Labor Income Risk and Stock Returns: The Role of Horizon Effects*

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Abstract

This paper shows that the impact of labor income risk on the cross-section of expected stock returns depends crucially on the horizon. We develop a stylized labor asset pricing model in which investors earn labor income over their remaining career length, generating horizon–specific prices of labor income risk. Our empirical tests include horizons ranging from one quarter to several years to the very long horizon. We find robust evidence that labor income risk over the two– to four–year horizon is significantly priced while at other horizons it is not priced. The cross–sectional R^2 for 25 size book–to–market and 25 size–investment portfolios increases remarkably from 7% to 71% after this simple horizon adjustment. Labor income risk is almost uncorrelated with consumption risk when measured over the same medium–term horizon. The dominant two–to–four year horizon is consistent with evidence of wage rigidity.

Keywords: Labor and Finance; Human Capital; Horizon Effects; Cross–Section of Stock Returns.

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1 Introduction

Labor and stock markets are fundamentally interconnected. Many investors participate in the labor market and a large share of their wealth is typically tied up in risky human capital. Indeed, an estimated 90 to 93 percent of overall wealth is embedded in human capital, making it by far the largest asset class in the economy (Lustig et al., 2013, Palacios, 2015). In addition, for most firms labor is a key input factor and the human capital of their employees forms an important intangible asset for the firm.[1]

Yet, in the data, contemporaneous short–term correlations between stock returns and labor income growth are typically close to zero (e.g., Fama and Schwert, 1977 and Cocco et al., 2005). Over longer time periods, correlations are more pronounced.[2] There are various economic reasons why linkages between stock markets and labor markets may be different at short, business cycle, and long horizons, such as wage rigidity (e.g., Shimer, 2005, Hall, 2005) or equity–labor market cointegration (Baxter and Jermann, 1997).

This paper shows that labor–equity market linkages and the consequences for asset pricing depend crucially on the time horizon. We find that one horizon strongly dominates: labor income risk over the next two to four years.

We first develop a stylized theoretical model that generates horizon–specific prices of labor income risk. In our model, investors have different career lengths and the covariances between labor income growth and stock returns may vary across horizons. In this setting, optimal portfolio allocation decisions and expected stock returns are explicitly affected by covariances between one–period equity returns and (log) labor income growth rates across different horizons. The resulting pricing equation includes, besides the equity market returns, labor income growth rates over different horizons as separate factors.

To empirically estimate this model, we need to remove the partial overlap between the multi–period labor income growth rates and choose a maximum number of factors. To this end, we suitably adapt the methodology developed in Ortu et al. (2013, 2015), Bandi and Tamoni (2017), and Boons and Tamoni (2016). Specifically, we use a HAAR decomposition of labor income growth rates to identify different components capturing

[1]The growing literature on labor and finance has developed substantial theoretical and empirical evidence of the interplay between labor markets and asset pricing (among many others, e.g., Danthine and Donaldson, 2002, Santos and Veronesi, 2006, Belo et al., 2014, Dittmar et al., 2016, Donangelo, 2014, Kuehn et al., 2017, Berk and Walden, 2013, Donangelo et al., 2018).

[2]Baxter and Jermann (1997) find higher correlations when using annual returns. Benzoni et al. (2007) assume that labor income and dividends are cointegrated and that labor markets catch up with the aggregate economy in about 20 years. Storesletten et al. (2004) find that idiosyncratic labor income risk varies countercyclically over the business cycle.

labor income risk at different horizons, which are only weakly correlated. These components are in fact measures of labor income growth acceleration or deceleration over different horizons. We then match the pricing equation of our model to a multi–factor specification that includes labor income growth deceleration over various horizons. We estimate the model including labor income risk at all horizons, ranging from one quarter to one, two, four, eight and more than eight years. We then let the data speak on which horizon(s) dominate.

Our empirical results clearly show that only one horizon matters: the two– to four–year horizon. First, stock returns are significantly exposed to labor income risk at the two– to four–year horizon. Betas are statistically and economically highly significant. On the other hand, stock returns are much less exposed to labor income risk at other horizons, where betas are lower and typically not significant. Most stocks are negatively exposed to labor income risk at the medium horizon. Negative betas suggest that stocks tend to deliver poor returns when labor income growth slows down over the next two to four years. This makes these stocks less desirable and will lead to a higher risk premium, as confirmed by our cross–sectional regression results.

Second, we find that labor income risk at this medium horizon is a significantly priced systematic risk factor, while labor income risk at other horizons is not priced. The estimated price of risk is negative, which is in line with economic intuition. Stocks that are positively exposed to the risk factor tend to do well when labor income growth slows down in the medium term. These hedging benefits lead to a lower risk premium. On the other hand, stocks that are negatively exposed to medium term wage growth deceleration earn a higher risk premium.

The empirical performance of this new labor factor is remarkable. A simple two–factor model with equity market returns and labor income risk at the two– to four–year horizon can explain a striking 73% of the cross–sectional variation of 25 size book–to–market portfolios. When adding 25 size–investment portfolios, the adjusted R^2 remains high at 71%. The empirical performance of this macro–factor model is very similar to the performance of the Fama and French (2015) five–factor model, that has adjusted R^2s of 77% and 76% respectively. By comparison, the standard human capital CAPM with quarterly labor income growth (e.g., Jagannathan and Wang, 1996)[3] can explain very little of the cross–sectional return variation with adjusted R^2s of close to 0% and 7%. Hence, the simple adjustment of including labor income risk, measured as labor income growth deceleration, over a medium–term horizon has a striking effect on the

[3]See also Mayers (1972), Campbell (1996) and Palacios-Huerta (2003).

model performance.

The dominance of the two–to–four year horizon is consistent with existing studies on wage rigidity that find that the frequency of wage setting is about every three years.[4] Due to infrequent wage setting, infrequent negotiations between workers and the firm, or other labor market frictions, there is typically much less uncertainty about the labor income growth rate over the next two or three years. Our findings indicate that investors care about how their labor income growth develops after the coming two years. Will the labor income growth decelerate or accelerate? The dominant factor captures exactly this type of labor income risk. To the best of our knowledge, we are the first to show that labor income growth acceleration or deceleration over the medium term is a key driver of expected stock returns.

While the two– to four–year horizon is similar to the three–year horizon identified by Parker and Julliard (2005) for measuring ultimate consumption risk, the two factors are distinct.[5] When we add the three–year consumption growth factor to our model, we find that ultimate consumption growth does not carry a significant risk premium, while the risk premium estimate for medium–term labor income risk remains unaffected. By itself, the ultimate consumption CAPM can explain 30% to 37% of the cross–sectional stock return variation, which is substantially lower than our model. Furthermore, the correlation between the fourth HAAR scale of labor income (that we use to capture two–to–four year labor income risk) and the fourth HAAR scale of consumption is very close to zero. In all, this suggests that the medium–term labor income risk factor is not a mere proxy for ultimate consumption risk.

Interestingly, stock return exposures to labor income risk at the two–to–four year horizon show strong patterns in the value dimension. We find that value stocks are substantially more negatively exposed to medium–term labor income risk than growth stocks. Hence, value stocks tend to perform worse than growth stocks when labor income growth is slowing down over the next two to four years.[6]

To further study the dynamic relation between stock portfolio returns and labor in-

[4]For example, Rich and Tracy (2004), Marfe (2018), and Favilukis and Lin (2016b). See also Shimer (2005) and Hall (2005).

[5]Note that due to mechanics of the HAAR transformation that we use to decompose labor income growth rates into different frequencies, we cannot use a three–year horizon for labor income risk but rather use a two–to–four year horizon.

[6]We also find that at the quarterly horizon value stocks have relatively higher exposures to labor income risk than growth stocks, which is in line with Addoum et al. (2019) who argue that growth stocks are more suitable for hedging (short–term) labor income risk. However, at the quarterly horizon betas are less pronounced and we show that labor income risk at this very short horizon does not carry a significant risk premium.

come growth, we employ the methodology proposed by Bryzgalova and Julliard (2021) in our setting. The cumulative impulse response function shows that the immediate impact of a common shock in stock returns on labor income growth is close to zero. However, in later quarters the impact is positive and the cumulative impulse response peaks at a horizon of four years. This confirms our results from the two–pass cross–sectional regressions.

An extensive series of robustness tests confirms that our results are robust when estimating the model for the cross–section of 25 size book–to–market and 30 industry portfolios, when using alternative classifications of the horizons, when using univariate rather than multivariate betas in the first–stage regressions, and when using real instead of nominal labor income growth.

This paper also relates to a growing literature of asset pricing models that allow for lower frequency risks to affect expected returns. These papers tend to focus on consumption risk and none of them consider labor income risk. Daniel and Marshall (1997) and Parker and Julliard (2005) find that consumption risk at the two– or three–year horizon matters for asset pricing. Bansal and Yaron (2004), among others, show the importance of long-run consumption shocks. Estimates of what constitutes the long run vary. Malloy et al. (2009) consider four to six years, whereas Dew-Becker and Giglio (2016) quantify long run as "centuries". Koijen et al. (2017) and Bandi and Tamoni (2017) find that shocks at the business cycle frequency matter for asset pricing.

The remainder of this paper is structured as follows. Section 2 presents the simple theoretical framework underlying our empirical analysis. Section 3 discusses the estimation methodology and Section 4 provides more details on the data. Section 5 presents the main empirical results. In Section 6 we discuss a series of robustness tests and Section 7 concludes. The Appendix provides details of the model derivation and derives an expression for the standard error corrections in the second–stage cross–sectional regressions.

2 Theoretical Framework: Asset Pricing with Labor Income Risk at Multiple Horizons

This section develops the theoretical framework that serves as a motivation for examining the relation between expected stock returns and labor income risk across different horizons. The aim of the model is to show that, even in a stylized setting, horizon–specific labor income risk can already play a role in asset pricing. In particular, we consider a

CAPM–type setup in which there are multiple cohorts of labor income earning investors with different investment horizons. We show that our framework gives rise to a linear asset pricing model with a standard one–period equity market risk factor and horizon–specific (log) labor income growth risk factors. Details of the derivations can be found in Appendix A.

We start by considering an individual investor whose evolution of wealth W_t at time $t = 0, 1, \ldots$ is given by

$$W_{t+1} = R_{p,t+1} W_t + L_{t+1}, \tag{1}$$

in the spirit of Campbell and Viceira (2002), Chapter 6. Here, $R_{p,t+1} = R_f + \alpha_t'(R_{t+1} - R_f)$ denotes the gross return on the investment portfolio, where R_f is the constant return on a riskless asset, R_t is a vector of equity returns assumed to be jointly lognormal and i.i.d. over time, the vector α_t denotes the proportions of wealth invested in the respective equities at time t, and L_t denotes nontradable labor income at time t assumed to be lognormal. Hence, given the wealth level W_t at time t and a stream of labor income L_{t+i}, $i = 1, \ldots, h$, the investor's wealth at horizon h can be expressed as

$$W_{t+h} = (R_{p,t+h} \cdots R_{p,t+1}) W_t + (R_{p,t+h} \cdots R_{p,t+2}) L_{t+1} + \ldots + R_{p,t+h} L_{t+h-1} + L_{t+h}, \tag{2}$$

with gross portfolio return in period $t + i$ given by $R_{p,t+i} = R_f + \alpha_{t+i-1}'(R_{t+i} - R_f)$.

We aim to keep the model as flexible as possible in order to let the data speak on whether and how horizon effects play a role. Therefore, we do not a–priori specify the horizon h. Rather, in our analysis we include all horizons, ranging from the short, to medium–term, long and very long horizons. Furthermore, we do not specify in advance the sign of the price of labor income risk. Traditionally, in the Human Capital CAPM of Mayers (1972), labor income risk carries a positive price of risk. However, several recent papers find a negative price of labor income risk (e.g., Gomez et al. (2009), Gomez et al. (2016) and Maio and Min (2018)). To allow for both positive and negative prices of labor income risk, we assume that the investor has "Keeping up with the Joneses" (KUJ) preferences.

Following Abel (1990), the investor maximizes the utility of h–period terminal wealth W_{t+h} relative to the aggregate labor income $\bar{L}_{t+h}$. That is, she cares about her wealth relative to the labor income of an average "peer".[7] Labor income risk affects expected stock returns through two distinct channels: KUJ effects and traditional hedging effects.

[7] The multiplicative habit specification of Abel (1990) has some advantages over an additive specification; see Bilsen et al. (2020) and the references therein for further details.

On the one hand, investors prefer stocks that positively correlate with aggregate labor income growth, as these help them keep up with their "peers." This results in a negative price of labor income risk, similar to Gomez et al. (2009) and Gomez et al. (2016). On the other hand, following the logic of the Human Capital CAPM of Mayers (1972), the investor's own labor income can also generate a hedging demand for stocks, creating a preference for stocks that are negatively exposed to labor income risk. The traditional hedging demand channel results in a positive price of labor income risk. The relative importance of the KUJ effects versus the hedging demand effects will determine the sign of the price of risk. Our empirical analysis helps shed light on this question.

More precisely, the investor aims to maximize over admissible investment strategies the expected utility

$$U(W_{t+h}) = \mathbb{E}_t \left[\left(\frac{W_{t+h}}{\bar{L}^{\psi}_{t+h}} \right)^{1-\gamma} \right] /(1-\gamma), \tag{3}$$

with $\gamma > 0$ the relative risk aversion coefficient, and where $0 \leq \psi \leq 1$ measures the strength of the KUJ effect: for $\psi = 0$, we obtain the standard CRRA function defined over terminal wealth, whereas for $\psi = 1$ we scale wealth by aggregate labor income, both at time $t + h$. Here, $\mathbb{E}_t$ denotes the expectation conditional upon information at time t. Labor income is assumed to be jointly lognormal.[8]

Using a suitable log–linearization of W_{t+h} and a second-order Taylor expansion of the objective function (see Appendix A), we find the optimal portfolio choice vector at time t to be

$$\begin{aligned} \alpha_t = \; & \frac{W_t + hL_t}{W_t} \frac{1}{\gamma} \mathrm{Var}(r_{t+1})^{-1} \left(\mathbb{E}[r_{t+1}] + \frac{1}{2}\sigma^2 - r_f \right) \\ & + \left(1 - \frac{1}{\gamma}\right) \mathrm{Var}(r_{t+1})^{-1} \left[\psi \frac{W_t + hL_t}{W_t} \mathrm{Cov}_t(r_{t+1}, \bar{l}_{t+h}) - \frac{L_t}{W_t} \sum_{i=1}^{h} \mathrm{Cov}_t(r_{t+1}, l_{t+i}) \right], \end{aligned} \tag{4}$$

where $r_f = \log{(R_f)}$, $r_{t+1} = \log{(R_{t+1})}$, σ^2 denotes the diagonal of the variance-covariance matrix $\mathrm{Var}(r_{t+1})$, $l_{t+i} = \log{(L_{t+i})}$ is the log of the investor's labor income at time $t+i$, and $\bar{l}_{t+h} = \log{(\bar{L}_{t+h})}$ is log aggregate labor income at time $t+h$. The first term in (4) can be recognized as the standard speculative demand arising from CRRA portfolio optimization. The second term in (4) denotes the portfolio adjustment induced by future labor income

[8] Throughout we abstract away from intermediate consumption decisions. This assumption is made to keep the model as simple as possible. The main aim of our theoretical model is to make a case for considering labor income risk across different horizons. Thus, we want to show that horizon effects already arise in the simplest possible setup.

risk. This term has two parts. The first part, which depends on the covariance with aggregate labor income risk, arises because of the KUJ utility specification. Due to the "Keeping up with the Joneses" effect, investors prefer stocks that are positively exposed to labor income risk. The second part is the hedging demand that arises from the investor's own labor income risk, which is indirectly exposed to equity risk. To hedge these risks, the investor has to adapt his optimal portfolio holdings and prefers stocks that are negatively exposed to labor income risk. Eqn. (4) shows that the portfolio adjustments are driven by the investor's income–to–wealth ratio and the covariances between one–period equity returns and multi–period (log) labor income growth rates.

We now show the implications of the optimal portfolio choice rule (4) on equilibrium asset prices. Let there be, at any time t, H cohorts with investment horizon $h = 1, \ldots, H$, initial wealth W_h, and current labor income L_h. Assuming stationarity, aggregating asset demands from (4) over all cohorts and rewriting (see Appendix A) gives the following asset pricing equation:

$$\mathbb{E}[R] = r_f + \gamma \left[\frac{\sum_{h=1}^{H} W_h}{\sum_{h=1}^{H} (W_h + hL_h)} \right] \operatorname{Cov}(r_{t+1}, r_{m,t+1}) + (\gamma - 1) \sum_{h=1}^{H} \left[\frac{\sum_{i=h}^{H} L_i - \psi(W_h + hL_h)}{\sum_{i=1}^{H} (W_i + iL_i)} \right] \operatorname{Cov}\left(r_{t+1}, \bar{l}_{t+h} - \bar{l}_t\right), \tag{5}$$

with $\mathbb{E}[R] = \mathbb{E}[r_{t+1}] + \frac{1}{2}\sigma^2$. Note that aggregate labor income growth at each horizon h is a separate risk factor, whose price of risk depends on the labor income share of all cohorts with investment horizons equal to or longer than h in total wealth. The asset pricing relation can be re–written in beta form, as follows:

$$\mathbb{E}[R] = r_f + \beta_m \lambda_m + \sum_{h=1}^{H} \beta_{l,h} \lambda_{l,h}, \tag{6}$$

with $\beta_m = \operatorname{Cov}(r_{t+1}, r_{m,t+1})/\operatorname{Var}(r_{m,t+1})$ and $\beta_{l,h} = \operatorname{Cov}\left(r_{t+1}, \bar{l}_{t+h} - \bar{l}_t\right)/\operatorname{Var}(\bar{l}_{t+h} - \bar{l}_t)$ the asset return exposures to the market portfolio return and aggregate labor income growth at horizon h, and where

$$\lambda_m = \gamma \left[\frac{\sum_{h=1}^{H} W_h}{\sum_{h=1}^{H} (W_h + hL_h)} \right] \mathrm{Var}(r_{m,t+1}), \tag{7}$$

$$\lambda_{l,h} = (\gamma - 1) \left[\frac{\sum_{i=h}^{H} L_i - \psi(W_h + hL_h)}{\sum_{i=1}^{H} (W_i + iL_i)} \right] \mathrm{Var}(\bar{l}_{t+h} - \bar{l}_t), \tag{8}$$

are the prices of market risk and labor income growth risk at horizon h. For $\psi = 0$, i.e., in the absence of the KUJ effect, and $\gamma > 1$, all prices of risk are positive. This is natural, as in that case the assets that correlate strongly with labor income growth are undesirable and require a higher expected return in equilibrium. If the KUJ effect is strong enough, the price of labor income risk may become negative as investors now prefer stocks that are positively exposed to aggregate labor income risk in order to keep up with their "neighbours." Ultimately it is an empirical question whether the hedging or the KUJ effect dominates.

Summarizing, the key ingredients for obtaining horizon effects in our model are: (i) the presence of labor income, (ii) a nonzero covariance between stock returns and labor income growth at a given horizon, and (iii) investors with longer–term investment horizons (i.e., exceeding at least one quarter). Note that the existence of multiple cohorts with heterogeneous investment horizons is not essential for generating horizon effects in our asset pricing equation. Even in the case where we only have one cohort with long–term investment horizon h, the asset pricing equation (6) would still contain labor income growth rates up to horizon h. The heterogeneity in investment horizons of the different cohorts mainly serves as a relaxation of the assumption that all investors in the economy have the same horizon. For example, if investors want to accumulate wealth for retirement, their investment horizons depend on how far away they are from their retirement age.

Our model relates to the standard human capital CAPM of Mayers (1972), in which contemporaneous labor income risk is priced. According to that model, the expected excess returns of an asset are given by a linear function of the asset's exposures to equity market risk and human capital risk. There, the main argument for including human capital is that it is part of the overall wealth portfolio. As the relative value of human capital is unobserved, it is included as a separate factor. In empirical applications, quarterly or monthly labor income growth is often used as a proxy for human capital returns (see, e.g., Jagannathan and Wang, 1996, and Eiling, 2013). In our setting, a similar result would be obtained by assuming that the investment horizon of all investors in the economy is only one period ahead (or, equivalently, by assuming $\lambda_h = 0$ for all $h > 1$) and assuming no KUJ effects (i.e., $\psi = 0$).

3 Empirical Methodology

The model proposed in the previous section results in a pricing equation that includes labor income growth over various horizons as different factors with distinct horizon-specific prices of risk. Before we can estimate this cross-sectional model, we have to deal with two issues: multicollinearity due to partially overlapping horizons and a potentially large number of factors corresponding to many different horizons. This section shows how we can decompose labor income growth shocks into components with different degrees of persistence, which are only weakly correlated. The advantage of this approach is that it leads to a parsimonious empirical model specification that includes a wide range of horizons with relatively few risk factors.

Our plan is as follows. We first discuss the frequency decomposition of a (quarterly) labor income growth series, based on the classical HAAR transform, named after Alfréd Haar. This results in different components (i.e., HAAR scales) that capture labor income growth risk at different horizons, which are only weakly correlated. We then map these components to our theoretical model of the previous section and show how the pricing equation can be rewritten as a multi–factor model that includes the HAAR scales as factors. We also derive the implications for the horizon–specific price of risk estimates in the context of our theoretical model. Finally, we discuss how to estimate the model using the two–pass cross–sectional regression methodology with modified standard errors.

3.1 Decomposition of Labor Income Growth into Different Frequencies

In principle, labor income growth risk at any horizon could be a priced risk factor. However, from an empirical perspective, it would be infeasible to include a separate labor income risk factor for every possible horizon. Therefore, in the empirical specification, we group together labor income growth shocks into components with different degrees of persistence corresponding to six categories: 1–2 quarters, 3–4 quarters, 1–2 years, 2–4 years, 4–8 years and more than eight years. By including these categories we effectively include all horizons.[9]

We start by decomposing a single labor income growth series into diffferent frequency components, based on a HAAR decomposition. Let us denote quarterly aggregate (log) labor income growth as $f_{t+1} = \bar{l}_{t+1} - \bar{l}_t$, with $\bar{l}_t = \log(\bar{L}_t)$ quarterly per worker aggregate log labor income. This series of quarterly labor income growth f_{t+1} can be written as the sum of components $f_t^{(j)}$ working on different time scales:

$$f_{t+1} = \sum_{j=1}^{J} f_t^{(j)} + f_t^{(j>J)}, \tag{9}$$

where $f_t^{(j)}$ and $f_t^{(j>J)} = \sum_{j>J} f_t^{(j)}$ are the components at time t and scale $j = 1, \ldots, J$, and $j > J$. Ortu et al. (2015) show that such a decomposition holds for any weakly stationary time series. We estimate the components in a procedure similar to Ortu et al. (2013) and Bandi and Tamoni (2017).[10] More precisely, given time series $\{f_t\}_{t\in\mathbb{Z}}$, we first construct moving averages $\pi_t^{(j)}$ of length 2^j as

$$\pi_t^{(j)} = \frac{1}{2^j} \sum_{h=1}^{2^j} f_{t+h}, \tag{10}$$

for $j = 0, \ldots, J$. Next, we define the component $f_t^{(j)}$ to be the difference between moving averages of length 2^{j-1} and 2^j, i.e.,

$$f_t^{(j)} = \pi_t^{(j-1)} - \pi_t^{(j)}, \tag{11}$$

for $j = 1, \ldots, J$. As a result, the components $f_t^{(j)}$ can be interpreted as containing those fluctuations with half–life in the interval of $[2^{j-1}, 2^j)$ quarters. We also define $f_t^{(j>J)} = \pi_t^{(J)}$ as containing those fluctuations with half–life exceeding 2^J quarters. In our empirical specification, detailed below, we include a separate risk factor for every scale component $j = 1, 2, \ldots, J$ and $j > J$. Therefore, for the number of risk factors to remain parsimonious, we need to set a maximum level of persistence. We choose $J = 5$, which means that the scale component $f^{(j>5)}$ groups together shocks with a half–life exceeding $2^5 = 32$ quarters (or 8 years). Table 1 provides more details on the mapping between

[9]In a robustness test we vary the number of horizons and find that our results remain very similar.

[10]Note that Ortu et al. (2013) and Bandi and Tamoni (2017) define the moving averages $\pi_t^{(j)}$ backwards in time. In our setting with labor income risk, however, it is more natural to define them forwards. This implies that the scale factors $f_t^{(j)}$ are random variables whose outcome is realized only at time $t + 2^j$. Note also that $f_t^{(j>J)}$ is realized at time $t + 2^J$.

scales j and their corresponding time spans.

We emphasize that to decompose quarterly labor income growth into different frequencies, we do not need to estimate any time–series parameters. Rather, as shown above, quarterly labor income growth can be rewritten as a sequence of moving averages using a HAAR transformation. To see explicitly what the different components (i.e., HAAR scales) represent, we write in full the decomposition for $J = 2$. Following Eqn. (10) we have

$$\pi_t^{(0)} = f_{t+1} = \bar{l}_{t+1} - \bar{l}_t \tag{12}$$

$$\pi_t^{(1)} = (f_{t+1} + f_{t+2})/2 = (\bar{l}_{t+2} - \bar{l}_t)/2 \tag{13}$$

$$\pi_t^{(2)} = (f_{t+1} + f_{t+2} + f_{t+3} + f_{t+4})/4 = (\bar{l}_{t+4} - \bar{l}_t)/4. \tag{14}$$

This shows that $\pi_t^{(2)}$ can be interpreted as the per quarter aggregate labor income growth rate over the next four quarters. The corresponding HAAR scales are defined as:

$$f_t^{(1)} = \pi_t^{(0)} - \pi_t^{(1)} = (f_{t+1} - f_{t+2})/2 \tag{15}$$

$$f_t^{(2)} = \pi_t^{(1)} - \pi_t^{(2)} = (f_{t+1} + f_{t+2})/4 - (f_{t+3} + f_{t+4})/4 \tag{16}$$

$$f_t^{(>2)} = \pi_t^{(2)} = (f_{t+1} + f_{t+2} + f_{t+3} + f_{t+4})/4. \tag{17}$$

Further rewriting reveals that $f_t^{(2)}$ is actually the difference between the labor income growth over the next two quarters and the labor income growth over quarters 3 to 4:

$$f_t^{(2)} = (f_{t+1} + f_{t+2})/4 - (f_{t+3} + f_{t+4})/4 = (\bar{l}_{t+2} - \bar{l}_t)/4 - (\bar{l}_{t+4} - \bar{l}_{t+2})/4. \tag{18}$$

In other words, the HAAR scale for $j = 2$ measures the *deceleration* in labor income growth. When $f_t^{(2)} > 0$, labor income growth slows down: the growth rate from $t + 2$ to $t + 4$ is lower than the growth rate from t to $t + 2$.

In sum, when we decompose quarterly labor income growth into different frequency components using a HAAR transform, the resulting components in fact measure labor income growth acceleration or deceleration. Our theoretical asset pricing model shows that expected returns are related to labor income growth measured over different horizons. Below we show how to rewrite this pricing equation such that it is a function of the HAAR scales making it feasible to empirically estimate it. We also derive the implications for the price of risk estimates in the context of our theoretical model when using the HAAR scales as factors.

3.2 Mapping the Frequency Decomposition to the Theoretical Asset Pricing Model

This section explains how the pricing equation that follows from our theoretical model can be rewritten as a multi-factor model with HAAR scales $f_t^{(j)}$ as factors.

Remember that, according to Eqn. (5),

$$\mathbb{E}[R] = r_f + \tilde{\gamma}\text{Cov}(r_{t+1}, r_{m,t+1}) \\ + (\gamma - 1)\sum_{h=1}^{H} \omega_h \text{Cov}\left(r_{t+1}, \bar{l}_{t+h} - \bar{l}_t\right), \tag{19}$$

where $\tilde{\gamma} = \gamma\left[\frac{\sum_{h=1}^{H} W_h}{\sum_{h=1}^{H}(W_h + hL_h)}\right]$ and $\omega_h = \left[\frac{\sum_{i=h}^{H} L_i - \psi(W_h + hL_h)}{\sum_{i=1}^{H}(W_i + iL_i)}\right]$. Let $H = 2^J$ and define, for $j = 0, \ldots, J$, the moving averages

$$\pi_t^{(j)} = (\bar{l}_{t+2^j} - \bar{l}_t)/2^j. \tag{20}$$

Let us also assume that the covariances between stock returns and aggregate labor income growth up to period h are the same in each block of length 2^{j-1}, starting at $h = 2^{j-1}$ and ending at $h = 2^j$. This implies that

$$\text{Cov}\left(r_{t+1}, \bar{l}_{t+h} - \bar{l}_t\right) = \text{Cov}\left(r_{t+1}, 2^j \pi_t^{(j)}\right), \quad h = 2^{j-1} + 1, \ldots, 2^j. \tag{21}$$

Under this assumption, the pricing equation can be written as

$$\mathbb{E}[R] = r_f + \tilde{\gamma}\text{Cov}(r_{t+1}, r_{m,t+1}) + (\gamma - 1)\sum_{j=0}^{J} \zeta_j \text{Cov}\left(r_{t+1}, \pi_t^{(j)}\right), \tag{22}$$

with $\zeta_j = 2^j \sum_{h=2^{j-1}+1}^{2^j} \omega_h$. When there are no KUJ effects, $\zeta_j > 0$.

We now use the HAAR transform $f_t^{(j)} = \pi_t^{(j-1)} - \pi_t^{(j)}$ for $j = 1, \ldots, J$ and additionally we define $f_t^{(>J)} = \pi_t^{(J)}$. Obviously, one can write for $j = 1, \ldots, J$

$$\text{Cov}\left(r_{t+1}, f_t^{(j)}\right) = \text{Cov}\left(r_{t+1}, \pi_t^{(j-1)}\right) - \text{Cov}\left(r_{t+1}, \pi_t^{(j)}\right), \tag{23}$$

and $\text{Cov}\left(r_{t+1}, f_t^{(>J)}\right) = \text{Cov}\left(r_{t+1}, \pi_t^{(J)}\right)$.

This implies that we can rewrite the pricing equation (22) in terms of the covariances between returns and the HAAR scales:

$$\begin{aligned}\mathbb{E}[R] &= r_f + \tilde{\gamma}\mathrm{Cov}(r_{t+1}, r_{m,t+1}) \\ &\quad + (\gamma - 1)\left[\sum_{j=1}^{J} \Omega_j \mathrm{Cov}\left(r_{t+1}, f_t^{(j)}\right) + \Omega_{>J}\mathrm{Cov}\left(r_{t+1}, f_t^{(>J)}\right)\right], \end{aligned} \tag{24}$$

with $\Omega_j = \sum_{i=0}^{j-1} \zeta_i$ for $j = 1, \ldots, J$ and $\Omega_{>J} = \sum_{i=0}^{J} \zeta_i$. Looking at the definition of ω_h and ζ_j, we can easily show that $\Omega_j > 0$ and $\Omega_{>J} > 0$ if there are no KUJ effects. Assuming $\gamma > 1$, this implies that the price of risk of the HAAR scales is positive in the absence of KUJ effects but can be negative when KUJ effects are sufficiently strong.

In sum, the pricing equation of our theoretical model can be expressed as a multi-factor model with, besides the market returns, the different HAAR scales of labor income growth as risk factors, capturing labor income risk at different frequencies. These HAAR scales in fact represent labor income growth deceleration (or acceleration) over different horizons. A natural interpretation is that investors prefer stocks that are positively exposed to labor income growth deceleration; these stocks tend to deliver high returns when labor income growth (over a certain horizon) slows down. As such, the price of risk of the labor income growth deceleration is expected to be negative—which is confirmed by our empirical results in the next section.

3.3 Horizon–Specific Labor Income Risk and Two–Pass Cross–Sectional Regression

We can estimate the multi-factor model in (24) using a straightforward two–pass cross–sectional regression approach. The full model includes the excess equity market return and the HAAR scales of labor income growth as risk factors (setting $J = 5$).

In the first stage, we obtain the risk exposures (betas) by running a multivariate ordinary least squares time–series regression of portfolio excess returns on the different risk factors at a quarterly frequency. In particular, we run for each portfolio, i.e., test asset, i the following quarterly multivariate regression:

$$R_{t+1}^{e,i} = \alpha_{0,i} + \beta_{mkt,i} R_{t+1}^{e,mkt} + \sum_{j=1}^{J} \beta_{l,i}^{(j)} f_t^{(j)} + \beta_{l,i}^{(j>J)} f_t^{(j>J)} + \epsilon_{i,t+1}. \tag{25}$$

In the second stage, we estimate the market prices of risk by running for each time t

the cross–sectional regression using the estimated betas from the first stage, i.e.,

$$R_{t+1}^{e,i} = \lambda_{0,t+1} + \hat{\beta}_{mkt,i}\lambda_{mkt,t+1} + \sum_{j=1}^{J} \hat{\beta}_{l,i}^{(j)}\lambda_{l,t+1}^{(j)} + \hat{\beta}_{l,i}^{(j>J)}\lambda_{l,t+1}^{(j>J)} + \eta_{i,t+1}, \tag{26}$$

for $t = 0, \ldots, T-1$. The estimated market prices of risk are given by their time–series averages, i.e., $\hat{\lambda}_0 = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_{0,t}$, $\hat{\lambda}_{mkt} = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_{mkt,t}$ and $\hat{\lambda}_l^{(j)} = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_{l,t}^{(j)}$. Here λ_{mkt} and $\beta_{mkt,i}$ are again the price of equity market risk and asset i's exposure to that risk, respectively. The $\lambda_l^{(j)}$, $j = 1, \ldots, J$, now denote the prices of risk for exposure to labor income growth shocks with fluctuations between 2^{j-1} and 2^j quarters, and $\lambda_l^{(j>J)}$ denotes the price of risk for exposure to labor income shocks with fluctuations beyond 2^J quarters.

We derive expressions for the standard errors that account for autocorrelation in the factors and the fact that we use estimated betas in the second–stage regression. Details can be found in Appendix B.[11]

Apart from the full model (26), we are also interested in several restricted and adapted specifications. In particular, we assess the performance of parsimonious two–factor specifications that include the equity market return and labor income risk for one scale at a time. Furthermore, we combine scales $j = 1, 2, 3$ into one 'high-frequency' component capturing shocks with fluctuations between 1 and 8 quarters, and scales $j = 4, 5$ into one 'medium–frequency' component capturing shocks with fluctuations between 8 and 32 quarters. The corresponding betas and prices of risk are denoted by $\beta_{l,i}^{(1:3)}$, $\beta_{l,i}^{(4:5)}$, $\lambda_l^{(1:3)}$, and $\lambda_l^{(4:5)}$.

4 Data and Summary Statistics

The basis of our analysis consists of quarterly (log) labor income growth series, which we define as

$$f_t = \log(L_t) - \log(L_{t-1}), \tag{27}$$

[11] Compared to this paper, Ortu et al. (2013), Boons and Tamoni (2016) and Bandi and Tamoni (2017) consider a somewhat different setup in which they not only decompose the right–hand side factor of the first–stage regressions (25) into different scale components, but also the left–hand side test asset returns. As a consequence, the left–hand side variables of the first–stage regressions are different from the left–hand side variables in the second–stage regressions, and therefore standard Shanken–like corrections to the standard errors cannot be applied to these second–stage regressions. Because of this, these authors resort to using GMM to estimate their models, as this methodology allows them to obtain robust standard errors. It is, however, straightforward to generalize our derivation of the robust standard errors in Appendix B to a setting in which there are different left–hand side variables in the first stage, and therefore the standard two–pass regression methodology also becomes applicable to their setup.

where L_t denotes the per worker labor income in quarter t. To obtain multi–horizon human capital returns, we simply sum the quarterly growth rates of the corresponding horizons.

We retrieve quarterly labor income data from the State Quarterly (Q) Table 7, which is published by the Bureau of Economic Analysis. This table provides quarterly wages and salaries at the industry level, which we aggregate across all industries. Labor income data is scaled by the average number of workers in each quarter using monthly employment data from the Current Employment Statistics survey, published by the Bureau of Labor Statistics. The sample period runs from 1958Q1 until 2017Q4, resulting in a total of 240 quarterly observations of per worker labor income. These quarterly series form the basis for constructing labor income growth series components across different scales.

Next to labor income growth rates, our model also contains an equity market risk factor. For this, we use the standard market excess return factor, defined as the value–weighted return of all CRSP stocks listed on the NYSE, AMEX, or NASDAQ minus the one-month Treasury bill rate, which we obtain from Kenneth French's website.[12] We use the monthly series running from April 1958 until December 2017, and convert these to quarterly series by compounding the monthly returns within each quarter.

To test our asset pricing model, we use returns on 25 size and book–to–market portfolios, 25 size and investment portfolios, and 30 industry portfolios. Again, we obtain monthly series for all these portfolios from Kenneth French's website, and we convert these into quarterly excess return series by compounding the monthly excess returns within each quarter. The quarterly return series of the 25 size and book–to–market and the 30 industry portfolios run from 1958Q2 until 2017Q4, whereas the quarterly return series of the size and investment portfolios run from 1963Q3 to 2017Q4. We observe the typical patterns that returns are decreasing in the size dimension (i.e., the 'size–effect'), increasing in the book-to-market dimension (i.e., the 'value premium'), and decreasing in the investment dimension.

We also compare our model to several existing asset pricing models. In particular, we consider the consumption CAPM, the ultimate consumption CAPM of Parker and Julliard (2005) that includes three-year ahead consumption growth, and the Fama and French (1993) three-factor and Fama and French (2015) five-factor models. When considering the (ultimate) consumption CAPM models, we use real (chain-weighted) personal consumption expenditures on nondurable goods and services per capita, which we obtain from the National Income and Product Accounts (NIPA). The factors for the Fama and

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

French (1993) three–factor and Fama and French (2015) five–factor models are again obtained from Kenneth French's website.

Table 2 provides the factor correlations of all risk factors that are used throughout the paper. First, the table confirms that the correlations between the different HAAR scales are low, ranging from -0.12 to 0.19. Second, the correlations with other return–based factors are also low, ranging from -0.19 (between $f^{(3)}$ and RMW) to 0.14 (between $f^{(5)}$ and SMB). Third, the correlations with the different consumption–based factors are low as well. This holds for quarterly consumption growth, Parker and Julliard (2005)'s ultimate consumption growth and also for the HAAR components of consumption growth (in the table we focus on $j = 3$ and $j = 4$). Hence, when we apply the same decomposition to consumption growth as to labor income growth, the resulting HAAR components display very low correlations. For example, the correlation between labor income and consumption for $j = 4$ is -0.02. These summary statistics suggest that labor income risk and consumption risk measured over the same medium–term horizon capture different sources of risk. Our asset pricing tests discussed in the next section confirm this.

For illustrative purposes, we plot the original aggregate labor income growth series and the combined high, medium, and low frequency scale components in Figure 1. The figure shows that the scale components become more persistent for lower frequencies, as expected.

5 Empirical Results

This section discusses how aggregate labor income risk at different horizons affects the cross–section of expected stock returns. As outlined in Section 3, we use a standard two–pass regression methodology, in which we first estimate risk exposures to horizon–specific labor income risk factors using a multivariate time–series regression, and subsequently use these to estimate market prices of risk in a second-stage cross–sectional regression. Throughout this section, we focus on the 25 size and book–to–market portfolios as test assets. Section 6 shows that our results are robust to a broader cross–section of test portfolios, including size–investment and industry portfolios.

5.1 Exposures to Labor Income Risk across Different Horizons

We first analyze stock return's exposures to labor income risk at different horizons. Table 3 reports the estimated first–stage betas and their corresponding Newey–West adjusted

t–statistics resulting from multivariate time–series regressions of portfolio excess returns on excess market returns and labor income growth rates across different horizons. For ease of comparison, we also present a graphical representation of the estimated labor income growth betas across different horizons in Figure 2. Three issues stand out.

First, labor income betas at the two– to four–year horizon (i.e., scale $j = 4$) are substantially more significant, both economically and statistically, than labor betas at other horizons. At this medium–term horizon, most betas are individually statistically significant and a Wald test of the null hypothesis that all betas at a certain horizon are jointly equal to zero can be rejected for $j = 4$. Betas are mostly negative and are economically meaningful, where many individual betas have estimates around -6 or even -7. Stock return exposures to labor income risk at other horizons are much smaller, often between 0 and 1 and not statistically significant. Besides $j = 4$, the Wald test can only be rejected for labor income betas at the very long horizon (scale $j > 5$). However, this is likely driven by one highly significant beta as many individual betas are still insignificant at that horizon.

Second, the betas with respect to labor income risk at the medium horizon are overwhelmingly negative. To better understand this, remember that the HAAR scale of labor income risk at $j = 4$ represents the difference between labor growth in the next two years and labor income growth from two to four years from now. In other words, when the factor realization is positive, labor income growth slows down. The factor hence captures labor income growth deceleration. Negative betas with respect to this factor show that stocks tend to do poorly when labor income growth decelerates. This makes them more risky. Indeed, in the next section we show that the price of risk estimates for this horizon are negative, showing that the total risk premium is positive; stocks with low returns when labor income growth slows down over the two to four year horizon earn a higher risk premium.

Third, labor income betas at the two– to four–year horizon display important cross-sectional variation, especially along the value dimension. First, we can reject the null hypothesis that all labor income betas for $j = 4$ are jointly equal for all 25 size–BM portfolios. Further, we find that value stocks have substantially more negative labor betas (on average, across size quintiles, -6.3) than growth stocks (on average, across size quintiles, -0.7). This suggests that value stocks are more negatively exposed to labor income growth deceleration, making them riskier. Value stocks tend to do worse than growth stocks when labor income growth over the medium horizon shows down. Coupled with a negative price of risk estimate (as shown in the next section), this leads to a higher risk premium for value stocks compared to growth stocks.

5.2 Cross–Sectional Asset Pricing Tests across Different Horizons

Table 4 reports the estimated market prices of risk at different horizons resulting from the second–stage cross–sectional regressions. We report both Fama and MacBeth (1973) t–statistics, as well as adjusted t–statistics based on our robust standard errors that correct for heteroskedasticity, autocorrelation, and the fact that the betas are estimated in first–stage regressions. All specifications under consideration always contain an intercept term and the equity market risk factor. As the model is estimated using excess returns, the intercept should be statistically insignificant. We note that in most specifications this is indeed the case. At the same time, in all specifications, the price of equity market risk is also statistically insignificant, a well–known result.

Our results strongly show that labor income risk at the two– to four–year horizon dominates. In the full model specification, in which we include labor income risk across all different horizons (i.e., all HAAR scales for $J = 5$), the market price of labor income risk at the two– to four–year horizon ($\lambda_l^{(4)}$) is the only one that is statistically significant. The estimated market price of labor income risk at scale $j = 4$ is statistically significant at –0.0020, which means that a (positive) unit exposure to this risk factor lowers expected returns with 24 basis points per quarter. As reported in Table 4, the betas at scale $j = 4$ are typically negative and therefore the risk premium (exposure $\times$ market price of risk) is positive and economically significant. For example, the quarterly risk premium for stocks on small growth firms is $-1.89 \times -0.0020 \approx 40$ basis points, whereas the quarterly risk premium for small value firms is $-7.96 \times -0.0020 \approx 160$ basis points. The negative price of risk is in line with the fourth HAAR scale capturing labor income growth deceleration over the two–to–four year horizon. Stocks with positive exposures do well when labor income growth is slowing down, making them a type of hedge which leads to a lower risk premium. On the other hand, stocks with negative exposures tend to do poorly exactly when medium–term labor income growth is slowing down, making them riskier. This leads to a higher risk premium.

In the context of our theoretical model, the negative sign of the price of labor income risk is possible when $\psi > 0$, that is, if agents benchmark their wealth to aggregate labor income, that proxies the labor income of their “peers”. When these “Keeping up with the Joneses” preferences are strong enough (and outweigh the hedging demand channel), investors want to invest in securities that are strongly correlated with aggregate labor income. They are therefore willing to pay a higher price for these securities, resulting in a negative labor income risk premium. This is in line with Gomez et al. (2009) and Gomez et al. (2016) who also find strong empirical evidence for such a "Keeping up with the Joneses" benchmark mechanism. However, these papers do not consider horizon effects.[13]

The previous results are based on a model with a relatively large number of factors. When considering two–factor specifications in which we only include the equity market risk factor and one labor income growth factor at one specific horizon, the adjusted R^2 peaks for the two– to four–year horizon. In particular, the adjusted R^2 of the two–factor specification with scale $j = 4$ is 73%. By comparison, the adjusted R^2s of the other two–factor specifications with labor income risk at different horizons all range between –6% ($j > 5$) and 18% ($j = 2$). These differences in cross–sectional fit remain when we consider the combined high and medium frequency scales $j = 1 : 3$ and $j = 4 : 5$. Therefore, our preferred model specification is the two–factor model that includes only labor income risk at scale $j = 4$ and the equity market risk factor.

We compare the performance of our preferred model to a number of well–known benchmark asset pricing models. In particular, we consider the static CAPM, the traditional human capital CAPM, which augments the standard CAPM with a (contemporaneous) aggregate labor income growth factor, the consumption CAPM (CCAPM) with quarterly consumption growth, the ultimate consumption CAPM of Parker and Julliard (2005) that includes three-year ahead consumption growth, the Fama and French (1993) three–factor (FF3) and Fama and French (2015) five–factor (FF5) models. We also include a version of the Consumption CAPM with the third HAAR scale of consumption growth model as the risk factor, and a version of the preferred specification where the fourth labor income growth HAAR scale is interacted with Marfe (2018)'s labor income share variable.

Table 5 reports the results. Consistent with the literature we find the cross–sectional fit of the static CAPM to be poor. The intercept is statistically significant and positive, the (adjusted) R^2 is low, and the market price of equity market risk is not statistically

[13]Other authors, albeit in different settings, also find empirical evidence of a negative market price of labor income risk. For example, Julliard (2007) shows that a variable capturing expected future labor income growth rates is negatively related to stock market excess returns. He argues that changes in expected future labor income are closely related to time–varying risk premia. In his narrative, high expected future labor income growth rates represent a state of the world where high labor income can be used to finance consumption, thereby decreasing the fear of low stock market returns. Maio and Min (2018) develop a consumption–based asset pricing model that includes labor income growth as a risk factor. Their model implies a negative market price of risk for labor income growth, since higher labor income growth is associated with lower leisure hours as opportunity costs of leisure increase when wages are higher. Other things equal, less leisure time increases the marginal utility of consumption.

significant. The addition of the quarterly aggregate labor income growth factor in the human capital CAPM does not improve the cross–sectional fit. The intercept remains positive and statistically significant, the R^2 hardly improves, and the market price of labor income growth risk is not statistically significant. These results confirm the findings in previous literature that contemporaneous aggregate labor income growth does not seem to play an important role in asset pricing (see, e.g., Eiling, 2013). Comparing the results of the traditional human capital CAPM with our preferred specification clearly highlights the effect of taking into account the 'right' horizon. Indeed, replacing the contemporaneous labor income growth factor with the labor income growth factor at scale $j = 4$ drastically improves the adjusted R^2 from 0% to 73%.

Our preferred parsimonious two–factor specification captures the cross–section of stock returns better or almost as well as the Fama and French (1993) three–factor (FF3) and Fama and French (2015) five–factor (FF5) models, which are particularly designed to perform well on the size–BM portfolios and show adjusted R^2 of 65% and 77% respectively. The version of the human capital CAPM where the two– to four–year labor income risk factor is interacted with Marfe (2018)'s labor income share variable fits slightly better than the base specification without the interaction, and has an adjusted R^2 of 75%. The significance of the of two– to four–year labor income risk factor is also robust to including the FF3 and FF5 factors.

The dominant horizon for labor income risk is similar to the three–year horizon of the ultimate consumption CAPM of Parker and Julliard (2005), who use 11–quarter ahead real per capita labor income growth rate as risk factor. Consistent with the findings of Parker and Julliard (2005), we find that this specification greatly outperforms the traditional consumption CAPM with an adjusted R^2 of 30% as opposed to –3%. We find a similar result when we replace the consumption growth in the CCAPM by the $j = 3$ HAAR scale transformation of the consumption growth (labeled $CONS3$ in the table). When including these (ultimate) consumption CAPM risk factors to our preferred model specification, the market price of two– to four–year labor income risk remains statistically significant, whereas the market prices of the (ultimate) consumption CAPM risk factors become statistically insignificant. This shows that the two– to four–year labor income risk factor is not a mere proxy for (ultimate) consumption risk.

In summary, our empirical results reveal that labor income risk at the two– to four–year horizon strongly and robustly affects the cross-section of expected stock returns. In sharp contrast, labor income risk at other horizons does not matter. In terms of cross-sectional fit, a simple two–factor model that includes labor income risk at the two– to four–year horizon strongly outperforms the standard CAPM, the consumption CAPM, the ultimate consumption CAPM of Parker and Julliard (2005), and the standard human capital CAPM models, and has similar performance to the Fama and French (1993) three–factor and Fama and French (2015) five–factor models.

5.3 Discussion of the Results

Our goal is to empirically examine whether the relation between labor income risk and expected stock returns displays horizon effects, and if so, to identify the dominant horizon(s). The data paint a clear picture. Labor income risk at the two– to four–year horizon strongly and robustly affects the cross–section of expected stock returns. In sharp contrast, labor income risk at other horizons does not matter.

In our theoretical model, labor income risk over different horizons is priced because investors earn labor income over different horizons. We show that the pricing equation can be expressed as a multi-factor model that includes labor income growth deceleration over different horizons as factors, rather than labor income growth rates themselves. The remarkably strong empirical performance of this model with labor income growth deceleration over the medium term suggests that investors care a lot about how their labor income growth, rather than the labor income level, fluctuates over time.

The dominance of the two–to–four year horizon is consistent with evidence from existing studies on wage rigidity. Due to infrequent wage setting, infrequent negotiations between workers and the firm, or other labor market frictions, there is typically much less uncertainty about the labor income growth rate over the next two or three years. Indeed, several studies find that the frequency of wage setting is about every three years, which falls within our dominant horizon.[14]

During the period of wage rigidity, wages are smoother than the marginal product of labor, and hence smoother than output. This could result in lower short–term correlations between wage growth and stock returns. When wages are reset to match the marginal product of labor every three years, we would expect higher comovements between wage

[14]For instance, Marfe (2018) measures labor rigidity as employee compensation over net value added (i.e., the labor share). He finds that the labor share fluctuates counter–cyclically and has a half–life of 3.5 years. Rich and Tracy (2004) show that for most of their sample of labor contracts, the median duration is 35 months. Favilukis and Lin (2016b) find an optimal wage resetting frequency of one every three years in their production–based asset pricing model. That frequency helps generate both smooth wages and volatile stock returns in their model. Various papers find that for search–and–matching models to generate realistic patterns in unemployment and vacancies, assuming wage rigidity is key (see, e.g., Shimer (2005) and Hall (2005)).

growth and stock returns at this three–year horizon. This is exactly what comes out of our empirical analysis. Stocks' exposures to labor income risk peak at the two– to four–year horizon.

Our results suggest that what investors care about is how their labor income growth develops after the coming two years. Will the labor income growth decelerate or accelerate? Our dominant factor, the HAAR scale at $j = 4$, captures exactly this type of labor income risk. To the best of our knowledge, we are the first to show that labor income growth acceleration or deceleration over the medium term is a key driver of expected stock returns.

5.4 Dynamic Response of Labor Income Growth to Stock Returns

In this section, we employ an alternative methodology to empirically analyze the dynamic relation between stock returns and labor income growth. According to our theoretical asset pricing model, the covariances between stock returns and future aggregate labor income growth are priced. This suggests that for those covariances to matter, stock returns should have predictive power for future (multi–horizon) labor income growth rates. Our first–stage regression results are in line with this predictive relationship as they reveal economically and statistically significant exposures of quarterly stock returns with respect to aggregate labor income growth in the next two–to–four years. Below, we use a different methodology to analyze dynamic comovements between stock returns and future labor income growth, which is very flexible. This approach allows us to analyze the cumulative impact of a common shock in stock returns on future labor income growth and identify the horizon for which the impact peaks. In short, we confirm that the two–to–four year horizon dominates.

More specifically, we use the factor model structure proposed by Bryzgalova and Julliard (2021) to study the dynamic relation between stock portfolio returns and future aggregate labor income growth. The model specification reads as follows:

$$f_t = \rho' \bar{X}_t + \varepsilon_t, \tag{28}$$

where the dependent variable $f_t = \log \bar{L}_t - \log \bar{L}_{t-1}$ is quarterly log aggregate labor income growth, $\bar{X}_t = (X_t, X_{t-1}, \ldots, X_{t-S})'$ is a vector of latent factors, for some integer $S \geq 0$, and ε_t is an error component. The latent factor X_t is supposed to have a linear relation to the stock returns:

$$r_t = \theta X_t + w_t, \tag{29}$$

with r_t an $N \times 1$ vector of stock portfolio returns, θ an $N \times 1$ vector of coefficients, and w_t an error term. The (latent) variable X_t can be thought of as a common factor driving contemporaneous stock returns and predicting future labor income growth. The impact of stock returns in period $t-s$ on labor income growth in period t is measured by the coefficient ρ_s, $s = 0, \ldots, S$, in (28). Hence, we can also see the series $\rho_0, \ldots, \rho_S$ as the impulse response function measuring the impact of a shock in current stock returns on labor income growth in future (and current when $s = 0$) periods.

Bryzgalova and Julliard (2021) develop a Bayesian method to estimate this model. Instead, assuming the error terms to be i.i.d. and normally distributed, and ε_t and w_t to be independent, we develop a Maximum Likelihood filtering method to estimate the model. We estimate the model using aggregate labor income growth as the dependent variable and the 25 Fama–French size and book–to–market portfolio returns as the return vector.

Figure 3 plots the cumulative impulse response function $\sum_{i=1}^{s} \rho_{i-1}$, i.e., the effect of a common shock in the stock returns r_{t+1} on the cumulative aggregate labor income growth $\log \bar{L}_{t+s} - \log \bar{L}_t$, as a function of the horizon. We observe that the immediate impact of a shock in the stock returns on labor income growth is close to zero. This is in line with the well-known result that the contemporaneous correlation between stock returns and labor income growth is close to zero. However, in later quarters the impact is positive and the cumulative impulse response peaks at a horizon of four years.

In sum, this analysis confirms the existence of horizon effects in the dynamic relation between stock returns and labor income growth. The medium term horizon, approximately two to four years, displays the strongest relation, which is in line with our two–pass cross–sectional regression results.

6 Robustness Tests

In this section we discuss a variety of robustness checks for our cross-sectional asset pricing tests, including using different sets of test assets, univariate first–stage betas, real labor income growth and different classifications of the horizons.

6.1 Other Test Assets

Next to the standard 25 size–BM portfolios, we also consider different sets of test assets. In particular, we consider a broader cross–section of stock returns and add 25 size–investment and 30 industry portfolios to the 25 size–BM portfolios. Table 6 reports the results for the combined 25 size–BM and 25–size investment portfolios, and Table 7 reports the results for the 25 size–BM and 30 industry portfolios. As a benchmark, we also present the results of the traditional human capital CAPM, the consumption CAPM, the ultimate consumption CAPM, the Fama and French (1993) three-factor and Fama and French (2015) five-factor models for both sets of test assets.

In line with our previous results, we again find that the medium frequency scale $j = 4$ strongly dominates. The R^2s of the simple two–factor model that contains the equity market factor and the labor income growth factor at scale $j = 4$ are substantially higher than those of model specifications that include other scale components. In fact, the cross–sectional fit is in both cases much better than those of the traditional human capital CAPM, and (ultimate) consumption CAPM models, and comparable to those of the Fama and French (1993) three–factor and Fama and French (2015) five–factor models, which should, in principle, perform particularly well on the 25 size–BM and 25 size–investment portfolios. The intercepts are not statistically significant for the two–factor model with scale $j = 4$, whereas the intercepts of the Fama and French (1993) three–factor model are always statistically significantly different from zero, and the intercept of the Fama and French (2015) five–factor model is as well for the 25 size–BM and 30 industry portfolios. Similar to our previous findings, the price of risk for scale $j = 4$ is statistically significantly negative for all test assets and all model specifications. When including the 30 industry portfolios, none of the Fama and French (2015) factors carry significant prices of risk. This suggests that the simple two–factor model outperforms the Fama and French (1993) three–factor and Fama and French (2015) five–factor models for these test assets as well.

6.2 Maximum Scale Specification

Throughout our analysis, we defined the maximum scale to be $J = 5$, corresponding to eight years. As a result, we have several scale components ($j = 1, 2, 3, 4, 5$) that capture heterogeneity in labor income risk up to typical business–cycle frequency horizons of eight years, and one residual component ($j > 5$) that groups together long–term labor income risk with horizons beyond eight years. The choice for $J = 5$ was made to strike a balance between allowing for enough flexibility of our analysis within the range of typical business–

cycle frequencies on the one hand, and maintaining a tractable empirical specification on the other hand. Therefore, specifying a maximum scale below five would result in losing information on risk at business–cycle frequencies, since more horizons would end up in the residual component. Going beyond scale $j = 5$, on the other hand, further increases the number of factors in the cross–sectional analysis. Furthermore, the construction of factors at scales beyond $j = 5$ requires taking moving averages over 64 (or more) labor income growth rates, resulting in highly persistent series. Nevertheless, in this robustness test we select $J = 4$ and $J = 6$. The results are reported in Table 8, panel A ($J = 4$) and panel B ($J = 6$). In both cases, the prices of risk of the $j = 4$ scale component is highly significant, while at other scales it is not. Only the price of risk for very long term labor income risk ($J > 6$) is marginally significant in Panel B. Again, the cross–sectional fit of the parsimonious two–factor model with scale $j = 4$ is remarkable. This confirms that our findings are robust to the specification of the maximum scale.[15]

6.3 Multivariate versus Univariate Betas

All second–stage cross–sectional results discussed so far use betas that are estimated in a single multivariate time–series regression in the first stage. In typical settings, re–estimation of the betas in the first stage is required when considering different model specifications in the second stage, since correlations between included and excluded factors might affect the second–stage results. In our case, however, the correlations between the components are very low.[16] Therefore, in the first–stage regressions, the correlations of the scale factors with the equity market factor mainly play a role. Since all specifications we consider include the equity market factor as well, our multivariate regression approach ought to be valid. To test this, we compare our cross–sectional results based on betas obtained by the multivariate first–stage regression with cross–sectional results based on betas obtained by univariate first–stage regressions. Table 9 reports the cross–sectional results using univariate betas and the 25 size–BM portfolios as test assets. Indeed, we find all market prices of labor income risk to be of similar magnitudes as those based on multivariate betas as in Table 4.

[15]Note that the results of the two–factor preferred specification in this table are slightly different from those in Table 4. This is due to a slightly different sample period as a result of a different maximum J.

[16]Unreported results show that the correlations between labor income risk factors for different j range between -0.11 (between $f(j > 5)$ and $f(j = 4)$) and 0.19 (between $f(j = 3)$ and $f(j = 4)$). The average pairwise correlation is 0.0044 and the average absolute pairwise correlation is 0.06.

6.4 Nominal versus Real Labor Income Growth

Our cross–sectional results are also robust to using real instead of nominal labor income growth rates. We obtain real labor income by deflating nominal wages by the Personal Consumer Expenditure price deflator as reported by the Bureau of Economic Analysis. Table 10 presents the cross–sectional regression results on the 25 size–BM portfolios when considering real aggregate labor income growth across different frequency scales. Again, the cross–sectional fit peaks for the two–factor specification with scale $j = 4$. The estimated value of the price of risk at scale $j = 4$ is also very similar to the estimated value when we take nominal labor income growth (see Table 4).

7 Conclusion

Labor and equity markets are interconnected. However, the strength of these connections may vary depending on the horizon. There are various possible economic reasons for these horizon effects, such as career length, wage stickiness or long–term cointegration between wages and dividends. This paper employs a flexible empirical approach to consider co-movements between labor income risk and equity returns at many different horizons. Our goal is to determine whether there are any horizon effects, and if so, to extract the dominant horizon(s) from the data and to understand the economic mechanism.

We first derive a simple theoretical model, in which investors have different career lengths and the covariance between labor income risk and equity returns may vary across horizons. In this model, expected excess stock returns are explicitly driven by their exposures to labor income risk across different horizons. Before we can test the resulting multi–factor model, we need to remove overlap between labor income growth rates over multiple horizons. To this end, we use a HAAR transformation of quarterly labor income growth. The resulting components are only weakly correlated and capture wage growth acceleration (or deceleration) over different horizons. We map the HAAR components to the original asset pricing model and derive the corresponding expresssions for horizon–specific prices of labor income risk.

In our empirical specification, we include equity market returns and aggregate labor income risk at six different horizons ranging from one quarter up to more than eight years. The result is striking: only labor income risk at the two– to four–year horizon is significantly priced. Even more so, when we focus on the two–factor model that includes labor income risk at this frequency (in addition to equity market returns), we find that the model performs similarly to the Fama and French (2015) five–factor model for the cross–section of size and book–to–market and size–investment portfolios. In sharp contrast, the standard human capital CAPM with quarterly labor income growth barely captures any of the cross–sectional variation in expected returns. Hence, the simple adjustment of measuring labor income risk over a medium–term horizon has a dramatic effect on the model's ability to capture cross–sectional differences in expected stock returns.

Our new labor factor captures the difference between wage growth in the next two years and wage growth in the two years thereafter. Hence, a negative factor realization means that wage growth is slowing down. We find that most stock portfolios have negative exposures, suggesting that they tend to experience poor returns when wage growth is slowing down at the medium horizon. This makes these stocks riskier, resulting in a higher risk premium. Indeed, we find that the price of risk is negative.

Several papers that examine consumption–based models without labor (e.g., Daniel and Marshall (1997) and Parker and Julliard (2005)) find that these models performs best when using consumption growth at the two– to three–year horizon. This suggests that investors make decisions with a medium–term horizon in mind. Nevertheless, our model strongly outperforms the ultimate consumption CAPM of Parker and Julliard (2005), indicating that the medium–term labor income risk factor is not a mere proxy for ultimate consumption risk. Furthermore, the correlation between the fourth HAAR scale of labor income (that we use to capture two–to–four year labor income risk) and the fourth HAAR scale of consumption is very close to zero.

Instead, our results are consistent with evidence of wage rigidity where wages are slow to adjust to changes in the marginal product of labor. Various papers suggest that wages are reset every three years (e.g., Rich and Tracy (2004), Favilukis and Lin (2016b) and Marfe (2018)). This implies that wage growth over the next two to three years tends to be less uncertain than the wage growth in the years thereafter. The strikingly strong empirical performance of our new labor factor suggests that investors care about stocks' exposure to fluctuations in wage growth, rather than wage levels, over the medium horizon.

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Appendices

Appendix A Model Derivations

In this Appendix, we provide the details of the derivations in our theoretical model. We first derive a log–linear approximation of multi–period wealth, which we subsequently use in the portfolio optimization problem. When aggregating the resulting optimal portfolio demands over cohorts of investors with heterogeneous investment horizons, we finally obtain our asset pricing equation.

A.1 Log–Linearization of the Wealth Dynamics

For notational convenience, we only discuss the case of one risky asset and hence a scalar portfolio weight α_t. The generalization to multiple risky assets and a vector of portfolio weights is straightforward. Defining the log returns variables $r_f = \log(R_f)$ and $r_{t+1} = \log(R_{t+1})$ we can write the one–period portfolio returns as

$$R_{p,t+1} = R_f[1 + \alpha_t(\exp(r_{t+1} - r_f) - 1)]. \tag{A.1}$$

Let $w_t = \log(W_t)$ and $l_{t+i} = \log(L_{t+i})$ denote log wealth and log labor income, respectively. We consider a Taylor expansion of w_{t+h} as a function of $(w_t, l_{t+i}, r_{t+1} - r_f)$.[17] The first derivatives are

$$\frac{\partial w_{t+h}}{\partial w_t} = \frac{(R_{p,t+h} \cdots R_{p,t+1})W_t}{W_{t+h}}, \tag{A.2}$$

$$\frac{\partial w_{t+h}}{\partial l_{t+i}} = \frac{(R_{p,t+h} \cdots R_{p,t+i+1})L_{t+i}}{W_{t+h}}, \tag{A.3}$$

$$\frac{\partial w_{t+h}}{\partial (r_{t+1} - r_f)} = \frac{\alpha_t R_{t+1}(R_{p,t+h} \cdots R_{p,t+2})W_t}{W_{t+h}}, \tag{A.4}$$

and the second derivative with respect to $r_{t+1} - r_f$ is

$$\frac{\partial^2 w_{t+h}}{\partial (r_{t+1} - r_f)^2} = \frac{\alpha_t R_{t+1}(R_{p,t+h} \cdots R_{p,t+2})W_t W_{t+h} - (\alpha_t R_{t+1}(R_{p,t+h} \cdots R_{p,t+2})W_t)^2}{W_{t+h}^2}, \tag{A.5}$$

[17] We do not expand the wealth around $r_{t+i} - r_f$ for $i > 1$ because the associated terms in the Taylor expansion do not depend on α_t.

where we use

$$\frac{\partial R_{p,t+1}}{\partial(r_{t+1}-r_f)} = \frac{\partial^2 R_{p,t+1}}{\partial(r_{t+1}-r_f)^2} = R_f\alpha_t\exp(r_{t+1}-r_f) = \alpha_t R_{t+1}. \tag{A.6}$$

Evaluating these derivatives in the point $r_{t+1}-r_f=0$, $R_{p,t+i}=R_f$, and $L_{t+i}=\mathbb{E}_t[L_{t+i}]$ for all i, and defining $\bar{W}_{t+h}=R_f^hW_t+\sum_{j=1}^h R_f^{h-j}\mathbb{E}_t[L_{t+j}]$, we find

$$\frac{\partial w_{t+h}}{\partial w_t} = \rho, \tag{A.7}$$
$$\frac{\partial w_{t+h}}{\partial l_{t+i}} = \rho_i, \tag{A.8}$$
$$\frac{\partial w_{t+h}}{\partial(r_{t+1}-r_f)} = \rho\alpha_t, \tag{A.9}$$
$$\frac{\partial^2 w_{t+h}}{\partial(r_{t+1}-r_f)^2} = \rho\alpha_t-(\rho\alpha_t)^2 = \rho\alpha_t(1-\rho\alpha_t), \tag{A.10}$$

with

$$\rho = \frac{R_f^hW_t}{\bar{W}_{t+h}} = \frac{W_t}{W_t+\sum_{j=1}^h R_f^{-j}\mathbb{E}_t[L_{t+j}]}, \tag{A.11}$$

and

$$\rho_i = \frac{R_f^{h-i}\mathbb{E}_t[L_{t+i}]}{\bar{W}_{t+h}} = \frac{R_f^{-i}\mathbb{E}_t[L_{t+i}]}{W_t+\sum_{j=1}^h R_f^{-j}\mathbb{E}_t[L_{t+j}]}. \tag{A.12}$$

The Taylor expansion using these derivatives gives the log–linearized wealth at horizon h:

$$w_{t+h} = k(h)+\rho w_t+\rho\alpha_t(r_{t+1}-r_f)+\frac{1}{2}\rho\alpha_t(1-\rho\alpha_t)\mathrm{Var}(r_{t+1})+\sum_{i=1}^h\rho_i l_{t+i}. \tag{A.13}$$

Notice that by definition $\rho+\sum_{i=1}^h\rho_i=1$ so that the log–wealth at $t+h$ can be seen as a weighted average of current log wealth and the present value of the expected stream of labor income up to the horizon h, augmented with the log excess stock return, a convexity effect and a linearization constant $k(h)$.

A.2 Optimal Portfolio

Maximizing (3) is now, in a second order approximation, equivalent to maximizing the mean–variance utility function defined over log wealth $w_{t+h}=\log(W_{t+h})$ and log aggregate labor income $\bar{l}_{t+h} = \log\left(\bar{L}_{t+h}\right)$,

$$V(w_{t+h} - \psi\bar{l}_{t+h}) = \mathbb{E}_t[w_{t+h} - \psi\bar{l}_{t+h}] + \frac{1}{2}(1-\gamma)\text{Var}_t\left(w_{t+h} - \psi\bar{l}_{t+h}\right). \tag{A.14}$$

We only maximize with respect to the short–term portfolio choice variable α_t, since a simple backwards induction argument shows that we can take the portfolio choice rules α_{t+i}, $i = 1, \ldots, h$ as given when considering portfolio choice at time t (see also Campbell, 2018).

Using (A.13) and with shorthand notation $\mu = \mathbb{E}_t[r_{t+1}]$ and $\sigma^2 = \text{Var}(r_{t+1})$, the expectation and variance of log wealth minus ψ times labor income growth at horizon h are given by

$$\begin{aligned}\mathbb{E}_t[w_{t+h} - \psi\bar{l}_{t+h}] = k(h) + \rho w_t + \rho\alpha_t(\mu - r_f) + \frac{1}{2}\rho\alpha_t(1-\rho\alpha_t)\sigma^2 \\ + \sum_{i=1}^{h}\rho_i\mathbb{E}_t[l_{t+i}] - \psi\mathbb{E}_t[\bar{l}_{t+h}],\end{aligned} \tag{A.15}$$

and

$$\begin{aligned}\text{Var}_t\left(w_{t+h} - \psi\bar{l}_{t+h}\right) &= (\rho\alpha_t)^2\sigma^2 \\ &+ 2\rho\alpha_t\sum_{i=1}^{h}\rho_i\text{Cov}_t(r_{t+1}, l_{t+i}) - 2\rho\alpha_t\psi\text{Cov}_t(r_{t+1}, \bar{l}_{t+h}),\end{aligned} \tag{A.16}$$

where we omitted from the expression for the variance all terms that do not depend on α_t. The derivative of the mean–variance utility V defined in (A.14) with respect to α_t then is

$$\begin{aligned}\frac{\partial V}{\partial \alpha_t} &= \rho\left(\mu - r_f + \frac{1}{2}\sigma^2\right) - \rho^2\alpha_t\sigma^2 \\ &+ (1-\gamma)\left\{\rho^2\alpha_t\sigma^2 + \rho\sum_{i=1}^{h}\rho_i\text{Cov}_t(r_{t+1}, l_{t+i}) - \rho\psi\text{Cov}_t(r_{t+1}, \bar{l}_{t+h})\right\},\end{aligned} \tag{A.17}$$

which can be simplified to

$$0 = \rho\left(\mu - r_f + \frac{1}{2}\sigma^2\right)$$
$$- \gamma\rho^2\alpha_t\sigma^2 + (1-\gamma)\rho\left[\sum_{i=1}^{h}\rho_i\text{Cov}_t(r_{t+1}, l_{t+i}) - \psi\text{Cov}_t(r_{t+1}, \bar{l}_{t+h})\right]. \tag{A.18}$$

Solving this for α_t gives

$$\alpha_t = \frac{1}{\rho}\frac{\mu - r_f + \frac{1}{2}\sigma^2}{\gamma\sigma^2}$$
$$- \left(1 - \frac{1}{\gamma}\right)\frac{1}{\rho}\left[\sum_{i=1}^{h}\rho_i\text{Cov}_t(r_{t+1}, l_{t+i}) - \psi\text{Cov}_t(r_{t+1}, \bar{l}_{t+h})\right]/\sigma^2. \tag{A.19}$$

Suppose now that labor income in expectation grows at the risk free rate. Then, $R_f^{-i}\mathbb{E}_t[L_{t+i}] = L_t$ and since $\rho_i/\rho = R_f^{-i}\mathbb{E}_t[L_{t+i}]/W_t = L_t/W_t$ we can write

$$\alpha_t = \frac{W_t + hL_t}{W_t}\frac{\mu - r_f + \frac{1}{2}\sigma^2}{\gamma\sigma^2}$$
$$+ \left(1 - \frac{1}{\gamma}\right)\left[\psi\frac{W_t + hL_t}{W_t}\text{Cov}_t(r_{t+1}, \bar{l}_{t+h}) - \frac{L_t}{W_t}\sum_{i=1}^{h}\text{Cov}_t(r_{t+1}, l_{t+i})\right]/\sigma^2, \tag{A.20}$$

where L_t is the current labor income. With multiple assets, we can write the vector of optimal portfolio weights as

$$\alpha_t = \frac{W_t + hL_t}{W_t}\frac{1}{\gamma}\text{Var}(r_{t+1})^{-1}\left(\mu - r_f + \frac{1}{2}\sigma^2\right)$$
$$+ \left(1 - \frac{1}{\gamma}\right)\left[\psi\frac{W_t + hL_t}{W_t}\text{Cov}_t(r_{t+1}, \bar{l}_{t+h}) - \frac{L_t}{W_t}\sum_{i=1}^{h}\text{Cov}_t(r_{t+1}, l_{t+i})\right], \tag{A.21}$$

where σ^2 now denotes the diagonal of $\text{Var}(r_{t+1})$.

A.3 Equilibrium Pricing

We now show the implications of the optimal portfolio choice rule on equilibrium asset prices. Let there be, at any time t, H cohorts with investment horizon $h = 1, \ldots, H$, initial wealth W_h and current labor income L_h. Furthermore, assume that the covariance of the returns with future individual labor income growth rate is the same as the covariance with future aggregate labor income growth, so that $\text{Cov}_t(r_{t+1}, l_{t+i}) = \text{Cov}_t(r_{t+1}, \bar{l}_{t+i})$ for all i. The optimal portfolio equation is in terms of conditional expectations and variances, given the information at time t. To simplify notation, we now replace all conditional expectations, variances and covariances by their unconditional counterparts, and furthermore define $\gamma_i = \text{Cov}(r_{t+1}, \bar{l}_{t+i} - \bar{l}_t)$, $\mathbb{E}[R] = \mathbb{E}[r_{t+1}] + \frac{1}{2}\sigma^2$, and $\Omega = \text{Var}(r_{t+1})$. Then, from Eqn. (A.21), the dollar portfolio demand of cohort h is

$$
\begin{aligned}
W_h \alpha_h = {} & (W_h + hL_h)\frac{1}{\gamma}\Omega^{-1}(\mathbb{E}[R] - r_f) \\
& + \left(1 - \frac{1}{\gamma}\right)\Omega^{-1}\left[\psi(W_h + hL_h)\gamma_h - L_h \sum_{i=1}^{h} \gamma_i\right].
\end{aligned} \tag{A.22}
$$

Adding this up over the cohorts and dividing by aggregate wealth gives the aggregate portfolio weight

$$
\begin{aligned}
\alpha_m = {} & \frac{\sum_{h=1}^{H}(W_h + hL_h)}{\sum_{h=1}^{H} W_h}\frac{1}{\gamma}\Omega^{-1}(\mathbb{E}[R] - r_f) \\
& + \left(1 - \frac{1}{\gamma}\right)\Omega^{-1}\frac{\sum_{h=1}^{H}\left[\psi(W_h + hL_h)\gamma_h - L_h \sum_{i=1}^{h}\gamma_i\right]}{\sum_{h=1}^{H} W_h}.
\end{aligned} \tag{A.23}
$$

Re-writing this with the expected return on the left hand side gives

$$
\begin{aligned}
\mathbb{E}[R] - r_f = {} & \gamma \frac{\sum_{h=1}^{H} W_h}{\sum_{h=1}^{H}(W_h + hL_h)}\Omega\alpha_m \\
& + (\gamma - 1)\frac{\sum_{h=1}^{H}\left[L_h \sum_{i=1}^{h}\gamma_i - \psi(W_h + hL_h)\gamma_h\right]}{\sum_{h=1}^{H}(W_h + hL_h)}.
\end{aligned} \tag{A.24}
$$

Interchanging the summations over h and i in the second term, we find

$$
\begin{aligned}
\mathbb{E}[R] - r_f = {} & \gamma \left[\frac{\sum_{h=1}^{H} W_h}{\sum_{i=h}^{H}(W_h + hL_h)}\right]\Omega\alpha_m \\
& + (\gamma - 1)\sum_{h=1}^{H}\left[\frac{\sum_{i=h}^{H} L_i - \psi(W_h + hL_h)}{\sum_{i=1}^{H}(W_i + iL_i)}\right]\gamma_h.
\end{aligned} \tag{A.25}
$$

Defining the log market portfolio return as $r_{m,t+1} = \alpha_m' r_{t+1}$ and recalling the definitions $\gamma_h = \text{Cov}(r_{t+1}, \bar{l}_{t+h} - \bar{l}_t)$ and $\Omega = \text{Var}(r_{t+1})$ produces Eqn. (5) in the main text.

Appendix B Cross-Sectional Standard Errors

In this appendix, we derive a suitable Shanken–type correction for the second-stage cross–sectional standard errors that accounts for the fact that the betas are estimated in the first-stage time–series regressions and that are robust to heteroskedasticity and autocorrelation in the factors. The exposition follows Cochrane (2005), Chapter 12. We derive the corrected standard errors both for a setting where there is one multivariate first–stage regression, as well as for a setting with multiple univariate first–stage regressions.

B.1 Multivariate Betas

The time–series regressions in the first stage are of the form

$$R_t^e = \alpha + \beta f_t + \epsilon_t, \qquad t = 1, \dots, T, \tag{B.1}$$

where R_t^e is an $N \times 1$ vector of portfolio excess returns, α is an $N \times 1$ vector of intercepts, β is an $N \times K$ coefficient-matrix, f_t a $K \times 1$ vector of factors, which in our case includes the equity market risk factor and the labor income risk factors at scales $j = 1, \dots, J, > J$, and ϵ_t is an $N \times 1$ vector of zero-mean errors that are allowed to be heteroskedastic and correlated over time. The OLS estimator of the first–stage betas is given by

$$\hat{\beta} = T^{-1} \sum_t \left(R_t^e - \bar{R}^e \right) f_t' \left(\sum_t f_t f_t' \right), \tag{B.2}$$

with $\bar{R}^e = T^{-1} \sum_t R_t^e$ an $N \times 1$ vector of average excess returns of the portfolios, and where we assume without loss of generality that $\mathbb{E}[f] = 0$, which can easily be achieved by demeaning the factors.

The second–stage regression is given by (ignoring for a moment an intercept term)

$$\bar{R}^e = \hat{\beta}\lambda + \eta, \tag{B.3}$$

with λ an $K \times 1$ vector of market prices of risk, and η an $N \times 1$ vector of zero–mean errors. The OLS estimator of the second-stage regression is given by

$$\hat{\lambda} = (\hat{\beta}'\hat{\beta})^{-1}\hat{\beta}'\bar{R}^e, \tag{B.4}$$

and the difference with the true value is

$$\hat{\lambda} - \lambda = (\hat{\beta}'\hat{\beta})^{-1}\hat{\beta}'\eta. \tag{B.5}$$

Notice that η can be written as

$$\eta = \bar{R}^e - \beta\lambda - (\hat{\beta} - \beta)\lambda = \bar{R}^e - \mathbb{E}[\bar{R}^e] - (\hat{\beta} - \beta)\lambda. \tag{B.6}$$

Hence, the variance of the second–stage regression is

$$\text{Var}(\hat{\lambda}) = (\hat{\beta}'\hat{\beta})^{-1}\hat{\beta}'\text{Var}(\eta)\hat{\beta}(\hat{\beta}'\hat{\beta})^{-1}, \tag{B.7}$$

with

$$\text{Var}(\eta) = \text{Var}(\bar{R}^e) + \text{Var}\left((\hat{\beta} - \beta)\lambda\right). \tag{B.8}$$

To calculate these variances, we first write

$$\bar{R}^e - \mathbb{E}[\bar{R}^e] = T^{-1}\sum_t u_t, \quad u_t = R^e_t - \mathbb{E}[R^e], \tag{B.9}$$

and, hence, $\text{Var}(\bar{R}^e) = T^{-1}\Sigma_u$ with $\Sigma_u = \text{Var}(u_t)$.

The difference between the first–stage estimator and its true value can be expressed as

$$\hat{\beta} - \beta = T^{-1}\sum_t \epsilon_t f_t'\Sigma_f^{-1}, \tag{B.10}$$

with $\Sigma_f = T^{-1}\left(\sum_t f_t f_t'\right)$. Hence, the variance of $(\hat{\beta} - \beta)\lambda$ is

$$\text{Var}\left((\hat{\beta} - \beta)\lambda\right) = T^{-2}\text{Var}\left(\sum_t \epsilon_t f_t'\Sigma_f^{-1}\lambda\right). \tag{B.11}$$

Using these expressions, the asymptotic variance of $\hat{\lambda}$ is given by

$$\text{Var}(\hat{\lambda}) = T^{-1}(\hat{\beta}'\hat{\beta})^{-1}\hat{\beta}'\left(\Sigma_u + T^{-1}\text{Var}\left(\sum_t \epsilon_t f_t'\Sigma_f^{-1}\lambda\right)\right)\hat{\beta})\hat{\beta}('\hat{\beta})^{-1}, \tag{B.12}$$

or

$$\text{Var}(\hat{\lambda}) = T^{-1}(\hat{\beta}'\hat{\beta})^{-1}\hat{\beta}'\left(\Sigma_u + S(\epsilon_t f_t'\Sigma_f^{-1}\lambda\right)\hat{\beta}(\hat{\beta}'\hat{\beta})^{-1}, \tag{B.13}$$

with $S(x)$ the long–run covariance matrix of $x_t = \epsilon_t f_t'\Sigma_f^{-1}\lambda$. The matrix Σ_u can be consistently estimated by the sample variance–covariance matrix of the excess returns, and $S(x_t)$ by a Newey-West procedure. Note that these corrected standard errors explicitly account for the errors–in–variables bias and are robust to heteroskedasticity and autocorrelation.

Adding a constant term to the second–stage regression is straightforward. The second–stage regression is then

$$\bar{R}^e = \lambda_0 + \hat{\beta}\lambda + \eta, \tag{B.14}$$

which can be succinctly written as

$$\bar{R}^e = Z\gamma + \eta, \tag{B.15}$$

with $Z = [\iota\hat{\beta}]$ and $\gamma = (\lambda_0, \lambda)'$. The OLS estimator of the second–stage regression is

$$\hat{\gamma} = (Z'Z)^{-1}Z'\bar{R}^e, \tag{B.16}$$

with variance

$$\mathrm{Var}(\hat{\gamma}) = (Z'Z)^{-1}Z'\mathrm{Var}(\eta)Z(Z'Z)^{-1}, \tag{B.17}$$

where $\mathrm{Var}(\eta)$ is defined as before.

B.2 Univariate Betas

In the case where we consider univariate betas, we have multiple first–stage regressions of the form:

$$R_t^e = \alpha_j + \beta^{(j)} f_t^{(j)} + \epsilon_t^{(j)}, \qquad \text{for } j = 1, \ldots, J, > J, \qquad t = 1, \ldots, T, \tag{B.18}$$

where R_t^e is again the $N \times 1$ vector of portfolio excess returns components, and where $f_t^{(j)}$ is a scalar denoting the labor income growth rate component at scale j.[18] The OLS estimator of the first-stage beta is

$$\hat{\beta}^{(j)} = T^{-1} \sum_t \left(R_t^e - \bar{R}^e\right) f_t^{(j)} / \sigma^2_{f^{(j)}}, \tag{B.19}$$

[18] The additional regression for the equity market beta can be included in a straightforward manner and for brevity of notation we omit this extra regression in this appendix.

where $\sigma^2_{f^{(j)}} = T^{-1}\sum_t \left(f_t^{(j)}\right)^2$, and where we assume without loss of generality that $\mathbb{E}[f^{(j)}] = 0$, which can easily be achieved by demeaning the factors. We can compactly write the first–stage regressions and the beta estimator as

$$R_t = \alpha + \beta F_t + \epsilon_t, \tag{B.20}$$

and

$$\hat{\beta} = T^{-1}\sum_t (R_t - \bar{R}) F_t \Sigma_F^{-1}, \tag{B.21}$$

with R_t an $N \times K$ matrix ($K = J+1$) with columns R_t^e, β an $N \times K$ matrix with columns $\beta^{(j)}$, ϵ_t an $N \times K$ matrix with columns $\epsilon_t^{(j)}$, F_t a $J \times J$ diagonal matrix with elements $f_t^{(j)}$, and Σ_F a $J \times J$ diagonal matrix with elements $\sigma^2_{f^{(j)}}$. Hence, the difference between the first–stage estimator and its true value can be written as

$$\hat{\beta} - \beta = T^{-1}\sum_t \epsilon_t F_t \Sigma_F^{-1}. \tag{B.22}$$

The second–stage regression is the same as before, $\bar{R}^e = \hat{\beta}\lambda + \eta$. Following the same reasoning as in the multivariate case, the variance of the second–stage estimator for λ is

$$\text{Var}(\hat{\lambda}) = T^{-1}(\hat{\beta}'\hat{\beta})^{-1}\hat{\beta}'\left(\Sigma_u + T^{-1}\text{Var}\left(\sum_t \epsilon_t F_t \Sigma_F^{-1}\lambda\right)\right)\hat{\beta})\hat{\beta}('\hat{\beta})^{-1}, \tag{B.23}$$

or

$$\text{Var}(\hat{\lambda}) = T^{-1}(\hat{\beta}'\hat{\beta})^{-1}\hat{\beta}'\left(\Sigma_u + S(\epsilon_t F_t \Sigma_F^{-1}\lambda\right)\hat{\beta}(\hat{\beta}'\hat{\beta})^{-1}, \tag{B.24}$$

with $S(x)$ the long–run covariance matrix of $x_t = \epsilon_t F_t \Sigma_F^{-1}\lambda$. The matrix Σ_u can be consistently estimated by the sample variance–covariance matrix of the excess returns, and $S(x_t)$ by a Newey–West procedure.

Tables

Table 1. Mapping between time–scales and time spans. This table provides the mapping between the time–scales j and the corresponding time spans.

Time–scale	Frequency resolution	Interpretation
$j = 1$	1–2 quarters	
$j = 2$	2–4 quarters	
$j = 3$	4–8 quarters	
$j = 4$	8–16 quarters	
$j = 5$	16–32 quarters	
$j = 1 : 3$	1–8 quarters	High frequency
$j = 4 : 5$	8–32 quarters	Medium frequency
$j > 5$	$>$ 32 quarters	Low frequency

Table 2. Correlation between risk factors. This table reports the factor correlations between all risk factors used throughout the paper. In particular, the table reports on the five Fama-French factors (R_m, SMB, HML, RMV, CMA), the quarterly labor income growth factor (f), the interaction term between the fourth HAAR scale of labor income and Marfe's measure of labor income share ($f^{(4)}_{Marfe}$), the quarterly consumption growth factor (C), the ultimate consumption growth at the three-year horizon (C_{ult}), the third and fourth HAAR scales of consumption growth ($C^{(3)}$ and $C^{(4)}$), and the HAAR scales of labor income growth ($f^{(1)}$, $f^{(2)}$, $f^{(3)}$, $f^{(4)}$,$f^{(5)}$,$f^{(>5)}$).

	R_m	SMB	HML	RMW	CMA	f	$f^{(4)}_{Marfe}$	C	C_{ult}	$C^{(3)}$	$C^{(4)}$	$f^{(1)}$	$f^{(2)}$	$f^{(3)}$	$f^{(4)}$	$f^{(5)}$	$f^{(>5)}$
R_m	1.000	0.437	-0.319	-0.255	-0.454	0.015	0.086	0.268	0.133	0.258	0.139	-0.067	0.023	0.107	0.094	0.073	-0.043
SMB	0.437	1.000	-0.121	-0.203	-0.225	0.079	-0.049	0.111	0.023	0.139	0.092	0.002	0.018	0.063	-0.046	0.136	0.057
HML	-0.319	-0.121	1.000	0.062	0.743	0.045	-0.166	-0.048	0.085	-0.158	0.010	0.063	0.090	-0.005	-0.146	-0.076	0.050
RMW	-0.255	-0.203	0.062	1.000	0.037	-0.196	-0.135	-0.067	-0.089	-0.062	-0.105	-0.060	0.023	-0.188	-0.140	0.028	-0.156
CMA	-0.454	-0.225	0.743	0.037	1.000	0.007	-0.120	-0.172	0.022	-0.193	-0.050	0.051	0.023	0.004	-0.114	-0.073	0.020
f	0.015	0.079	0.045	-0.196	0.007	1.000	0.317	0.107	0.104	0.036	-0.046	0.601	0.397	0.249	0.323	0.221	0.491
$f^{(4)}_{Marfe}$	0.086	-0.049	-0.166	-0.135	-0.120	0.317	1.000	-0.137	-0.196	-0.042	-0.034	0.043	0.007	0.197	0.989	0.188	-0.109
C	0.268	0.111	-0.048	-0.067	-0.172	0.107	-0.137	1.000	0.487	0.518	0.370	-0.076	0.088	0.128	-0.128	-0.065	0.233
C_{ult}	0.133	0.023	0.085	-0.089	0.022	0.104	-0.196	0.487	1.000	-0.062	0.335	-0.008	-0.001	-0.030	-0.199	-0.265	0.414
$C^{(3)}$	0.258	0.139	-0.158	-0.062	-0.193	0.036	-0.042	0.518	-0.062	1.000	0.155	-0.048	-0.058	0.242	-0.028	0.113	0.004
$C^{(4)}$	0.139	0.092	0.010	-0.105	-0.050	-0.046	-0.034	0.370	0.335	0.155	1.000	-0.037	-0.052	-0.100	-0.020	0.095	0.011
$f^{(1)}$	-0.067	0.002	0.063	-0.060	0.051	0.601	0.043	-0.076	-0.008	-0.048	-0.037	1.000	-0.009	-0.031	0.055	-0.029	0.008
$f^{(2)}$	0.023	0.018	0.090	0.023	0.023	0.397	0.007	0.088	-0.001	-0.058	-0.052	-0.009	1.000	0.023	0.009	0.012	-0.021
$f^{(3)}$	0.107	0.063	-0.005	-0.188	0.004	0.249	0.197	0.128	-0.030	0.242	-0.100	-0.031	0.023	1.000	0.194	-0.067	-0.075
$f^{(4)}$	0.094	-0.046	-0.146	-0.140	-0.114	0.323	0.989	-0.128	-0.199	-0.028	-0.020	0.055	0.009	0.194	1.000	0.188	-0.115
$f^{(5)}$	0.073	0.136	-0.076	0.028	-0.073	0.221	0.188	-0.065	-0.265	0.113	0.095	-0.029	0.012	-0.067	0.188	1.000	-0.076
$f^{(>5)}$	-0.043	0.057	0.050	-0.156	0.020	0.491	-0.109	0.233	0.414	0.004	0.011	0.008	-0.021	-0.075	-0.115	-0.076	1.000

Table 3. Exposures of 25 size–BM portfolios to labor income risk across different horizons. This table presents the first–stage scale–wise betas with respect to aggregate labor income risk. The betas are estimated by running for each portfolio i the following (quarterly) multivariate time–series regression:

$$R_{t+1}^{e,i} = \alpha_{0,i} + \beta_{mkt,i} R_{t+1}^{e,mkt} + \sum_{j=1}^{J} \beta_{l,i}^{(j)} f_t^{(j)} + \beta_{l,i}^{(j>J)} f_t^{(j>J)} + \epsilon_{i,t+1},$$

where $f_t^{(j)}$ denotes the j–th scale component of aggregate labor income growth and $R_{t+1}^{e,mkt}$ the excess equity market returns. The associated t–statistics (in parentheses) are based on Newey–West adjusted standard errors with 32 lags. $*, **, ***$ indicate significance at the 10%, 5%, and 1% level, respectively. For each scale, the table also reports the p–values of two Wald tests on the joint significance of the corresponding betas. The sample period is 1958Q2 to 2017Q4.

	Betas					t-statistics				
	Panel A: Scale $j = 1$									
	Growth	BM2	BM3	BM4	Value	Growth	BM2	BM3	BM4	Value
Small	1.87	1.94^{*}	2.21^{**}	2.48^{**}	2.26^{*}	(1.10)	(1.69)	(2.18)	(2.35)	(1.81)
SMB2	1.23	0.87	0.54	1.29^{*}	2.05^{**}	(1.56)	(1.02)	(0.82)	(1.85)	(2.42)
SMB3	-0.55	0.92^{**}	1.14	0.20	1.19^{**}	(-0.61)	(1.97)	(1.42)	(0.44)	(1.99)
SMB4	-0.24	0.60	0.35	0.20	1.18	(-0.49)	(1.03)	(0.97)	(0.59)	(1.29)
Big	-0.52	0.64^{*}	0.83	0.83	1.77	(-1.32)	(1.94)	(1.58)	(1.11)	(1.48)
H_0: all betas are zero	(0.1025)									
H_0: all betas are equal	(0.0972)									
	Panel B: Scale $j = 2$									
	Growth	BM2	BM3	BM4	Value	Growth	BM2	BM3	BM4	Value
Small	1.32	1.24	0.42	1.04	1.10	(1.15)	(1.14)	(0.29)	(0.56)	(0.53)
SMB2	0.10	0.34	1.05	1.24	2.34	(0.10)	(0.39)	(0.76)	(0.73)	(1.14)
SMB3	-0.66	0.46	0.44	0.51	0.82	(-0.84)	(0.52)	(0.30)	(0.28)	(0.51)
SMB4	-0.05	-0.14	0.17	0.33	1.64	(-0.07)	(-0.14)	(0.21)	(0.24)	(1.16)
Big	0.21	0.08	0.64	1.35	1.33	(0.19)	(0.11)	(0.95)	(0.71)	(0.69)
H_0: all betas are zero	(0.5460)									
H_0: all betas are equal	(0.8205)									
	Panel C: Scale $j = 3$									
	Growth	BM2	BM3	BM4	Value	Growth	BM2	BM3	BM4	Value
Small	5.27	7.20	2.55	3.05	3.87	(0.85)	(1.44)	(0.87)	(0.92)	(1.51)
SMB2	1.56	1.96	-0.15	1.56	2.42	(0.49)	(0.88)	(-0.06)	(0.72)	(1.03)
SMB3	-0.43	0.97	0.52	1.78	2.35	(-0.23)	(0.57)	(0.25)	(0.82)	(0.78)
SMB4	2.38	-0.70	0.56	1.60	2.38	(0.78)	(-0.54)	(0.42)	(0.85)	(0.97)
Big	-1.06	-1.26	-1.66^{*}	0.53	1.99	(-1.23)	(-0.76)	(-1.64)	(0.19)	(1.10)
H_0: all betas are zero	(0.1442)									
H_0: all betas are equal	(0.1351)									
	Panel D: Scale $j = 4$									
	Growth	BM2	BM3	BM4	Value	Growth	BM2	BM3	BM4	Value
Small	-1.89	-5.52^{**}	-4.57	-6.88^{**}	-7.96^{**}	(-0.63)	(-2.14)	(-1.44)	(-2.03)	(-2.18)
SMB2	-2.16	-4.91^{*}	-6.19^{**}	-6.76^{**}	-7.95^{**}	(-0.97)	(-1.85)	(-2.12)	(-2.42)	(-2.16)
SMB3	-0.96	-4.15^{**}	-7.00^{***}	-7.76^{**}	-7.72^{***}	(-0.50)	(-2.19)	(-3.60)	(-2.56)	(-2.77)
SMB4	-0.54	-4.35^{**}	-3.88	-5.95^{**}	-4.82	(-0.30)	(-2.01)	(-1.41)	(-2.44)	(-1.41)
Big	2.02	-0.06	-3.08^{**}	-0.17	-2.86	(1.07)	(-0.04)	(-1.97)	(-0.06)	(-1.39)
H_0: all betas are zero	(0.0012)									
H_0: all betas are equal	(0.0058)									
	Panel E: Scale $j = 5$									
	Growth	BM2	BM3	BM4	Value	Growth	BM2	BM3	BM4	Value
Small	4.70	5.55^{*}	4.47^{*}	4.61^{**}	4.53^{*}	(1.16)	(1.92)	(1.87)	(2.19)	(1.65)
SMB2	4.56	4.00^{**}	2.18	4.08^{**}	1.93	(1.45)	(2.05)	(1.10)	(2.41)	(1.15)
SMB3	2.57	1.29	2.81	1.35	1.50	(0.86)	(0.53)	(1.64)	(1.05)	(0.59)
SMB4	0.59	1.75	0.87	-1.10	0.32	(0.26)	(1.30)	(0.76)	(-1.22)	(0.25)
Big	-1.98	-0.26	0.33	0.25	-2.63^{***}	(-1.38)	(-0.35)	(0.41)	(0.19)	(-2.84)
H_0: all betas are zero	(0.2574)									
H_0: all betas are equal	(0.4053)									
	Panel F: Scale $j > 5$									
	Growth	BM2	BM3	BM4	Value	Growth	BM2	BM3	BM4	Value
Small	3.85^{**}	1.70	1.28	1.15	1.68	(1.97)	(1.32)	(1.05)	(0.90)	(1.26)
SMB2	1.89	0.59	0.14	0.99	1.57	(1.40)	(0.55)	(0.14)	(1.14)	(1.58)
SMB3	0.68	0.33	0.10	0.32	-0.14	(0.76)	(0.40)	(0.12)	(0.43)	(-0.13)
SMB4	-0.44	-0.93	0.76	0.37	1.06	(-0.64)	(-1.10)	(0.80)	(0.47)	(1.32)
Big	-0.65	-0.49	-0.71	1.60^{*}	-0.62	(-1.18)	(-0.83)	(-1.10)	(1.68)	(-1.33)
H_0: all betas are zero	(0.0000)									
H_0: all betas are equal	(0.0001)									

Table 4. Cross–sectional regressions for 25 size–BM portfolios (multivariate betas). This table reports the second–stage cross–sectional regression results for different model specifications using aggregate labor income growth rates and 25 double–sorted size–BM portfolios as test assets. In particular, we consider the following specifications (and subsets thereof):

$$\mathbb{E}[R^{e,i}_{t+1}] = \lambda_0 + \hat{\beta}_{mkt,i}\lambda_{mkt} + \sum_{j=1}^{5} \hat{\beta}^{(j)}_{l,i}\lambda^{(j)}_{l} + \hat{\beta}^{(j>5)}_{l,i}\lambda^{(j>5)}_{l} + \alpha_i,$$

and

$$\mathbb{E}[R^{e,i}_{t+1}] = \lambda_0 + \hat{\beta}_{mkt,i}\lambda_{mkt} + \hat{\beta}^{(1:3)}_{l,i}\lambda^{(1:3)}_{l} + \hat{\beta}^{(4:5)}_{l,i}\lambda^{(4:5)}_{l} + \hat{\beta}^{(j>5)}_{l,i}\lambda^{(j>5)}_{l} + \alpha_i.$$

Here $\hat{\beta}_{mkt,i}$, $\hat{\beta}^{(j)}_{l,i}$, $\hat{\beta}^{(1:3)}_{l,i}$, $\hat{\beta}^{(4:5)}_{l,i}$, and $\hat{\beta}^{(j>5)}_{l,i}$ are the estimated first–stage component–wise betas obtained from a multivariate time–series regression of quarterly excess returns of portfolio i on quarterly excess market returns and the scale components of aggregate labor income growth (using $j = 1, 2, 3, 4, 5, > 5$ or $j = 1:3, 4:5, > 5$, respectively). We report time–series averages of the second–stage market prices of risk (per quarter) with Fama and MacBeth (1973) t-statistics in parentheses and error–in–variable and autocorrelation corrected t–statistics in square brackets (using Newey–West adjustments with 2^j lags). The last column reports the cross–sectional R^2 and adjusted–R^2 (in square brackets). $*, **, ***$ indicate significance at the 10%, 5%, and 1% level, respectively, based on the adjusted t–statistics. The sample period runs from 1958Q2 until 2017Q4.

	λ_0	λ_{mkt}	$\lambda_l^{(1)}$	$\lambda_l^{(2)}$	$\lambda_l^{(3)}$	$\lambda_l^{(4)}$	$\lambda_l^{(5)}$	$\lambda_l^{(1:3)}$	$\lambda_l^{(4:5)}$	$\lambda_l^{(j>5)}$	R^2
All	0.0136	-0.0001	0.0004	0.0012	0.0006	-0.0020^{***}	-0.0003			-0.0010	0.83
	(1.62)	(-0.01)	(0.33)	(1.06)	(1.65)	(-4.23)	(-0.49)			(-1.11)	[0.76]
	[1.20]	[-0.01]	[0.26]	[0.87]	[1.21]	[-2.72]	[-0.39]			[-0.75]	
$j = 1:3$, $j = 4:5$, & $j > 5$	0.0024	0.0117						0.0033	-0.0042^{***}	-0.0001	0.71
	(0.27)	(1.09)						(2.34)	(-4.55)	(-0.07)	[0.65]
	[0.12]	[0.52]						[1.37]	[-2.81]	[-0.04]	
$j = 1$	0.0270	-0.0068	0.0043^{*}								0.23
	(2.94)	(-0.64)	(2.73)								[0.16]
	[2.25]	[-0.51]	[1.76]								
$j = 2$	0.0222	-0.0025		0.0053							0.25
	(2.46)	(-0.23)		(3.02)							[0.18]
	[1.27]	[-0.15]		[1.07]							
$j = 3$	0.0349^{*}	-0.0114			0.0015^{*}						0.10
	(3.59)	(-1.04)			(2.61)						[0.02]
	[2.41]	[-0.76]			[1.77]						
$j = 4$	0.0116	0.0024				-0.0024^{**}					0.75
	(1.25)	(0.22)				(-4.47)					[0.73]
	[0.78]	[0.15]				[-1.92]					
$j = 5$	0.0313^{***}	-0.0079					0.0006				0.02
	(3.69)	(-0.81)					(1.03)				[-0.06]
	[3.34]	[-0.75]					[0.97]				
$j > 5$	0.0344^{***}	-0.0119								0.0026	0.09
	(3.33)	(-1.05)								(1.92)	[0.01]
	[2.76]	[-0.89]								[1.52]	

Table 5. Cross–sectional regressions for 25 size–BM portfolios - comparison with alternative asset pricing models. This table evaluates the cross–sectional regression results of six benchmark asset pricing models for quarterly excess returns on 25 size–BM equity portfolios. The first model is the standard CAPM. The second model is the standard human capital CAPM which augments the classic CAPM with an aggregate labor income growth factor. The third model is the classic consumption CAPM (CCAPM), which is a one–factor model containing (real, per capita) consumption growth as a factor. The fourth model is a version of the CCAPM with the third HAAR scale of the consumption growth (CONS3) as the risk factor. The fifth model is the preferred specification of the ultimate consumption CAPM of Parker and Julliard (2005), which uses 11–quarter ahead consumption growth as priced factor. The sixth model is the Fama and French (1993) 3–factor model, which we denote by FF3. The last model is the Fama and French (2015) 5–factor model, which we denote by FF5. We also add our preferred specification of the scale–specific human capital CAPM model, and its version where the fourth labor income scale is interacted with the labor income share variable of Marfe (2018). Finally, we present several setups that augment our preferred model specification. The cross–sectional regressions are estimated using the Fama and MacBeth (1973) procedure. We report the second–stage cross–sectional regression coefficients and corresponding Fama–MacBeth t–statistic in parenthesis and adjusted t–statistics in square brackets. $*, **, ***$ indicate significance at the 10%, 5%, and 1% level, respectively, based on the adjusted t–statistics. The last column reports the R^2 and adjusted–R^2 (in square brackets).

	λ_0	λ_{mkt}	λ_l	λ_c	λ_{uc}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	$\lambda_l^{(4)}$	R^2
CAPM	0.0271^{***}	-0.0036									0.01
	(2.96)	(-0.33)									[-0.03]
	[2.95]	[-0.33]									
Human capital CAPM	0.0333^{***}	-0.0106	0.0032								0.08
	(3.41)	(-0.98)	(1.73)								[-0.00]
	[2.65]	[-0.81]	[1.49]								
CCAPM	0.0203^{***}			0.0005							0.01
	(2.74)			(0.28)							[-0.04]
	[2.72]			[0.28]							
CONS3	0.0004			-0.0108^{*}							0.38
	(0.06)			(-2.93)							[0.35]
	[0.04]			[-1.89]							
Ultimate CCAPM	0.0083				0.0347^{**}						0.33
	(1.17)				(3.21)						[0.30]
	[0.83]				[2.12]						
FF3	0.0284^{***}	−0.0127				0.0066^{*}	0.0134^{***}				0.78
	(3.13)	(-1.18)				(1.70)	(3.25)				[0.65]
	[2.91]	[-1.13]				[1.69]	[3.23]				
FF5	0.0160	−0.0029				0.0083^{**}	0.0127^{***}	0.0090	0.0074		0.82
	(1.51)	(-0.23)				(1.98)	(2.85)	(1.69)	(1,68)		[0.77]
	[1.06]	[-0.18]				[1.98]	[2.79]	[1.40]	[1.45]		
Preferred specification	0.0116	0.0024								-0.0024^{**}	0.75
	(1.25)	(0.22)								(-4.47)	[0.73]
	[0.78]	[0.15]								[-1.92]	
Preferred (Marfe version)	0.0094	0.0045								-0.0019^{**}	0.77
	(1.00)	(0.40)								(-4.40)	[0.75]
	[0.66]	[0.29]								[-2.09]	
Preferred + CCAPM	0.0122	0.0025		0.0034						-0.0025^{**}	0.78
	(1.32)	(0.23)		(2.24)						(-4.44)	[0.75]
	[0.83]	[0.16]		[1.27]						[-2.07]	
Preferred + CONS3	0.0069	0.0078		-0.0079						-0.0021^{**}	0.83
	(0.71)	(0.69)		(-2.75)						(-4.58)	[0.81]
	[0.40]	[0.43]		[-1.49]						[-2.35]	
Preferred + ultimate CCAPM	0.0076	0.0070			0.0240					-0.0023^{**}	0.81
	(0.78)	(0.61)			(2.60)					(-4.60)	[0.78]
	[0.42]	[0.36]			[1.40]					[-2.36]	
Preferred + FF3	0.0185	-0.0043				0.0077^{**}	0.0125^{***}			-0.0012^{**}	0.83
	(1.96)	(-0.39)				(1.99)	(3.06)			(-2.66)	[0.79]
	[1.49]	[-0.33]				[1.97]	[3.02]			[-1.98]	
Preferred + FF5	0.0151	-0.0025				0.0085^{**}	0.0123^{***}	0.0070	0.0077	-0.0012^{*}	0.83
	(1.40)	(-0.21)				(2.04)	(2.76)	(1.34)	(1.67)	(-2.25)	[0.78]
	[1.16]	[-0.18]				[2.02]	[2.72]	[1.20]	[1.41]	[-1.84]	

Table 6. Cross–sectional regressions for 50 combined 25 size–BM and 25 size–investment portfolios (multivariate betas). This table reports the second–stage cross–sectional regression results for different model specifications using aggregate labor income growth rates and a combination of 25 double–sorted size–BM and 25 size–investment portfolios as test assets. In particular, we consider the following specification (and subsets thereof):

$$\mathbb{E}[R^{e,i}_{t+1}] = \lambda_0 + \hat{\beta}_{mkt,i}\lambda_{mkt} + \sum_{j=1}^{5} \hat{\beta}^{(j)}_{l,i}\lambda^{(j)}_l + \hat{\beta}^{(j>5)}_{l,i}\lambda^{(j>5)}_l + \alpha_i.$$

Here $\hat{\beta}_{mkt,i}$, $\hat{\beta}^{(j)}_{l,i}$, and $\hat{\beta}^{(j>5)}_{l,i}$ are the estimated first–stage component–wise betas obtained from a multivariate quarterly time–series regressions of quarterly excess returns of portfolio i on quarterly excess market returns and the scale components of aggregate labor income growth (using $j = 1, 2, 3, 4, 5, > 5$). As a benchmark, we also present the results of the classic human capital CAPM, the consumption CAPM, the ultimate consumption CAPM of Parker and Julliard (2005), the Fama and French (1993) three–factor and Fama and French (2015) five–factor models. We report time–series averages of the second–stage market prices of risk (per quarter) with Fama and MacBeth (1973) t–statistics in parentheses and error–in–variable and autocorrelation corrected t–statistics in square brackets (using Newey–West adjustments with 2^j lags). The last column reports the cross–sectional R^2 and adjusted–R^2 (in square brackets). $*, **, ***$ indicate significance at the 10%, 5%, and 1% level, respectively, based on the adjusted t–statistics. The sample period runs from 1963Q3 until 2017Q4.

	λ_0	λ_{mkt}	$\lambda_l^{(1)}$	$\lambda_l^{(2)}$	$\lambda_l^{(3)}$	$\lambda_l^{(4)}$	$\lambda_l^{(5)}$	$\lambda_l^{(j>5)}$	λ_l	λ_c	λ_{uc}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	R^2
All	0.0169	−0.0036	0.0008	0.0006	0.0009	−0.0020**	−0.0006	−0.0006								0.79
	(2.21)	(-0.36)	(0.97)	(1.18)	(2.36)	(-4.02)	(-1.25)	(-0.66)								[0.76]
	[1.52]	[-0.28]	[0.70]	[0.86]	[1.24]	[-2.34]	[-0.75]	[-0.40]								
$j = 1$	0.0260*	−0.0072	0.0043*													0.29
	(3.10)	(-0.69)	(2.79)													[0.26]
	[1.81]	[-0.47]	[1.81]													
$j = 2$	0.0186	0.0009		0.0044												0.25
	(2.14)	(0.08)		(3.43)												[0.21]
	[0.95]	[0.05]		[1.51]												
$j = 3$	0.0353**	-0.0145			0.0022*											0.26
	(4.17)	(-1.42)			(3.53)											[0.22]
	[2.30]	[-0.92]			[1.88]											
$j = 4$	0.0180	-0.0044				−0.0022*										0.72
	(2.08)	(-0.41)				(-3.97)										[0.71]
	[1.41]	[-0.31]				[-1.94]										
$j = 5$	0.0320***	−0.0110					0.0014*									0.12
	(3.88)	(-1.11)					(2.08)									[0.08]
	[3.08]	[-0.92]					[1.84]									
$j > 5$	0.0316***	−0.0100						0.0024								0.06
	(3.39)	(-0.93)						(1.67)								[0.02]
	[3.06]	[-0.85]						[1.54]								
human capital CAPM	0.0309***	-0.0095							0.0038							0.10
	(3.66)	(-0.94)							(1.91)							[0.07]
	[2.68]	[-0.76]							[1.62]							
CCAPM	0.0183**									0.0006						0.01
	(2.37)									(0.32)						[-0.01]
	[2.35]									[0.32]						
Ultimate CCAPM	0.0034										0.0406*					0.38
	(0.47)										(2.80)					[0.37]
	[0.31]										[1.75]					
FF3	0.0291***	-0.0140										0.0064	0.0136***			0.76
	(3.69)	(-1.39)										(1.50)	(3.02)			[0.75]
	[3.35]	[-1.32]										[1.49]	[3.00]			
FF5	0.0144	−0.0001										0.0073	0.0121***	0.0058	0.0092***	0.79
	(1.47)	(-0.00)										(1.74)	(2.73)	(1.25)	(2.82)	[0.76]
	[1.10]	[-0.00]										[1.54]	[2.68]	[1.09]	[2.75]	

Table 7. Cross–sectional regressions for 55 combined 25 size–BM and 30 industry portfolios (multivariate betas). This table reports the second–stage cross–sectional regression results for different model specifications using aggregate labor income growth rates and a combination of 25 double–sorted size–BM and 30 industry portfolios as test assets. In particular, we consider the following specification (and subsets thereof):

$$\mathbb{E}[R^{e,i}_{t+1}] = \lambda_0 + \hat{\beta}_{mkt,i}\lambda_{mkt} + \sum_{j=1}^{5} \hat{\beta}^{(j)}_{l,i}\lambda^{(j)}_l + \hat{\beta}^{(j>5)}_{l,i}\lambda^{(j>5)}_l + \alpha_i.$$

Here $\hat{\beta}_{mkt,i}$, $\hat{\beta}^{(j)}_{l,i}$, and $\hat{\beta}^{(j>5)}_{l,i}$ are the estimated first–stage component–wise betas obtained from a multivariate quarterly time–series regressions of quarterly excess returns of portfolio i on quarterly excess market returns and the scale components of aggregate labor income growth (using $j = 1, 2, 3, 4, 5, > 5$). As a benchmark, we also present the results of the classic human capital CAPM, the consumption CAPM, the ultimate consumption CAPM of Parker and Julliard (2005), the Fama and French (1993) three–factor and Fama and French (2015) five–factor models. We report time–series averages of the second–stage market prices of risk (per quarter) with Fama and MacBeth (1973) t-statistics in parentheses and error–in–variable and autocorrelation corrected t–statistics in square brackets (using Newey–West adjustments with 2^j lags). The last column reports the cross–sectional R^2 and adjusted–R^2 (in square brackets). $*, **, ***$ indicate significance at the 10%, 5%, and 1% level, respectively, based on the adjusted t–statistics. The sample period runs from 1958Q2 until 2017Q4.

	λ_0	λ_{mkt}	$\lambda^{(1)}_l$	$\lambda^{(2)}_l$	$\lambda^{(3)}_l$	$\lambda^{(4)}_l$	$\lambda^{(5)}_l$	$\lambda^{(j>5)}_l$	λ_l	λ_c	λ_{uc}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	R^2
All	0.0220**	−0.0045	−0.0015	0.0013	0.0001	−0.0011**	0.0005	0.0005								0.47
	(2.93)	(-0.47)	(-2.09)	(1.67)	(0.43)	(-2.65)	(1.07)	(0.59)								[0.40]
	[2.32]	[-0.41]	[-1.24]	[1.35]	[0.37]	[-1.97]	[0.89]	[0.43]								
$j = 1$	0.0206***	0.0002	0.0003													0.01
	(2.82)	(0.03)	(0.39)													[-0.03]
	[2.81]	[0.03]	[0.39]													
$j = 2$	0.0213**	−0.0009		0.0012												0.13
	(2.90)	(-0.10)		(1.77)												[0.09]
	[2.42]	[-0.09]		[1.40]												
$j = 3$	0.0202***	0.0008			0.0001*											0.00
	(2.90)	(0.09)			(0.14)											[-0.03]
	[2.89]	[0.09]			[0.14]											
$j = 4$	0.0191	-0.0019				−0.0012*										0.36
	(2.67)	(-0.21)				(-3.22)										[0.33]
	[2.11]	[-0.18]				[-1.93]										
$j = 5$	0.0223***	−0.0019					0.0007									0.07
	(3.15)	(-0.21)					(1.75)									[0.03]
	[2.95]	[-0.20]					[1.61]									
$j > 5$	0.0202***	0.0008						0.0001								0.00
	(2.83)	(0.08)						(0.08)								[-0.04]
	[2.83]	[0.08]						[0.08]								
human capital CAPM	0.0210***	-0.0000							0.0003							0.00
	(2.74)	(-0.00)							(0.22)							[-0.04]
	[2.73]	[-0.00]							[0.21]							
CCAPM	0.0255***									-0.0003						0.00
	(3.91)									(-0.25)						[-0.01]
	[3.90]									[-0.25]						
Ultimate CCAPM	0.0199***										0.0033					0.01
	(3.39)										(0.45)					[-0.01]
	[3.37]										[0.44]					
FF3	0.0295***	-0.0122										0.0056	0.0081*			0.36
	(4.05)	(-1.33)										(1.41)	(1.92)			[0.33]
	[3.85]	[-1.29]										[1.41]	[1.91]			
FF5	0.0246***	−0.0097										0.0068	0.0072	0.0021	0.0084	0.40
	(3.35)	(-0.99)										(1.60)	(1.53)	(0.42)	(1.44)	[0.34]
	[3.01]	[-0.92]										[1.60]	[1.54]	[0.40]	[1.33]	

Table 8. Cross–sectional regressions for 25 size–BM portfolios - different maximum scales J. This table reports the second–stage cross–sectional regression results for different model specifications using aggregate labor income growth rates and 25 double–sorted size–BM portfolios as test assets. In particular, we consider the following specification (and subsets thereof):

$$\mathbb{E}[R^{e,i}_{t+1}] = \lambda_0 + \hat{\beta}_{mkt,i}\lambda_{mkt} + \sum_{j=1}^{J} \hat{\beta}^{(j)}_{l,i}\lambda^{(j)}_l + \hat{\beta}^{(j>J)}_{l,i}\lambda^{(j>J)}_l + \alpha_i.$$

Here $\hat{\beta}_{mkt,i}$, $\hat{\beta}^{(j)}_{l,i}$, and $\hat{\beta}^{(j>J)}_{l,i}$ are the estimated first–stage component–wise betas obtained from a multivariate time–series regression of quarterly excess returns of portfolio i on quarterly excess market returns and the scale components of aggregate labor income growth (using $j = 1, \dots, J, > J$). Panel A reports the results for $J = 4$ and panel B reports the results for $J = 6$. We report time–series averages of the second–stage market prices of risk (per quarter) with Fama and MacBeth (1973) t–statistics in parentheses and error–in–variable and autocorrelation corrected t–statistics in square brackets (using Newey–West adjustments with 2^j lags). The last column reports the cross–sectional R^2 and adjusted–R^2 (in square brackets). $*, **, ***$ indicate significance at the 10%, 5%, and 1% level, respectively, based on the adjusted t–statistics. The sample period runs from 1958Q2 until 2017Q4.

	λ_0	λ_{mkt}	$\lambda^{(1)}_l$	$\lambda^{(2)}_l$	$\lambda^{(3)}_l$	$\lambda^{(4)}_l$	$\lambda^{(5)}_l$	$\lambda^{(6)}_l$	$\lambda^{(j>4)}_l$	$\lambda^{(j>6)}_l$	R^2
Panel A: $J = 4$											
$j = 4$	0.0125	0.0032				-0.0025^{**}					0.81
	(1.35)	(0.30)				(-4.57)					[0.79]
	[0.93]	[0.22]				[-1.97]					
$j > 4$	0.0384^{***}	-0.0146							0.0031^{*}		0.13
	(3.52)	(-1.25)							(2.11)		[0.05]
	[2.82]	[-1.03]							[1.75]		
All	0.0215	-0.0056	0.0021	-0.0018	0.0006	-0.0025^{**}			0.0002		0.84
	(2.40)	(-0.53)	(1.59)	(-1.93)	(1.58)	(-5.16)			(0.18)		[0.79]
	[1.11]	[-0.28]	[0.79]	[-1.18]	[0.68]	[-2.09]			[0.07]		
Panel B: $J = 6$											
$j = 4$	0.0120	0.0032				-0.0015^{***}					0.79
	(1.22)	(0.28)				(-3.80)					[0.77]
	[1.03]	[0.25]				[-2.70]					
$j > 6$	0.0309^{***}	-0.0058								0.0001	0.02
	(3.02)	(-0.52)								(0.11)	[-0.06]
	[3.01]	[-0.52]								[0.11]	
All	0.0108	0.0051	-0.0009	-0.0001	0.0008	-0.0012^{***}	-0.0000	0.0002		-0.0013^{*}	0.83
	(1.20)	(0.47)	(-1.31)	(-0.08)	(2.24)	(-3.24)	(-0.06)	(0.35)		(-2.26)	[0.75]
	[0.98]	[0.38]	[-1.19]	[-0.07]	[1.58]	[-2.97]	[-0.05]	[0.31]		[-1.80]	

Table 9. Cross–sectional regressions for 25 size–BM portfolios (univariate betas). This table reports the second–stage cross–sectional regression results for different model specifications using aggregate labor income growth rates and 25 double–sorted size–BM portfolios as test assets. In particular, we consider the following specifications (and subsets thereof):

$$\mathbb{E}[R^{e,i}_{t+1}] = \lambda_0 + \hat{\beta}_{mkt,i}\lambda_{mkt} + \sum_{j=1}^{5} \hat{\beta}^{(j)}_{l,i}\lambda^{(j)}_l + \hat{\beta}^{(j>5)}_{l,i}\lambda^{(j>5)}_l + \alpha_i,$$

and

$$\mathbb{E}[R^{e,i}_{t+1}] = \lambda_0 + \hat{\beta}_{mkt,i}\lambda_{mkt} + \hat{\beta}^{(1:3)}_{l,i}\lambda^{(1:3)}_l + \hat{\beta}^{(4:5)}_{l,i}\lambda^{(4:5)}_l + \hat{\beta}^{(j>5)}_{l,i}\lambda^{(j>5)}_l + \alpha_i.$$

Here $\hat{\beta}^{(j)}_{l,i}$, $\hat{\beta}^{(1:3)}_{l,i}$, $\hat{\beta}^{(4:5)}_{l,i}$, and $\hat{\beta}^{(j>5)}_{l,i}$ are the estimated first–stage component–wise betas obtained from univariate quarterly time–series regressions of excess returns of portfolio i on the j–th component of aggregate labor income growth rates (with $j = 1, 2, 3, 4, 5, > 5, 1:3$, or $4:5$). Similarly, $\hat{\beta}_{mkt,i}$ denotes the estimated first–stage beta obtained from a quarterly univariate time–series regression of portfolio i's excess returns ($R^{e,i}_{t+1}$) on excess market returns. We report time–series averages of the second–stage market prices of risk (per quarter) with Fama and MacBeth (1973) t–statistics in parentheses and error–in–variable and autocorrelation corrected t–statistics in square brackets (using Newey–West adjustments with 2^j lags). The last column reports the cross–sectional R^2 and adjusted–R^2 (in square brackets). $*, **, ***$ indicate significance at the 10%, 5%, and 1% level, respectively, based on the adjusted t–statistics. The sample period runs from 1958Q2 until 2017Q4.

	λ_0	λ_{mkt}	$\lambda_l^{(1)}$	$\lambda_l^{(2)}$	$\lambda_l^{(3)}$	$\lambda_l^{(4)}$	$\lambda_l^{(5)}$	$\lambda_l^{(1:3)}$	$\lambda_l^{(4:5)}$	$\lambda_l^{(j>5)}$	R^2
All	0.0136	0.0041	0.0008	0.0012	0.0011	-0.0023^{**}	0.0002			-0.0014	0.83
	(1.62)	(0.37)	(0.69)	(1.04)	(2.56)	(-4.96)	(0.26)			(-1.61)	[0.76]
	[1.23]	[0.26]	[0.47]	[0.74]	[1.23]	[-2.47]	[0.15]			[-1.11]	
$j = 1:3$, $j = 4:5$, & $j > 5$	0.0024	0.0272						0.0037	-0.0044^{***}	-0.0007	0.71
	(0.27)	(2.41)						(2.60)	(-4.90)	(-0.81)	[0.65]
	[0.12]	[1.31]						[1.38]	[-2.84]	[-0.42]	
$j = 1$	0.0270	-0.0007	0.0043^{*}								0.23
	(2.95)	(-0.06)	(2.72)								[0.16]
	[1.68]	[-0.04]	[1.65]								
$j = 2$	0.0222	-0.0064		0.0053							0.25
	(2.46)	(-0.60)		(3.02)							[0.18]
	[0.82]	[-0.22]		[1.04]							
$j = 3$	0.0349^{**}	-0.0193			0.0015^{*}						0.10
	(3.59)	(-1.62)			(2.64)						[0.02]
	[2.37]	[-1.21]			[1.83]						
$j = 4$	0.0116	0.0142				-0.0025^{**}					0.75
	(1.25)	(1.21)				(-4.45)					[0.73]
	[0.81]	[0.83]				[-2.01]					
$j = 5$	0.0313^{***}	-0.0104					0.0006				0.02
	(3.69)	(-1.04)					(1.05)				[-0.06]
	[3.27]	[-0.98]					[0.99]				
$j = 1:3$	0.0238^{*}	-0.0084						0.0050^{*}			0.26
	(3.14)	(-0.79)						(2.86)			[0.20]
	[1.94]	[-0.55]						[1.88]			
$j = 4:5$	0.0004	0.0329							-0.0049^{**}		0.61
	(0.04)	(2.57)							(-4.69)		[0.57]
	[0.02]	[1.44]							[-2.41]		
$j > 5$	0.0344^{***}	-0.0093								0.0026^{*}	0.09
	(3.33)	(-0.85)								(1.92)	[0.01]
	[2.95]	[-0.74]								[1.66]	

Table 10. Cross–sectional regressions for 25 size–BM portfolios - real aggregate labor income growth (multivariate betas). This table reports the second–stage cross–sectional regression results for different model specifications using real aggregate labor income growth rates and 25 double–sorted size–BM portfolios as test assets. In particular, we consider the following specification (and subsets thereof):

$$\mathbb{E}[R^{e,i}_{t+1}] = \lambda_0 + \hat{\beta}_{mkt,i}\lambda_{mkt} + \sum_{j=1}^{5} \hat{\beta}^{(j)}_{l,i}\lambda^{(j)}_l + \hat{\beta}^{(j>5)}_{l,i}\lambda^{(j>5)}_l + \alpha_i.$$

Here $\hat{\beta}_{mkt,i}$, $\hat{\beta}^{(j)}_{l,i}$, and $\hat{\beta}^{(j>5)}_{l,i}$ are the estimated first–stage component–wise betas obtained from a multivariate time–series regression of quarterly excess returns of portfolio i on quarterly excess market returns and the scale components of real aggregate labor income growth (using $j = 1, 2, 3, 4, 5, > 5$). We report time–series averages of the second–stage market prices of risk (per quarter) with Fama and MacBeth (1973) t-statistics in parentheses and error–in–variable and autocorrelation corrected t-statistics in square brackets (using Newey–West adjustments with 2^j lags). The last column reports the cross–sectional R^2 and adjusted–R^2 (in square brackets). $*, **, ***$ indicate significance at the 10%, 5%, and 1% level, respectively, based on the adjusted t–statistics. The sample period runs from 1958Q2 until 2017Q4.

	λ_0	λ_{mkt}	$\lambda^{(1)}_l$	$\lambda^{(2)}_l$	$\lambda^{(3)}_l$	$\lambda^{(4)}_l$	$\lambda^{(5)}_l$	$\lambda^{(j>5)}_l$	R^2
All	0.0179	0.0020	-0.0008	-0.0012	0.0022	−0.0019*	−0.0002	-0.0010	0.53
	(1.75)	(0.17)	(-0.63)	(-1.13)	(3.88)	(-3.65)	(-0.57)	(-1.37)	[0.34]
	[0.71]	[0.07]	[-0.28]	[-0.53]	[1.48]	[-1.81]	[-0.28]	[-0.84]	
$j = 1$	0.0276***	-0.0046	0.0009						0.02
	(3.08)	(-0.45)	(0.67)						[-0.07]
	[2.98]	[-0.44]	[0.64]						
$j = 2$	0.0274**	-0.0042		0.0023					0.07
	(3.01)	(-0.40)		(2.00)					[-0.02]
	[2.12]	[-0.32]		[1.37]					
$j = 3$	0.03248	-0.0006			0.0023**				0.25
	(2.73)	(-0.06)			(3.49)				[0.18]
	[1.25]	[-0.03]			[2.07]				
$j = 4$	0.0124	0.0059				−0.0028**			0.41
	(1.39)	(0.0055)				(-3.59)			[0.36]
	[0.77]	[0.33]				[-1.99]			
$j = 5$	0.0219*	0.0019					0.0010*		0.06
	(2.25)	(0.16)					(1.88)		[-0.03]
	[1.70]	[0.13]					[1.65]		
$j > 5$	0.0333**	−0.0133						−0.0026*	0.19
	(3.29)	(-1.14)						(-2.98)	[0.12]
	[2.17]	[-0.79]						[-1.84]	

Figures

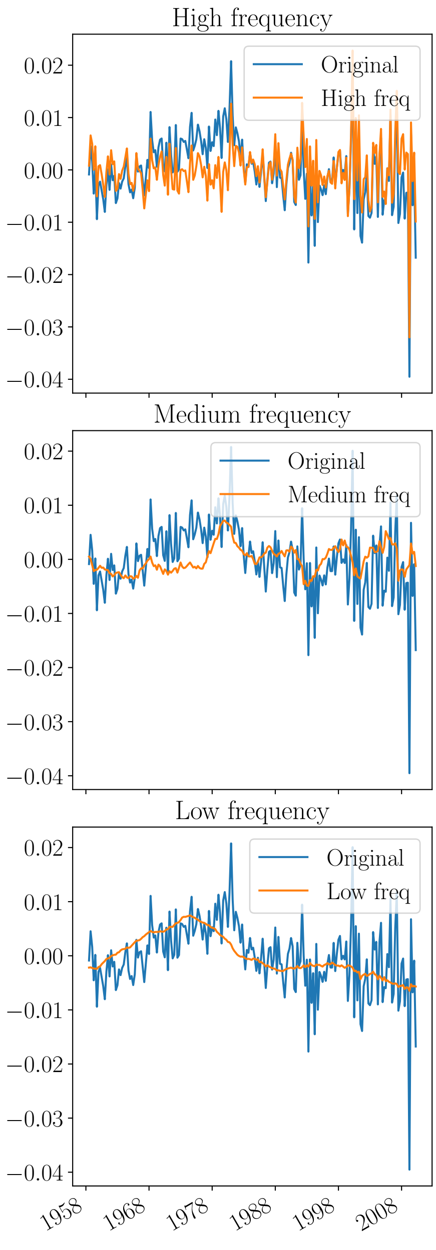

Figure 1. Aggregate labor income growth scales at different frequencies. This figure plots the quarterly aggregate labor income growth series against its high, medium, and low frequency components. The high frequency component is defined as the sum of the components at scales $j = 1, 2, 3$, and contains fluctuations with a half–life of less than 2 years. The medium frequency component is defined as the sum of the components at scales $j = 4, 5$, and contains fluctuations with a half–life of between 2 and 8 years. The low frequency component is defined as the sum of components $j > 5$, and contains fluctuations with a half–life of more than 8 years.

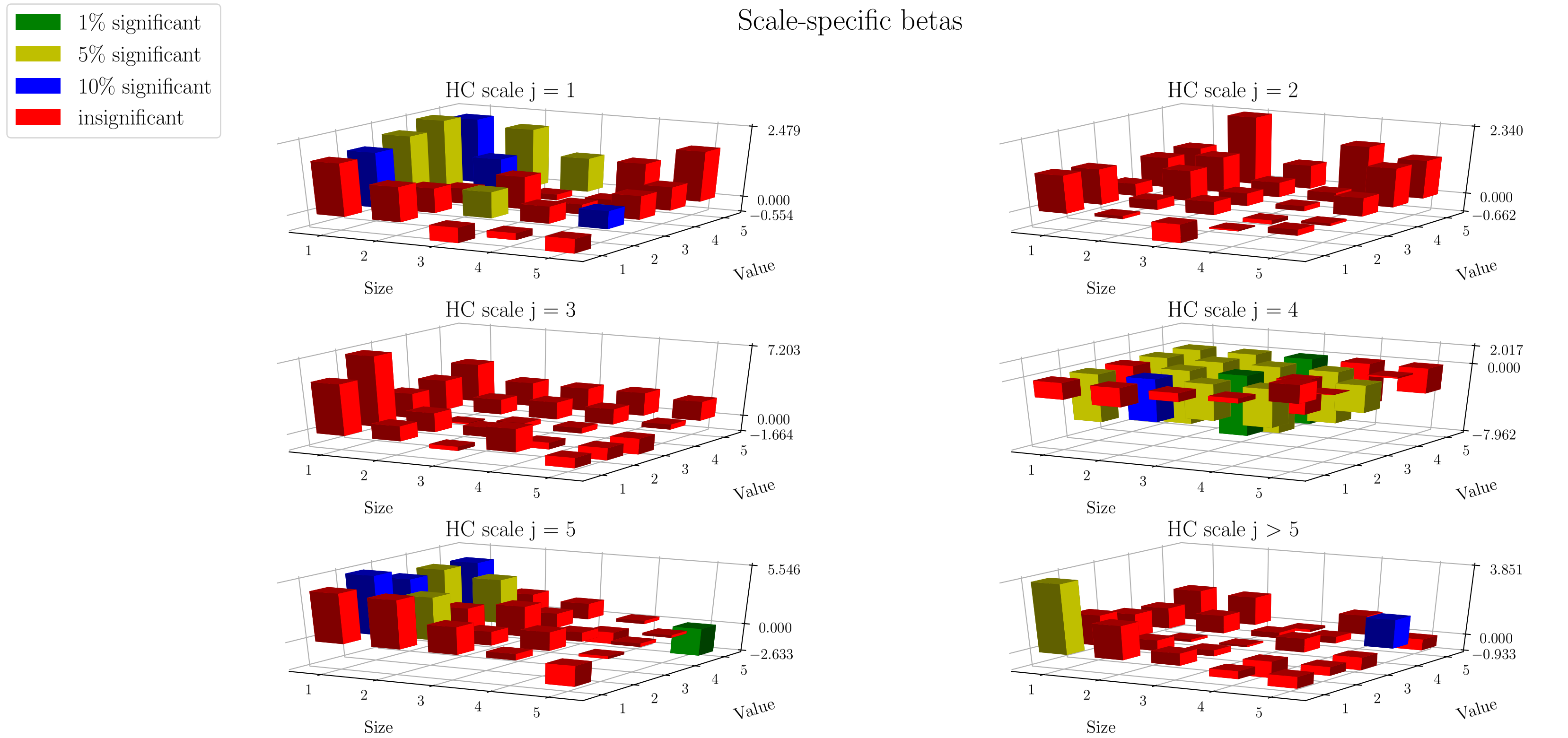

Figure 2. Scale–specific labor income risk betas 25 Size–BM portfolios. This figure displays the scale–specific betas for the 25 size–BM portfolios. The betas are obtained by running for each test portfolio i the following multivariate time series regression:

$$R_{t+1}^{e,i} = \alpha_0 + \beta_{mkt,i} R_{t+1}^{e,mkt} + \sum_{j=1}^{5} \beta_{l,i}^{(j)} f_t^{(j)} + \beta_{l,i}^{(j>5)} f^{(j>5)} + \epsilon_{i,t+1}.$$

Here, $R_t^{e,i}$ denotes portfolio i's excess return, $R_t^{e,mkt}$ the aggregate equity market excess return, and $f_t^{(j)}$ $(j = 1, 2, 3, 4, 5, j > 5)$ the aggregate labor income growth scales at different frequencies. Statistical significance is based on Newey–West adjusted standard errors using 32 lags.

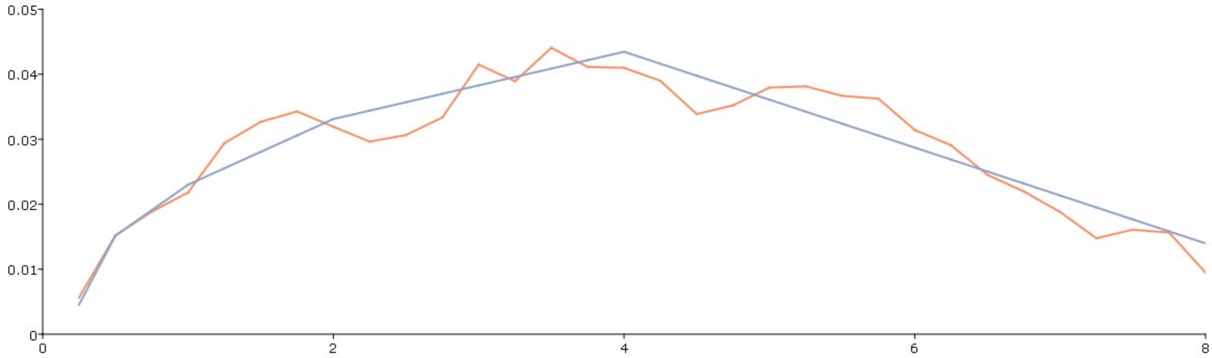

Figure 3. Impulse response of stock returns on labor income growth. This figure plots the cumulative impulse response $\sum_{i=1}^{s} \rho_{i-1}$ of aggregate labor income growth to the stock return factor as a function of the time horizon, estimated using the Bryzgalova and Julliard (2021) factor model structure given in Eqns. (28) and (29). The blue line plots the same function estimated under the restrictions that $\rho_i = \rho_h$ for $i = 2^{h-1} + 1, \ldots, 2^h$ and $h = 1, \ldots, H$. The scale on the horizontal axis is in years.