally adjusted form. I choose the former because seasonal adjustment is likely to smooth the variation in income streams across industries. The industry classification system of CES can be translated into the more familiar 2017 North American Industry Classification System (NAICS) with the exception that CES does not cover all industries in NAICS. Earnings for production and nonsupervisory employees are available for 73 of the 86 subsectors at the three-digit NAICS level (85% coverage) and for 177 of the 285 industry groups at the four-digit NAICS level (62% coverage). The coverage of less aggregated industries at the five- and six-digit level is substantially worse. Given the wider coverage at the three-digit classification level, I use the 73 subsectors for my analysis but I will refer to them as industries. I create monthly income growth series from earnings, which are then converted into real labor income growth using the CRSP inflation series. Table 3 presents detailed descriptive statistics for the industry-specific real labor income growth. Here and in some of the following tables, I present results for all industries because some of these results may prove useful for the calibration of the income process in future work on life-cycle portfolio choice.

For each of the 73 industries, Table 3 shows the mean and variance of monthly real labor income growth in industry i (G_i) as well as some of its standardized cross central moments ($SCCM_i$) with real stock returns (R)

$$SCCM_i(a,b) = \frac{E\left[(G_i - E[G_i])^a (R - E[R])^b\right]}{\sigma(G_i)\,\sigma(R)}, \tag{16}$$

where $\sigma(\cdot)$ denotes the standard deviation. From (16) follows skewness ($a = 3, b = 0$), kurtosis ($a = 4, b = 0$), correlation ($a = 1, b = 1$), coskewness ($a = 2, b = 1$), and cokurtosis ($a = 3, b = 1$). The empirical moments in Table 3 are estimated by replacing expectation operators in (16) with sample averages. While most of these moments are familiar, coskewness and cokurtosis may be less known. I include these higher-order cross-moments to account for business cycle variation in industry-specific labor income risk:[16] An industry with a low negative value of coskewness between labor income growth and aggregate stock returns is likely to exhibit high labor income growth volatility during recessions. An

[16] Storesletten et al. (2004) report high values of idiosyncratic labor income growth volatility during recessions, while Guvenen et al. (2014) document negative skewness in labor income growth during recessions. These buisness cycle variations in idiosyncratic risk optimally lead to reduced stock market exposures (Lynch and Tan, 2011; Shen, 2018).

industry with a high positive value of cokurtosis between industry-specific labor income growth and aggregate stock returns is likely to exhibit negative skewness in labor income growth during recessions. Table 3 also shows CES identifiers for each industry. For space reasons, industry names are given in Table 4 below.[17]

Table 3 shows substantial variation in all moments of monthly real labor income growth and its cross-moments with real stock returns across industries. The average growth across industries is 1.0006 with an average variance of 0.0005. On average, the real labor income growth distribution is slightly skewed to the left (skewness of -0.0618) and slightly leptokurtic (kurtosis of 3.5472). The average correlation between income growth and stock returns is slightly negative (-0.018). Coskewness is on average close to zero (0.0030) and cokurtosis slighly negative (-0.0380). Two industries stand out: The "Petroleum and coal products" industry exhibits the lowest correlation between labor income growth and stock returns (-0.0966) and the lowest coskewness (-0.1608). The highest correlation between labor income growth and stock returns (0.1105) is observed in the "Couriers and messengers" industry, which also exhibits the highest mean income growth (1.0022), income risk (variance of 0.0019), kurtosis (7.2197), and cokurtosis (0.7032) among all industries.

2.2. Parameter Choice

Several choices are required for the empirical analysis: I choose investment horizons of $T = 120$ and $T = 240$ months. Recall that the sample consists of $S = 342$ months. Thus, a maximum investment horizon of 20 years still leaves $S - T = 102$ observations for the

[17] Again for space reasons, some of these industry names are slightly abbreviated. For instance the full name of the "Securities, investments, funds and trust industry" also includes "commodity contracts".

estimator (see Table 1). Given that only asymptotic properties of the Method of Moments estimator of nonlinear models are established (Hansen, 1982), I rule out investment horizons beyond 20 years. Investment horizons below 10 years are arguably not informative for the value of life-cycle portfolio choice. I consider two rebalancing frequencies, annual and biannual. This is done to allow for variation in the horizon relevant for the predictability of stock returns and income growth in the conditional models. I combine annual rebalancing with a 10-year investment horizon and biannual rebalancing with a 20-year horizon. The two state variables, W/C and D/P, are used separately. The investor either conditions on one or the other in line with the predictability literature (Santos and Veronesi, 2006). I choose a linear function in the state variable in the conditional models, $z_t^p = \begin{pmatrix} 1 & z_t \end{pmatrix}'$, because Inkmann and Shi (2015) show that most of the gains of predictability are already realized with a linear function, which is also used by Brandt et al. (2009). Because state variables are demeaned, the sample average of the optimal policies does not depend on the state variable. There are $q = 2$ parameters to be estimated in each application of the Method of Moments estimator in the solution of the unconditional model and $q = 4$ parameters in the conditional models.[18]

Regarding the household's preference parameters, I set relative risk aversion to $\gamma = 10$ and the subjective discount factor to $\beta = 0.98$ ($\beta = 0.96$) in combination with annual (biannual) rebalancing. I choose a high value of relative risk aversion to avoid that the portfolio share in stocks consistently reaches unity and to increase the importance of second and higher moments of labor income growth for the value of life-cycle portfolio choice. For

[18] All optimziations are performed with GAUSS 19 using the Constrained Optimization MT 2.0 module.

example, a result which indicates that the correlation between income growth and stock returns hardly matters for such a high coefficient of relative risk aversion is certainly more interesting than a result which claims the same for $\gamma = 1$. Finally, I choose an inital labor income of $L_0 = 1$ (unit) and endow the household with an initital cash-on-hand to labor income ratio of $x_0 = 2$. I choose a relatively small value because my stylized framework assumes labor income growth over an extended period in line with industry average for production and non-supervisory employees, which seems more appropriate for households at the beginning of their career when financial wealth is small.

2.3. Results

Table 4 shows the value of life-cycle portfolio choice in terms of CEC across the 73 industries for an investment horizon of 10 years and annual rebalancing. Results for the unconditional model and the two conditional models are given. Table 5 displays the corresponding results for an investment horizon of 20 years and biannual rebalancing. Because the results in both tables are qualitatively similar, I will simultaneously discuss both cases throughout this section. The median CEC across industries in Table 4 is 1.117 for the unconditional model and 1.115 and 1.118 for the two conditional models using the state variables W/C and D/P, respectively. The corresponding figures in Table 5 are 1.192, 1.191, and 1.193, respectively. The similarity of results for the three models at both investment horizons is striking and holds across the distribution of CEC. As far as these two state variables are concerned, this result suggests that households were not able to benefit from predicting labor income growth and stock returns over the period 1990-2018, irrespective of the length of the rebalancing period. Since the unconditional model is nested in the conditional one, the conditional CEC should exceed the unconditional one. This is not the case when W/C is used as a state variable. This is most likely due to estimation error since there are twice as many parameters to be estimated in the conditional models.[19] For this reason it is also doubtful that a parameterization, which includes polynomial terms in the state variables, improves the performance of the conditional models.

There is substantial cross-sectional variation in CEC at both investment horizons. This becomes obvious in Figures 1 and 2, which show the empirical cumulative distribution functions of the percentage deviation of CEC from its median value (referred to as $\%CEC$ from now on) for the three models and two investment horizons. The distribution of $\%CEC$ ranges from about -10% to 7.5% in Figure 1 and from about -11% to 13% in Figure 2. These are economically very important magnitudes. Using the same welfare mesasure (CEC), Cocco et al. (2005) derive an utility loss of 0.152% for households that implement a portfolio choice strategy that completely ignores the stochastic nature of labor income instead of the optimal portfolio choice strategy for their benchmark model. Thus, the variation in CEC across industries is of several orders of magnitude larger than the variation in CEC resulting from completely ignoring all labor income risk offsetting and hedging motives in a standard life-cycle model without industry-epecific human capital. The distribution of $\%CEC$ in Figure 1 is slightly left-skewed (about -0.08) and moderately platykurtic (i.e. displaying shorter and thinner tails compared to a normal distribution). The skewness of $\%CEC$ becomes moderately positive (about 0.44) in Figure 2 for the longer investment horizon, indicating

[19] This is similar to the case of the equally-weighted portfolio, which achieves higher mean-variance utility than the optimal mean-variance portfolio due to estimation risk (DeMiguel, Garlappi, and Uppal, 2009).

the longer tail of positive deviations of CEC from its median.

Is the variation in CEC across industries reflected in the variation of the optimal choice variables over the life cycle? Tables 6 and 7 show the 10th, 50th and 90th percentiles of the distribution of the sample averages of the optimal choice variables across industries for the three models and two investment horizons. As expected, there is substantial variation in optimal consumption and portfolio choice in the cross-section. For example, the median terminal consumption (which is equal to terminal cash-on-hand in the absence of a bequest motive) is 1.174 in the unconditional model in Table 6, while the 10th and 90th percentiles equal 1.146 and 1.277, respectively. The corresponding figures for Table 7 are 1.292, 1.231 and 1.446 in line with the positive skewness in CEC at the longer investment horizon. Despite the assumed high value of relative risk aversion ($\gamma = 10$), the average optimal portfolio shares in stocks are large across all industries, in particular for the shorter investment horizon in Table 6. This is certainly a consequence of the relatively small assumed initial ratio of cash-on-hand to labor income ($x_0 = 2$). For the longer investment horizon in Table 7, the cross-sectional heterogeneity in average optimal portfolio shares is largest for the portfolios in the second half of the life cycle. For example, while the median value for w_8 is 0.966, the 10th and 90th percentiles are 0.580 and 1.000, respectively.

Which industries offers the smallest and largest values of life-cycle portfolio choice? Tables 4 and 5 give a consistent answer across all investment horizons and conditioning sets: Hollywood offers the worst value of life-cycle portfolio choice and Wall Street the best. More specifically, the "Motion picture and sound recording industry" generates the smalles values of CEC, while the "Securities, investments, funds and trusts" industry generates the largest values. What distinguishes the empirical labor income growth distribution in these industries from others? Table 3 reveals that labor income growth is risky in both industries. In terms of the cross-sectional distribution of income growth variance, Hollywood ranks in the top 7% of all industries, while Wall Street ranks in the top 12%. Differences in the correlation between income growth and stock returns turn out to be small as well: Both industries exhibit negative correlation of a similar magnitude (-0.0703 for Hollywood and -0.0807 for Wall Street, corresponding to the 10th and 6th percentiles of the cross-sectional distribution). However, Wall Street has experienced the second highest average real income growth (1.0020) of all industries while Hollywood ranks in the bottom 4% with an average monthly income growth of 0.9999. Thus, nominal wage increases in Hollywood are unable to cover inflation during the sample period. Tables 8 and 9 compare the average optimal policies for both industries across the three models and two investment horizons. At the 10-year horizon, the optimal portfolios in both industries look very similar over the life cycle. The differences are much more pronounced at the 20-year horizon. The Wall Street household optimally invests much more risky in the first half of the life cycle than the Hollywood household. Optimal consumption on Wall Street exceeds optimal consumption in Hollywood at all rebalancing times and across all models and investment horizons.

I previously singled out two industries, which account for many of the most extreme positions in the cross-sectional ranking of labor income growth moments: "Petroleum and coal products", which has the lowest correlation (-0.0966) and coskewness of real labor income growth and real stock returns and "Couriers and messengers", which not only has the highest correlation (0.1105) but also the highest mean, variance, kurtosis and cokurtosis of all industries.[20] Tables 10 and 11 compare the average optimal policies for both industries across the three models and two investment horizons. The tables also show CEC and $\%CEC$ values for both industries, which differ substantially across models and horizons. Despite its highest income growth among all industries, the "Couriers and messengers" industry performs very poorly as a consequence of its higher income growth moments. I estimate large negative deviations from the median industry CEC in the magnitude of about -3% and -5%, respectively, for the two investment horizons. Interestingly, the "Petroleum and coal products" industry outperforms the median industry CEC by about 0.8% for the unconditional model at the shorter investment horizon but deviates by about -1.1% at the longer horizon. Households in this industry also seem to benefit from conditioning on the labor income to consumption ratio (W/C), which generates substantially higher CEC values compared to the unconditional model or the model that conditions on the dividend-price ratio (D/P). This indicates variation in the benefits of predictability across industries. While the average optimal portfolio shares in stocks in the "Couriers and messengers" industry are almost always smaller than the corresponding shares in the "Petroleum and coal products" industry, the differences are much more pronounced at the 20-year horizon. The household in the "Couriers and messengers" industry also remain exposed to considerable life-cycle variation in consumption, which is absent from the "Petroleum and coal products" industry and clearly contributes to the low values of CEC achieved in this industry.

[20] One possible explanation for this accumulation of extreme ranks in the latter industry is the emergence of online shopping during the sample period. The sample starts in 1990. Amazon.com was incorporated in July 1994 and ranks among the most valuable public companies in the world at the end of the sample period in June 2018.

Summarizing the univariate results so far, I have documented both a strong positive effect of the first moment of real labor income growth on the value of life-cycle portfolio choice (in the case of the Wall Street industry) and a strong negative effect of labor income growth variance and the correlation of labor income growth with stock returns (in the case of the "Couriers and messengers" industry). I now perform a multivariate analysis to see which moments and cross-moments matter for the value of life-cyle portfolio choice when they are simultaneously controlled for. For this purpose, I estimate cross-sectional linear regressions of CEC on the moments of monthly real income growth and its cross-moments with monthly real stock retuns at the industry level. For ease of interpretation, I take the log of the dependent variable and standardize all explantory variables. Thus, any slope coefficient can be interpreted in terms of the percentage change in CEC resulting from a one standard deviation change in the independent variable. Because the estimates for the three models turn out to be very similar at both investment horizons, I only discuss the results for the unconditional model.

The results are given in Tables 12 and 13 for the two investment horizons. The first empirical specification in Table 12 includes three regressors: Mean, variance and correlation. All three variables are statistically significant at the 1% level. A one standard deviation increase in mean real income growth increases CEC by about 3%. A one standard deviation increase in the risk (variance) of labor income growth reduces CEC by about 2.3%. The impact of a one standard deviation increase in the correlation between labor income growth and stock returns is smaller and reduces CEC by about -0.6%. While larger in absolute value, the results turn out to be qualitatively very similar for the 20-year horizon: A one standard deviation increase in mean, variance and correlation leads to a 4.4%, -3.4% and -1% change in CEC, respectively.

In a second empirical specification, I add skewness and kurtosis to the set of regressors.[21] The additional variables turn out to be insignificant at the 20-year horizon and do not affect previous results. However, at 10-year horizon, correlation looses some of its economic and statistical significance. This is due to the inclusion of kurtosis. A one standard deviation increase in either of these variables decreases CEC by about 0.4%, statistically significant at the 10% level. Skewness remains insignificant at the 10-year horizon. Finally, I add higher-order cross-moments, coskewness and cokurtosis, in the third empirical specification to account for business cycle variation in industry-specific labor income risk. While both cross-moments have the expected sign, they turn out to be insignificant. Previous results for the 20-year horizon remain largely unaffected from the inclusion of these variables with the exception of correlation, which just remains significant at the 10% level. Correlation becomes insignificant at the 10-year horizon while the impact of kurtosis now turns out to be significant at the 5% level.

In summary, I find strong effects of average income growth and its variance, moderate effects of correlation and kurtosis, while other moments and cross-moments of industry-specific labor income growth do not matter for the value of life-cycle portfolio choice. The variation in the industry-specific moments and cross-moments of monthly real labor income growth explains about 66% of the variation in CEC across industries at the 10-year horizon and about 69% at the 20-year horizon.

[21] Investors who receive utility from terminal wealth prefer higher odd and lower even moments (Horvath and Scott, 1980; Martellini and Ziemann, 2010).

3. Conclusion

I investigate the impact of a particular source of idiosyncratic labor income risk, industry-specifc human capital, on the value of life-cycle portfolio choice. I solve a life-cycle portfolio choice model for households employed in 73 different industries at the three-digit NAICS classification level and derive the cross-sectional distribution of certainty-equivalent consumption (CEC). The joint distribution of industry-specific real labor income growth and aggregate stock returns is left unrestricted by using a Method of Moments estimator to solve the Euler equations. I generate substantial cross-sectional variation in the value of life-cycle portfolio choice across industries: The CEC of a household employed in an industry closely related to Hollywood (Wall Street) deviates by -11% (+13%) from the median CEC across industries at a 20-year investment horizon.

I then relate the cross-sectional variation in the value of life-cyle portfolio choice to variation in the moments of the empirical distribution of real labor income growth and its cross-moments with real aggregate stock returns. I find strong effects of average income growth and its variance, moderate effects of correlation and kurtosis, while other moments and cross-moments do not matter for the value of life-cycle portfolio choice. This includes coskewness and cokurtosis cross-moments, which I propose to capture business cycle variation in the variance and skewness of industry-specific labor income growth. I also allow for the predictability of labor income growth and stock returns. However, it turns out that households do not benefit from conditioning on either the labor income-consumption ratio or the dividend-price ratio during my sample period, which ranges from January 1990–June 2018 and includes three NBER recessions.

My findings may explain the inconclusive results of an empirical literature that uses micro data to discover income hedging motives in household portfolio choice. Households may not engage in labor income hedging when they realize that the associated economic benefits are small. However, this argument does not explain the inconclusive result of the empirical literature with respect to labor income volatility because my results consistently suggest that substantial economic benefits can be gained from offsetting labor income risk.

The reported substantial variation in the value of life-cycle portfolio choice across industries suggests using heterogeneity in industry-specific human capital in life-cycle portfolio choice models to match the observed cross-sectional variation in household portfolios as an alternative to preference parameter heterogeneity (Gomes and Michaelides, 2005). The summary statistics of labor income growth given in my paper for a wide range of industries may be helpful in calibrating such a life-cycle model with industry-specific human capital.

Finally, my results imply that trustees of defined contribution pension plans organized at industry level should take into account the first two moments of industry-specific labor income growth when designing default asset allocation products like target or life-cycle funds. A product that works well for the pension plan members of one industry may be less suitable for members of another industry.

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Table 1: Relationship between sample size (S) and investment horizon (T)

#	s=1	s=2	s=3	s=4	s=5	s=6	s=7	…	s=14	s=15	s=16	s=17	s=18	s=19	s=S=20
1	t=0	t=1	t=2	t=3	t=4	t=T=5									
2		t=0	t=1	t=2	t=3	t=4	t=T=5								
3			t=0	t=1	t=2	t=3	t=4	…							
4				t=0	t=1	t=2	t=3	…							
5					t=0	t=1	t=2	…							
6						t=0	t=1	…							
7							t=0	…							
8								…							
9								…	t=T=5						
10								…	t=4	t=T=5					
11								…	t=3	t=4	t=T=5				
12								…	t=2	t=3	t=4	t=T=5			
13								…	t=1	t=2	t=3	t=4	t=T=5		
14									t=0	t=1	t=2	t=3	t=4	t=T=5	
S-T=15										t=0	t=1	t=2	t=3	t=4	t=T=5

Notes: The table shows the mechanism of the Method of Moments estimator for a simple example with sample size S = 20 months, investment horizon T = 5 months, and monthly rebalancing. For each rebalancing time, t = 0, ..., T-1, the estimator averages over S-T solutions of the life-cycle model from s = t+1, …, S-(T-t). The real data consists of S = 342 months and I consider investment horizons of T = 120 and T = 240 months with annual and biannual rebalancing, respectively.

Table 2: Descriptive statistics of real asset returns and conditioning variables

Variable	Symbol	Mean	Standard deviation
Real return on T-bills	R^f	1.0022	0.0019
Real return on stocks	R	1.0085	0.0421
Labor income-consumption ratio	W/C	0.8227	0.0356
Dividend-price ratio	D/P	0.0204	0.0056

Notes: The table shows descriptive statistics for monthly real asset returns and conditioning variables for the period January 1990 – June 2018. Returns on a 30-day T-bill and value-weighted returns including dividends on a broad stock market index are obtained from CRSP, which is also the source for the inflation series used to calculate real returns. Dividends for the CRSP market index are accumulated over 12 months at a zero rate of return and then divided by the total market value to obtain the dividend-price ratio. The labor income-consumption ratio relates the compensation of employees to personal consumption expenditures. Both series are obtained from NIPA Table 2.6 provided by the BEA.

Table 3: Real labor income growth moments and cross-moments with real stock returns by industry

Industry	Mean	Variance	Skewness	Kurtosis	Correlation	Coskewn.	Cokurtosis
10211000	1.0014	0.0012	0.2368	2.5727	0.0238	0.0064	0.0539
10212000	0.9999	0.0002	-0.1595	3.6197	-0.0306	-0.0827	-0.2166
10213000	1.0013	0.0007	0.1655	4.3764	-0.0493	0.0394	-0.5239
20236000	1.0005	0.0003	-0.0618	5.4981	0.0208	0.2881	0.5478
20237000	1.0016	0.0014	-0.2969	3.5472	-0.0595	0.2262	0.0696
20238000	1.0005	0.0005	-0.3169	3.8449	0.0179	0.2076	0.1506
31321000	1.0004	0.0003	-0.4556	3.1362	0.0106	0.0261	0.0112
31327000	1.0005	0.0004	-0.3405	4.4476	-0.0367	0.0888	-0.2347
31331000	1.0001	0.0002	-0.0816	3.2211	0.0993	-0.0108	0.2156
31332000	1.0002	0.0002	-0.4436	3.8748	0.0487	0.1319	0.1455
31333000	1.0002	0.0003	-0.3376	3.9506	0.0752	0.1269	0.2003
31334000	1.0006	0.0002	-0.4166	3.7541	-0.0106	0.0285	-0.1322
31335000	1.0004	0.0004	-0.3156	3.5151	0.0761	0.0687	0.4122
31336000	1.0005	0.0008	-0.2558	3.7985	-0.0113	-0.1517	0.0188
31337000	1.0005	0.0004	-0.8146	6.5145	0.0263	0.0522	-0.0836
31339000	1.0005	0.0002	-0.3727	3.5370	-0.0075	0.0491	-0.2245
32311000	1.0002	0.0002	-0.6130	3.3509	0.0008	0.0088	-0.0380
32313000	1.0006	0.0005	0.0725	6.8068	0.0172	0.0072	0.0637
32314000	1.0006	0.0006	-0.4979	5.8744	0.0357	0.0288	-0.0288
32315000	1.0012	0.0004	-0.1383	9.8502	0.0654	0.0458	-0.0278
32322000	0.9999	0.0002	-0.1291	2.9245	0.0394	0.0865	0.2042
32323000	0.9998	0.0002	-0.3758	3.6233	-0.0374	-0.0857	0.0354
32324000	1.0009	0.0008	0.0732	4.3732	-0.0966	-0.1608	-0.4054
32325000	1.0000	0.0002	0.0910	2.9743	-0.0276	-0.0164	-0.2364
32326000	1.0001	0.0002	-0.1970	3.2011	0.0224	0.0086	0.1144
32329000	1.0003	0.0005	-0.1407	4.1715	-0.0801	-0.0796	-0.7598
41423000	1.0005	0.0003	-0.0109	2.4360	-0.0469	-0.0827	-0.2076
41424000	1.0004	0.0002	0.1404	3.1787	-0.0332	-0.1101	-0.1209
41425000	1.0008	0.0005	-0.0147	2.8988	-0.0617	-0.1103	-0.0040
42441000	1.0003	0.0004	-0.0326	3.0831	0.0181	-0.1073	0.0360
42442000	1.0004	0.0004	-0.4383	3.5469	-0.0235	-0.1119	0.0764
42443000	1.0016	0.0008	0.6571	5.2868	0.0374	0.2280	1.2740
42444000	0.9999	0.0002	-0.3582	5.0397	-0.0882	0.0668	-0.4390
42445000	0.9996	0.0002	-0.4481	5.5462	-0.0254	0.2406	-0.3946
42446000	1.0010	0.0002	0.0080	2.8681	0.0287	-0.0237	-0.2180
42447000	0.9999	0.0001	0.4435	4.9199	0.0178	-0.0686	-0.1088
42448000	1.0005	0.0009	-0.0765	4.5716	0.0697	0.1094	0.3334
42451000	1.0009	0.0008	0.2874	3.4808	0.0288	0.0403	0.3347
42452000	1.0013	0.0011	-0.6953	5.4225	0.1033	0.0931	0.3665
42453000	0.9999	0.0004	0.0236	3.0000	0.0246	0.0311	-0.0588
42454000	1.0004	0.0005	0.5684	4.3447	0.0458	0.1445	0.3245
43481000	1.0014	0.0018	0.0690	3.5641	-0.0696	0.0196	-0.0764

43484000	1.0002	0.0002	-1.0818	5.2800	-0.0080	0.0369	-0.2161
43485000	1.0004	0.0007	0.1276	3.3224	0.0889	-0.0642	0.4928
43486000	1.0016	0.0006	0.4974	5.7529	-0.0703	-0.0489	-0.0842
43488000	0.9999	0.0002	-0.0007	2.9240	-0.0562	0.0030	-0.1208
43492000	1.0022	0.0019	0.5865	7.2197	0.1105	-0.0619	0.7032
43493000	1.0001	0.0005	-0.6005	6.0678	0.0603	-0.0665	0.1342
50512000	0.9999	0.0012	0.0649	3.1292	-0.0703	-0.0739	-0.0621
50515000	1.0011	0.0004	0.0103	2.9542	-0.0337	-0.0845	-0.0112
50517000	1.0004	0.0003	0.1335	3.4644	-0.0180	-0.0883	-0.1804
50518000	1.0015	0.0007	0.1470	3.6592	-0.0352	-0.0623	-0.1420
50519000	1.0011	0.0012	0.1516	4.2853	-0.0644	0.0094	0.0871
55522000	1.0014	0.0008	0.0515	2.2202	-0.0874	-0.0210	-0.1306
55523000	1.0020	0.0011	0.0943	2.4561	-0.0807	0.0593	-0.1039
55524000	1.0012	0.0004	-0.1434	2.1807	-0.0966	-0.0114	-0.1599
55531000	1.0009	0.0003	0.2136	2.3931	-0.0310	-0.0681	-0.1442
55532000	1.0010	0.0002	0.0583	3.3868	-0.0359	-0.0788	-0.0095
60561000	1.0006	0.0001	-0.2122	4.8120	0.0506	0.0684	0.2753
60562000	1.0005	0.0001	-0.3411	3.7587	-0.0411	-0.0198	-0.3788
65620001	1.0009	0.0001	0.1600	2.8490	-0.0379	-0.0256	-0.2563
65621000	1.0010	0.0001	0.2380	2.8052	-0.0337	0.0137	-0.0360
65622000	1.0011	0.0001	0.3642	4.0940	0.0291	-0.0339	-0.2635
65623000	1.0005	0.0003	-0.1188	2.6888	-0.0477	-0.0211	-0.1420
65624000	1.0002	0.0002	0.0374	2.2930	-0.0484	-0.0967	-0.0152
70711000	1.0006	0.0013	0.2741	3.7892	-0.0539	-0.0058	-0.0187
70712000	1.0000	0.0006	-0.1087	2.7538	-0.0436	0.0295	-0.2167
70713000	0.9997	0.0004	-0.3165	2.7360	0.0755	-0.0782	0.2328
70721000	1.0005	0.0003	0.2090	3.1072	-0.0216	0.1262	0.1297
70722000	1.0009	0.0004	-0.5722	3.2735	0.0023	-0.0939	-0.1493
80811000	1.0003	0.0001	-0.1110	3.2902	-0.0190	-0.0580	-0.1100
80812000	1.0000	0.0003	-0.6220	3.7678	0.0182	0.0095	-0.0556
80813000	1.0005	0.0001	0.0789	4.3024	-0.0409	-0.0667	-0.1459
Median	1.0005	0.0004	-0.0618	3.5472	-0.0180	0.0030	-0.0380
Mean	1.0006	0.0005	-0.0922	3.8981	-0.0066	0.0058	-0.0089
Std. dev.	0.0006	0.0004	0.3345	1.3263	0.0520	0.0943	0.2886

Notes: The table shows moments of real labor income growth across industries based on monthly CES labor income data from January 1990 – June 2018 (342 observations), deflated by the CRSP inflation series. All 73 CES industries with an equivalent three-digit 2017 NAICS code are selected, accounting for 85% of the 86 industries at the three-digit level in the 2017 NAICS classification. Industry names are given in Table 3 below. The cross-moments with real stock returns in the final three columns are based on monthly data of the CRSP value-weighted broad stock market index for the US for the same period.

Table 4: Certainty-equivalent consumption by industry and conditioning information ($T = 10$ years)

		Conditioning information		
CES ID	Industry	None	W/C	D/P
10211000	Oil and gas extraction	1.116	1.112	1.116
10212000	Mining, except oil and gas	1.108	1.107	1.108
10213000	Support activities for mining	1.135	1.134	1.135
20236000	Construction of buildings	1.140	1.138	1.140
20237000	Heavy and civil engineering construction	1.146	1.143	1.146
20238000	Specialty trade contractors	1.121	1.117	1.121
31321000	Wood products	1.105	1.102	1.106
31327000	Nonmetallic mineral products	1.100	1.098	1.101
31331000	Primary metals	1.095	1.093	1.096
31332000	Fabricated metal products	1.117	1.115	1.117
31333000	Machinery	1.103	1.101	1.104
31334000	Computer and electronic products	1.163	1.161	1.162
31335000	Electrical equipment and appliances	1.110	1.108	1.111
31336000	Transportation equipment	1.111	1.110	1.112
31337000	Furniture and related products	1.124	1.122	1.124
31339000	Misc. durable goods manufacturing	1.142	1.140	1.142
32311000	Food manufacturing	1.112	1.109	1.112
32313000	Textile mills	1.096	1.093	1.097
32314000	Textile product mills	1.081	1.078	1.082
32315000	Apparel	1.161	1.159	1.161
32322000	Paper and paper products	1.100	1.098	1.101
32323000	Printing and related support activities	1.091	1.089	1.092
32324000	Petroleum and coal products	1.126	1.126	1.126
32325000	Chemicals	1.091	1.089	1.092
32326000	Plastics and rubber products	1.113	1.112	1.113
32329000	Misc. nondurable goods manufacturing	1.096	1.093	1.096
41423000	Durable goods	1.118	1.116	1.119
41424000	Nondurable goods	1.138	1.135	1.138
41425000	Electronic markets, agents and brokers	1.135	1.130	1.136
42441000	Motor vehicle and parts dealers	1.091	1.088	1.092
42442000	Furniture and home furnishings stores	1.086	1.085	1.087
42443000	Electronics and appliance stores	1.116	1.112	1.121
42444000	Building material and garden supply stores	1.077	1.080	1.077
42445000	Food and beverage stores	1.067	1.066	1.068
42446000	Health and personal care stores	1.173	1.175	1.172
42447000	Gasoline stations	1.101	1.099	1.101
42448000	Clothing and clothing accessories stores	1.028	1.029	1.029
42451000	Sporting goods, hobby, book, music stores	1.074	1.070	1.074
42452000	General merchandise stores	1.129	1.131	1.129
42453000	Miscellaneous store retailers	1.092	1.089	1.093
42454000	Nonstore retailers	1.133	1.130	1.134

43481000	Air transportation	1.115	1.113	1.114
43484000	Truck transportation	1.099	1.096	1.100
43485000	Transit & ground passenger transportation	1.080	1.077	1.081
43486000	Pipeline transportation	1.185	1.185	1.185
43488000	Support activities for transportation	1.132	1.132	1.132
43492000	Couriers and messengers	1.080	1.081	1.082
43493000	Warehousing and storage	1.073	1.071	1.074
50512000	Motion picture and sound recording	1.009	1.005	1.011
50515000	Broadcasting, except Internet	1.174	1.176	1.174
50517000	Telecommunications	1.126	1.127	1.126
50518000	Data processing, hosting and related	1.192	1.188	1.192
50519000	Other information services	1.077	1.073	1.079
55522000	Credit intermediation and related activity	1.160	1.157	1.160
55523000	Securities, investments, funds and trusts	1.201	1.196	1.201
55524000	Insurance carriers and related activities	1.172	1.170	1.173
55531000	Real estate	1.163	1.161	1.163
55532000	Rental and leasing services	1.163	1.159	1.162
60561000	Administrative and support services	1.153	1.151	1.153
60562000	Waste management and remediation	1.134	1.134	1.134
65620001	Health care	1.178	1.177	1.177
65621000	Ambulatory health care services	1.182	1.181	1.182
65622000	Hospitals	1.195	1.194	1.194
65623000	Nursing and residential care facilities	1.127	1.127	1.127
65624000	Social assistance	1.119	1.119	1.118
70711000	Performing arts and spectator sports	1.142	1.143	1.141
70712000	Museums, historical sites, and similar	1.103	1.101	1.103
70713000	Amusements, gambling, and recreation	1.102	1.101	1.103
70721000	Accommodation	1.125	1.125	1.124
70722000	Food services and drinking places	1.138	1.135	1.138
80811000	Repair and maintenance	1.117	1.114	1.117
80812000	Personal and laundry services	1.094	1.092	1.094
80813000	Membership associations and organization	1.128	1.125	1.129
Median		1.117	1.115	1.118
Mean		1.121	1.119	1.121
Std. dev.		0.037	0.037	0.036

Notes: The table shows certainty-equivalent consumption (CEC) across 73 industries at the three-digit NAICS level for three different conditioning variables: none (unconditional model), labor income-consumption ratio (W/C), dividend-price ratio (D/P). CEC is calculated from solving the life-cycle portfolio choice model with an investment horizon of $T = 10$ years, an annual rebalancing period, a relative risk aversion coefficient of $\gamma = 10$, a subjective discount factor of $\beta = 0.98$, an initial wealth-income ratio of $x_0 = 2$, and an initial income of $L_0 = 1$.

Table 5: Certainty-equivalent consumption by industry and conditioning information ($T = 20$ years)

CES ID	Industry	Conditioning information none	W/C	D/P
10211000	Oil and gas extraction	1.173	1.161	1.174
10212000	Mining, except oil and gas	1.141	1.136	1.141
10213000	Support activities for mining	1.185	1.175	1.186
20236000	Construction of buildings	1.224	1.215	1.224
20237000	Heavy and civil engineering construction	1.228	1.225	1.229
20238000	Specialty trade contractors	1.192	1.191	1.193
31321000	Wood products	1.175	1.173	1.176
31327000	Nonmetallic mineral products	1.180	1.176	1.182
31331000	Primary metals	1.149	1.149	1.151
31332000	Fabricated metal products	1.179	1.177	1.179
31333000	Machinery	1.144	1.143	1.146
31334000	Computer and electronic products	1.247	1.246	1.247
31335000	Electrical equipment and appliances	1.169	1.167	1.171
31336000	Transportation equipment	1.158	1.156	1.159
31337000	Furniture and related products	1.219	1.215	1.220
31339000	Misc. durable goods manufacturing	1.216	1.214	1.217
32311000	Food manufacturing	1.178	1.176	1.179
32313000	Textile mills	1.155	1.154	1.157
32314000	Textile product mills	1.167	1.165	1.162
32315000	Apparel	1.262	1.259	1.262
32322000	Paper and paper products	1.154	1.151	1.155
32323000	Printing and related support activities	1.153	1.151	1.154
32324000	Petroleum and coal products	1.179	1.173	1.180
32325000	Chemicals	1.150	1.144	1.152
32326000	Plastics and rubber products	1.182	1.179	1.182
32329000	Misc. nondurable goods manufacturing	1.211	1.206	1.215
41423000	Durable goods	1.206	1.202	1.207
41424000	Nondurable goods	1.219	1.217	1.219
41425000	Electronic markets, agents and brokers	1.205	1.201	1.207
42441000	Motor vehicle and parts dealers	1.189	1.184	1.193
42442000	Furniture and home furnishings stores	1.181	1.179	1.182
42443000	Electronics and appliance stores	1.265	1.262	1.268
42444000	Building material and garden supply stores	1.202	1.195	1.203
42445000	Food and beverage stores	1.139	1.125	1.141
42446000	Health and personal care stores	1.307	1.293	1.306
42447000	Gasoline stations	1.160	1.158	1.161
42448000	Clothing and clothing accessories stores	1.136	1.135	1.140
42451000	Sporting goods, hobby, book, music stores	1.145	1.138	1.147
42452000	General merchandise stores	1.237	1.235	1.238
42453000	Miscellaneous store retailers	1.154	1.151	1.157
42454000	Nonstore retailers	1.209	1.209	1.210

43481000	Air transportation	1.155	1.153	1.155
43484000	Truck transportation	1.139	1.137	1.140
43485000	Transit & ground passenger transportation	1.120	1.117	1.123
43486000	Pipeline transportation	1.286	1.287	1.284
43488000	Support activities for transportation	1.206	1.204	1.206
43492000	Couriers and messengers	1.130	1.122	1.133
43493000	Warehousing and storage	1.139	1.134	1.141
50512000	Motion picture and sound recording	1.059	1.050	1.061
50515000	Broadcasting, except Internet	1.333	1.333	1.333
50517000	Telecommunications	1.204	1.200	1.205
50518000	Data processing, hosting and related	1.314	1.311	1.308
50519000	Other information services	1.143	1.141	1.148
55522000	Credit intermediation and related activity	1.280	1.276	1.280
55523000	Securities, investments, funds and trusts	1.346	1.342	1.345
55524000	Insurance carriers and related activities	1.287	1.285	1.288
55531000	Real estate	1.264	1.261	1.264
55532000	Rental and leasing services	1.262	1.259	1.262
60561000	Administrative and support services	1.257	1.255	1.257
60562000	Waste management and remediation	1.264	1.262	1.265
65620001	Health care	1.286	1.285	1.285
65621000	Ambulatory health care services	1.299	1.298	1.299
65622000	Hospitals	1.314	1.313	1.313
65623000	Nursing and residential care facilities	1.232	1.230	1.233
65624000	Social assistance	1.209	1.207	1.210
70711000	Performing arts and spectator sports	1.258	1.260	1.256
70712000	Museums, historical sites, and similar	1.179	1.177	1.180
70713000	Amusements, gambling, and recreation	1.166	1.163	1.167
70721000	Accommodation	1.216	1.204	1.217
70722000	Food services and drinking places	1.233	1.222	1.234
80811000	Repair and maintenance	1.187	1.165	1.170
80812000	Personal and laundry services	1.168	1.141	1.170
80813000	Membership associations and organization	1.213	1.194	1.214
Median		1.192	1.191	1.193
Mean		1.204	1.199	1.204
Std. dev.		0.057	0.058	0.057

Notes: The table shows certainty-equivalent consumption (CEC) across 73 industries at the three-digit NAICS level for three different conditioning variables: none (unconditional model), labor income-consumption ratio (W/C), dividend-price ratio (D/P). CEC is calculated from solving the life-cycle portfolio choice model with an investment horizon of $T = 20$ years, a biannual rebalancing period, a relative risk aversion coefficient of $\gamma = 10$, a subjective discount factor of $\beta = 0.96$, an initial wealth-income ratio of $x_0 = 2$, and an initial income of $L_0 = 1$.

Table 6: Distribution of average optimal choice variables across industries by conditioning information ($T = 10$ years)

		None			W/C			D/P	
	10th	Median	90th	10th	Median	90th	10th	Median	90th
C_0	1.067	1.100	1.141	1.066	1.098	1.139	1.069	1.099	1.140
C_1	1.079	1.109	1.153	1.076	1.111	1.152	1.082	1.109	1.152
C_2	1.090	1.121	1.166	1.088	1.120	1.166	1.092	1.120	1.166
C_3	1.100	1.131	1.177	1.096	1.129	1.177	1.101	1.130	1.176
C_4	1.107	1.139	1.183	1.103	1.139	1.183	1.109	1.138	1.182
C_5	1.117	1.149	1.195	1.112	1.150	1.197	1.117	1.148	1.197
C_6	1.124	1.156	1.213	1.121	1.157	1.208	1.123	1.155	1.213
C_7	1.132	1.163	1.231	1.128	1.162	1.229	1.131	1.162	1.229
C_8	1.137	1.167	1.250	1.138	1.165	1.251	1.135	1.166	1.248
C_9	1.143	1.170	1.264	1.146	1.173	1.269	1.140	1.169	1.263
C_{10}	1.146	1.174	1.277	1.151	1.182	1.288	1.144	1.173	1.275
w_0	1.000	1.000	1.000	0.924	1.000	1.000	1.000	1.000	1.000
w_1	0.997	1.000	1.000	0.957	0.996	0.996	0.999	1.000	1.000
w_2	0.994	1.000	1.000	0.977	0.991	0.991	0.997	0.999	0.999
w_3	0.956	1.000	1.000	0.940	0.986	0.986	0.975	0.999	0.999
w_4	0.975	1.000	1.000	0.952	0.981	0.981	0.985	0.999	0.999
w_5	0.975	1.000	1.000	0.953	0.977	0.977	0.984	0.998	0.998
w_6	0.955	1.000	1.000	0.929	0.974	0.974	0.973	0.998	0.998
w_7	0.921	0.999	1.000	0.883	0.971	0.971	0.945	0.997	0.998
w_8	0.970	0.997	1.000	0.916	0.967	0.967	0.976	0.996	0.999
w_9	0.991	0.995	0.997	0.948	0.961	0.963	0.991	0.995	0.996

Notes: The table shows the 10th, 50th and 90th percentiles of the distribution of the average optimal choice variables across 73 industries at the three-digit NAICS level for three different conditioning variables: none (unconditional model), labor income-consumption ratio (W/C), dividend-price ratio (D/P). C_0 to C_{10} denotes consumption and w_0 to w_9 the share of wealth allocated to stocks at rebalancing times $t = 0, \ldots, 10$ ($w_{10} = 0$). The optimal choice variables are calculated from solving the life-cycle portfolio choice model with an investment horizon of $T = 10$ years, an annual rebalancing period, a relative risk aversion coefficient of $\gamma = 10$, a subjective discount factor of $\beta = 0.98$, an initial wealth-income ratio of $x_0 = 2$, and an initial income of $L_0 = 1$.

Table 7: Distribution of average optimal choice variables across industries by conditioning information ($T = 20$ years)

	None			W/C			D/P		
	10th	Median	90th	10th	Median	90th	10th	Median	90th
C_0	1.086	1.135	1.219	1.073	1.129	1.216	1.089	1.138	1.218
C_1	1.118	1.169	1.257	1.111	1.168	1.258	1.120	1.172	1.256
C_2	1.143	1.197	1.282	1.139	1.197	1.285	1.146	1.197	1.281
C_3	1.160	1.212	1.296	1.161	1.214	1.299	1.161	1.212	1.295
C_4	1.177	1.226	1.312	1.176	1.232	1.315	1.178	1.226	1.311
C_5	1.179	1.234	1.317	1.179	1.234	1.318	1.181	1.232	1.316
C_6	1.179	1.235	1.325	1.177	1.235	1.322	1.180	1.234	1.324
C_7	1.189	1.249	1.342	1.188	1.249	1.337	1.188	1.247	1.341
C_8	1.202	1.262	1.354	1.204	1.265	1.360	1.199	1.263	1.353
C_9	1.210	1.266	1.379	1.211	1.270	1.381	1.204	1.263	1.375
C_{10}	1.231	1.292	1.446	1.231	1.295	1.440	1.225	1.285	1.437
w_0	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
w_1	1.000	1.000	1.000	0.997	0.997	0.997	0.995	0.995	0.995
w_2	0.712	0.948	1.000	0.657	0.954	0.994	0.702	0.942	0.992
w_3	0.656	0.932	1.000	0.651	0.928	0.988	0.668	0.935	0.990
w_4	0.454	0.850	1.000	0.514	0.851	0.980	0.456	0.843	0.991
w_5	0.000	0.170	0.752	0.000	0.151	0.724	0.000	0.222	0.782
w_6	0.593	0.985	1.000	0.601	0.941	0.952	0.680	0.992	0.995
w_7	0.645	0.972	1.000	0.605	0.913	0.939	0.728	0.980	0.996
w_8	0.580	0.966	1.000	0.569	0.872	0.932	0.641	0.973	0.997
w_9	0.994	0.999	1.000	0.913	0.925	0.926	0.991	0.997	0.998

Notes: The table shows the 10th, 50th and 90th percentiles of the distribution of the average optimal choice variables across 73 industries at the three-digit NAICS level for three different conditioning variables: none (unconditional model), labor income-consumption ratio (W/C), dividend-price ratio (D/P). C_0 to C_{10} denotes consumption and w_0 to w_9 the share of wealth allocated to stocks at rebalancing times $t = 0, \ldots, 10$ ($w_{10} = 0$). The optimal choice variables are calculated from solving the life-cycle portfolio choice model with an investment horizon of $T = 20$ years, a biannual rebalancing period, a relative risk aversion coefficient of $\gamma = 10$, a subjective discount factor of $\beta = 0.96$, an initial wealth-income ratio of $x_0 = 2$, and an initial income of $L_0 = 1$.

Table 8: Average optimal choice variables for industries with lowest and highest certainty-equivalent consumption by conditioning information ($T = 10$ years)

	None		W/C		D/P	
	Motion picture and sound recording	Securities, investments, funds and trusts	Motion picture and sound recording	Securities, investments, funds and trusts	Motion picture and sound recording	Securities, investments, funds and trusts
C_0	1.009	1.170	1.009	1.167	1.010	1.170
C_1	1.027	1.180	1.027	1.178	1.028	1.179
C_2	1.044	1.189	1.044	1.188	1.045	1.188
C_3	1.061	1.199	1.061	1.199	1.062	1.198
C_4	1.077	1.209	1.077	1.209	1.077	1.208
C_5	1.091	1.221	1.091	1.221	1.091	1.220
C_6	1.105	1.233	1.103	1.233	1.104	1.232
C_7	1.119	1.245	1.113	1.246	1.116	1.245
C_8	1.131	1.257	1.128	1.259	1.128	1.256
C_9	1.143	1.270	1.142	1.275	1.140	1.270
C_{10}	1.151	1.283	1.153	1.287	1.147	1.284
w_0	1.000	1.000	1.000	0.978	1.000	1.000
w_1	1.000	1.000	0.996	0.996	1.000	1.000
w_2	1.000	1.000	0.991	0.991	0.999	0.999
w_3	1.000	1.000	0.986	0.986	0.999	0.999
w_4	1.000	1.000	0.981	0.981	0.999	0.999
w_5	1.000	1.000	0.977	0.977	0.998	0.998
w_6	1.000	1.000	0.974	0.974	0.998	0.998
w_7	0.999	1.000	0.969	0.971	0.997	0.998
w_8	0.994	1.000	0.961	0.967	0.993	0.998
w_9	0.977	0.998	0.947	0.963	0.938	0.998
CEC	1.009	1.201	1.005	1.196	1.011	1.201
$\%CEC$	-9.669	7.520	-9.865	7.265	-9.571	7.424

Notes: The table shows the average optimal choice variables for the two industries with lowest ("Motion picture and sound recording") and highest ("Securities, investments, funds and trusts") estimated certainty-equivalent consumption (CEC) for three different conditioning variables: none (unconditional model), labor income-consumption ratio (W/C), dividend-price ratio (D/P). C_0 to C_{10} denotes consumption and w_0 to w_9 the share of wealth allocated to stocks at rebalancing times $t = 0, \dots, 10$ ($w_{10} = 0$). $\%CEC$ denotes the percentage deviation of CEC from the median CEC. CEC, $\%CEC$ and the optimal choice variables are calculated from solving the life-cycle portfolio choice model with an investment horizon of $T = 10$ years, an annual rebalancing period, a relative risk aversion coefficient of $\gamma = 10$, a subjective discount factor of $\beta = 0.98$, an initial wealth-income ratio of $x_0 = 2$, and an initial income of $L_0 = 1$.

Table 9: Average optimal choice variables for industries with lowest and highest certainty-equivalent consumption by conditioning information ($T = 20$ years)

	None		W/C		D/P	
	Motion picture and sound recording	Securities, investments, funds and trusts	Motion picture and sound recording	Securities, investments, funds and trusts	Motion picture and sound recording	Securities, investments, funds and trusts
C_0	1.011	1.270	1.002	1.262	1.016	1.269
C_1	1.046	1.308	1.035	1.302	1.050	1.306
C_2	1.089	1.336	1.080	1.334	1.092	1.333
C_3	1.115	1.352	1.112	1.352	1.115	1.349
C_4	1.155	1.362	1.145	1.359	1.154	1.358
C_5	1.167	1.366	1.155	1.368	1.165	1.364
C_6	1.169	1.367	1.157	1.372	1.167	1.364
C_7	1.176	1.389	1.167	1.394	1.173	1.388
C_8	1.185	1.426	1.180	1.436	1.179	1.428
C_9	1.191	1.461	1.187	1.477	1.183	1.468
C_{10}	1.220	1.531	1.217	1.537	1.210	1.543
w_0	1.000	1.000	1.000	1.000	1.000	1.000
w_1	0.998	1.000	0.953	0.997	0.989	0.995
w_2	0.458	1.000	0.334	0.990	0.468	0.992
w_3	0.797	0.999	0.801	0.985	0.800	0.990
w_4	0.654	0.967	0.662	0.959	0.655	0.942
w_5	0.443	0.256	0.466	0.151	0.461	0.191
w_6	1.000	1.000	0.951	0.951	0.995	0.994
w_7	0.969	0.998	0.937	0.939	0.966	0.967
w_8	0.956	0.999	0.659	0.931	0.945	0.996
w_9	0.933	0.995	0.860	0.671	0.935	0.993
CEC	1.058	1.344	1.050	1.340	1.060	1.343
$\%CEC$	-11.092	12.941	-11.392	13.080	-10.999	12.762

Notes: The table shows the average optimal choice variables for the two industries with lowest ("Motion picture and sound recording") and highest ("Securities, investments, funds and trusts") estimated certainty-equivalent consumption (CEC) for three different conditioning variables: none (unconditional model), labor income-consumption ratio (W/C), dividend-price ratio (D/P). C_0 to C_{10} denotes consumption and w_0 to w_9 the share of wealth allocated to stocks at rebalancing times $t = 0, \dots, 10$ ($w_{10} = 0$). $\%CEC$ denotes the percentage deviation of CEC from the median CEC. CEC, $\%CEC$ and the optimal choice variables are calculated from solving the life-cycle portfolio choice model with an investment horizon of $T = 20$ years, a biannual rebalancing period, a relative risk aversion coefficient of $\gamma = 10$, a subjective discount factor of $\beta = 0.96$, an initial wealth-income ratio of $x_0 = 2$, and an initial income of $L_0 = 1$.

Table 10: Average optimal choice variables for industries with lowest and highest income growth-stock return correlation by conditioning information ($T = 10$ years)

	None		W/C		D/P	
	Petroleum and coal products	Couriers and messengers	Petroleum and coal products	Couriers and messengers	Petroleum and coal products	Couriers and messengers
C_0	1.100	1.053	1.093	1.046	1.098	1.057
C_1	1.111	1.076	1.112	1.072	1.110	1.080
C_2	1.122	1.101	1.124	1.097	1.121	1.103
C_3	1.134	1.129	1.136	1.126	1.133	1.130
C_4	1.145	1.155	1.146	1.151	1.145	1.156
C_5	1.158	1.177	1.158	1.172	1.158	1.176
C_6	1.171	1.201	1.168	1.193	1.171	1.198
C_7	1.184	1.225	1.174	1.224	1.183	1.221
C_8	1.195	1.246	1.182	1.252	1.195	1.240
C_9	1.206	1.261	1.207	1.274	1.205	1.254
C_{10}	1.216	1.274	1.236	1.291	1.214	1.265
w_0	1.000	1.000	1.000	1.000	1.000	1.000
w_1	1.000	1.000	0.996	0.996	1.000	1.000
w_2	1.000	0.994	0.991	0.991	0.999	0.999
w_3	1.000	0.966	0.986	0.963	0.999	0.984
w_4	1.000	0.974	0.981	0.951	0.999	0.984
w_5	1.000	0.966	0.978	0.921	0.998	0.978
w_6	1.000	0.955	0.974	0.903	0.998	0.972
w_7	1.000	0.935	0.971	0.877	0.998	0.954
w_8	0.999	0.974	0.967	0.916	0.998	0.987
w_9	0.996	0.992	0.961	0.948	0.995	0.992
CEC	1.126	1.080	1.126	1.081	1.126	1.082
$\%CEC$	0.806	-3.312	0.987	-3.049	0.716	-3.220

Notes: The table shows the average optimal choice variables for the two industries with the lowest ("Petroleum and coal products", corr = -0.10) and highest ("Couriers and messengers", corr = 0.11) correlation between real labor income growth and real stock returns for three different conditioning variables: none (unconditional model), labor income-consumption ratio (W/C), dividend-price ratio (D/P). C_0 to C_{10} denotes consumption and w_0 to w_9 the share of wealth allocated to stocks at rebalancing times $t = 0, \dots, 10$ ($w_{10} = 0$). $\%CEC$ denotes the percentage deviation of CEC from the median CEC. CEC, $\%CEC$ and the optimal choice variables are calculated from solving the life-cycle portfolio choice model with an investment horizon of $T = 10$ years, an annual rebalancing period, a relative risk aversion coefficient of $\gamma = 10$, a subjective discount factor of $\beta = 0.98$, an initial wealth-income ratio of $x_0 = 2$, and an initial income of $L_0 = 1$.

Table 11: Average optimal choice variables for industries with lowest and highest income growth-stock return correlation by conditioning information ($T = 20$ years)

	None		W/C		D/P	
	Petroleum and coal products	Couriers and messengers	Petroleum and coal products	Couriers and messengers	Petroleum and coal products	Couriers and messengers
C_0	1.107	1.081	1.106	1.079	1.107	1.086
C_1	1.140	1.147	1.140	1.141	1.141	1.152
C_2	1.167	1.209	1.166	1.200	1.167	1.212
C_3	1.186	1.246	1.177	1.241	1.184	1.247
C_4	1.202	1.266	1.197	1.264	1.200	1.264
C_5	1.209	1.273	1.210	1.265	1.207	1.270
C_6	1.219	1.279	1.221	1.268	1.218	1.276
C_7	1.239	1.312	1.239	1.307	1.237	1.307
C_8	1.266	1.348	1.265	1.348	1.263	1.340
C_9	1.269	1.380	1.272	1.383	1.268	1.370
C_{10}	1.293	1.425	1.295	1.426	1.294	1.413
w_0	1.000	1.000	1.000	1.000	1.000	1.000
w_1	1.000	1.000	0.997	0.997	0.996	0.995
w_2	0.917	0.882	0.916	0.734	0.921	0.885
w_3	0.730	0.924	0.728	0.926	0.737	0.939
w_4	0.775	0.787	0.701	0.788	0.758	0.799
w_5	0.477	0.234	0.467	0.192	0.477	0.274
w_6	1.000	0.857	0.952	0.880	0.995	0.924
w_7	1.000	0.822	0.939	0.773	0.996	0.871
w_8	0.999	0.602	0.931	0.510	0.996	0.655
w_9	1.000	0.993	0.921	0.921	0.997	0.991
CEC	1.177	1.128	1.176	1.126	1.177	1.131
$\%CEC$	-1.092	-5.210	-0.759	-4.979	-1.175	-5.038

Notes: The table shows the average optimal choice variables for the two industries with the lowest ("Petroleum and coal products", corr = -0.10) and highest ("Couriers and messengers", corr = 0.11) correlation between real labor income growth and real stock returns for three different conditioning variables: none (unconditional model), labor income-consumption ratio (W/C), dividend-price ratio (D/P). C_0 to C_{10} denotes consumption and w_0 to w_9 the share of wealth allocated to stocks at rebalancing times $t = 0, \dots, 10$ ($w_{10} = 0$). $\%CEC$ denotes the percentage deviation of CEC from the median CEC. CEC, $\%CEC$ and the optimal choice variables are calculated from solving the life-cycle portfolio choice model with an investment horizon of $T = 20$ years, a biannual rebalancing period, a relative risk aversion coefficient of $\gamma = 10$, a subjective discount factor of $\beta = 0.96$, an initial wealth-income ratio of $x_0 = 2$, and an initial income of $L_0 = 1$.

Table 12: Cross-sectional regressions of certainty-equivalent consumption on moments of real labor income growth by conditioning information ($T = 10$ years)

A. Conditioning information: None

	(1)		(2)		(3)	
	Estimate	t-value	estimate	t-value	estimate	t-value
Intercept	0.1133	50.33 ***	0.1133	50.87 ***	0.1133	50.82 ***
Mean	0.0304	10.99 ***	0.0313	10.69 ***	0.0314	10.69 ***
Variance	-0.0234	-8.50 ***	-0.0230	-8.39 ***	-0.0219	-7.64 ***
Skewness			-0.0007	-0.29	0.0005	0.19
Kurtosis			-0.0047	-1.86 *	-0.0055	-2.12 **
Correlation	-0.0059	-2.58 ***	-0.0042	-1.70 *	-0.0013	-0.38
Coskewness					0.0023	0.92
Cokurtosis					-0.0046	-1.27
Adjusted R^2	0.659		0.666		0.666	

B. Conditioning information: W/C

	(1)		(2)		(3)	
	Estimate	t-value	Estimate	t-value	estimate	t-value
Intercept	0.1116	48.86 ***	0.1116	49.24 ***	0.1116	49.28 ***
Mean	0.0304	10.82 ***	0.0313	10.47 ***	0.0314	10.50 ***
Variance	-0.0236	-8.44 ***	-0.0232	-8.31 ***	-0.0220	-7.55 ***
Skewness			-0.0007	-0.27	0.0006	0.24
Kurtosis			-0.0045	-1.75 *	-0.0053	-2.03 **
Correlation	-0.0058	-2.52 **	-0.0042	-1.68 *	-0.0010	-0.28
Coskewness					0.0023	0.90
Cokurtosis					-0.0051	-1.38
Adjusted R^2	0.652		0.658		0.658	

C. Conditioning information: D/P

	(1)		(2)		(3)	
	Estimate	t-value	estimate	t-value	estimate	t-value
Intercept	0.1136	51.52 ***	0.1136	52.05 ***	0.1136	51.91 ***
Mean	0.0303	11.15 ***	0.0311	10.82 ***	0.0312	10.80 ***
Variance	-0.0232	-8.59 ***	-0.0228	-8.48 ***	-0.0219	-7.75 ***
Skewness			-0.0006	-0.25	0.0005	0.19
Kurtosis			-0.0045	-1.86 *	-0.0053	-2.09 **
Correlation	-0.0056	-2.52 **	-0.0040	-1.65 *	-0.0015	-0.43
Coskewness					0.0023	0.91
Cokurtosis					-0.0041	-1.15
Adjusted R^2	0.664		0.671		0.669	

Notes: The sample consists of 73 industries at the three-digit NAICS level. The table shows regressions of log certainty-equivalent consumption for an investment horizon of $T = 10$ years and annual rebalancing on moments of real labor income growth for three different conditioning variables: none (unconditional model), labor income-consumption ratio (W/C), dividend-price ratio (D/P). All explanatory variables are standardized. Stars *,**,*** denote significance at the 10%, 5% and 1% level.

Table 13: Cross-sectional regressions of certainty-equivalent consumption on moments of real labor income growth by conditioning information ($T = 20$ years)

A. Conditioning information: None

	(1)		(2)		(3)	
	Estimate	t-value	estimate	t-value	estimate	t-value
Intercept	0.1829	59.80 ***	0.1829	59.69 ***	0.1829	59.57 ***
Mean	0.0442	11.74 ***	0.0452	11.21 ***	0.0450	11.12 ***
Variance	-0.0336	-8.98 ***	-0.0332	-8.80 ***	-0.0330	-8.35 ***
Skewness			-0.0012	-0.35	-0.0004	-0.10
Kurtosis			-0.0045	-1.32	-0.0054	-1.53
Correlation	-0.0097	-3.12 ***	-0.0080	-2.38 **	-0.0079	-1.65 *
Coskewness					0.0046	1.30
Cokurtosis					-0.0014	-0.28
Adjusted R^2	0.692		0.691		0.690	

B. Conditioning information: W/C

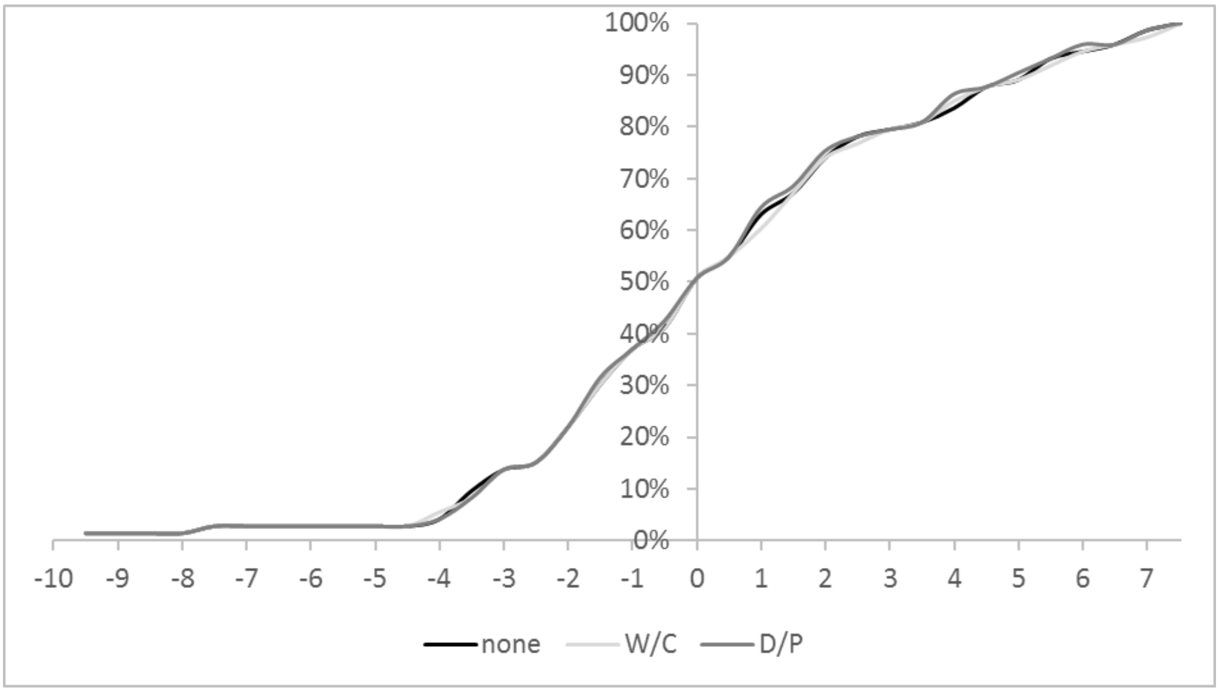
	(1)		(2)		(3)	
	Estimate	t-value	estimate	t-value	Estimate	t-value
Intercept	0.1805	57.61 ***	0.1805	57.53 ***	0.1805	57.43 ***
Mean	0.0447	11.61 ***	0.0459	11.10 ***	0.0456	10.98 ***
Variance	-0.0334	-8.71 ***	-0.0329	-8.54 ***	-0.0333	-8.23 ***
Skewness			-0.0012	-0.35	-0.0009	-0.24
Kurtosis			-0.0047	-1.34	-0.0054	-1.47
Correlation	-0.0096	-3.03 ***	-0.0079	-2.30 **	-0.0093	-1.90 *
Coskewness					0.0042	1.18
Cokurtosis					0.0008	0.16
Adjusted R^2	0.685		0.684		0.683	

C. Conditioning information: D/P

	(1)		(2)		(3)	
	Estimate	t-value	estimate	t-value	estimate	t-value
Intercept	0.1838	61.25 ***	0.1838	61.13 ***	0.1838	61.01 ***
Mean	0.0436	11.82 ***	0.0447	11.29 ***	0.0445	11.19 ***
Variance	-0.0331	-9.00 ***	-0.0326	-8.83 ***	-0.0325	-8.39 ***
Skewness			-0.0012	-0.36	-0.0004	-0.12
Kurtosis			-0.0044	-1.31	-0.0053	-1.51
Correlation	-0.0093	-3.05 ***	-0.0077	-2.32 **	-0.0077	-1.63
Coskewness					0.0044	1.29
Cokurtosis					-0.0012	-0.24
Adjusted R^2	0.694		0.692		0.691	

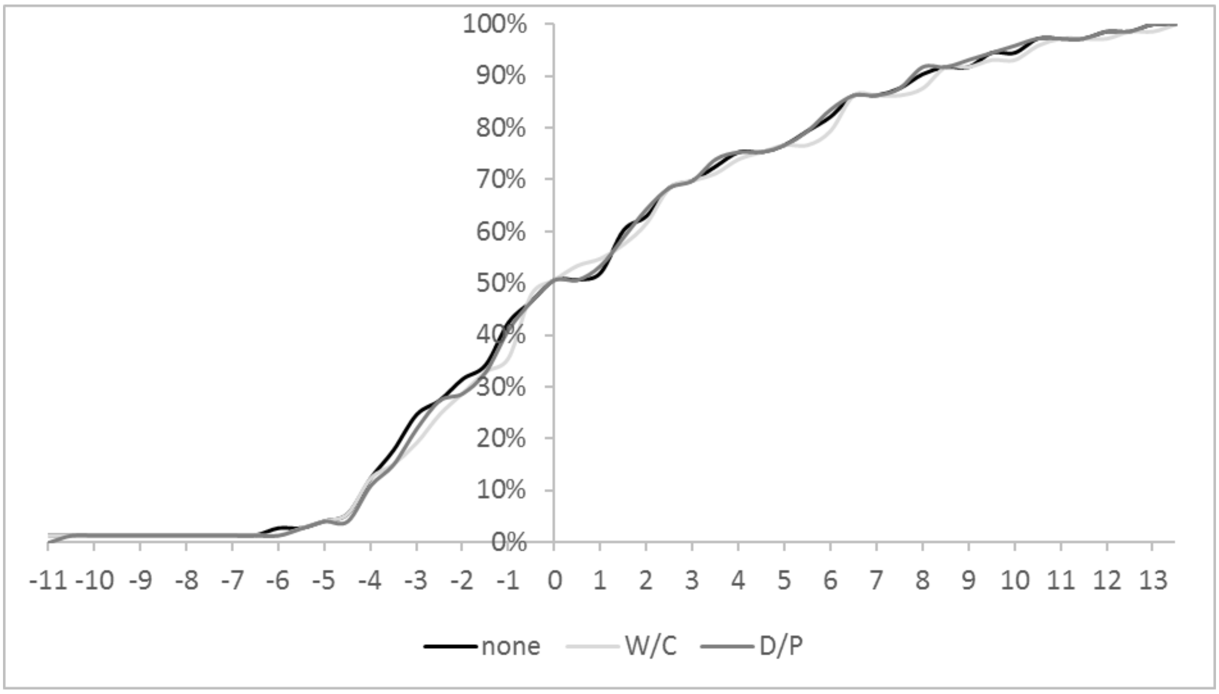
Notes: The sample consists of 73 industries at the three-digit NAICS level. The table shows regressions of log certainty-equivalent consumption for an investment horizon of $T = 20$ years and biannual rebalancing on moments of real labor income growth for three different conditioning variables: none (unconditional model), labor income-consumption ratio (W/C), dividend-price ratio (D/P). All explanatory variables are standardized. Stars *,**,*** denote significance at the 10%, 5% and 1% level.

Figure 1: Distribution of certainty-equivalent consumption across industries ($T = 10$ years)



Notes: The figure shows the cumulative distribution of the percentage deviation of certainty-equivalent consumption from its median value across 73 industries at the three-digit NAICS level for an investment horizon of $T = 10$ years and annual rebalancing. See the Table 3 notes for more details.

Figure 2: Distribution of certainty-equivalent consumption across industries ($T = 20$ years)



Notes: The figure shows the cumulative distribution of the percentage deviation of certainty-equivalent consumption from its median value across 73 industries at the three-digit NAICS level for an investment horizon of $T = 20$ years and biannual rebalancing. See the Table 4 notes for more details.