Industry affiliation and the value of portfolio choice

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October 24, 2020

Abstract

In the presence of inter-industry wage differentials, the value of portfolio choice varies across otherwise identical households employed in different industries. I solve a dynamic portfolio choice model for 72 industries using 30 years of data and investigate the impact of the joint distribution of earnings growth and stock returns on certainty equivalent consumption. I find that inequality in certainty equivalent consumption mirrors inequality in initial earnings. Cross-sectional heterogeneity in certainty equivalent consumption is explained by variation in the covariance structure of earnings growth and stock returns and kurtosis of earnings growth. Cyclical variation in industry-specific earnings risk is inconsequential.

JEL Codes: E21, G11, J31.

Keywords: Dynamic portfolio choice; inter-industry wage differentials; inequality; kurtosis.

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1 Introduction

In the presence of persistent inter-industry wage differentials (as documented, e.g., by Dickens and Katz (1987), Krueger and Summers (1987), Krueger and Summers (1988), Katz and Summers (1989), Thaler (1989), Neal (1995), and Weinberg (2001)), the value of portfolio choice varies across otherwise identical households employed in different industries. If human capital is nontradable, hedging demands for stocks vary with industry affiliation because the moments of labor income growth and its comoments with aggregate stock returns vary across industries.[1] A small literature in finance investigates these industry-specific hedging demands: Campbell, Cocco, Gomes, and Maenhout (2001) report differences in the variance of labor income shocks across 12 industries at the two-digit industry classification level. For 3 of these industries, Cocco, Gomes, and Maenhout (2005) show how these differences in labor income risk affect the age profile of optimal stock market exposure in a life cycle portfolio choice framework. Using a static portfolio choice model, Eiling (2013) documents variation in hedging demands across households working in 5 industries, which differ in the covariance structure between earnings growth and stock returns, and derives asset pricing implications. The author shows that the cross-section of expected returns is predominantly affected by industry-level rather than aggregate earnings risk.

Motivated by these studies, I investigate the impact of industry affiliation on the value of dynamic portfolio choice, as measured by certainty equivalent consumption. For this purpose, I solve a dynamic model of consumption and portfolio choice for employees in 72 industries defined at the three-digit industry classification level, using data on industry-specific average earnings from January 1990 – December 2019 from the Current Employment Statistics (CES). Importantly, I leave the joint distribution of industry-specific earnings growth and aggregate stock returns completely unspecified by adopting solution methods similar to those proposed by Brandt (1999), Brandt and Santa-Clara (2006), and Brandt, Santa-Clara, and Valkanov (2009). Rather than specifying industry-specific earnings processes ex ante, I investigate ex post which statistical properties of industry-specific earnings affect the value of portfolio choice. From solving the model for all in-

[1] I will use the term earnings and labor income synonymously. Earnings risk varies across other dimensions as well. Davis and Willen (2000) and Davis and Willen (2014) investigate the portfolio choice implications of variations in the covariance structure of asset returns and labor income due to heterogeneity in sex, education and birth cohort and across 10 occupations, respectively. Chang, Hong, and Karabarbounis (2018) and Bagliano, Fugazza, and Nicodano (2019) allow for age-dependent labor market uncertainty in life cycle portfolio choice models.

dustries, I obtain the cross-sectional distribution of certainty equivalent consumption. I analyze this distribution to answer three main research questions, which have not been addressed in existing literature: First, do households in higher paid industries, i.e. those with a higher level of initial average earnings, benefit more from optimal portfolio choice than households in lower paid industries? Second, which moments of earnings growth and comoments of earnings growth and stock returns determine the value of portfolio choice? Third, does cyclical variation in the risk of industry-specific earnings growth matter for the value of portfolio choice?

The first research question is related to a substantial literature in macroeconomics on several dimensions of economic inequality, including earnings, income, consumption and wealth (see, e.g., the special issue on "Cross-sectional facts for macroeconomists" in the *Review of Economic Dynamics*, introduced by Krueger, Perri, Pistaferri, and Violante (2010)). A part of this literature, reviewed by Attanasio and Pistaferri (2016) investigates whether consumption inequality mirrors income inequality. Recent literature concludes that consumption inequality indeed closely tracks income inequality (see, e.g., Aguiar and Bils (2015)). Whether or not consumption tracks income depends on the tools available to move resources across time and states of the world (Attanasio and Pistaferri (2016)). Dynamic portfolio choice is such a tool. Its effectiveness is bounded by the borrowing and short-sale constraints faced by a typical household and varies with the statistical properties of the joint distribution of earnings growth and asset returns. I investigate whether heterogeneity in these properties across industries has the potential to affect inequality in consumption. According to Fagereng, Guiso, Malacrino, and Pistaferri (2016), the returns on wealth increase in the level of wealth, which suggests that the tools available vary across the distribution of wealth. I compare the distributions of initial (i.e. at the time the dynamic portfolio choice problem is solved) earnings and certainty equivalent consumption across industries. While the inter-decile range of initial earnings exceeds the corresponding range of certainty equivalent consumption, further analysis reveals that inequality in the value of portfolio choice mirrors inequality in the level of initial labor income. The Gini coeffcients of both distributions are exactly the same. This is in line with Benhabib, Bisin, and Luo (2019) who observe that models that "focus on precautionary savings as an optimal response to stochastic earnings [...] tend to produce tail indices of wealth close to the distribution of labor earnings which has been fed into the model." My findings show that this observation holds as well for tail indices of certainty equivalent consumption.

However, I also document substantial variation in certainty equivalent consumption across the distribution of initial earnings that is not systematically related to the level of earnings. Since households in my analysis only differ in industry-specific earnings, these differences must be due to inter-industry differences in the joint distribution of earnings growth and stock returns. To answer my second research question, I relate the ratio of certainty equivalent consumption to initial earnings to the moments of industry-specific real earnings growth and its comoments with real stock returns. This research question is related to the studies by Campbell et al. (2001), Cocco et al. (2005) and Eiling (2013) mentioned earlier, who analyse the hedging demands resulting from industry differences in the variance of earnings shocks and the correlation between earnings growth and stock returns.[2] I contribute to this literature in several ways. I focus on the value of portfolio choice expressed in terms of certainty equivalent consumption. Variations in hedging demands not necessarily generate variations in certainty equivalent consumption of the same magnitude. Moreover, I consider a much larger set of industries, 72 versus 3 or 5 in previous studies, and a much larger set of moments and comoments of earnings growth and stock returns. Finally, I investigate whether different moments and comoments matter for different coefficients of risk aversion, investment horizons, and the ability of the household to predict earnings growth and stock returns using the log dividend-price ratio.

I find a strong and statistically significant effect of the first two moments of earnings growth on certainty equivalent consumption that is of an order of magnitude larger than the impact of any other moment or comoment. The importance of earnings risk as a predictor of the value of portfolio choice increases with risk aversion and investment horizon. In most specifications, certainty equivalent consumption decreases with an increasing correlation between earnings growth and stock returns. However, correlation becomes an insignificant predictor of certainty equivalent consumption once kurtosis of earnings growth is controlled for. This is a new result. Commonly employed earnings processes that rely on (log) normally distributed income shocks do not generate heterogeneity in the kurtosis of earnings growth and therefore are unable to detect the importance of kurtosis. Kurtosis describes the propensity of the data generating process to generate outliers in the tails of the distribution. My results show that the value of portfolio choice increases with

[2] Hedging demands depend on whether human capital is bond-like as in Cocco et al. (2005) or stock-like as in Benzoni, Collin-Dufresne, and Goldstein (2007). Huggett and Kaplan (2016) find that the bond component of human capital dominates its stock component at all ages.

decreasing kurtosis. Households prefer earnings growth distributions with thinner tails. This result is robust against most variations of model parameters and whether or not households are able to predict earnings growth and stock returns. Unlike kurtosis, skewness of earnings growth does not contribute to the value of portfolio choice.

While my second research question analyzes the impact of moments and comoments of average earnings growth at industry level on the value of portfolio choice, a related empirical literature in finance estimates the relationship between earnings risk and observed portfolio choice at household level. Guiso, Jappelli, and Terlizzese (1996) and Hochguertel (2003) report a negative impact of expected wage volatility on the risky portfolio share. Betermier, Jansson, Parlour, and Walden (2012) find that households tend to offset increases in human capital risk due to job changes with reduced holdings of risky assets. Fagereng, Guiso, and Pistaferri (2018) use variation in firm profitability that is passed on to employees as an instrument for wage variability and document a strong negative effect of uninsurable wage risk on the risky portfolio share. Several studies document a significant negative impact of earnings risk on financial risk-taking while the impact of the correlation between earnings growth and stock returns turns out to be insignificant (Heaton and Lucas (2000), Vissing-Jorgensen (2002), Angerer and Lam (2009)). Palia, Qi, and Wu (2014) find negative and significant effects for both variables on stock market participation. Massa and Simonov (2006) find that instead of hedging income risk, households tend to invest in stocks closely related to their income and explain this finding with familiarity. However, Bonaparte, Korniotis, and Kumar (2014) and Bagliano, Corvino, Fugazza, and Nicodano (2019) document a negative and significant relationship between stock market participation and the correlation between earnings shocks and stock returns. Brugler, Inkmann, and Rizzo (2020) find a negative impact of background risk related to human capital, measured as the perceived stock market beta of the return on human capital, on financial risk-taking at the extensive and intensive margins.

My third research question is related to a highly influential recent literature on the business cycle variation of idiosyncratic earnings risk. Storesletten, Telmer, and Yaron (2004) find countercyclical variation in idiosyncratic labor income volatility and Lynch and Tan (2011) explore its portfolio choice implications. Guvenen, Ozkan, and Song (2014) document cyclical skewness in the distribution of idiosyncratic earnings shocks. Specifically, the worst labor income shocks happen in recessions, which tend to coincide with adverse outcomes on financial markets. This is not mirrored during economic expansions, which implies that left-skewness is countercyclical, not the variance of income shocks. Catherine (2020) and Shen (2018) explore the portfolio choice implications. Using a life cycle portfolio choice model, Catherine (2020) shows that cyclical skewness can explain the observed low stock market participation of young households and an allocation to stocks conditional on participation that increases with age during working life. Using Swedish administrative panel data, Catherine, Sodini, and Zhang (2020) show that these predictions of the life cycle model are in line with observed household risk-taking behavior. To address my third research questions, whether cyclicality of industry-specific earnings growth risk can predict the value of portfolio choice, I propose to use higher-order comoments of industry-specific real earnings growth and real stock returns. An industry with a low negative value of coskewness between earnings 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 earnings growth and aggregate stock returns is likely to exhibit negative skewness in labor income growth during recessions. It turns out that none of these comoments helps predicting the value of portfolio choice across the sample period, which includes three NBER recessions. Cyclical variation in earnings growth risk at the industry level is not important for portfolio choice decisions.

As a byproduct, this paper introduces two methodological innovations regarding the solution of dynamic portfolio choice models with predictability. Like Brandt (1999), I estimate the policy functions from solving a sample counterpart of the Euler equations for consumption and portfolio choice. I extend the parameterization approach proposed by Brandt (1999), Brandt and Santa-Clara (2006) and Brandt et al. (2009) to a model, in which the value function is not homogeneous in wealth, due to the presence of labor income. I also propose a simple way of imposing borrowing and short-sale constraints within this optimization framework.

2 Dynamic portfolio choice with labor income

2.1 Household's optimization problem

In line with much of the life cycle portfolio choice literature (e.g. Cocco et al. (2005), the household is assumed to maximize the time-0 conditionally expected power utility in consumption

$$\mathbb{E}_0\left[\sum_{t=0}^{T}\delta^t\frac{C_t^{1-\gamma}}{1-\gamma}\right], \tag{1}$$

where $\gamma > 0$ ($\gamma \neq 1$) denotes the household's coefficient of relative risk aversion, δ its subjective discount factor and T its investment horizon, by optimally choosing consumption, C_t, and the allocation, w_t, to a risky asset with real return R_{t+1} for $t = 0, ..., T$. Assuming that the remainder $1 - w_t$ is invested in a riskfree asset with real return R^f_{t+1}, the real return on the portfolio, R^p_{t+1}, follows as

$$R^p_{t+1} = R^f_{t+1} + w_t R^e_{t+1}, \tag{2}$$

where $R^e_{t+1} = R^e_{t+1} - R^f_{t+1}$ denotes the excess return on the risky asset. Consumption is financed from cash-on-hand, X_t, which evolves according to

$$X_{t+1} = (X_t - C_t)\,R^p_{t+1} + L_{t+1} \tag{3}$$

$$\Leftrightarrow \frac{X_{t+1}}{L_{t+1}} = G^{-1}_{t+1}\left(\frac{X_t}{L_t} - \frac{C_t}{L_t}\right)R^p_{t+1} + 1 \tag{4}$$

$$\Leftrightarrow x_{t+1} = G^{-1}_{t+1}\,(x_t - c_t)\,R^p_{t+1} + 1 \tag{5}$$

$$\Leftrightarrow x_{t+1} = G^{-1}_{t+1}x_t\,(1 - q_t)\,R^p_{t+1} + 1, \tag{6}$$

where L_{t+1} denotes the household's labor income and $G_{t+1} = {}^{L_{t+1}}/_{L_t}$ real earnings growth. Lower letters for cash-on-hand and consumption refer to ratios of these variables to labor income. Using these scaled variables, the optimization problem can be expressed in terms of earnings *growth*.[3] This is possible because the value function of the problem is homogeneous in labor income. The evolution of cash-on-hand is rewritten in (6) in terms of the consumption share $q_t = {}^{c_t}/_{x_t} = {}^{C_t}/_{X_t}$.

Unlike existing literature on dynamic consumption and portfolio choice, I leave the stochastic processes governing the evolution of real earnings growth and asset returns unspecified. Instead, time series data on labor income growth and asset returns are used below to estimate the household's optimal decisions. Differences in the joint empirical distribution of these random variables across industries will generate variation in the value of dynamic portfolio choice. I assume that the household conditions on a state variable, z_t, when forming expectations of labor income and asset

[3] In life cycle models that rely on a specification of the stochastic process for income (e.g. Carroll (1997)), cash-on-hand is often scaled by permanent income in order to save one state variable.

returns. This assumption allows for return predictability in contrast to the assumption of *iid* returns commonly employed in the life cycle portfolio choice literature.[4]

The model is solved using dynamic programming. The Bellman equation of the problem can be written as (see Appendix A.1 for a derivation)

$$V_t\left(x_t, z_t\right) = \max_{c_t, w_t} \left\{ \frac{c_t^{1-\gamma}}{1-\gamma} + \delta \mathbb{E}_t \left[G_{t+1}^{1-\gamma} V_{t+1}\left(x_{t+1}, z_{t+1}\right) \right] \right\}. \tag{7}$$

The terminal condition of the problem is

$$V_T\left(x_T, z_T\right) = \frac{x_T^{1-\gamma}}{1-\gamma} \tag{8}$$

because the household optimally consumes all available cash-on-hand at the investment horizon T, i.e. $c_T = x_T$ or $q_T = 1$. The Euler equations for the consumption share and the allocation to the risky asset follow from (7) as (see Appendix A.2)

$$\mathbb{E}_t \left[\delta \left(G_{t+1} \frac{x_{t+1} q_{t+1}}{x_t q_t} \right)^{-\gamma} R_{t+1}^p - 1 \right] = 0 \tag{9}$$

$$\mathbb{E}_t \left[\delta \left(G_{t+1} x_{t+1} q_{t+1} \right)^{-\gamma} R_{t+1}^e \right] = 0. \tag{10}$$

2.2 GMM estimation of optimal control variables

For given cash-on-hand, x_t, the pair of Euler equations, (9) and (10), defines a 2×1 vector of conditional moment functions, $\rho\left(y_{t+1}, \beta_t\right)$ satisfying

$$\mathbb{E}_t \left[\rho\left(y_{t+1}, \beta_t^0 \right) \right] = \mathbb{E}\left[\rho\left(y_{t+1}, \beta_t^0 \right) \mid z_t \right] = 0, \tag{11}$$

where $y_{t+1} = \left(G_{t+1}, R_{t+1}^f, R_{t+1}^e \right)$ collects the involved random variables and $\beta_t = \left(q_t, w_t\right)'$ is the 2×1 vector of unknown control variables (or parameters) to be estimated. The 0-superscript indicates the true parameter vector solving the Euler equations.

The conditional expectation in (11) is a possibly nonlinear function of the state variable, z_t. Hence, the true parameter vector satisfying the Euler equations is a function of z_t as well. I will

[4]Exceptions are Benzoni et al. (2007), Koijen et al. (2010), Lynch and Tan (2011), and Michaelides and Zhang (2017).

make this function explicit by parameterizing the unknown vector of control variables as

$$\beta_t^0 = \Lambda\left(\Theta_t^0\left(x_t\right) z_t^p\right) \tag{12}$$

$$= \Lambda\left(\mathrm{vec}\left(\Theta_t^0\left(x_t\right) z_t^p\right)\right) \tag{13}$$

$$= \Lambda\left(\left(z_t^p \otimes I_2\right)' \mathrm{vec}\left(\Theta_t^0\left(x_t\right)\right)\right) \tag{14}$$

$$= \Lambda\left(\left(z_t^p \otimes I_2\right)' \theta_t^0\right), \tag{15}$$

where z_t^p is a $m \times 1$ vector of polynomial terms in the state variable, z_t. For example, $m = 3$ for a second-order polynomial $z_t^p = \left(1, z_t, z_t^2\right)'$. The idea is that any nonlinear function can be approximated by a sequence of polynomial terms. An unconditional model results from $m = 1$. The parameter matrix $\Theta_t\left(x_t\right)$ is of dimension $2 \times m$. I write this matrix as a function of cash-on-hand, x_t, to reflect that different vectors of control variables will solve the Euler equations for different values of cash-on-hand. For notational simplicity, I omit this argument from the $2m \times 1$ parameter vector $\theta_t^0 = \mathrm{vec}\left(\Theta_t^0\left(x_t\right)\right)$.[5] The function $\Lambda\left(\cdot\right)$, which is applied element-wise, ensures that both control variables, the consumption share, q_t, and the allocation to the risky asset, w_t, fall into the unit interval in line with the borrowing and short-sale constraints typically faced by households. I use the cdf of the Logistic distribution, $\Lambda\left(a\right) = {}^1\!/_{1+exp(-a)}$ for this purpose.[6]

The econometric problem of estimating β_t^0 now has been transformed into estimating θ_t^0. The conditional moment restriction (11) implies by the law of iterated expectations that the vector of conditional moment functions is uncorrelated with all functions of the state variable, z_t. In the simplest case, θ_t^0 solves the orthogonality conditions $\mathbb{E}\left[\left(I_2 \otimes z_t^p\right) \rho\left(y_{t+1}, \theta_t^0\right)\right] = 0$, where I_2 denotes the 2×2 identity matrix. This assumes that the borrowing and short-sale constraints imposed by the $\Lambda\left(\cdot\right)$ function in (15) are not binding. To allow for these constraints, I use an extended vector of unconditional moment functions

$$\psi\left(y_{t+1}, z_t, \theta_t\right) = \begin{pmatrix} \left(I_2 \otimes z_t^p\right) \rho\left(y_{t+1}, \beta_t\right) \\ \beta_t - \Lambda\left(\left(z_t^p \otimes I_2\right)' \theta_t\right) \end{pmatrix} \tag{16}$$

satisfying the orthogonality conditions $\mathbb{E}\left[\psi\left(y_{t+1}, z_t, \theta_t^0\right)\right] = 0$. The role of the extra two moment

[5]The vec-operator stacks the columns of a matrix into a column vector. I use $\mathrm{vec}\left(AXB\right) = \left(B' \otimes A\right) \mathrm{vec}\left(X\right)$ in (14).
[6]Any other sigmoid function would work as well.

functions added by the parameterization (15) is as follows: When the borrowing and short-sale constraints are binding, a sample equivalent of $\mathbb{E}\left[\left(I_2 \otimes z_t^p\right) \rho\left(y_{t+1}, \theta_t^0\right)\right]$ will not be zero. The extra moment functions then provide two overidentifying restrictions. Correspondingly, I use GMM (Hansen, 1982) with identity weight matrix

$$\hat{\theta}_t = \underset{\theta_t}{\operatorname{argmin}} \left(\frac{1}{S-T} \sum_{s=t+1}^{S-(T-t)} \psi\left(y_{s+1}, z_s, \theta_t\right) \right)' \left(\frac{1}{S-T} \sum_{s=t+1}^{S-(T-t)} \psi\left(y_{s+1}, z_s, \theta_t\right) \right) \tag{17}$$

to estimate θ_t^0 from a sample of time series observations $\{y_{s+1}, z_s : s = 1, ..., S-1\}$. Recall that T denotes the household's investment horizon, while S denotes the length of the sample.

Starting from $t = T-1$, the problem (17) is solved at every rebalancing time, $t = 0, ..., T-1$,[7] for all cash-on-hand values, x_t, in a grid of possible values. For every grid point, a different vector of optimal control variables is obtained from (15). I will make the relationship between cash-on-hand and control variables explicit by parameterizing θ_t as

$$\theta_t = \operatorname{vec}\left(\Theta_t\left(x_t\right)\right) = \Gamma_t x_t^p + \varepsilon_t, \tag{18}$$

where x_t^p is a $n \times 1$ vector of polynomial terms in cash-on-hand, x_t. For example, $n = 3$ for a second-order polynomial $x_t^p = \left(1, x_t, x_t^2\right)'$. The $2m \times n$ parameter matrix Γ_t can be estimated by OLS once θ_t has been estimated for all grid values of x_t. Given the OLS estimator $\hat{\Gamma}_t$, the policy functions in x_t and z_t can be estimated from (15) as

$$\hat{\beta}_t = \Lambda\left(\left(z_t^p \otimes I_2\right)' \hat{\Gamma}_t x_t^p\right). \tag{19}$$

The optimal control variables are now functions of all polynomial terms in cash-on-hand, x_t, and state variable, z_t, and of all possible interactions of these polynomial terms. At every rebalancing time t, the optimal future consumption share, q_{t+1}, entering the Euler equations (9) and (10) can be found from evaluating the policy functions (19) at next period's cash-on-hand, x_{t+1}, obtained from (6), and next period's state variable, z_{t+1}, observed in the data, using the parameter matrix $\hat{\Gamma}_{t+1}$ previously estimated at rebalancing time $t+1$.

[7] For $t = T$, the optimal control variables are trivial, $q_T = 1$ and $w_T = 0$.

Directly modeling the optimal control variables as functions of state variables has been proposed by Brandt (1999), Brandt and Santa-Clara (2006), and Brandt et al. (2009).[8] Using Kernel-M and GMM estimators of nonparametric and parametric policy functions in the state variables, respectively, the former paper solves the Euler equations of a dynamic consumption and portfolio choice problem without labor income.[9] The latter two papers propose parameterized portfolio policies similar to (15) for a portfolio choice problem without consumption and labor income. Unlike competing approaches to solve dynamic portfolio choice problems,[10] the data generating process for asset returns and – in my case – labor income growth can be left unspecified when directly modeling the optimal control variables as functions of state variables, which is a major advantage of this methodology.

The estimation approach described in this section makes two methodological contributions to this literature. First, I impose the borrowing and short-sale constraints faced by households using the function $\Lambda(\cdot)$ in (15). Second, and more importantly, I extent the parameterization approach to a problem that involves a value function that is not homothetic in cash-on-hand. Without labor income, the last term in (6) disappears and the value function becomes homothetic in cash-on-hand. Solving the consumption and portfolio choice problem without labor income is much less demanding because it avoids the problem of interpolating optimal control variables across a grid of possible cash-on-hand values. In my approach, this interpolation is achieved by the regression (18), which leads to the parameterized policy functions (19).

2.3 Measuring the value of portfolio choice

I follow Cocco et al. (2005) and compute the certainty equivalent consumption, CEC, that makes the household indifferent between receiving a stream of certain consumption and implementing the optimal consumption and portfolio choice decisions. Starting from $t = 0$, I obtain the initial optimal consumption share, $\hat{q}_0$, from (15) for the observed state variables, z_0. Using the initial

[8] Applications include Ghysels and Pereira (2008), Inkmann and Shi (2015) and Beber, Brandt, Cen, and Kavajecz (2019).

[9] GMM estimation of Euler equations is used in this literature to estimate optimal consumption and portfolio choice policies given a household's preference parameters. A parallel literature in the tradition of Hansen and Singleton (1982) uses GMM estimation of Euler equations to estimate the preference parameters of a representative investor from time series of asset returns and aggregate consumption.

[10] Such as the simulation approach proposed by Brandt, Goyal, Santa-Clara, and Stroud (2005) and applied by Koijen et al. (2010) to solve an investor's problem similar to the one considered here.

values of (scaled) cash-on-hand, x_0, and labor income, L_0, the initial optimal consumption follows from $\hat{C}_0 = \hat{q}_0 x_0 L_0$. Using the then observed realizations of asset returns and labor income growth, G_1, I calculate cash-on-hand at the next rebalancing time, x_1, from (6). From evaluating the policy functions (19) for $t = 1$ at the then observed state variables, z_1, I obtain $\hat{q}_1$ and $\hat{C}_1 = \hat{q}_1 x_1 L_1 = \hat{q}_1 x_1 L_0 G_1$. 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 the sample and estimate the household's time-0 value function $V_0(x_0, z_0)$ as

$$\widehat{V}_0 = \frac{1}{S-T} \sum_{s=1}^{S-T} \sum_{t=0}^{T} \delta^t \frac{\widehat{C}_{st}^{1-\gamma}}{1-\gamma}. \tag{20}$$

CEC then follows from

$$\sum_{t=0}^{T} \delta^t \frac{CEC^{1-\gamma}}{1-\gamma} = \widehat{V}_0 \Leftrightarrow CEC = \left(\frac{(1-\delta)(1-\gamma)}{1-\delta^{T+1}} \widehat{V}_0 \right)^{\frac{1}{1-\gamma}}. \tag{21}$$

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

3 Real earnings growth across industries

Data on monthly industry-specific earnings from January 1990 – December 2019 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"[11] in 1982-84 dollars. 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 employees start in January 2006 and are therefore too short for my purposes. 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 15 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

[11] According to the CES website, "In service-providing industries, these data are collected for nonsupervisory employees – those who are not owners or who are not primarily employed to direct, supervise, or plan the work of others. In goods-producing industries, the data are collected for production employees in mining and logging and in manufacturing, and for construction employees in construction. Production and construction employees include working supervisors or group leaders who may be "in charge" of some employees, but whose supervisory functions are only incidental to their regular work."

seasonally adjusted form. I choose the former because seasonal adjustment is likely to smooth the inter-temporal variation in earnings, which may conceal potential hedging demands. The industry classification system of CES can be translated into the more familiar 2017 North American Industry Classification System (NAICS). Real earnings for production and nonsupervisory employees are available for 72 of the 86 subsectors at the three-digit NAICS level (84% coverage). The CES coverage of less aggregated industries at the four-, five- and six-digit NAICS level is substantially worse. For this reason, I use the 72 subsectors for my analysis but for simplicity I refer to them as industries.

Table 1 shows the mean real earnings growth and its volatility, skewness and kurtosis for all industries. Table 2 shows comoments of industry-specific real earnings growth (G_i) and the real return on the CRSP value-weighted broad stock market index (R). Table 2 also shows the initial, January 1990, observation of annualized real earnings for each industry in thousands of 1982-84 dollars. The tables report CES industry identifiers and industry names. For space reasons, some of these names are slightly abbreviated.[12] Most of the earnings moments follow from the definition of a comoment

$$C_i\left(a,b\right)=\frac{\mathbb{E}\left[\left(G_i-\mathbb{E}\left[G_i\right]\right)^a\left(R-\mathbb{E}\left[R\right]\right)^b\right]}{\sigma\left(G_i\right)^a\sigma\left(R\right)^b}, \tag{22}$$

where $\sigma\left(\cdot\right)$ denotes the standard deviation. From (22) 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 Tables 1 and 2 are estimated by replacing expectation operators in (22) with sample averages.

Tables 1 and 2 about here

I propose to use coskewness and cokurtosis to measure business cycle variation in industry-specific labor income risk. Storesletten et al. (2004) report high values of idiosyncratic labor income growth volatility during recessions, while Guvenen et al. (2014) document negative skewness in idiosyncratic labor income growth during recessions.[13] An industry with a (low) negative value of

[12]E.g., the full name of the "Securities, investments, funds and trusts" industry also includes "commodity contracts".
[13]These business cycle variations in idiosyncratic risk optimally lead to reduced stock market exposures (Lynch and

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.

Tables 1 and 2 show substantial variation in initial earnings and in the moments of monthly real labor income growth and its comoments with real stock returns across industries. Initial annual earnings vary between $5,257$ (1982-84) dollars in the "Food services and drinking places" industry and $30,317$ dollars in the "Petroleum and coal products" industry.[14] The average growth across industries is 1.001 with an average volatility of 0.021. The "Couriers and messengers" industry shows the highest earnings growth and the highest earnings volatility across all industries over the sample period. On average, the real earnings growth distribution is slightly skewed to the left (skewness of -0.076) and leptokurtic (kurtosis of 3.836). The average correlation between income growth and stock returns is slightly negative (-0.012) and ranges from -0.087 in "Insurance carriers and related industries" to 0.092 in "General merchandise stores". Coskewness is on average close to zero (0.005) and cokurtosis slightly negative (-0.049). According to these measures, the "Transportation equipment" industry is most likely to experience high earnings volatility during recessions, while employees in "Electronics and appliance stores" are most likely to face negative skewness in earnings during recessions. Note that the sample period covers three NBER recessions.

Below, I will use these moments and comoments of industry-specific real earnings growth to explain the variation in certainty equivalent consumption across industries.

4 The value of portfolio choice across industries

4.1 Financial market data

Because I am focusing on the joint distribution of earnings growth and stock returns, I follow Cocco et al. (2005) and consider a simple asset universe consisting of Treasury bills and an aggregate

Tan (2011); Catherine (2020); and Shen (2018)).

[14] Krueger and Summers (1988) already note the high wages in the petroleum industry in 1984, which remain the highest among 42 industries at the two-digit industry classification level after controlling for human capital and demographic background.

stock market index for the United States.[15] Monthly returns on a 30-day T-bill and value-weighted monthly returns including dividends on a broad stock market index are obtained from CRSP for the period January 1990 – December 2019. The data period is determined by the availability of the industry-specific labor income data described earlier. I use the log dividend-price ratio as a predictor variable for stock returns and earnings growth in the conditional versions of the dynamic portfolio choice model. The log dividend-price ratio has been used in numerous predictive regressions of aggregate stock returns and can be motivated by the present-value relation (Campbell and Shiller, 1988). It has been used as a predictor variable in the life cycle portfolio choice models of Lynch and Tan (2011) and Michaelides and Zhang (2017). The dividend-price ratio also predicts cyclical variation in labor income risk in Lynch and Tan (2011). Dividends for the CRSP broad stock market index are accumulated over 12 months at a zero rate of return and then related to the total market value of the index to obtain the dividend-price ratio. I also obtain monthly inflation series from CRSP to convert nominal returns into real ones. Table 3 contains descriptive statistics for the time series of real asset returns and the log dividend-price ratio.

Table 3 about here

4.2 Parameter choice

For the baseline model, I choose an investment horizon of $T = 180$ months, which leaves half of the observations to estimate the optimal policy functions from (17). For comparative statics, I also consider a reduced investment horizon of $T = 90$ months. Consumption and portfolio rebalancing occurs every 18 months. Most life cycle portfolio choice model assume a rebalancing period of 12 months. I deviate from this because of the computational burden involved in solving the dynamic portfolio choice model separately for 72 industries. In the baseline model, households are endowed with an initial ratio of cash-on-hand to annual earnings of $x_0 = 1$. The ratio is increased to $x_0 = 2$ in a comparative statics exercise. In all cases, I consider coefficients of relative risk aversion of $\gamma = 10$ and $\gamma = 5$. The subjective discount factor is set to $\delta = 0.97$.

All dynamic portfolio choice models rely on a third-order polynomial in cash-on-hand. Thus,

[15] Hedging demands for other asset classes arise if returns covary with earnings. For example, Davidoff (2006) shows that the value of housing owned by households decreases when income is positively correlated with house prices.

$n = 4$ in equation (18). At each rebalancing time, I solve the consumption and portfolio choice problem for a grid of 20 values of cash-on-hand. Doubling the number of grid points yields very similar results. I show results for $m = 1, 2, 3$ in (15) corresponding to an unconditional model ($m = 1$), and to conditional models involving linear ($m = 2$) or quadratic ($m = 3$) functions in the log dividend-price ratio.[16] For a dynamic portfolio choice and consumption problem involving recursive preferences and an infinite investment horizon, Campbell et al. (2003) show that the policy function for portfolio choice (consumption) is linear (quadratic) in the state variable, when the Euler conditions and budget constraints are log-linearized. For a portfolio choice problem in which long-term investors receive utility from terminal wealth, Inkmann and Shi (2015) demonstrate that most benefits of predictability are already realized with a linear function. Moreover, in line with these authors, I show below that parameterizations above $m = 2$ not necessarily increase certainty equivalent consumption. The reason for this is estimation error. While a more flexible parameterization always should lead to better results in theory, in reality the estimation error resulting from estimating a larger number of unknown parameters may offset these gains.[17]

4.3 Policy functions

Figures 1 and 2 depict surface plots of the policy functions (19) for the allocation to stocks for two selected industries and three rebalancing times ($t = 1, 5, 9$) for coefficients of relative risk aversion $\gamma = 10$ and $\gamma = 5$, respectively. Figures 3 and 4 contain the corresponding surface plots of the policy functions for the consumption share. All policy functions involve a cubic polynomial ($n = 4$) in cash-on-hand and a linear function ($m = 2$) in the log dividend-price ratio. Percentiles of the log dividend-price ratio are shown on the axis labeled z, while ratios of cash-on-hand to earnings between zero and three are shown on the axis labeled x.

Figures 1 and 2 about here

By construction, all policy functions fall into the unit interval. This is due to the $\Lambda(\cdot)$ function in

[16] All optimizations were performed with GAUSS 20 using the Constrained Optimization MT 2.0 module. For numerical reasons, it turned out to be beneficial to standardize the log dividend-price ratio. There is no loss of generality because for every regression in a standardized regressor there exists an equivalent regression in the original regressor. Brandt et al. (2009) use standardized state variables as well.

[17] 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 error (DeMiguel, Garlappi, and Uppal, 2009).

(15), which reflects the borrowing and short-sale constraints of the household. The same function is also responsible for the shape of the policy functions for the allocation to stocks in the log dividend-price ratio, which is nonlinear despite relying on a linear parameterization ($m = 2$). For this reason, the policy functions for $m = 3$ are similar to those obtained for $m = 2$.

Panel A of all figures contains policy functions for the "Petroleum and coal products" industry, while Panel B contains results for the "Securities, investments, funds and trusts" industry. While I obtained the surface plots for all 72 industries, these two industries are selected based on optimization results discussed below. The "Petroleum and coal product" industry performs best in terms of certainty equivalent consumption, while the "Securities, investments, funds and trusts" industry performs best with respect to certainty equivalent consumption in relation to initial earnings. Regarding the latter criterion, the "Petroleum and coal products" industry achieves median performance. Figures 1 and 2 reflect a number of well-known results from the dynamic portfolio choice and life cycle portfolio choice literature: First, the optimal allocation to stocks generally decreases with increasing cash-on-hand (see, e.g., Cocco et al. (2005) and Fagereng et al. (2017)). Second, the optimal allocation to stocks generally increases with the log dividend-price ratio (see, e.g., Brandt (1999)). High values of this state variable indicate valuable investment opportunities. Only for the myopic investment problem at $t = 9$, the optimal portfolio remains largely unaffected by variations in the state variable because no future rebalancing times, and therefore opportunities to shift stock exposure over time, remain at this stage. Third, the allocation to stocks generally increases with the investment horizon (see, e.g., Brandt (1999)), a result which is consistent with mean reversion in stock returns. Correspondingly, the optimal asset allocation is constrained at unity when cash-on-hand is low and the log dividend-price ratio is high. The constrained area increases with the investment horizon (i.e., is larger at $t = 1$ than at $t = 9$). Fourth, the optimal allocation to stocks decreases with an increasing coefficient of relative risk aversion (see, e.g., Brandt (1999) and Campbell et al. (2003)). These results hold for all industries at almost all rebalancing times.

The surface plots also reveal new results that are the outcome of a parameterization of the policy function that includes interaction terms of both state variables. For example, while the optimal allocation to stocks generally increases with decreasing cash-on-hand, this relationship is reversed for very low values of the log dividend-price ratio. In the presence of adverse investment opportunities, relatively poor households stay out of the stock market. Such results only become obvious from simultaneously plotting the policy functions along both dimensions of state variables. Plotting a univariate policy function in one state variable for a median value of the second state variable would conceal these results.

The main contribution of these surface plots to the literature rests on the comparison of Panels A and B, which show the results for two selected industries, which only differ in their observed labor income outcomes. Recall that the industry in Panel A is median in terms of certainty equivalent consumption performance relative to initial earnings while the industry in Panel B is top. Figures 1 and 2 show clearly that this ranking is not simply the result of increased allocations to stocks in the "Securities, investments, funds and trusts" industry. On the contrary, employees in this industry optimally invest less in risky assets than employees in the "Petroleum and coal products" industry.

Figures 3 and 4 about here

The policy functions for the optimal share of consumption in Figures 3 and 4 are comparably less interesting because they are less sensitive to variations in state variables. This holds in particular for variations in the log dividend-price ratio, which only have a negligible impact on optimal consumption. The share of optimal consumption generally increases with decreasing cash-on-hand. Poor households are financially constrained and consume almost all their cash-on-hand. This holds in particular when the investment horizon is short. Relative risk aversion only has a very modest impact on the share of cash-on-hand that is optimally consumed. Households employed in the "Securities, investments, funds and trusts" industry optimally consume a larger share of cash-on-hand than households in the "Petroleum and coal products" industry for all combinations of state variables at $t = 1$ and $t = 5$ but a smaller share at $t = 9$ for small values of cash-on-hand.

4.4 Certainty equivalent consumption

Table 4 shows the value of life cycle portfolio choice in terms of CEC across the 72 industries for the baseline model using an investment horizon of $T = 180$ months and an initial ratio of cash-on-hand to annual earnings of $x_0 = 1$. The table shows the mean, standard deviation, minimum, maximum, and the 10th, 50th, and 90th percentiles of the CEC distribution across industries. In addition, several measures of inequality are shown, which I will describe below. For comparison, the distribution of initial earnings, L_0, is shown as well.

Table 4 about here

Given $x_0 = 1$, CEC is directly comparable to initial earnings, L_0. It turns out that the average CEC across industries for households with relative risk aversion $\gamma = 10$ in the unconditional model is identical to the average initial earnings. Both averages equal $15,080$ (1982-84) dollars. Recall that the unconditional model assumes that investors ignore the log dividend-price ratio as a potential predictor of stock returns and income growth. Investors are indifferent between consuming their initial labor income at every rebalancing time with certainty and implementing the optimal consumption and portfolio choice policies in the presence of stochastic labor income growth and stock returns. The standard deviation of CEC across industries, $5,280$ dollars, is very similar to the standard deviation of initial earnings, $5,290$ dollars.

The conditional models that allow for predictability on average achieve higher CEC but the differences are relatively small. The average CEC increases from $15,080$ for the unconditional model ($m = 1$) to $15,100$ dollars for both conditional models with linear ($m = 2$) and quadratic ($m = 3$) policy functions in the log dividend-price ratio. The table also shows the percentage of industries that benefit from predictability: In 88% of industries, employees achieve higher average CEC in the conditional model with $m = 2$ compared to the unconditional model with $m = 1$. However, allowing for a quadratic function in the state variable, $m = 3$, only increases average CEC in 19% of industries beyond the average achieved with $m = 2$. As mentioned earlier, estimation error is the likely explanation for this result. The more flexible quadratic specification requires an additional parameter to be estimated for each control variable at each of the 10 rebalancing times. Thus, an extra 20 parameters need to be estimated by GMM for each of the 20 grid points of cash-on-hand.

When relative risk aversion decreases to $\gamma = 5$, households on average achieve a CEC of $15,370$ dollars in the unconditional model and of $15,410$ dollars in the preferred conditional model with $m = 2$. Thus, the benefits of predictability increase with decreasing risk aversion of households. Average CEC increases in 99% of industries if the log dividend-price ratio is taken into account. Allowing for a nonlinear impact, further increases average CEC in only 14% of industries. Recall that the household in my model is constrained from borrowing and short-selling. The benefits of predictability likely were higher without these constraints because households would invest more than 100% of their wealth in stocks for combinations of state variables that involve low wealth and promising investment opportunities.

Tables 5 and 6 about here

Tables 5 and 6 contain the results from two comparative statics exercises in which either the investment horizon is reduced to $T = 90$ months or the initial endowment is raised to $x_0 = 2$. In the former case, average CEC across industries increases for both $\gamma = 10$ and $\gamma = 5$. This is because the household's initial endowment can be spread over a smaller number of rebalancing periods. Households in all industries benefit from predictability if $\gamma = 5$, households in all but one industries benefit from conditioning on the log dividend-price ratio if $\gamma = 10$. When the initial endowment is increased to $x_0 = 2$ (Table 6), average CEC increases as expected. Moreover, in the presence of a larger initial endowment, risk averse households with $\gamma = 10$ hardly benefit from predictability. In this case, average CEC only increases for households in 36% of industries. This can be explained by the policy functions discussed earlier. The allocation to stocks generally decreases with cash-on-hand, which reduces the potential benefits from predicting stock returns.

Is inequality in the distribution of initial earnings reflected in the distribution of certainty equivalent consumption or can optimal portfolio choice mitigate inequality? I answer this question by calculating well-known measures of inequality for the distributions of CEC and initial earnings, L_0, across industries. Specifically, I calculate the ratio of the 90th and 10th percentiles ($Q90/Q10$) of each distribution and decompose this ratio into $Q90/Q50$ and $Q50/Q10$. I also calculate the Gini coefficient as a further measure of inequality. These results are presented in Tables 4 – 6. On first sight, the decile ratios in all tables seem to suggest that portfolio choice reduces inequality. The $Q90/Q10$ ratio for CEC is smaller for all parameter constellations than the corresponding ratio of L_0. This is because an increase in the $Q90/Q50$ ratio is more than offset by a decrease in the $Q50/Q10$ ratio. These results seem to suggest that households in higher and in particular in lower paid industries benefit more from portfolio choice than household in median pay industries. This could be the case if, for example, earnings in lower paid industries tend to be less correlated with the aggregate stock market. However, given the relatively small sample size of 72 industries, these results need to be interpreted with caution. The results may as well change for other tail indices. Indeed, the Gini coefficients for initial earnings and CEC in Tables 4 – 6 are all equal to 0.20 regardless of the parameter constellation. This implies that the moderate level of inequality in initial earnings across industries is fully reflected in the distribution of certainty equivalent consumption. This result is in line with findings from the macroeconomics literature regarding the impact of the earnings distribution on the distribution of wealth (Benhabib et al., 2019).

To shed more light on the impact of optimal portfolio choice on inequality, I plot the ratio of CEC/L_0 against L_0. If portfolio choice can mitigate inequality because households in industries with lower earnings benefit more from portfolio choice than households in median earnings industries as suggested by the $Q50/Q10$ ratio, then we should see higher values of CEC/L_0 for smaller observations of L_0. These plots are shown in Figure 5 for $\gamma = 10$ and in Figure 6 for $\gamma = 5$. I focus on the conditional model with linear predictability, $m = 2$. The results for $m = 1$ and $m = 3$ are very similar. The three panels in both figures show the results for the benchmark model (Panel A, corresponding to Table 4), the model with reduced investment horizon (Panel B, corresponding to Table 5) and the model with increased initial endowment (Panel C, corresponding to Table 6).

Figures 5 and 6 about here

The results are very clear, none of the six scatter plots in Figures 5 and 6 shows any systematic differences in the distribution of CEC relative to L_0, which is related to initial earnings. In general, the earnings structure in lower paid industries does not enhance the value of portfolio choice. Thus, within the optimization framework considered here, optimal portfolio choice does not affect inequality in the distribution of consumption relative to initial earnings. However, while the *overall* distribution remains unaffected, the figures show that there is substantial variation in relative CEC which is unrelated to the level of initial earnings. The statistical properties of the industry-specific earnings process place some households in a better position to benefit from portfolio choice than other households. The figures show that these advantages are mostly unaffected by relative risk aversion, investment horizon and initial endowment. The scatter plots look very similar for all parameter constellations. Compared to the benchmark case, a shorter investment horizon slightly compresses the distribution of CEC relative to L_0, while an increase in initial endowments causes the opposite effect. In the first case, portfolio choice has less time to operate, while in the second case the returns from portfolio choice are larger in terms of dollar value.

Who are the winners and losers of this exercise? Which industries offer the largest and smallest values of portfolio choice relative to initial earnings? It turns out that the answer to these questions in independent of the parameter constellations considered in Figures 5 and 6. In all cases, households employed in the "Securities, investments, funds and trusts" industry are able to benefit most from portfolio choice while households in the "Motion picture and sound recording" industry benefit least. Wall Street beats Hollywood. Recall that CEC is scaled by initial earnings. Thus, these differences are independent of inter-industry differences in the initial earnings level. The differences are large. For the benchmark case, CEC/L_0 is about 1.09 (1.12) for households working at Wall Street and 0.78 (0.88) for those working in Hollywood when relative risk aversion is $\gamma = 10$ ($\gamma = 5$). For risk averse households, CEC exceeds initial earnings at Wall Street by 9% but falls short of initial earnings by 22% in Hollywood. Figures 5 and 6 reveal that the value of portfolio choice for households in the "Motion picture and sound recording" industry is exceptionally low. This industry is an obvious outlier in all scatter plots. The median industry in terms of CEC/L_0 performance is "Petroleum and coal products", which coincidentally is also the industry in the sample that pays the highest wages and therefore achieves the highest absolute value of CEC.

The high value of portfolio choice for households working at Wall Street is somewhat unexpected. Textbook wisdom suggests that the earnings of these households should be highly correlated with the stock market. While this may be the case for households holding supervisory positions in the "Securities, investments, funds and trusts" industry, Table 2 shows that the earnings of nonsupervisory employees in this industry are actually negatively correlated with stock returns (correlation $= -0.0799$). Interestingly, the same holds for households working in Hollywood (correlation $= -0.0726$). Recall that the minimum correlation in the sample is -0.0865 for the insurance industry. Thus, earnings in both industries exhibit very low correlations with the stock market. This clearly suggests that other statistical moments of industry-specific real earnings growth matter as well for the value of portfolio choice.

4.5 Which moments of real earnings growth matter?

I relate the ratio of certainty equivalent consumption to initial earnings (CEC/L_0), referred to as "scaled CEC" in this section, to the industry-specific moments of real earnings growth in Table 1 and its comoments with real stock returns in Table 2. The resulting cross-sectional regressions for the benchmark model using $T = 180$ and $x_0 = 1$ are shown in Table 7. Table 8 shows the corresponding regressions for $T = 90$ and $x_0 = 1$ and Table 9 for $T = 180$ and $x_0 = 2$.

Tables 7 – 9 about here

Panel A of each table shows results for $\gamma = 10$ and Panel B for $\gamma = 5$. I report estimates from the full sample and from a restricted sample that excludes the "Motion picture and sound recording" industry that has been shown to drastically underperform all other industries with respect to CEC/L_0 in the previous section. In a first specification, I just include the mean earnings growth and the two moments that have received most attention in the life cycle portfolio choice literature (e.g., in Haliassos and Michaelides (2003), Cocco et al. (2005), and Benzoni et al. (2007)), the variance of earnings growth and its correlation with stock returns. In a second specification, I add skewness and kurtosis of earnings growth. In the third and final specification, I add coskewness and cokurtosis between earnings growth and stock returns. All explanatory variables in this section are standardized across industries for ease of interpretation. Several robust results emerge from Tables 7 – 9: First, mean earnings growth has a large positive effect on scaled CEC in all regressions. The effect is always statistically significant at 1% level. For example, in the first specification in Panel A of Table 7, a one standard deviation increase in mean earnings growth increases scaled CEC by 0.0416 using the full sample. Second, a one standard deviation decrease in the variance of earnings growth has an effect of similar magnitude on scaled CEC when $\gamma = 10$, which reduces to about half of this magnitude when $\gamma = 5$. Not surprisingly, earnings risk is a stronger determinant of scaled CEC when risk aversion is high. The effect of the first two moments on scaled CEC is usually of an order of magnitude larger than the effect of all other moments and comoments. Third, the correlation between earnings growth and stock returns often turns out insignificant for the full sample. Correlation becomes statistically significant in the basic specification once the "Motion picture and sound recording" industry is removed from the sample. The sign of the impact is as expected: The lower the correlation the higher scaled CEC. Fourth, the significant impact of correlation always disappears once kurtosis of earnings growth is controlled for. Kurtosis is a highly significant predictor of CEC over the longer investment horizon ($T = 180$). As far as I know, this result has not been documented before. For example, a one standard deviation increase in kurtosis in column (2) of Table 9, decreases scaled CEC by about 1%, which suggests that households prefer earnings growth distributions with thinner tails. The impact is twice as large as the impact of correlation in column (1) of Table 9. Kurtosis becomes insignificant over the shorter horizon ($T = 90$) when $\gamma = 5$ but remains significant for $\gamma = 10$. Fifth, all results remain largely unaffected from adding coskewness and cokurtosis. Both measures of business cycle variation of earnings risk at the industry level are insignificant in all regressions. Sixth, these regressions explain about $70 - 75\%$ of the variation in scaled CEC over the longer investment horizon and about 55% over the shorter horizon. Because all inter-industry differentials in scaled CEC are caused by differences in the industry-specific earnings process, this result suggests that higher moments and comoments still play a role. However, interpreting these higher moments becomes difficult.

The most interesting finding of this section is related to the role of kurtosis in predicting scaled CEC. Storesletten et al. (2004) and Guvenen et al. (2014) stress the importance of volatility and negative skewness of earnings during recessions. Kurtosis describes the propensity of the earnings process to generate outliers in the tails of the earnings distribution, unrelated to the business cycle. My findings suggest that tail risk in earnings growth is an important predictor of the cross-sectional variation in the value of portfolio choice, independent of the business cycle.

5 Conclusions

I investigate the impact of the joint distribution of industry-specific earnings growth and aggregate stock returns on the value of portfolio choice using data on industry-specific earnings from the Current Employment Statistics for the period January 1990 – December 2019. From solving a dynamic model of consumption and portfolio choice for 72 industries at the three-digit industry classification level, I obtain the cross-sectional distribution of certainty equivalent consumption. I first relate this distribution to the distribution of the *level* of initial earnings. Specifically, I am interested whether households affiliated to industries with high initial earnings benefit more from portfolio choice than households in lower paid industries. This is motivated by Fagereng et al. (2016) who show that the returns on wealth increase in the level of wealth. I do not find any evidence that portfolio choice fosters inequality in certainty equivalent consumption. Inequality in certainty equivalent consumption mirrors inequality in the level of initial earnings across industries. This is similar to the relationship between inequalities in the income and wealth distributions generated by buffer stock saving models (Benhabib et al., 2019).

However, there remains substantial heterogeneity in certainty equivalent consumption across the distribution of initial earnings. I then use inter-industry variation in the moments of real earnings *growth* and its comoments with real stock returns to explain this heterogeneity. I document large cross-sectional variation in these moments. For example, the correlation between monthly earnings growth and stock returns ranges from -0.087 to 0.092. I find strong effects of average earnings growth and its variance on certainty equivalent consumption. Interestingly, an economically modest impact of the correlation between earnings growth and stock returns disappears once kurtosis of earnings growth is controlled for. This finding is robust against most variations in model parameters including relative risk aversion, investment horizon, and whether or not households are able to use the dividend-price ratio to predict earnings growth and stock returns. Households affiliated to industries that exhibit thinner tails of earnings growth, benefit more from portfolio choice than households in industries with thicker tails of earnings growth.

Cyclical variation in the risk of earnings growth across industries does not predict certainty equivalent consumption over the sample period, which includes three NBER recessions. I propose to use coskewness and cokurtosis of earnings growth and stock returns to capture business cycle variation in the variance and skewness of industry-specific labor income growth. This is motivated by Storesletten et al. (2004) and Guvenen et al. (2014), who document countercyclical volatility and left skewness, respectively, in idiosyncratic earnings risk. At industry level, business cycle variation in tail risks does not explain cross-sectional variation in certainty equivalent consumption. This does not mean that households do not care about tail risks in earnings growth because kurtosis remains significant after controlling for coskewness and cokurtosis.

My analysis is relevant for the calibration of life cycle portfolio choice models. Heterogeneity in the joint distribution of earnings growth and stock returns at industry level could be used as an alternative to preference parameter heterogeneity (Gomes and Michaelides, 2005) to match the observed cross-sectional variation in household portfolios. The previously undocumented result regarding the insignificance of the correlation between earnings growth and stock returns in predicting the value of portfolio choice once kurtosis of earnings growth is controlled for, could motivate extensions of asset pricing models with industry-specific human capital in the spirit of Eiling (2013) that are beyond the scope of this paper. My findings are particularly relevant for occupational pension plans that are organized at the industry level in many countries. Given the power of defaults (e.g., Madrian and Shea (2001) and Choi, Laibson, Madrian, and Metrick (2004)), the default fund in industry-level pension plans should account for the industry-specific joint distribution of earnings growth and stock returns. A default product that works well for the pension plan members of one industry may be less suitable for members of another industry.

References

Aguiar, M. and M. Bils (2015). Has consumption inequality mirrored income inequality? *American Economic Review 105*(9), 2725–56.

Angerer, X. and P.-S. Lam (2009). Income risk and portfolio choice: An empirical study. *The Journal of Finance 64*(2), 1037–1055.

Attanasio, O. P. and L. Pistaferri (2016). Consumption inequality. *Journal of Economic Perspectives 30*(2), 3–28.

Back, K. (2010). *Asset pricing and portfolio choice theory.* Oxford University Press.

Bagliano, F. C., R. Corvino, C. Fugazza, and G. Nicodano (2019). Hedging labor income risk over the life-cycle. *Available at SSRN 3475446*.

Bagliano, F. C., C. Fugazza, and G. Nicodano (2019). Life-cycle portfolios, unemployment and human capital loss. *Journal of Macroeconomics 60*, 325–340.

Beber, A., M. W. Brandt, J. Cen, and K. A. Kavajecz (2019). Mutual fund performance: Using bespoke benchmarks to disentangle mandates, constraints and skill. Technical report.

Benhabib, J., A. Bisin, and M. Luo (2019). Wealth distribution and social mobility in the us: A quantitative approach. *American Economic Review 109*(5), 1623–47.

Benzoni, L., P. Collin-Dufresne, and R. S. Goldstein (2007). Portfolio choice over the life-cycle when the stock and labor markets are cointegrated. *The Journal of Finance 62*(5), 2123–2167.

Betermier, S., T. Jansson, C. Parlour, and J. Walden (2012). Hedging labor income risk. *Journal of Financial Economics 105*(3), 622–639.

Bonaparte, Y., G. M. Korniotis, and A. Kumar (2014). Income hedging and portfolio decisions. *Journal of Financial Economics 113*(2), 300–324.

Brandt, M. W. (1999). Estimating portfolio and consumption choice: A conditional euler equations approach. *The Journal of Finance 54*(5), 1609–1645.

Brandt, M. W., A. Goyal, P. Santa-Clara, and J. R. Stroud (2005). A simulation approach to dynamic portfolio choice with an application to learning about return predictability. *The Review of Financial Studies 18*(3), 831–873.

Brandt, M. W. and P. Santa-Clara (2006). Dynamic portfolio selection by augmenting the asset space. *The Journal of Finance 61*(5), 2187–2217.

Brandt, M. W., P. Santa-Clara, and R. Valkanov (2009). Parametric portfolio policies: Exploiting characteristics in the cross-section of equity returns. *The Review of Financial Studies 22*(9), 3411–3447.

Brugler, J., J. Inkmann, and A. Rizzo (2020). Did perceptions of background risk change over the great recession? *Available at SSRN 3428088*.

Campbell, J. Y., Y. L. Chan, and L. M. Viceira (2003). A multivariate model of strategic asset allocation. *Journal of Financial Economics 67*(1), 41–80.

Campbell, J. Y., J. F. Cocco, F. J. Gomes, and P. J. Maenhout (2001). Investing retirement wealth: A life-cycle model. In *Risk aspects of investment-based Social Security reform*, pp. 439–482. University of Chicago Press.

Campbell, J. Y. and R. J. Shiller (1988). The dividend-price ratio and expectations of future dividends and discount factors. *The Review of Financial Studies 1*(3), 195–228.

Carroll, C. D. (1997). Buffer-stock saving and the life cycle/permanent income hypothesis. *The Quarterly journal of economics 112*(1), 1–55.

Catherine, S. (2020). Countercyclical labor income tisk and portfolio choices over the life-cycle.

Catherine, S., P. Sodini, and Y. Zhang (2020). Countercyclical income risk and portfolio choices: Evidence from sweden. *Available at SSRN*.

Chang, Y., J. H. Hong, and M. Karabarbounis (2018). Labor market uncertainty and portfolio choice puzzles. *American Economic Journal: Macroeconomics 10*(2), 222–62.

Choi, J. J., D. Laibson, B. C. Madrian, and A. Metrick (2004). For better or for worse: Default effects and 401 (k) savings behavior. In *Perspectives on the Economics of Aging*, pp. 81–126. University of Chicago Press.

Cocco, J. F., F. J. Gomes, and P. J. Maenhout (2005). Consumption and portfolio choice over the life cycle. *The Review of Financial Studies 18*(2), 491–533.

Davidoff, T. (2006). Labor income, housing prices, and homeownership. *Journal of urban Economics 59*(2), 209–235.

Davis, S. and P. Willen (2000). Using financial assets to hedge labor income risks. *University of Chicago, working paper*.

Davis, S. J. and P. Willen (2014). Occupation-level income shocks and asset returns: Their covariance and implications for portfolio choice. *The Quarterly Journal of Finance 3*(03n04), 1350011.

DeMiguel, V., L. Garlappi, and R. Uppal (2009). Optimal versus naive diversification: How inefficient is the 1/n portfolio strategy? *The review of Financial studies 22*(5), 1915–1953.

Dickens, W. and L. F. Katz (1987). Inter-industry wage differences and industry characteristics. In K. Lang and J. S. Leonard (Eds.), *Unemployment and the Structure of Labor Markets*. Oxford: Basil Blackwell.

Eiling, E. (2013). Industry-specific human capital, idiosyncratic risk, and the cross-section of expected stock returns. *The Journal of Finance 68*(1), 43–84.

Fagereng, A., C. Gottlieb, and L. Guiso (2017). Asset market participation and portfolio choice over the life-cycle. *The Journal of Finance 72*(2), 705–750.

Fagereng, A., L. Guiso, D. Malacrino, and L. Pistaferri (2016). Heterogeneity in returns to wealth and the measurement of wealth inequality. *American Economic Review 106*(5), 651–55.

Fagereng, A., L. Guiso, and L. Pistaferri (2018). Portfolio choices, firm shocks, and uninsurable wage risk. *The Review of Economic Studies 85*(1), 437–474.

Ghysels, E. and J. P. Pereira (2008). Liquidity and conditional portfolio choice: A nonparametric investigation. *Journal of empirical finance 15*(4), 679–699.

Gomes, F. and A. Michaelides (2005). Optimal life-cycle asset allocation: Understanding the empirical evidence. *The Journal of Finance 60*(2), 869–904.

Guiso, L., T. Jappelli, and D. Terlizzese (1996). Income risk, borrowing constraints, and portfolio choice. *The American Economic Review*, 158–172.

Guvenen, F., S. Ozkan, and J. Song (2014). The nature of countercyclical income risk. *Journal of Political Economy 122*(3), 621–660.

Haliassos, M. and A. Michaelides (2003). Portfolio choice and liquidity constraints. *International Economic Review 44*(1), 143–177.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica: Journal of the Econometric Society*, 1029–1054.

Hansen, L. P. and K. J. Singleton (1982). Generalized instrumental variables estimation of nonlinear rational expectations models. *Econometrica: Journal of the Econometric Society*, 1269–1286.

Heaton, J. and D. Lucas (2000). Portfolio choice and asset prices: The importance of entrepreneurial risk. *Journal of Finance*, 1163–1198.

Hochguertel, S. (2003). Precautionary motives and portfolio decisions. *Journal of Applied Econometrics 18*(1), 61–77.

Huggett, M. and G. Kaplan (2016). How large is the stock component of human capital? *Review of Economic Dynamics 22*, 21–51.

Inkmann, J. and Z. Shi (2015). Parametric portfolio policies in the surplus consumption ratio. *International Review of Finance 15*(2), 257–282.

Katz, L. F. and L. H. Summers (1989). Industry rents: Evidence and implications. *Brookings Papers on Economic Activity. Microeconomics 1989*, 209–290.

Koijen, R. S., T. E. Nijman, and B. J. Werker (2010). When can life cycle investors benefit from time-varying bond risk premia? *The review of financial studies 23*(2), 741–780.

Krueger, A. B. and L. H. Summers (1987). Reflections on the inter-industry wage structure. unemployment and the structure of labour markets. In K. Lang and J. S. Leonard (Eds.), *Unemployment and the Structure of Labor Markets*. Oxford: Basil Blackwell.

Krueger, A. B. and L. H. Summers (1988). Efficiency wages and the inter-industry wage structure. *Econometrica: Journal of the Econometric Society*, 259–293.

Krueger, D., F. Perri, L. Pistaferri, and G. L. Violante (2010). Cross-sectional facts for macroeconomists. *Review of Economic dynamics 13*(1), 1–14.

Lynch, A. W. and S. Tan (2011). Labor income dynamics at business-cycle frequencies: Implications for portfolio choice. *Journal of Financial Economics 101*(2), 333–359.

Madrian, B. C. and D. F. Shea (2001). The power of suggestion: Inertia in 401 (k) participation and savings behavior. *The Quarterly Journal of Economics 116*(4), 1149–1187.

Massa, M. and A. Simonov (2006). Hedging, familiarity and portfolio choice. *The Review of Financial Studies 19*(2), 633–685.

Michaelides, A. and Y. Zhang (2017). Stock market mean reversion and portfolio choice over the life cycle. *Journal of Financial and Quantitative Analysis 52*(3), 1183–1209.

Neal, D. (1995). Industry-specific human capital: Evidence from displaced workers. *Journal of labor Economics 13*(4), 653–677.

Palia, D., Y. Qi, and Y. Wu (2014). Heterogeneous background risks and portfolio choice: Evidence from micro-level data. *Journal of Money, Credit and Banking 46*(8), 1687–1720.

Shen, J. (2018). Countercyclical risks and portfolio choice over the life cycle: Evidence and theory. In *9th Miami Behavioral Finance Conference*.

Storesletten, K., C. I. Telmer, and A. Yaron (2004). Cyclical dynamics in idiosyncratic labor market risk. *Journal of Political Economy 112*(3), 695–717.

Thaler, R. H. (1989). Anomalies: Interindustry wage differentials. *Journal of Economic Perspectives 3*(2), 181–193.

Vissing-Jorgensen, A. (2002). Towards an explanation of household portfolio choice heterogeneity: Nonfinancial income and participation cost structures. *NBER working paper*.

Weinberg, B. A. (2001). Long-term wage fluctuations with industry-specific human capital. *Journal of Labor Economics 19*(1), 231–264.

Appendix

A.1 Derivation of Bellman equation

At investment horizon T, all cash-on-hand optimally is consumed, $c_T = x_T$. Ignoring the state variables z_T from the set of arguments for notational simplicity in this appendix, the value function at time T becomes

$$V_T\left(X_T, L_T\right) = \frac{X_T^{1-\gamma}}{1-\gamma} = L_T^{1-\gamma}\frac{x_T^{1-\gamma}}{1-\gamma}. \tag{23}$$

Because the value function is homogeneous in L_T of degree $-\left(1-\gamma\right)$, it is convenient to work with

$$V_T\left(x_T\right) = L_T^{-(1-\gamma)} V_T\left(X_T, L_T\right) = \frac{x_T^{1-\gamma}}{1-\gamma}. \tag{24}$$

Working backwards, the value function at $T-1$ can be rewritten as follows

$$\begin{aligned}
V_{T-1}\left(X_{T-1}, L_{T-1}\right) &= \max_{C_{T-1}, w_{T-1}} \left(\frac{C_{T-1}^{1-\gamma}}{1-\gamma} + \delta \mathbb{E}_{T-1}\left[V_T\left(X_T, L_T\right)\right]\right) & (25)\\
&= \max_{C_{T-1}, w_{T-1}} \left(L_{T-1}^{1-\gamma}\frac{c_{T-1}^{1-\gamma}}{1-\gamma} + \delta \mathbb{E}_{T-1}\left[L_T^{1-\gamma} V_T\left(x_T\right)\right]\right) & (26)\\
&= \max_{C_{T-1}, w_{T-1}} \left(L_{T-1}^{1-\gamma}\frac{c_{T-1}^{1-\gamma}}{1-\gamma} + \delta \mathbb{E}_{T-1}\left[\left(G_T L_{T-1}\right)^{1-\gamma} V_T\left(x_T\right)\right]\right) & (27)\\
&= L_{T-1}^{1-\gamma} \max_{C_{T-1}, w_{T-1}} \left(\frac{c_{T-1}^{1-\gamma}}{1-\gamma} + \delta \mathbb{E}_{T-1}\left[G_T^{1-\gamma} V_T\left(x_T\right)\right]\right). & (28)
\end{aligned}$$

Again, it is more convenient to work with

$$\begin{aligned}
V_{T-1}\left(x_{T-1}\right) &= L_{T-1}^{-(1-\gamma)} V_{T-1}\left(X_{T-1}, L_{T-1}\right) & (29)\\
&= \max_{c_{T-1}, w_{T-1}} \left(\frac{c_{T-1}^{1-\gamma}}{1-\gamma} + \delta \mathbb{E}_{T-1}\left[G_T^{1-\gamma} V_T\left(x_T\right)\right]\right). & (30)
\end{aligned}$$

In the same way, the value function (7) in the main text is obtained for a general t.

A.2 Derivation of Euler equations

Replacing x_{t+1} in the Bellman equation (7) with (5) yields

$$V_t(x_t, z_t) = \max_{c_t, w_t} \left\{ u(c_t) + \delta \mathbb{E}_t \left[G_{t+1}^{1-\gamma} V_{t+1}(x_{t+1}, z_{t+1}) \right] \right\} \tag{31}$$

$$= \max_{c_t, w_t} \left\{ u(c_t) + \delta \mathbb{E}_t \left[G_{t+1}^{1-\gamma} V_{t+1} \left(G_{t+1}^{-1} (x_t - c_t) R_{t+1}^p + 1, z_{t+1} \right) \right] \right\}. \tag{32}$$

Using the definition of the portfolio return in equation (2), the first-order conditions for a maximum of (32) with respect to consumption, c_t, and the allocation to the risky asset, w_t, can be derived as

$$\mathbb{E}_t \left[\delta G_{t+1}^{-\gamma} \nabla_1 V_{t+1}(x_{t+1}, z_{t+1}) R_{t+1}^p \right] = u'(c_t) \tag{33}$$

$$\mathbb{E}_t \left[\delta G_{t+1}^{-\gamma} \nabla_1 V_{t+1}(x_{t+1}, z_{t+1}) R_{t+1}^e \right] = 0, \tag{34}$$

where $\nabla_1 V_{t+1}(x_{t+1}, z_{t+1})$ denotes the first derivative of the value function $V_{t+1}(x_{t+1}, z_{t+1})$ with respect to its first argument, x_{t+1}. These derivatives can be replaced with the envelope condition, $\nabla_1 V_{t+1}(x_{t+1}, z_{t+1}) = u'(c_{t+1})$ (see, e.g., Back (2010)), to obtain the Euler equations

$$\mathbb{E}_t \left[\delta \left(G_{t+1} \frac{c_{t+1}}{c_t} \right)^{-\gamma} R_{t+1}^p - 1 \right] = 0 \tag{35}$$

$$\mathbb{E}_t \left[\delta (G_{t+1} c_{t+1})^{-\gamma} R_{t+1}^e \right] = 0 \tag{36}$$

The Euler equations (9) and (10) in the main text are obtained from using the identities $c_t = x_t q_t$ and $c_{t+1} = x_{t+1} q_{t+1}$ in (35) and (36).

Table 1: Real earnings growth moments by industry

Industry	CES ID	Mean	Volatility	Skewness	Kurtosis
Oil and gas extraction	10211000	1.002	0.034	0.218	2.532
Mining, except oil and gas	10212000	1.000	0.016	0.017	3.863
Support activities for mining	10213000	1.001	0.026	0.160	4.479
Construction of buildings	20236000	1.001	0.017	-0.051	5.396
Heavy and civil engineering construction	20237000	1.002	0.037	-0.306	3.556
Specialty trade contractors	20238000	1.001	0.022	-0.307	3.821
Wood products	31321000	1.001	0.016	-0.416	3.147
Nonmetallic mineral products	31327000	1.001	0.019	-0.372	4.327
Primary metals	31331000	1.000	0.014	-0.042	3.216
Fabricated metal products	31332000	1.000	0.015	-0.428	3.839
Machinery	31333000	1.000	0.016	-0.335	3.984
Computer and electronic products	31334000	1.001	0.015	-0.397	3.727
Electrical equipment and appliances	31335000	1.000	0.019	-0.288	3.490
Transportation equipment	31336000	1.001	0.028	-0.250	3.751
Furniture and related products	31337000	1.001	0.021	-0.803	6.592
Miscellaneous durable goods manufact.	31339000	1.001	0.015	-0.368	3.527
Food manufacturing	32311000	1.000	0.014	-0.599	3.353
Textile mills	32313000	1.001	0.022	0.072	6.606
Textile product mills	32314000	1.001	0.025	-0.451	5.605
Apparel	32315000	1.001	0.019	-0.098	8.768
Paper and paper products	32322000	1.000	0.015	-0.109	2.923
Printing and related support activities	32323000	1.000	0.016	-0.346	3.535
Petroleum and coal products	32324000	1.001	0.030	0.186	4.344
Chemicals	32325000	1.000	0.013	0.133	3.135
Plastics and rubber products	32326000	1.000	0.014	-0.173	3.220
Miscellaneous nondurable goods manufact.	32329000	1.001	0.022	-0.028	4.129
Durable goods	41423000	1.001	0.017	-0.011	2.425
Nondurable goods	41424000	1.001	0.013	0.147	2.988
Electronic markets and agents and brokers	41425000	1.001	0.023	-0.043	2.950
Motor vehicle and parts dealers	42441000	1.000	0.019	-0.046	3.079
Furniture and home furnishings stores	42442000	1.000	0.020	-0.415	3.457
Electronics and appliance stores	42443000	1.002	0.028	0.665	5.278
Building material and garden supply stores	42444000	1.000	0.014	-0.299	4.828
Food and beverage stores	42445000	1.000	0.014	-0.431	5.495
Health and personal care stores	42446000	1.001	0.014	0.158	3.611
Gasoline stations	42447000	1.000	0.011	0.427	4.862
Clothing and clothing accessories stores	42448000	1.001	0.029	-0.049	4.415
Sporting, hobby, book, and music stores	42451000	1.001	0.030	0.287	3.414
General merchandise stores	42452000	1.001	0.033	-0.655	5.328
Miscellaneous store retailers	42453000	1.000	0.020	0.027	3.052
Nonstore retailers	42454000	1.001	0.023	0.575	4.186
Air transportation	43481000	1.001	0.042	0.018	3.356

Table 1 continued

Industry	CES ID	Mean	Volatility	Skewness	Kurtosis
Truck transportation	43484000	1.000	0.015	-1.053	5.190
Transit and ground passenger transportat.	43485000	1.000	0.026	0.114	3.349
Support activities for transportation	43488000	1.000	0.016	0.064	2.977
Couriers and messengers	43492000	1.002	0.044	0.538	7.091
Warehousing and storage	43493000	1.000	0.023	-0.506	5.975
Motion picture and sound recording	50512000	1.000	0.034	0.085	3.155
Broadcasting, except Internet	50515000	1.001	0.019	0.010	2.962
Telecommunications	50517000	1.000	0.017	0.136	3.725
Data processing, hosting and related	50518000	1.002	0.028	0.172	3.632
Other information services	50519000	1.001	0.036	0.147	3.982
Credit intermediation and related activities	55522000	1.001	0.028	0.053	2.215
Securities, investments, funds and trusts	55523000	1.002	0.033	0.115	2.393
Insurance carriers and related activities	55524000	1.001	0.020	-0.127	2.162
Real estate	55531000	1.001	0.017	0.221	2.444
Rental and leasing services	55532000	1.001	0.016	0.217	3.530
Administrative and support services	60561000	1.001	0.012	-0.147	4.653
Waste management and remediation	60562000	1.001	0.012	-0.367	3.624
Health care	65620001	1.001	0.009	0.213	2.967
Ambulatory health care services	65621000	1.001	0.012	0.265	2.836
Hospitals	65622000	1.001	0.008	0.333	3.998
Nursing and residential care facilities	65623000	1.001	0.017	-0.075	2.731
Social assistance	65624000	1.000	0.016	0.087	2.330
Performing arts and spectator sports	70711000	1.001	0.036	0.227	3.720
Museums, historical sites, and similar inst.	70712000	1.000	0.025	-0.090	2.752
Amusements, gambling, and recreation	70713000	1.000	0.021	-0.221	2.746
Accommodation	70721000	1.001	0.018	0.232	3.134
Food services and drinking places	70722000	1.001	0.021	-0.549	3.220
Repair and maintenance	80811000	1.000	0.010	-0.077	3.362
Personal and laundry services	80812000	1.000	0.017	-0.520	3.627
Membership associations and organizations	80813000	1.001	0.011	0.079	4.122
Mean		1.001	0.021	-0.076	3.836
Median		1.001	0.019	-0.042	3.545
Standard deviation		0.001	0.008	0.321	1.212

Notes: The table shows moments of real labor income growth across industries based on CES labor income data from January 1990 – December 2019 (360 observations) in 1982-84 Dollars. All 72 CES industries with an equivalent three-digit 2017 NAICS code are selected, accounting for 84% of the 86 industries at the three-digit level in the 2017 NAICS classification.

Table 2: Real earnings growth and stock return comoments by industry

Industry	CES ID	Correl.	Coskew.	Cokurt.	L_0
Oil and gas extraction	10211000	0.033	0.009	0.058	23.909
Mining, except oil and gas	10212000	-0.051	-0.129	-0.420	28.160
Support activities for mining	10213000	-0.046	0.037	-0.546	21.700
Construction of buildings	20236000	-0.008	0.273	0.464	19.542
Heavy and civil engineering construction	20237000	-0.075	0.238	0.033	21.203
Specialty trade contractors	20238000	-0.004	0.206	0.107	20.982
Wood products	31321000	-0.017	-0.002	-0.094	14.525
Nonmetallic mineral products	31327000	-0.063	0.136	-0.347	18.127
Primary metals	31331000	0.086	0.025	0.163	21.875
Fabricated metal products	31332000	0.033	0.125	0.093	17.807
Machinery	31333000	0.056	0.115	0.172	20.127
Computer and electronic products	31334000	-0.032	0.039	-0.317	18.228
Electrical equipment and appliances	31335000	0.048	0.079	0.312	17.010
Transportation equipment	31336000	-0.018	-0.131	0.002	23.631
Furniture and related products	31337000	0.016	0.052	-0.099	13.360
Miscellaneous durable goods manufact.	31339000	-0.030	0.053	-0.274	14.006
Food manufacturing	32311000	-0.003	0.003	-0.053	14.348
Textile mills	32313000	0.011	-0.004	0.019	13.333
Textile product mills	32314000	0.018	0.079	-0.171	11.407
Apparel	32315000	0.076	0.049	0.055	8.797
Paper and paper products	32322000	0.045	0.084	0.212	21.357
Printing and related support activities	32323000	-0.064	-0.096	-0.058	17.369
Petroleum and coal products	32324000	-0.083	-0.094	-0.279	30.317
Chemicals	32325000	-0.032	-0.005	-0.248	22.503
Plastics and rubber products	32326000	0.017	0.012	0.072	16.086
Miscellaneous nondurable goods manufact.	32329000	-0.075	-0.073	-0.694	15.566
Durable goods	41423000	-0.057	-0.088	-0.246	18.606
Nondurable goods	41424000	-0.043	-0.105	-0.207	16.186
Electronic markets and agents and brokers	41425000	-0.074	-0.111	-0.221	20.354
Motor vehicle and parts dealers	42441000	0.018	-0.095	0.003	14.804
Furniture and home furnishings stores	42442000	-0.012	-0.080	0.106	11.218
Electronics and appliance stores	42443000	0.030	0.235	1.259	11.111
Building material and garden supply stores	42444000	-0.068	0.043	-0.377	11.622
Food and beverage stores	42445000	-0.019	0.231	-0.397	9.536
Health and personal care stores	42446000	0.038	-0.081	-0.055	8.386
Gasoline stations	42447000	0.013	-0.079	-0.133	7.976
Clothing and clothing accessories stores	42448000	0.053	0.085	0.258	6.645
Sporting, hobby, book, and music stores	42451000	0.024	0.081	0.270	6.921
General merchandise stores	42452000	0.092	0.096	0.342	7.221
Miscellaneous store retailers	42453000	0.025	0.036	-0.064	9.139
Nonstore retailers	42454000	0.028	0.123	0.246	13.678
Air transportation	43481000	-0.060	0.020	-0.049	17.629

Table 2 continued

Industry	CES ID	Correl.	Coskew.	Cokurt.	L_0
Truck transportation	43484000	-0.033	0.049	-0.322	19.439
Transit and ground passenger transportat.	43485000	0.074	-0.062	0.475	13.094
Support activities for transportation	43488000	-0.044	-0.005	-0.135	17.641
Couriers and messengers	43492000	0.072	-0.047	0.311	8.896
Warehousing and storage	43493000	0.039	0.007	-0.046	16.288
Motion picture and sound recording	50512000	-0.073	-0.066	-0.066	17.232
Broadcasting, except Internet	50515000	-0.029	-0.077	-0.008	15.789
Telecommunications	50517000	-0.004	-0.061	-0.057	22.989
Data processing, hosting and related	50518000	-0.039	-0.073	-0.260	16.957
Other information services	50519000	-0.049	-0.021	0.143	20.302
Credit intermediation and related activities	55522000	-0.081	-0.027	-0.101	13.337
Securities, investments, funds and trusts	55523000	-0.080	0.041	-0.138	18.364
Insurance carriers and related activities	55524000	-0.087	-0.036	-0.149	16.649
Real estate	55531000	-0.033	-0.066	-0.184	12.046
Rental and leasing services	55532000	-0.057	-0.106	-0.131	10.915
Administrative and support services	60561000	0.025	0.036	0.095	10.708
Waste management and remediation	60562000	-0.047	-0.040	-0.393	17.380
Health care	65620001	-0.031	-0.057	-0.314	13.534
Ambulatory health care services	65621000	-0.035	-0.013	-0.122	12.419
Hospitals	65622000	0.035	-0.063	-0.271	16.327
Nursing and residential care facilities	65623000	-0.031	-0.024	-0.066	9.742
Social assistance	65624000	-0.057	-0.114	-0.097	8.573
Performing arts and spectator sports	70711000	-0.055	-0.016	-0.025	12.635
Museums, historical sites, and similar inst.	70712000	-0.043	0.002	-0.236	10.301
Amusements, gambling, and recreation	70713000	0.073	-0.077	0.300	7.836
Accommodation	70721000	-0.027	0.117	0.132	8.289
Food services and drinking places	70722000	-0.019	-0.085	-0.207	5.257
Repair and maintenance	80811000	-0.033	-0.051	-0.188	14.808
Personal and laundry services	80812000	-0.007	-0.014	-0.159	9.488
Membership associations and organizations	80813000	-0.046	-0.091	-0.215	12.087
Mean		-0.012	0.005	-0.049	15.078
Median		-0.023	-0.005	-0.066	14.806
Standard deviation		0.047	0.094	0.277	5.292

Notes: The table shows comoments (correlation, coskewness, cokurtosis) of real labor income growth across industries based on CES labor income data and real returns on the CRSP value-weighted broad stock market index based on monthly data from January 1990 – December 2019 (360 observations). The final column shows annualized real earnings in January 1990 in thousands of 1982-84 dollars (as provided by CES). All 72 CES industries with an equivalent three-digit 2017 NAICS code are selected, accounting for 84% of the 86 industries at the three-digit level in the 2017 NAICS classification.

Table 3: Descriptive statistics of real asset returns and conditioning variable

Variable	Symbol	Mean	Standard deviation
Real return on T-bills	R^f	1.0069	0.0421
Real return on stocks	R	1.0002	0.0035
Log dividend-price ratio	z	-3.9270	0.2615

Notes: The table shows descriptive statistics for monthly real asset returns and conditioning variables for the period January 1990 – December 2019 (360 observations). 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.

Table 4: Distribution of certainty equivalent consumption (CEC) by risk aversion: $T = 180$ & $x_0 = 1$

			$\gamma = 10$			$\gamma = 5$	
		$m = 1$	$m = 2$	$m = 3$	$m = 1$	$m = 2$	$m = 3$
	L_0	CEC	CEC	CEC	CEC	CEC	CEC
Mean	15.08	15.08	15.10	15.10	15.37	15.41	15.40
Std. dev.	5.29	5.28	5.31	5.29	5.38	5.40	5.39
Max	30.32	30.14	30.24	30.24	30.65	30.75	30.74
Q90	21.67	21.39	21.44	21.42	21.88	21.94	21.92
Q50	14.81	14.44	14.47	14.47	14.81	14.85	14.84
Q10	8.40	8.51	8.52	8.55	8.74	8.76	8.76
Min	5.26	5.38	5.38	5.38	5.45	5.46	5.45
Q90/Q10	2.58	2.51	2.52	2.51	2.50	2.50	2.50
Q90/Q50	1.46	1.48	1.48	1.48	1.48	1.48	1.48
Q50/Q10	1.76	1.70	1.70	1.69	1.70	1.70	1.69
Gini	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Mean($1[CEC(m) > CEC(m-1)]$)			0.88	0.19		0.99	0.14

Notes: The table shows the distribution of certainty equivalent consumption (CEC) across industries for coefficients of relative risk aversion $\gamma = 10$ and $\gamma = 5$. The investment horizon is $T = 180$ months. Consumption and portfolio rebalancing occur every 18 months. For each γ, CEC is calculated for three different parameterizations of the policy functions involving an intercept only ($m = 1$), a linear function in the log dividend-price ratio ($m = 2$), and a quadratic polynomial in this state variable ($m = 3$). All parameterizations are based on a cubic polynomial in cash-on-hand ($n = 4$). The second column of the table reports the distribution of initial annual earnings (L_0) across industries in thousands of 1982-84 dollars. The initial (January 1990) ratio of cash-on-hand to annual earnings is $x_0 = 1$.

Table 5: Distribution of certainty equivalent consumption (CEC) by risk aversion: $T = 90$ & $x_0 = 1$

		$\gamma = 10$			$\gamma = 5$		
		$m = 1$	$m = 2$	$m = 3$	$m = 1$	$m = 2$	$m = 3$
	L_0	CEC	CEC	CEC	CEC	CEC	CEC
Mean	15.08	15.10	15.11	15.11	15.69	15.71	15.71
Std. dev.	5.29	5.36	5.37	5.37	5.60	5.60	5.60
Max	30.32	30.96	30.99	30.98	32.37	32.40	32.40
Q90	21.67	21.62	21.67	21.67	22.42	22.44	22.44
Q50	14.81	14.71	14.73	14.73	15.20	15.21	15.21
Q10	8.40	8.51	8.52	8.52	8.80	8.81	8.81
Min	5.26	5.35	5.35	5.35	5.53	5.53	5.53
Q90/Q10	2.58	2.54	2.54	2.54	2.55	2.55	2.55
Q90/Q50	1.46	1.47	1.47	1.47	1.48	1.48	1.48
Q50/Q10	1.76	1.73	1.73	1.73	1.73	1.73	1.73
Gini	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Mean($1[CEC(m) > CEC(m-1)]$)			0.97	0.47		1.00	0.32

Notes: The table shows the distribution of certainty equivalent consumption (CEC) across industries for coefficients of relative risk aversion $\gamma = 10$ and $\gamma = 5$. The investment horizon is $T = 90$ months. Consumption and portfolio rebalancing occur every 18 months. For each γ, CEC is calculated for three different parameterizations of the policy functions involving an intercept only ($m = 1$), a linear function in the log dividend-price ratio ($m = 2$), and a quadratic polynomial in this state variable ($m = 3$). All parameterizations are based on a cubic polynomial in cash-on-hand ($n = 4$). The second column of the table reports the distribution of initial annual earnings (L_0) across industries in thousands of 1982-84 dollars. The initial (January 1990) ratio of cash-on-hand to annual earnings is $x_0 = 1$.

Table 6: Distribution of certainty equivalent consumption (CEC) by risk aversion: $T = 180$ & $x_0 = 2$

			$\gamma = 10$			$\gamma = 5$	
		$m = 1$	$m = 2$	$m = 3$	$m = 1$	$m = 2$	$m = 3$
	L_0	CEC	CEC	CEC	CEC	CEC	CEC
Mean	15.08	17.01	17.01	17.00	17.40	17.46	17.41
Std. dev.	5.29	6.01	6.00	5.97	6.13	6.15	6.12
Max	30.32	34.40	34.24	34.25	35.04	35.15	35.10
Q90	21.67	23.93	23.97	23.92	24.76	24.81	24.77
Q50	14.81	16.33	16.54	16.52	16.73	16.78	16.72
Q10	8.40	9.57	9.56	9.54	9.87	9.89	9.85
Min	5.26	6.06	6.06	6.05	6.13	6.17	6.14
Q90/Q10	2.58	2.50	2.51	2.51	2.51	2.51	2.52
Q90/Q50	1.46	1.47	1.45	1.45	1.48	1.48	1.48
Q50/Q10	1.76	1.71	1.73	1.73	1.70	1.70	1.70
Gini	0.20	0.20	0.20	0.20	0.20	0.20	0.20
Mean($1[CEC(m) > CEC(m-1)]$)			0.36	0.28		0.96	0.13

Notes: The table shows the distribution of certainty equivalent consumption (CEC) across industries for coefficients of relative risk aversion $\gamma = 10$ and $\gamma = 5$. The investment horizon is $T = 180$ months. Consumption and portfolio rebalancing occur every 18 months. For each γ, CEC is calculated for three different parameterizations of the policy functions involving an intercept only ($m = 1$), a linear function in the log dividend-price ratio ($m = 2$), and a quadratic polynomial in this state variable ($m = 3$). All parameterizations are based on a cubic polynomial in cash-on-hand ($n = 4$). The second column of the table reports the distribution of initial annual earnings (L_0) across industries in thousands of 1982-84 dollars. The initial (January 1990) ratio of cash-on-hand to annual earnings is $x_0 = 2$.

Table 7: Cross-sectional regressions of scaled certainty equivalent consumption (CEC/L_0) on moments of real earnings growth for $T = 180$ and $x_0 = 1$

A. Relative risk aversion: $\gamma = 10$

	(1)		(2)		(3)	
	$N = 72$	$N = 71$	$N = 72$	$N = 71$	$N = 72$	$N = 71$
Intercept	1.0014	1.0033	1.0014	1.0033	1.0014	1.0033
	(341.5)	(433.3)	(352.0)	(455.6)	(348.2)	(451.0)
Mean	0.0416	0.0360	0.0441	0.0377	0.0442	0.0377
	(11.37)	(12.03)	(11.55)	(12.26)	(11.44)	(12.12)
Variance	-0.0402	-0.0336	-0.0395	-0.0330	-0.0400	-0.0337
	(-11.04)	(-11.11)	(-11.16)	(-11.44)	(-10.66)	(-11.11)
Skewness			-0.0043	-0.0024	-0.0042	-0.0028
			(-1.35)	(-0.96)	(-1.21)	(-1.07)
Kurtosis			-0.0077	-0.0075	-0.0081	-0.0072
			(-2.37)	(-3.01)	(-2.31)	(-2.71)
Correlation	-0.0013	-0.0043	0.0019	-0.0012	0.0010	-0.0029
	(-0.43)	(-1.80)	(0.60)	(-0.47)	(0.23)	(-0.87)
Coskewness					0.0020	0.0000
					(0.56)	(0.01)
Cokurtosis					0.0010	0.0026
					(0.22)	(0.75)
Adjusted R^2	0.690	0.718	0.709	0.745	0.702	0.740

B. Relative risk aversion: $\gamma = 5$

	(1)		(2)		(3)	
	$N = 72$	$N = 71$	$N = 72$	$N = 71$	$N = 72$	$N = 71$
Intercept	1.0219	1.0230	1.0219	1.0230	1.0219	1.0230
	(381.0)	(403.5)	(388.0)	(414.0)	(387.6)	(413.5)
Mean	0.0442	0.0412	0.0449	0.0414	0.0451	0.0415
	(13.22)	(12.60)	(12.71)	(12.00)	(12.72)	(12.00)
Variance	-0.0290	-0.0255	-0.0285	-0.0249	-0.0296	-0.0261
	(-8.72)	(-7.72)	(-8.69)	(-7.70)	(-8.59)	(-7.75)
Skewness			-0.0002	0.0008	-0.0002	0.0005
			(-0.08)	(0.30)	(-0.08)	(0.17)
Kurtosis			-0.0063	-0.0062	-0.0066	-0.0062
			(-2.08)	(-2.20)	(-2.07)	(-2.07)
Correlation	-0.0048	-0.0063	-0.0022	-0.0039	-0.0043	-0.0063
	(-1.75)	(-2.44)	(-0.74)	(-1.39)	(-1.10)	(-1.73)
Coskewness					0.0027	0.0016
					(0.83)	(0.54)
Cokurtosis					0.0026	0.0034
					(0.62)	(0.89)
Adjusted R^2	0.722	0.716	0.732	0.730	0.731	0.730

Notes: The table shows OLS estimates from linear regressions of scaled certainty equivalent consumption (CEC/L_0) on standardized moments of real labor income growth by risk aversion ($\gamma = 10, 5$) for the full sample of industries ($N = 72$) and a selected sample, which excludes the Motion Picture and Sound Recording industry ($N = 71$). CEC is obtained as described in the notes of Table 4 for $m = 1$.

Table 8: Cross-sectional regressions of scaled certainty equivalent consumption (CEC/L_0) on moments of real earnings growth for $T = 90$ and $x_0 = 1$

A. Relative risk aversion: $\gamma = 10$

	(1)		(2)		(3)	
	$N = 72$	$N = 71$	$N = 72$	$N = 71$	$N = 72$	$N = 71$
Intercept	1.0007	1.0016	1.0007	1.0016	1.0007	1.0016
	(499.0)	(546.0)	(504.4)	(552.8)	(501.3)	(547.8)
Mean	0.0213	0.0186	0.0226	0.0195	0.0226	0.0196
	(8.50)	(7.85)	(8.47)	(7.72)	(8.42)	(7.65)
Variance	-0.0187	-0.0156	-0.0183	-0.0153	-0.0176	-0.0147
	(-7.50)	(-6.50)	(-7.42)	(-6.43)	(-6.75)	(-5.88)
Skewness			-0.0023	-0.0013	-0.0014	-0.0008
			(-1.00)	(-0.65)	(-0.59)	(-0.36)
Kurtosis			-0.0040	-0.0039	-0.0048	-0.0044
			(-1.77)	(-1.91)	(-1.96)	(-1.99)
Correlation	-0.0022	-0.0036	-0.0006	-0.0020	0.0014	-0.0004
	(-1.09)	(-1.93)	(-0.25)	(-0.98)	(0.48)	(-0.13)
Coskewness					0.0015	0.0006
					(0.63)	(0.28)
Cokurtosis					-0.0034	-0.0026
					(-1.07)	(-0.92)
Adjusted R^2	0.539	0.513	0.549	0.524	0.543	0.516

B. Relative risk aversion: $\gamma = 5$

	(1)		(2)		(3)	
	$N = 72$	$N = 71$	$N = 72$	$N = 71$	$N = 72$	$N = 71$
Intercept	1.0397	1.0406	1.0397	1.0406	1.0397	1.0406
	(495.3)	(533.1	(497.0	(538.6)	(493.8)	(532.8)
Mean	0.0251	0.0225	0.0254	0.0223	0.0254	0.0224
	(9.59)	(8.94)	(9.03)	(8.27)	(8.99)	(8.21)
Variance	-0.0137	-0.0107	-0.0134	-0.0103	-0.0132	-0.0103
	(-5.26)	(-4.20)	(-5.15)	(-4.08)	(-4.82)	(-3.87)
Skewness			0.0002	0.0012	0.0010	0.0017
			(0.10)	(0.54)	(0.41)	(0.71)
Kurtosis			-0.0036	-0.0035	-0.0044	-0.0041
			(-1.50)	(-1.59)	(-1.74)	(-1.73)
Correlation	-0.0033	-0.0047	-0.0018	-0.0033	-0.0010	-0.0028
	(-1.55)	(-2.33)	(-0.78)	(-1.50)	(-0.33)	(-0.96)
Coskewness					0.0027	0.0019
					(1.07)	(0.78)
Cokurtosis					-0.0019	-0.0011
					(-0.57)	(-0.37)
Adjusted R^2	0.576	0.575	0.579	0.583	0.573	0.574

Notes: The table shows OLS estimates from linear regressions of scaled certainty equivalent consumption (CEC/L_0) on standardized moments of real labor income growth by risk aversion ($\gamma = 10, 5$) for the full sample of industries ($N = 72$) and a selected sample, which excludes the Motion Picture and Sound Recording industry ($N = 71$). CEC is obtained as described in the notes of Table 5 for $m = 1$.

Table 9: Cross-sectional regressions of scaled certainty equivalent consumption (CEC/L_0) on moments of real earnings growth for $T = 180$ and $x_0 = 2$

A. Relative risk aversion: $\gamma = 10$

	(1)		(2)		(3)	
	$N = 72$	$N = 71$	$N = 72$	$N = 71$	$N = 72$	$N = 71$
Intercept	1.1275	1.1283	1.1275	1.1283	1.1275	1.1283
	(325.6)	(329.5)	(338.1)	(343.0)	(333.6)	(338.1)
Mean	0.0519	0.0494	0.0538	0.0511	0.0538	0.0511
	(12.00)	(11.18)	(12.03)	(11.11)	(11.86)	(10.94)
Variance	-0.0447	-0.0418	-0.0438	-0.0410	-0.0432	-0.0405
	(-10.40)	(-9.37)	(-10.55)	(-9.52)	(-9.79)	(-8.90)
Skewness			-0.0024	-0.0016	-0.0018	-0.0012
			(-0.64)	(-0.43)	(-0.44)	(-0.31)
Kurtosis			-0.0104	-0.0103	-0.0109	-0.0106
			(-2.71)	(-2.75)	(-2.66)	(-2.63)
Correlation	-0.0050	-0.0062	-0.0007	-0.0020	0.0008	-0.0008
	(-1.41)	(-1.78)	(-0.19)	(-0.55)	(0.17)	(-0.16)
Coskewness					0.0011	0.0002
					(0.26)	(0.06)
Cokurtosis					-0.0026	-0.0019
					(-0.49)	(-0.37)
Adjusted R^2	0.700	0.675	0.722	0.720	0.715	0.691

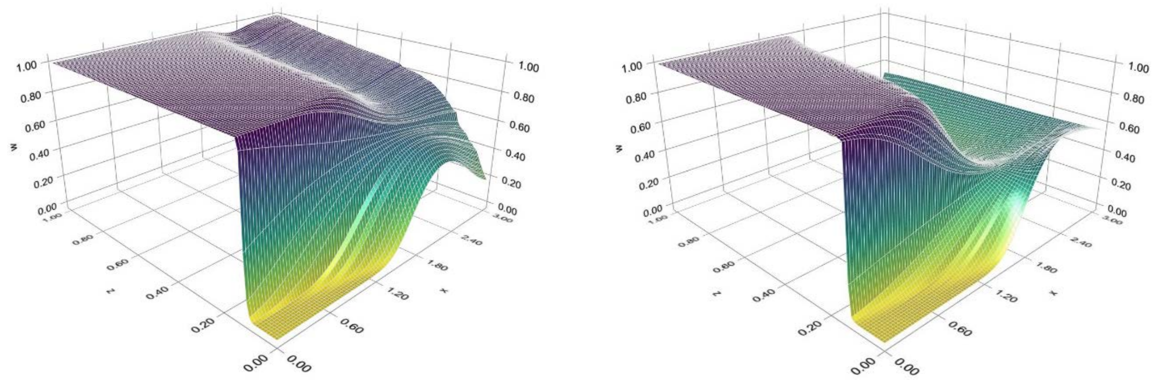
B. Relative risk aversion: $\gamma = 5$

	(1)		(2)		(3)	
	$N = 72$	$N = 71$	$N = 72$	$N = 71$	$N = 72$	$N = 71$
Intercept	1.1574	1.1583	1.1574	1.1583	1.1574	1.1583
	(372.0)	(382.4)	(379.1)	(392.0)	(376.6)	(388.7)
Mean	0.0489	0.0462	0.0493	0.0461	0.0494	0.0462
	(12.59)	(11.81)	(12.03)	(11.16)	(11.97)	(11.09)
Variance	-0.0303	-0.0272	-0.0297	-0.0264	-0.0305	-0.0273
	(-7.86)	(-6.88)	(-7.82)	(-6.84)	(-7.59)	(-6.73)
Skewness			0.0007	0.0017	0.0010	0.0017
			(0.20)	(0.50)	(0.27)	(0.47)
Kurtosis			-0.0071	-0.0070	-0.0077	-0.0073
			(-2.03)	(-2.09)	(-2.07)	(-2.04)
Correlation	-0.0065	-0.0079	-0.0036	-0.0051	-0.0048	-0.0067
	(-2.05)	(-2.55)	(-1.05)	(-1.54)	(-1.06)	(-1.51)
Coskewness					0.0031	0.0022
					(0.84)	(0.60)
Cokurtosis					0.0011	0.0019
					(0.23)	(0.41)
Adjusted R^2	0.703	0.692	0.714	0.707	0.711	0.702

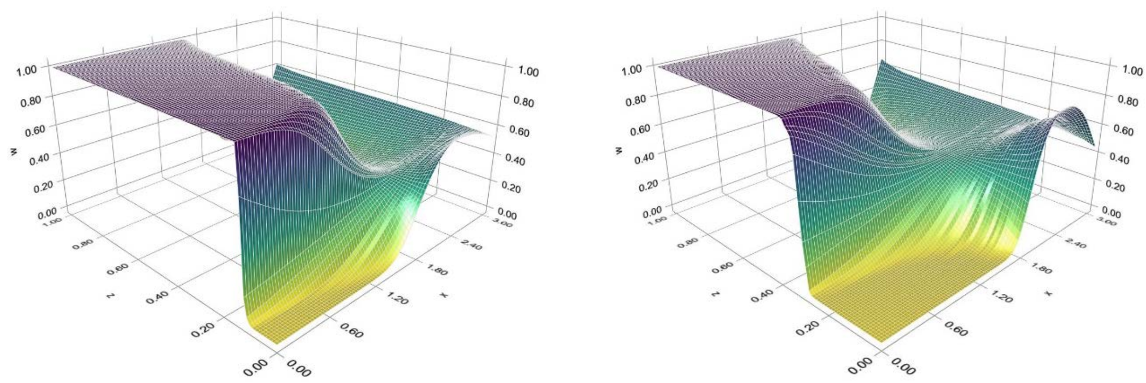
Notes: The table shows OLS estimates from linear regressions of scaled certainty equivalent consumption (CEC/L_0) on standardized moments of real labor income growth by risk aversion ($\gamma = 10, 5$) for the full sample of industries ($N = 72$) and a selected sample, which excludes the Motion Picture and Sound Recording industry ($N = 71$). CEC is obtained as described in the notes of Table 6 for $m = 1$.

Figure 1: Policy functions for allocation to stocks for two selected industries and $\gamma = 10$

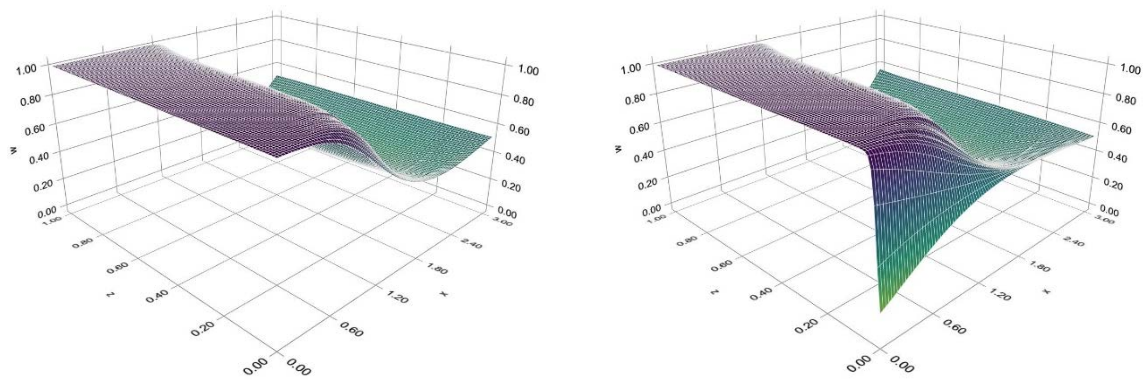
A. Petroleum and coal products $t = 1$ B. Securities and investments



$t = 5$



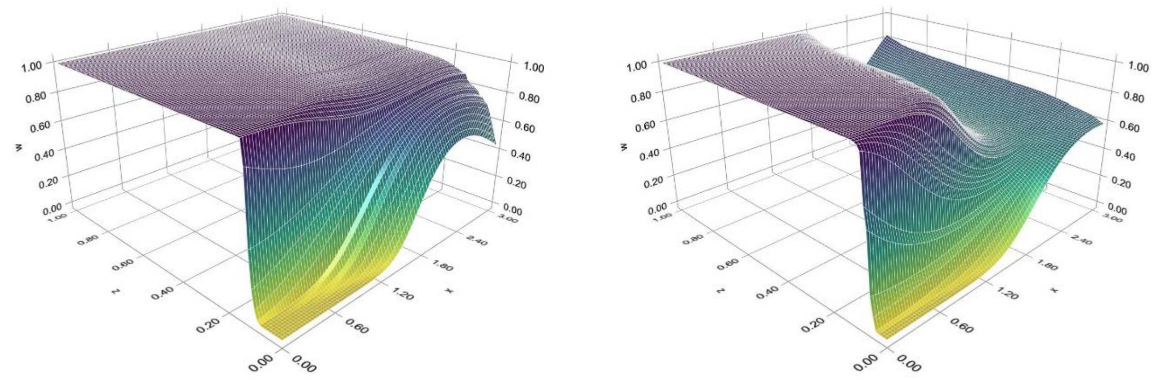
$t = 9$



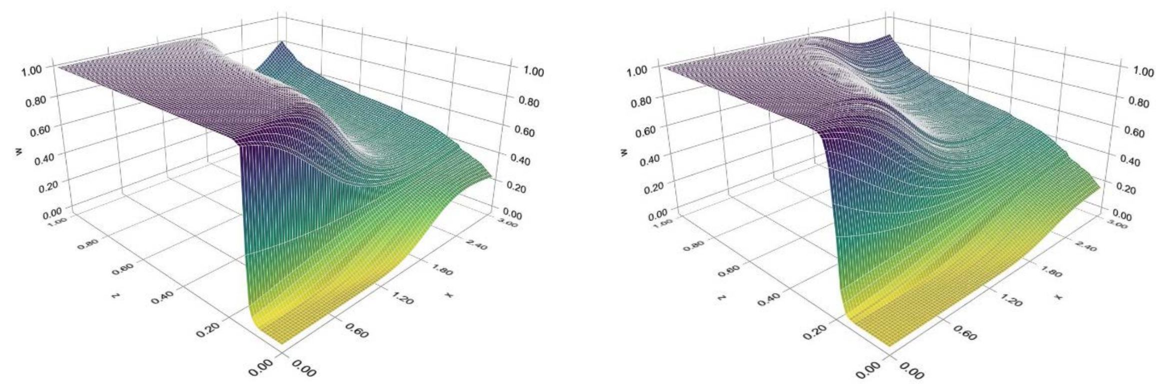
Notes: The figure shows surface plots of policy functions for the allocation to stocks for two selected industries ("Petroleum and coal products" and "Securities, investments, funds and trusts") at rebalancing times $t = 1, 5, 9$ for $\gamma = 10$. The investment horizon at $T = 10$ is 180 months. The policy functions are based on a logistic function of a linear function ($m = 2$) in the log dividend-price ratio, z, and a cubic polynomial ($n = 4$) in the ratio of cash-on-hand to labor income, x, as described in detail in the text. The logistic function restricts the policy functions to the unit interval in line with the borrowing and short-sale constraints typically faced by households. Percentiles of the log dividend-price ratio are shown in the plots.

Figure 2: Policy functions for allocation to stocks for two selected industries and $\gamma = 5$

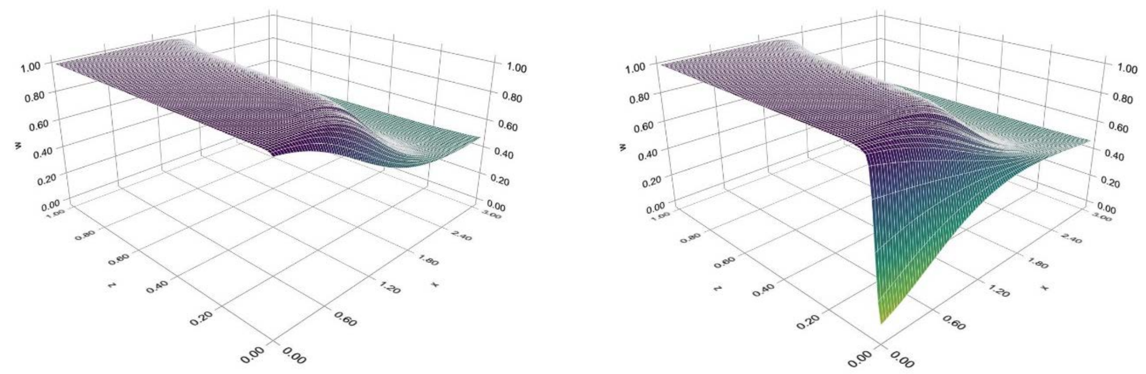
A. Petroleum and coal products $\quad t = 1 \quad$ B. Securities and investments



$t = 5$



$t = 9$



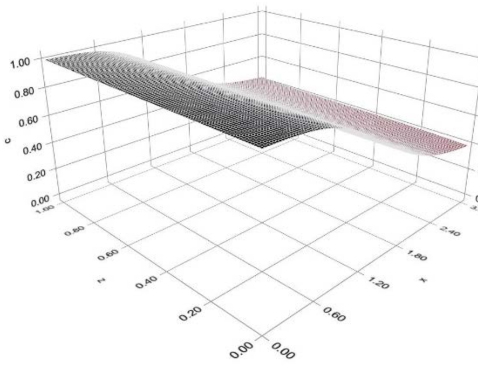
Notes: The figure shows surface plots of policy functions for the allocation to stocks for two selected industries ("Petroleum and coal products" and "Securities, investments, funds and trusts") at rebalancing times $t = 1, 5, 9$ for $\gamma = 5$. The investment horizon at $T = 10$ is 180 months. The policy functions are based on a logistic function of a linear function ($m = 2$) in the log dividend-price ratio, z, and a cubic polynomial ($n = 4$) in the ratio of cash-on-hand to labor income, x, as described in detail in the text. The logistic function restricts the policy functions to the unit interval in line with the borrowing and short-sale constraints typically faced by households. Percentiles of the log dividend-price ratio are shown in the plots.

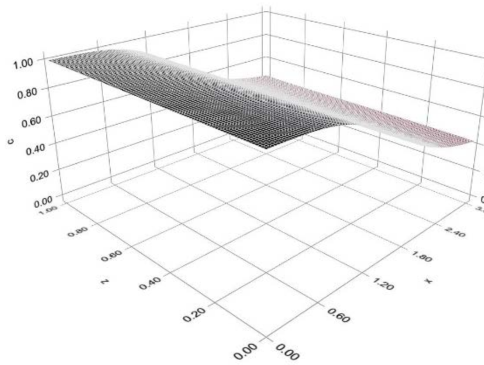
Figure 3: Policy functions for consumption share for two selected industries and $\gamma = 10$

A. Petroleum and coal products

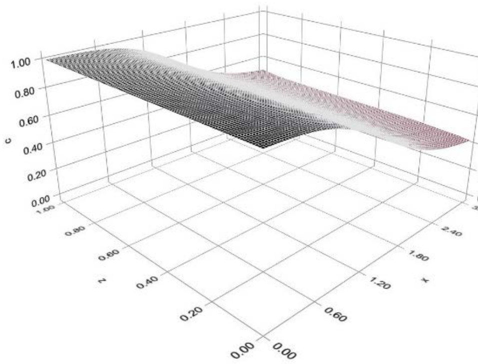
$t = 1$

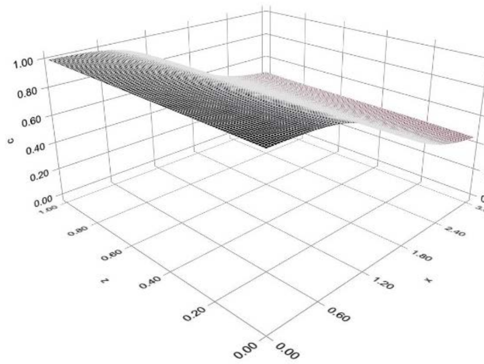
B. Securities and investments



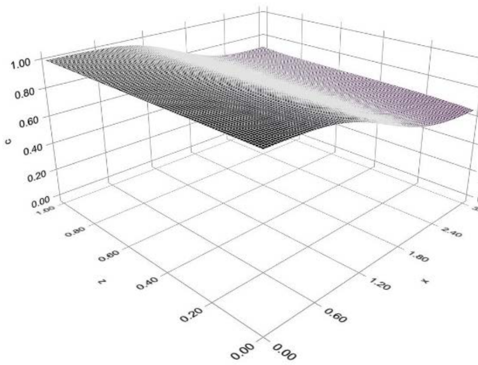


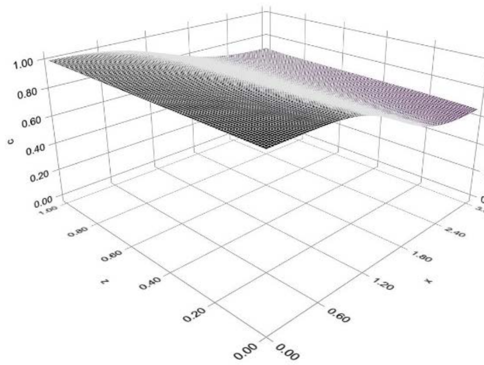
$t = 5$





$t = 9$

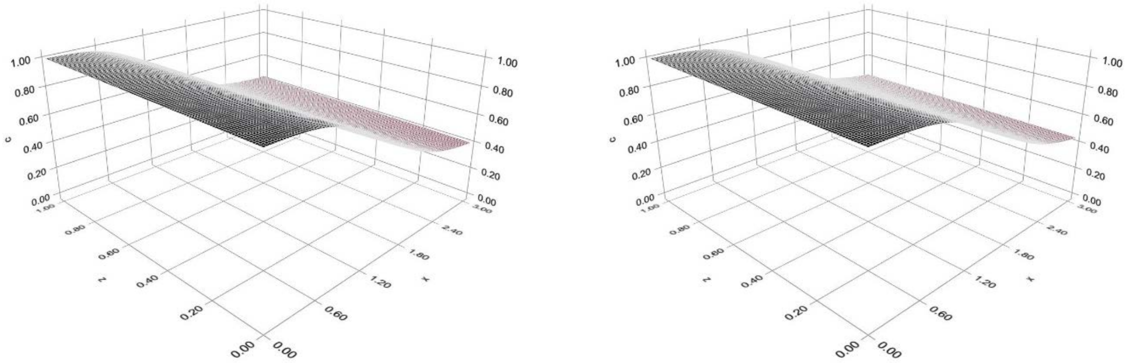




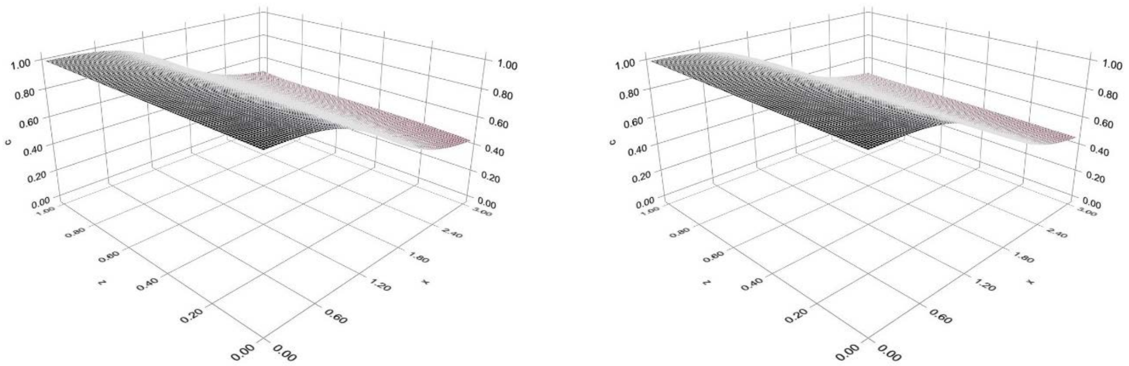
Notes: The figure shows surface plots of policy functions for the consumption share for two selected industries ("Petroleum and coal products" and "Securities, investments, funds and trusts") at rebalancing times $t = 1, 5, 9$ for $\gamma = 10$. The investment horizon at $T = 10$ is 180 months. The policy functions are based on a logistic function of a linear function ($m = 2$) in the log dividend-price ratio, z, and a cubic polynomial ($n = 4$) in the ratio of cash-on-hand to labor income, x, as described in detail in the text. The logistic function restricts the policy functions to the unit interval in line with the borrowing and short-sale constraints typically faced by households. Percentiles of the log dividend-price ratio are shown in the plots.

Figure 4: Policy functions for consumption share for two selected industries and $\gamma = 5$

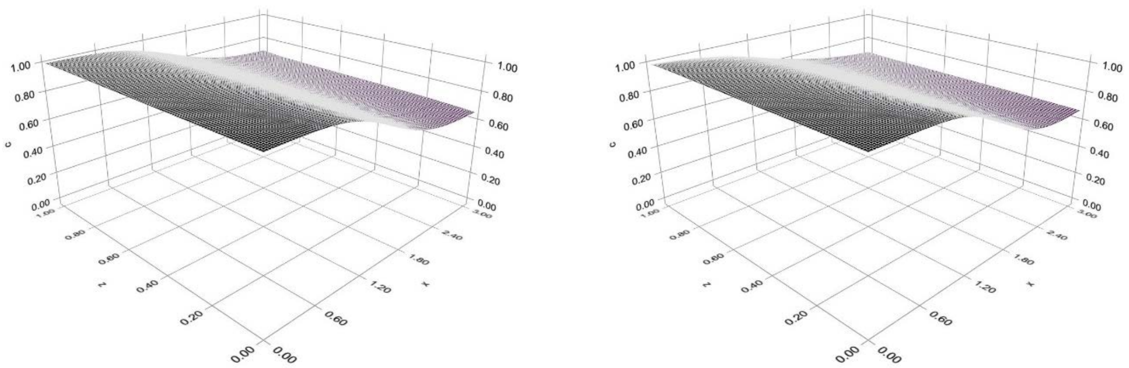
A. Petroleum and coal products $t = 1$ B. Securities and investments



$t = 5$



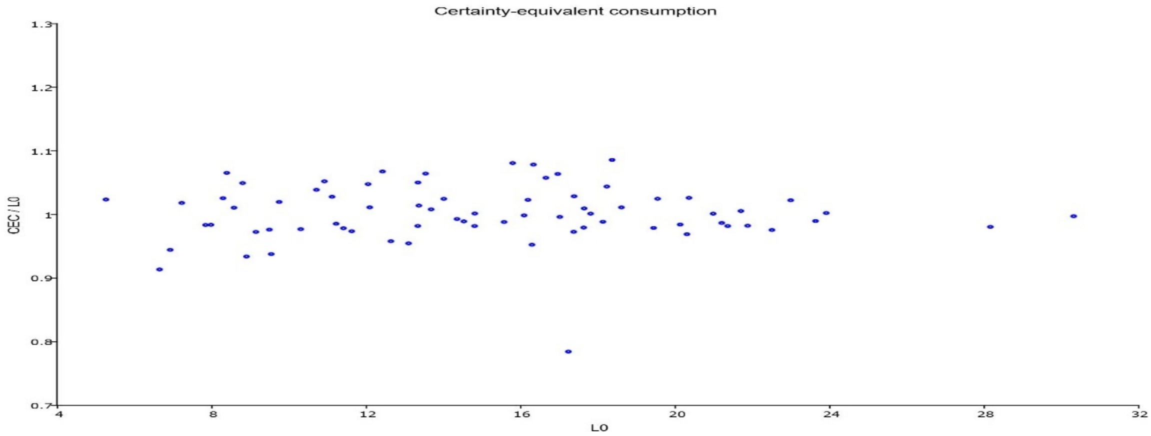
$t = 9$



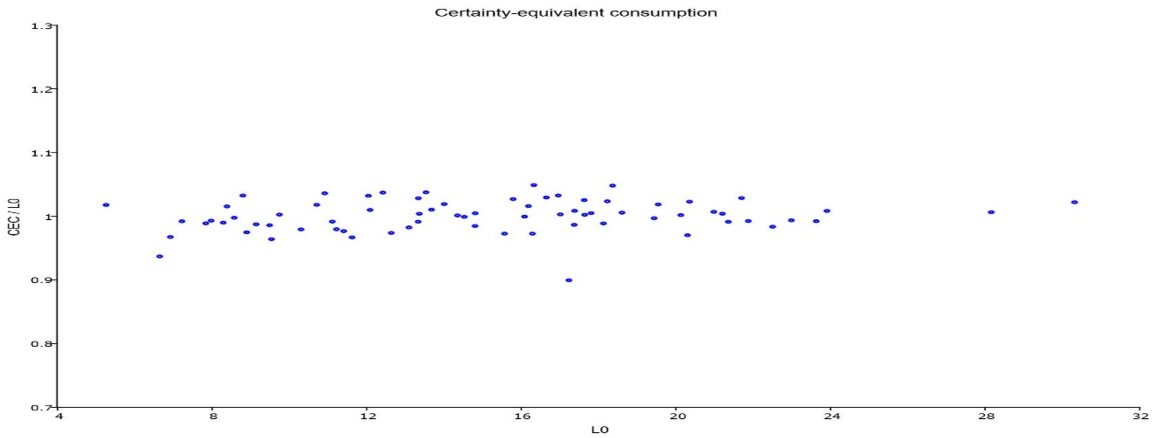
Notes: The figure shows surface plots of policy functions for the consumption share for two selected industries ("Petroleum and coal products" and "Securities, investments, funds and trusts") at rebalancing times $t = 1, 5, 9$ for $\gamma = 5$. The investment horizon at $T = 10$ is 180 months. The policy functions are based on a logistic function of a linear function ($m = 2$) in the log dividend-price ratio, z, and a cubic polynomial ($n = 4$) in the ratio of cash-on-hand to labor income, x, as described in detail in the text. The logistic function restricts the policy functions to the unit interval in line with the borrowing and short-sale constraints typically faced by households. Percentiles of the log dividend-price ratio are shown in the plots.

Figure 5: Scaled certainty equivalent consumption (CEC/L_0) by initial earnings (L_0) for $\gamma = 10$

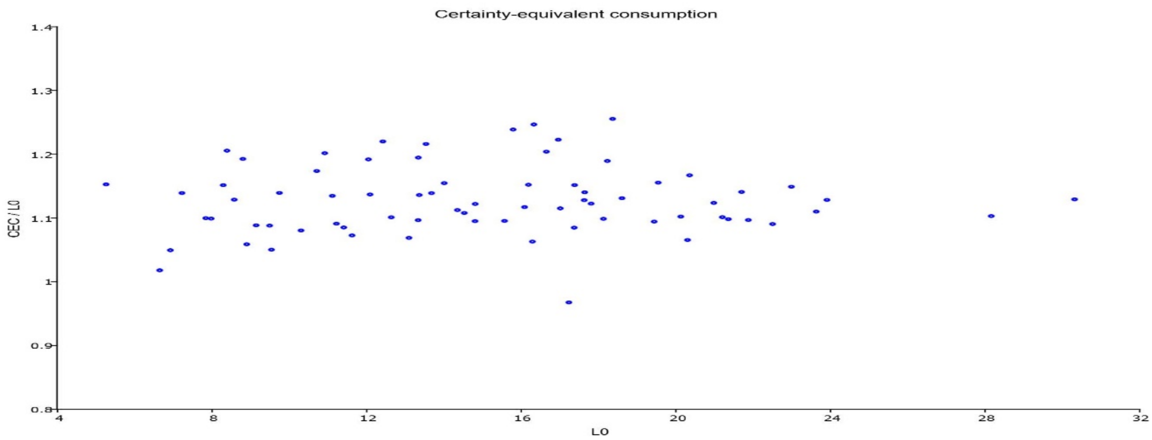
A. Investment horizon $T = 180$ months and initial cash-on-hand $x_0 = X_0/L_0 = 1$



B. Investment horizon $T = 90$ months and initial cash-on-hand $x_0 = X_0/L_0 = 1$



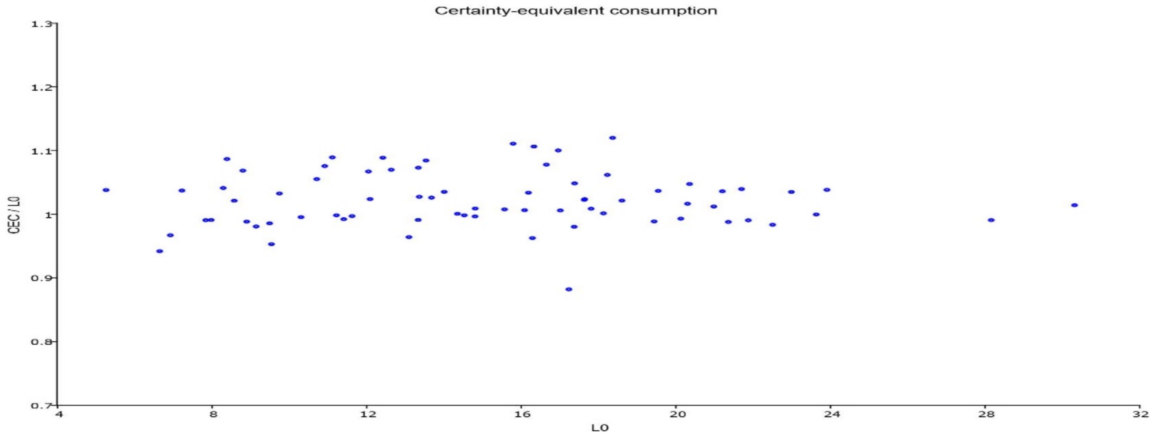
C. Investment horizon $T = 180$ months and initial cash-on-hand $x_0 = X_0/L_0 = 2$



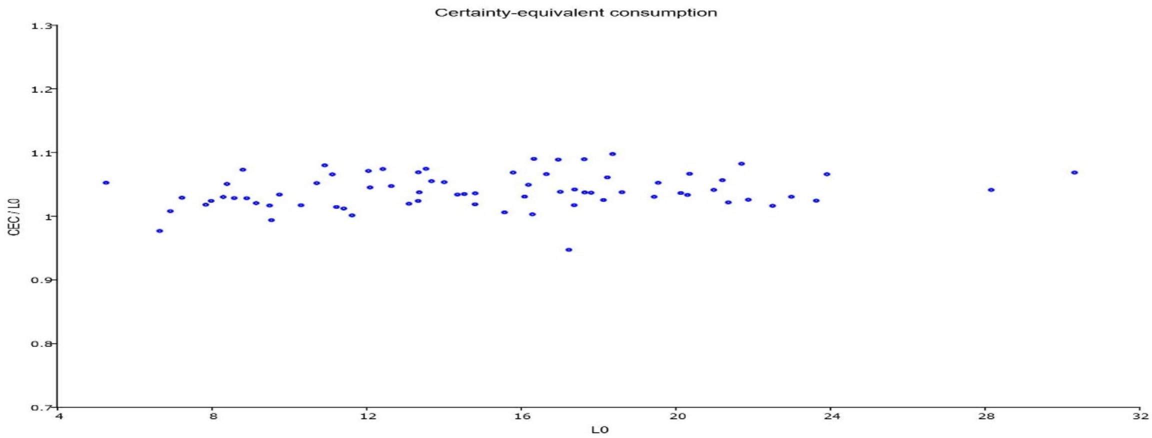
Notes: The figure shows scatter plots of scaled certainty equivalent consumption (CEC/L_0) by initial earnings (L_0) for $\gamma = 10$ for three different combinations of investment horizon (T) and the initial ratio of cash-on-hand to annual earnings (x_0). L_0 is given in thousands of 1982-84 dollars. The underlying policy functions involve a linear function ($m = 2$) in the log dividend-price ratio and a cubic polynomial ($n = 4$) in the ratio of cash-on-hand to annual earnings. The calculation of CEC in Panels A, B, and C follows the description in the notes of Tables 4, 5, and 6, respectively. CEC is obtained for 72 industries at the three-digit 2017 NAICS classification.

Figure 6: Scaled certainty equivalent consumption (CEC/L_0) by initial earnings (L_0) for $\gamma = 5$

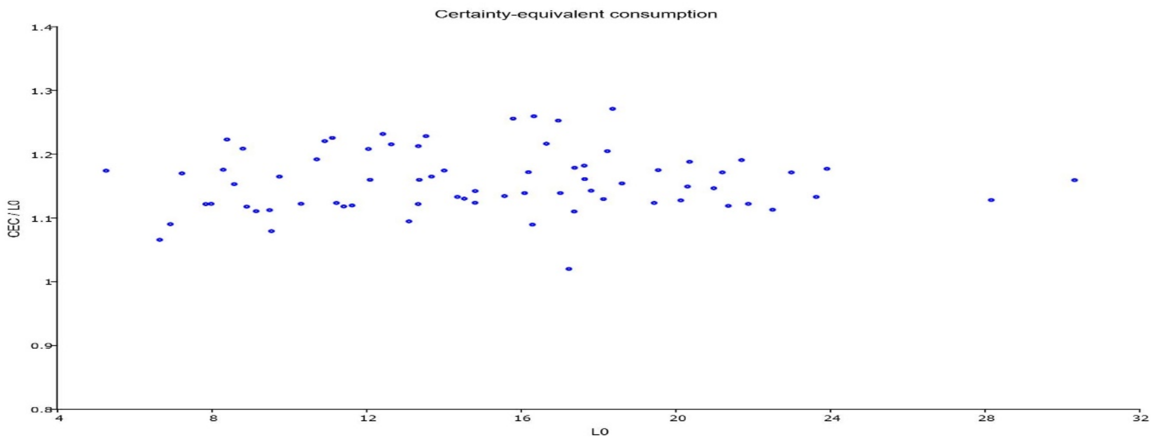
A. Investment horizon $T = 180$ months and initial cash-on-hand $x_0 = X_0/L_0 = 1$



B. Investment horizon $T = 90$ months and initial cash-on-hand $x_0 = X_0/L_0 = 1$



C. Investment horizon $T = 180$ months and initial cash-on-hand $x_0 = X_0/L_0 = 2$



Notes: The figure shows scatter plots of scaled certainty equivalent consumption (CEC/L_0) by initial earnings (L_0) for $\gamma = 5$ for three different combinations of investment horizon (T) and the initial ratio of cash-on-hand to annual earnings (x_0). L_0 is given in thousands of 1982-84 dollars. The underlying policy functions involve a linear function ($m = 2$) in the log dividend-price ratio and a cubic polynomial ($n = 4$) in the ratio of cash-on-hand to annual earnings. The calculation of CEC in Panels A, B, and C follows the description in the notes of Tables 4, 5, and 6, respectively. CEC is obtained for 72 industries at the three-digit 2017 NAICS classification.