Labor Income Risk across Horizons*

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Abstract

Labor income risk displays strong horizon effects. A shock in stock returns is reflected in aggregate wages with a delay of two to four years, consistent with wage rigidity. We show that this matters for asset pricing: medium–run labor income risk at the two–to–four year horizon is a robustly priced macro risk factor. By contrast, short– and long–run labor income risk are not robustly priced. Our empirical specification follows directly from a stylized labor asset pricing model with traditional labor income risk hedging and Keeping–Up–with–the–Joneses preferences. Investors have different employment horizons, leading to horizon–specific prices of labor income risk.

Keywords: Labor and Finance; Horizon Effects; Wage Rigidity; Cross–Section of Stock Returns; Relative Wealth Preferences.

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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 factor of production and the human capital of their employees forms an important intangible asset for the firm.

Nevertheless, as is more often the case with macroeconomic risk factors, the link between labor income risk and expected stock returns is not immediately clear in the data. For example, the contemporaneous correlation between stock returns and monthly income growth is typically close to zero (e.g., Fama and Schwert, 1977; Cocco et al., 2005). There are two main reasons why non-contemporaneous, horizon effects are particularly relevant for labor income risk. First, wages are known to be sticky. With wage rigidity, due to infrequent wage setting, infrequent negotiations between workers and the firm or other labor market frictions, shocks in stock returns are reflected in labor income growth with a delay. Second, different investors have different employment horizons, which may affect their labor income risk hedging demands.

This paper shows that labor income risk displays strong horizon effects that have significant cross–sectional asset pricing implications. We find that one horizon clearly dominates: the medium two–to–four year horizon. Stock returns are predominantly exposed to labor income risk at this medium horizon. Furthermore, we show that medium–run labor income risk is a robustly priced macroeconomic risk factor, in contrast to labor income risk at short or long horizons.

We first develop a stylized labor asset pricing model that endogenously generates horizon–specific prices of labor income risk. The key feature of the model is that there are multiple cohorts of investors with different employment horizons over which they earn future labor income. Investors' portfolio decisions are affected by labor income risk through two channels: (i) their traditional labor income risk hedging demand, and (ii) a different kind of hedging demand that arises through relative wealth concerns: investors desire to hedge the risk of falling behind their peers, where aggregate labor income serves as an exogenous reference level (similar to, e.g., Gomez et al., 2009). The model allows for horizon–dependent covariances between labor income growth and stock returns. In this setting, optimal portfolio allocation decisions and expected stock returns are explicitly affected by covariances between one–period equity returns and (log) aggregate labor income growth rates across different horizons. The horizon–specific price of labor income risk depends on the aggregate wages of all investors with at least that horizon, relative to total wealth. If relative wealth preferences outweigh the traditional labor income risk hedging demand at a certain horizon, the respective price of labor income risk can become negative.

Before empirically estimating the model, we first re–express the pricing equation as a function of so–called *labor income growth strips*, using nomenclature of fixed income markets and dividend yields, that each capture labor income risk at different horizons. These strips follow from a time–series frequency decomposition of quarterly aggregate labor income growth. The approach was originally developed by Haar (1910) and further developed and applied to asset pricing in Ortu et al. (2013, 2020), Boons and Tamoni (2017), and Bandi and Tamoni (2023); we suitably adapt it to our setting. This frequency decomposition has three distinct desirable features. First, we can map our labor asset pricing model into a multi–factor specification that features labor income growth strips as separate risk factors. This yields a parsimonious representation that includes labor income risk at short, medium and long horizons and allows us to back out deep model parameters from the estimated prices of risk. Second, the strips are only weakly correlated across horizons and, third, the decomposition itself is fully nonparametric hence does not require any estimations.

Existing studies on wage rigidity show that wages are reset infrequently. For example, Rich and Tracy (2004) find that wages are reset about every three years; see also Marfe (2018), Favilukis and Lin (2016a,b), Shimer (2005) and Hall (2005). We therefore expect stock returns and wage growth to comove more strongly at this medium horizon than at shorter or longer horizons. To analyze, we first conduct an impulse response and show that the immediate impact of a common shock in stock returns on aggregate labor income growth is indeed close to zero, in line with wage rigidity. In later quarters the impact is positive and the cumulative impulse response peaks at a horizon of four years.

Then, we estimate our labor asset pricing model. Our asset pricing tests show that labor income risk at the medium two–to–four year horizon strongly dominates. We measure medium–run labor income risk using the fourth labor income growth strip, denoted by $\text{WAGE}^{(4)}$. First, we find that stock returns are significantly exposed to $\text{WAGE}^{(4)}$. Betas are statistically and economically highly significant for many different types of test portfolios. By contrast, stock returns are much less exposed to labor income risk at other horizons, with betas closer to zero and mostly insignificant.

Second, we show that labor income risk at the medium horizon, $\text{WAGE}^{(4)}$, is a significantly and robustly priced systematic risk factor, while labor income risk at other horizons is not robustly priced. The empirical performance of the medium–run labor income risk factor is strong. A simple two–factor model with equity market returns and $\text{WAGE}^{(4)}$ can explain 62% of the cross–sectional variation of 25 size book–to–market portfolios and 25 size–investment sorted portfolios. The intercept is statistically insignificant, in line with the model that is estimated using excess returns. Even when we add 30 industry equity portfolios to the set of test assets and when we use the set of 202 portfolios from Giglio and Xiu (2017) and Dello-Preite et al. (2024) as test assets, medium–term labor income risk continues to be priced and the adjusted R^2 remains relatively high at 38% in both cases.

By comparison, when we instead include quarterly labor income growth as a risk factor as in the standard human capital CAPM (Jagannathan and Wang, 1996),[1] the model performance is very different. Quarterly labor income growth is not significantly priced, the intercept is highly significant, and the model explains very little of the cross–sectional return variation with an adjusted R^2 of 6% (vs. 62%) for the 50 size–BM–investment sorted portfolios, and lower for other test assets. We note that $\text{WAGE}^{(4)}$ is based on the same underlying data series as quarterly labor income growth. Hence, the simple adjustment of measuring labor income risk over a medium–term horizon has a striking effect on the model performance. Quarterly labor income growth equals the sum of all labor strips, corresponding to all horizons. Since besides $\text{WAGE}^{(4)}$, the other strips are not significantly priced, they confound the asset pricing effect of labor income risk at the two–to–four year horizon, leading to the well–known poor performance of standard human capital CAPM.

While the medium two– to four–year horizon is similar to the three–year horizon identified

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

by Parker and Julliard (2005) for measuring ultimate consumption risk, we show that the two factors are distinct. When we add the ultimate consumption growth factor to our model, we find that it does not carry a significant price of risk, whereas the price of risk estimate for WAGE$^{(4)}$ remains unaffected. Furthermore, the correlation between the fourth strip of labor income growth, WAGE$^{(4)}$, and the fourth strip of consumption growth, denoted by CONS$^{(4)}$, is very close to zero at 0.002. In all, this suggests that the medium–term labor income risk factor is not a mere proxy for ultimate consumption risk, or *vice versa*, but rather a distinct source of priced systematic risk.

The estimated price of risk for medium–term labor income risk is negative. This is consistent with our labor asset pricing model where agents have Keeping–Up–with–the–Joneses (KUJ) preferences. In line with various asset pricing models with labor, such as Gomez et al. (2009), Gomez et al. (2016) and Kogan et al. (2020), agents want to hedge the risk of falling behind their peers and hence prefer to invest in stocks that help them keep up with macro labor income growth. When these relative wealth preferences are strong enough compared to the traditional labor income risk hedging demand at a certain horizon, the respective price of labor income risk can become negative. Using a back–of–the envelope calculation, we calibrate the KUJ parameter of our model that is implied by our price of labor income risk estimates. We find that the implied KUJ parameter is 0.92, which is close to one (i.e., the habit specification in Abel, 1990).[2]

Our results are robust when using alternative test assets, when using per capita instead of per worker labor income, when using real instead of nominal labor income growth, when using alternative classifications of the horizons and when using a different sub sample period. Finally, as an alternative measure of longer–term labor income risk, we calculate the 11–quarter ahead labor income growth rate, akin to the ultimate consumption growth measure of Parker and Julliard (2005), but applied to wages. This ultimate labor income risk measure captures total labor income risk up to three years, rather than only the medium–run labor income risk that is captured by WAGE$^{(4)}$. This makes an important difference; ultimate labor income growth is not priced in the cross–section of returns and the model has a poor fit with an adjusted R^2 of 0.8%. It confirms that

[2]A number of existing papers also empirically find a negative price of labor income risk, such as Gomez et al. (2009) who study KUJ preferences in an international setting and Gomez et al. (2016) who confirm this finding for the U.S. These papers, however, do not consider horizon effects. Maio and Min (2022) find a negative price of risk of the growth rate in hourly wages, which they link to agents' preferences over leisure.

the inclusion of unpriced labor income risk at other horizons obscures the asset pricing effects of priced medium–run labor income risk.

In sum, this paper shows that labor income risk displays strong horizon effects that have significant cross–sectional asset pricing implications. One horizon dominates: the medium two–to–four year horizon. Stock returns are predominantly exposed to labor income risk at this horizon and medium–run labor income risk is a robustly priced macro risk factor.

1.1 Related Literature

This paper relates to a growing literature of asset pricing models that allow for lower–frequency risks to affect expected stock returns. Most papers focus on consumption risk and, to the best of our knowledge, 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. Koijen et al. (2017) and Bandi and Tamoni (2023) highlight the role of consumption shocks at the business cycle frequency. Bansal and Yaron (2004), among others, show the importance of long–run consumption risk. Estimates of what constitutes the long run vary. Malloy et al. (2009) consider four to six years. Dew-Becker and Giglio (2016) derive a frequency domain decomposition of shocks to the pricing kernel and show the importance of long–run risks, i.e., beyond business cycle frequencies, for asset pricing. Further, Kamara et al. (2016) show that investors with different investment horizons can affect the frequency at which systematic risk factors are priced. We contribute to this literature by developing a model that endogenously produces different market prices of risk for each horizon of labor income growth.

Various papers study the interaction between human capital returns and stock returns, typically either focusing on short–term labor income risk (e.g., Jagannathan and Wang, 1996) or analyzing the long–term cointegration between labor income and dividends (e.g., Benzoni et al., 2007). Other papers that consider longer–term comovements between wage labor income and stock returns are Baxter and Jermann (1997), who find higher correlations using annual returns, and Storesletten et al. (2004) who find that idiosyncratic labor income risk varies countercyclically over the business cycle. Instead, our results indicate that labor income risk at the medium two–to–four year horizon plays a dominant role for asset pricing.

More generally, studies on labor and finance have developed theoretical and empirical evidence of the interplay between labor markets and asset pricing. Among many others, this includes Danthine and Donaldson (2002), Santos and Veronesi (2006), Lustig and van Nieuwerburgh (2008), Berk and Walden (2013), Belo et al. (2014), Donangelo (2014), Dittmar et al. (2016), Kuehn et al. (2017), and Donangelo et al. (2019). Several papers analyze the asset pricing effects of heterogeneity in labor income risk. For example, Eiling (2013) studies industry–specific human capital and Campbell et al. (2016) study labor income risk of high– versus low–income households. Our paper considers heterogeneity in investors' labor income risk due to different employment horizons.

Finally, relative wealth concerns have been shown to affect various aspects of household and investor behavior, such as excessive trading (Hong et al., 2014), stock selection (Bursztyn et al., 2014), job satisfaction (Card et al., 2012), homeownership satisfaction (Bellet, 2024), consumption decisions (Kuhn et al., 2011; Bertrand and Morse, 2016), consumer debt decisions (Georgarakos et al., 2014; Agarwal et al., 2019), as well as well–being and happiness (Luttmer, 2005; Dynan and Ravina, 2007).[3] Our paper shows that relative wealth concerns also play a role for the pricing of labor income risk at the medium horizon.

2 Theoretical Framework

This section develops a stylized asset pricing model in which the price of labor income risk is horizon–specific. Our model relates to the well–known human capital CAPM of Mayers (1972) and Jagannathan and Wang (1996), in which contemporaneous labor income growth occurs as a priced risk factor.[4] We deviate in two ways: (i) investors have different investment horizons over which they earn labor income, and (ii) investors have relative wealth preferences with respect to aggregate labor income. Our framework gives rise to a linear labor asset pricing model with one–period equity market excess returns and horizon–specific labor income growth as risk factors. The model is directly empirically testable. Details of the derivations are in Appendix A.

[3] See Kuchler and Stroebel (2021) for a literature review of studies on relative wealth concerns and social finance and Gomes et al. (2021) for a review of related studies in the context of household finance.

[4] In Mayers (1972), the channel relies on hedging demand induced by investors' nontraded human capital. In Jagannathan and Wang (1996), the main argument for including human capital risk as a factor is that it is part of the overall wealth portfolio.

2.1 Model Setup

We start in the spirit of Campbell and Viceira (2002), Chapter 6, by considering an individual investor who invests for h periods and whose evolution of wealth W_t is given by

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

Here, $R_{p,t+1} = R_f + x_t'(R_{t+1} - R_f)$ denotes the gross return on the investment portfolio, where R_f is the constant return on a riskless asset (which is in zero net supply), R_{t+1} is a vector of stock returns, the vector x_t denotes the proportions of wealth invested in the respective stocks at time t, and L_t denotes nontradable labor income at time t. To keep the model simple and tractable, we abstract away from intermediate consumption decisions. The main purpose of our theoretical model is to link labor income risk across different horizons to cross–sectional asset pricing. Thus, we want to show that horizon effects already arise in the simplest possible setup.

Following Abel (1990) and Galí (1994), investors in our model have "Keeping–Up–with–the–Joneses" (KUJ) preferences and care about their wealth relative to their peers. The wealth of one's peers is typically not directly observable. Therefore, we use as an exogenous reference level the general standard of living in the economy, proxied by aggregate labor income, following Gomez et al. (2009) and Gomez et al. (2016).[5] The investor maximizes the utility of her h–period terminal wealth W_{t+h} relative to aggregate labor income $\bar{L}_{t+h}$,

$$U(W_{t+h}) = \mathbb{E}_t \left[\left(\frac{W_{t+h}}{\bar{L}^{\psi}_{t+h}} \right)^{1-\gamma} \right] / (1-\gamma), \tag{2}$$

where $\gamma > 0$ denotes the relative risk aversion coefficient, and where ψ measures the strength of the KUJ effect: for $\psi = 0$, there are no KUJ effects and we obtain the standard CRRA function defined over terminal wealth, whereas for $\psi = 1$ we scale terminal wealth by aggregate labor income $\bar{L}_{t+h}$,

[5] Similar to Abel (1990), we use exogenous KUJ preferences and a utility function that is multiplicative in the reference level. This has some advantages over an additive specification; see Bilsen et al. (2020) and the references therein for further details. Models with endogenous KUJ preferences include, for instance, DeMarzo et al. (2004) and DeMarzo et al. (2008). The model of Campbell and Cochrane (1999) specifies an external habit based on past aggregate consumption.

consistent with Abel (1990). $\mathbb{E}_t$ denotes the expectation conditional upon information at time t. The reference level $\bar{L}_{t+h}$ is determined by all investors who earn labor income at time $t+h$.

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 for an investor with horizon h, initial wealth $W_{t,(h)}$ and current labor income $L_{t,(h)}$ to be

$$\begin{aligned} x_{t,(h)} = \; & \frac{W_{t,(h)} + hL_{t,(h)}}{W_{t,(h)}} \frac{1}{\gamma} \mathrm{Var}(r_{t+1})^{-1} \left(\mathbb{E}_t[r_{t+1}] + \frac{1}{2}\sigma^2 - r_f \right) \\ & + \left(1 - \frac{1}{\gamma}\right) \mathrm{Var}(r_{t+1})^{-1} \left[\psi \frac{W_{t,(h)} + hL_{t,(h)}}{W_{t,(h)}} \mathrm{Cov}_t(r_{t+1}, \bar{l}_{t+h}) - \frac{L_{t,(h)}}{W_{t,(h)}} \sum_{i=1}^{h} \mathrm{Cov}_t(r_{t+1}, l_{t+i,(h)}) \right], \end{aligned} \tag{3}$$

where $r_f = \log(R_f)$, $r_{t+1} = \log(R_{t+1})$, σ^2 denotes the diagonal of the variance–covariance matrix $\mathrm{Var}(r_{t+1})$, $l_{t+i,(h)} = \log\left(L_{t+i,(h)}\right)$ is the log of the labor income at time $t+i$ of the investor who has horizon h at time t, and $\bar{l}_{t+h} = \log\left(\bar{L}_{t+h}\right)$ is log aggregate labor income at time $t+h$.

The first term in Eqn. (3) can be recognized as the standard speculative demand arising from CRRA portfolio optimization. The second term in Eqn. (3) denotes the portfolio adjustment induced by labor income risk. This term itself consists of two parts. The first part, which depends on the covariance with aggregate labor income growth,[6] arises because of the KUJ utility specification. Investors want to hedge the risk of falling behind aggregate labor income growth by investing in stocks that are positively exposed to aggregate labor income growth. The second part is the traditional 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 her optimal portfolio holdings and prefers stocks that are negatively exposed to labor income growth.

We now show the implications of the optimal portfolio choice rule (3) for equilibrium asset prices. To simplify, we assume that the covariance between individual investor labor income growth and stock returns at a given horizon is the same as the covariance between aggregate labor income growth and stock returns at that horizon. This implies that the equilibrium pricing equation only includes aggregate labor income growth and not individual labor income growth rates.[7] Further, to obtain an

[6]The conditional covariance between returns and log future labor income equals the conditional covariance between returns and log labor income growth, as covariances are insensitive to subtracting a constant.

[7]Allowing for more heterogeneity, for example by allowing the covariance between labor income growth and stock

unconditional asset pricing equation, we assume stationarity such that conditional expectations and covariances between returns and labor income growth can be replaced by unconditional expectations and covariances.

Now, let there be at any time t, H cohorts of investors with investment horizons $h = 1, \ldots, H$, current wealth $W_{(h)}$, and current labor income $L_{(h)}$.[8] Aggregating the asset demands from Eqn. (3) under the stated assumptions over all cohorts and rewriting (see Appendix A) gives the following asset pricing equation:

$$\mathbb{E}[R] = r_f + \tilde{\gamma}\mathrm{Cov}(r_{t+1}, r_{\mathrm{mkt},t+1}) + \sum_{i=1}^{H} \omega_i \mathrm{Cov}\left(r_{t+1}, \bar{l}_{t+i} - \bar{l}_t\right), \tag{4}$$

with $\mathbb{E}[R] = \mathbb{E}[r_{t+1}] + \frac{1}{2}\sigma^2$ and

$$\tilde{\gamma} = \gamma \left[\frac{\sum_{h=1}^{H} W_{(h)}}{\sum_{h=1}^{H}(W_{(h)} + hL_{(h)})}\right], \quad \omega_i = (\gamma - 1)\left[\frac{\sum_{h=i}^{H} L_{(h)} - \psi(W_{(i)} + iL_{(i)})}{\sum_{h=1}^{H}(W_{(h)} + hL_{(h)})}\right]. \tag{5}$$

This pricing equation shows that aggregate labor income growth at each horizon $i \leq H$ is a separate risk factor. The price of risk for horizon i depends on the labor income of all cohorts with investment horizons $h \geq i$ and total wealth. In other words, the price of labor income risk at horizon i is not only due to those investors with horizon i, but due to all investors with a horizon of *at least* i.

Expression (5) shows that while the price of risk of the equity market risk factor, $\tilde{\gamma}$, is always positive, in our model the price of labor income risk at a specific horizon can become negative if the KUJ effects are sufficiently strong, i.e., if ψ is sufficiently large, assuming $\gamma > 1$. Note that this does not require that wage growth is bad news for the economy, but merely that investors are willing to give up expected return for stocks that have high exposures to aggregate labor income growth to hedge against the risk of falling behind. On the other hand, if the traditional hedging channel dominates, investors prefer to hold stocks with low exposures to labor income growth in order to hedge labor income risk, leading to a positive price of risk. Which of the two effects dominates at a given horizon is ultimately an empirical question.

returns to vary across industries of employment as well, would lead to too many factors.

[8]Since we assume stationarity and to avoid excess notation, we omit the subscript t.

In sum, our theoretical framework provides a stylized setting in which labor income growth at different horizons is priced and where the price of risk is horizon–specific. The key ingredients for obtaining this result are: (i) different (nonzero) covariances between stock returns and labor income growth across horizons, and (ii) multiple cohorts of investors with longer–term investment horizons (i.e., exceeding at least one period).

2.2 Labor Income Growth Strips

From an empirical perspective, it would be infeasible to include a separate labor income risk factor for every possible horizon. In addition, the partially overlapping multi–period labor income growth rates would be highly correlated. Therefore, we re-express the pricing equation as a function of *labor income growth strips* that capture horizon–specific labor income risk. To this end, we decompose the quarterly aggregate labor income growth series into different frequency components, using a HAAR decomposition (Haar, 1910). Ortu et al. (2013, 2020) show that such a decomposition holds for any weakly stationary time series; see also Boons and Tamoni (2017) and Bandi and Tamoni (2023) for asset pricing applications.

The HAAR decomposition offers three key attractive features: (i) we can map the pricing equation of our labor asset pricing model into a multi–factor model with the labor growth strips as factors. This leads to a parsimonious empirical model specification that includes a wide range of horizons with relatively few risk factors and allows us to back out deep model parameters from the estimated prices of risk. (ii) The strips are only weakly correlated across horizons, allowing us to identify more clearly which horizon(s) dominate; and (iii) the decomposition is fully nonparametric, not requiring separate estimations, and although the strips capture labor income risk at different horizons, they are still available at the quarterly frequency. The decomposition allows us to estimate horizon–specific labor betas by regressing quarterly stock returns on the various labor income growth strips. We can then estimate the model using standard two–pass regressions.

Let us denote quarterly aggregate (log) labor income growth as

$$\Delta\bar{l}_{t+1} = \bar{l}_{t+1} - \bar{l}_t, \tag{6}$$

with $\bar{l}_t$ aggregate log labor income in quarter t. Similarly, let $\Delta\bar{l}_{t+i} = \bar{l}_{t+i} - \bar{l}_{t+i-1}$. We first construct moving averages $\pi_t^{(j)}$ of length 2^j quarters as

$$\pi_t^{(j)} = \frac{1}{2^j}\sum_{i=1}^{2^j} \Delta\bar{l}_{t+i} = \left(\bar{l}_{t+2^j} - \bar{l}_t\right)/2^j, \tag{7}$$

for $j = 0, \ldots, J$.[9] Next, we define the HAAR scales, denoted by $\text{WAGE}_t^{(j)}$, as the difference between moving averages of length 2^{j-1} and 2^j, i.e.,

$$\text{WAGE}_t^{(j)} = \pi_t^{(j-1)} - \pi_t^{(j)}, \tag{8}$$

for $j = 1, \ldots, J$. Using the nomenclature of fixed income markets and dividend yields, we can interpret the different HAAR scales as labor income growth *strips*. These strips capture labor income growth allocated to each time horizon, according to its level of persistence.[10] The decomposition ensures that the (quarterly) labor income growth rate $\Delta\bar{l}_{t+1}$ equals the sum of all labor income growth strips:

$$\Delta\bar{l}_{t+1} = \sum_{j=1}^{J} \text{WAGE}_t^{(j)} + \text{WAGE}_t^{(>J)}, \tag{9}$$

where $\text{WAGE}_t^{(>J)} = \pi_t^{(J)}$. We emphasize that to decompose quarterly labor income growth into different strips, we do not need to estimate any time–series parameters. Rather, quarterly labor income growth can be re–written as a sum of differences between moving averages.

To show this more explicitly, take $J = 2$ as the maximum scale and restrict attention to labor income growth in the first quarter, $\bar{l}_{t+1} - \bar{l}_t$. We can now decompose the quarterly labor income growth into the following three strips:

$$\bar{l}_{t+1} - \bar{l}_t = \text{WAGE}_t^{(1)} + \text{WAGE}_t^{(2)} + \text{WAGE}_t^{(>2)}, \tag{10}$$

where

[9] Note that Ortu et al. (2013) and Bandi and Tamoni (2023) define the moving averages $\pi_t^{(j)}$ backwards in time. In our setting with labor income risk it is more natural to define the moving averages forwards.

[10] We note that this interpretation is particularly natural for the *forward* definition of the HAAR scales.

$$\begin{aligned}
\mathrm{WAGE}_t^{(1)} &= \pi_t^{(0)} - \pi_t^{(1)} = \left(\bar{l}_{t+1} - \bar{l}_t\right) - \frac{1}{2}\left(\bar{l}_{t+2} - \bar{l}_t\right), \\
\mathrm{WAGE}_t^{(2)} &= \pi_t^{(1)} - \pi_t^{(2)} = \frac{1}{2}\left(\bar{l}_{t+2} - \bar{l}_t\right) - \frac{1}{4}\left(\bar{l}_{t+4} - \bar{l}_t\right), \\
\mathrm{WAGE}_t^{(>2)} &= \pi_t^{(2)} = \frac{1}{4}\left(\bar{l}_{t+4} - \bar{l}_t\right).
\end{aligned}$$

The first strip, $\mathrm{WAGE}_t^{(1)}$, contains labor income growth allocated to the 1–2 quarter horizon. Similarly, the second strip, $\mathrm{WAGE}_t^{(2)}$, captures labor income growth allocated to the 2–4 quarter horizon. In general, the strip $\mathrm{WAGE}_t^{(j)}$ contains those labor income growth fluctuations with half–life in the interval of $[2^{j-1}, 2^j)$ quarters. That is, $\mathrm{WAGE}_t^{(j)}$ represents fluctuations in labor income growth that persist when averaging over 2^{j-1} quarters but not when averaging over 2^j quarters. The final strip, $\mathrm{WAGE}_t^{(>2)}$, contains those fluctuations with half–life exceeding 4 quarters.

To keep the number of risk factors in our asset pricing tests parsimonious, we set $J = 5$ in our baseline empirical analysis. This implies that $\mathrm{WAGE}_t^{(>5)}$ captures labor income growth allocated to horizons beyond 32 quarters. The mapping between the labor growth strips at scales j and their corresponding time horizons is as follows:

Time–scale	Horizon
$j = 1$	1–2 quarters
$j = 2$	2–4 quarters
$j = 3$	4–8 quarters
$j = 4$	8–16 quarters
$j = J = 5$	16–32 quarters
$j > 5$	> 32 quarters

In addition to the full model with $J + 1 = 6$ labor risk factors and the equity market factor, we also estimate two–factor specifications with only one of the labor income growth strips along with the equity market factor.

Appendix B shows how to re–write asset pricing equation (4) in terms of the labor income growth strips. The asset pricing relation can then be re–written in familiar beta form:

$$\mathbb{E}[R] = r_f + \tilde{\beta}_{\text{mkt}}\lambda_{\text{mkt}} + \sum_{j=1}^{J} \tilde{\beta}^{(j)}\lambda_l^{(j)} + \tilde{\beta}^{(>J)}\lambda_l^{(>J)}, \tag{11}$$

where the univariate exposures of the stock returns to the market returns and labor income growth strips are defined as

$$\tilde{\beta}_{\text{mkt}} = \frac{\text{Cov}(r_{t+1}, r_{\text{mkt},t+1})}{\text{Var}(r_{\text{mkt},t+1})}, \quad \tilde{\beta}^{(j)} = \frac{\text{Cov}\left(r_{t+1}, \text{WAGE}_t^{(j)}\right)}{\text{Var}(\text{WAGE}_t^{(j)})}. \tag{12}$$

The price of equity market risk is denoted by λ_{mkt} and is given by

$$\lambda_{\text{mkt}} = \gamma \left[\frac{\sum_{h=1}^{H} W_{(h)}}{\sum_{h=1}^{H}(W_{(h)} + hL_{(h)})}\right] \text{Var}(r_{\text{mkt}}), \tag{13}$$

where we can again see that it is always positive in our model, regardless of the strength of the KUJ effects. The price of risk of labor income growth strip j is denoted by $\lambda_l^{(j)}$ and is given by

$$\lambda_l^{(j)} = \Omega_j \text{Var}(\text{WAGE}^{(j)}), \tag{14}$$

where $\Omega_j = \sum_{s=0}^{j-1} \zeta_s$ for $j = 1, \ldots, J$ and

$$\zeta_j = 2^j \sum_{i=2^{j-1}+1}^{2^j} \omega_i, \tag{15}$$

with $\zeta_0 = \omega_1$ and where ω_i is defined in Eqn. (5). Similarly, the price of risk of the final strip equals

$$\lambda_l^{(>J)} = \Omega_{>J} \text{Var}(\text{WAGE}^{(>J)}), \tag{16}$$

where $\Omega_{>J} = \sum_{s=0}^{J} \zeta_s$.

The HAAR scales jointly inherit the properties of quarterly log labor income growth, because the sum of all HAAR scales, i.e., labor income growth strips, exactly equals quarterly log labor income growth – see Eqn. (9). Looking at the definitions of ζ_j and ω_i, one can easily show that $\Omega_j > 0$ and $\Omega_{>J} > 0$ if there are no KUJ effects and assuming $\gamma > 1$. This implies that, similar to Eqn. (4), the prices of risk of all the labor income growth strips are positive in the absence of KUJ effects but can become negative when KUJ effects are sufficiently strong. In Section 4.2.3, we use our estimated prices of labor income risk to back out the KUJ parameter ψ.

3 Data and Summary Statistics

We retrieve quarterly labor income data from the State Quarterly Table 7, which is published by the Bureau of Economic Analysis. This table provides quarterly nonfarm wages and salaries at the industry level, which we aggregate across all industries. Aggregate labor income is scaled by the average number of workers in each quarter using monthly employment data (total number of nonfarm employees, seasonally adjusted) from the Current Employment Statistics survey, published by the Bureau of Labor Statistics. As a robustness test, we also scale labor income by population. The full sample period runs from 1963Q3 until 2020Q4 and we consider a shorter sub sample period as well.

As excess stock market returns we use the value–weighted return of all CRSP stocks listed on the NYSE, AMEX, and NASDAQ minus the one-month Treasury bill rate. We test the asset pricing model and all benchmark models using three sets of test assets: (i) excess returns on 25 size and book–to–market sorted portfolios and 25 size and investment sorted portfolios, (ii) we add 30 industry equity portfolios to the original set of 50 portfolios, and (iii) excess returns on 202 portfolios including 25 size book–to–market, 25 operating profitability–investment, 25 size–momentum, 25 size–beta, 35 size–net issuance, 25 size–accruals, 25 size–variance and 17 industry portfolios. The third set of test portfolios is also used in, among others, Giglio and Xiu (2017) and Dello-Preite et al. (2024). We obtain all stock return and risk free rate data from Kenneth French's website.[11] These financial return series are all monthly, which we convert to quarterly excess returns by compounding the monthly excess returns within each quarter. Given that our model includes long–horizon ($j > 5$) labor income risk and our labor income data runs until 2020Q4,

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

we can include stock returns from 1963Q3 to 2013Q1.

We compare our model to several existing asset pricing models. In addition to the human capital CAPM with quarterly aggregate labor income growth as a factor, we consider the consumption CAPM and the ultimate consumption CAPM of Parker and Julliard (2005) that includes three–year ahead consumption growth. We also consider the fourth HAAR scale of quarterly consumption growth (i.e., the fourth strip of consumption growth denoted as $\text{CONS}^{(4)}$). This fourth strip corresponds to the two–to–four year horizon, which is in line with three–year ahead ultimate consumption risk. By applying the exact same frequency decomposition to consumption growth as we do to labor income growth, we can compare the two more directly. We use real (chain–weighted) per capita personal consumption expenditures on nondurable goods and services, which we obtain from the National Income and Product Accounts (NIPA). Finally, as benchmark models we also consider the Fama and French (1993) three–factor (FF3) and Fama and French (2015) five–factor (FF5) models, where the factors are again obtained from Kenneth French's website.

Table 1 provides the correlations between all risk factors that are used throughout the paper. First, the table confirms that the correlations between the different labor income growth strips are low, ranging from -0.104 to 0.170. Second, the correlations with other return–based factors are also low, ranging from -0.155 (between $\text{WAGE}^{(3)}$ and RMW) to 0.121 (between $\text{WAGE}^{(2)}$ and HML). Third, the correlations between the labor income growth strips and the different consumption–based factors are low as well. Notably, even when we apply the same frequency decomposition to consumption growth as to labor income growth, the fourth labor income growth strip and the fourth consumption growth strip display a correlation of only 0.002. Overall, 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, in the Internet Appendix Figure IA.1, we plot the original aggregate labor income growth series as well as the combined high, intermediate and low frequency strips. The figure shows that the labor income growth strips become more persistent for lower frequencies, as expected.

3.1 Dynamic Response of Wages to Shocks in Stock Returns

In this subsection, we present preliminary evidence on the dynamic relation between stock returns and future labor income growth. In the presence of wage rigidity, a shock in the stock market is expected to have a muted effect on wages in the short run and a more pronounced effect at longer horizons. We empirically analyze how a shock in stock returns is transmitted to aggregate labor income growth over time. By considering the cumulative impact of a common shock in stock returns on future labor income growth we can identify the horizon for which the impact peaks.

We use the factor model structure proposed by Bryzgalova et al. (2023) to study the dynamic relation between stock portfolio returns and future aggregate labor income growth. The model specification is as follows:

$$\Delta \bar{l}_t = \rho' \bar{X}_t + \varepsilon_t, \tag{17}$$

where the dependent variable $\Delta \bar{l}_t$ is quarterly log aggregate labor income growth, $\rho = (\rho_0, \rho_1, \ldots, \rho_S)'$ is a vector of coefficients for some integer $S \geq 0$, $\bar{X}_t = (X_t, X_{t-1}, \ldots, X_{t-S})'$ is a vector of the current and lagged latent factor, and ε_t is an error component. The latent factor X_t is assumed to have a linear relation to the stock returns:

$$r_t = \theta X_t + w_t, \tag{18}$$

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 that drives contemporaneous stock returns and, because labor income growth responds with delay, predicts contemporaneous and future labor income growth. We estimate the model on our quarterly data with $S = 31$ lags, using aggregate labor income growth as the dependent variable and the 25 size and book–to–market sorted portfolio returns as the return vector.[12]

Bryzgalova et al. (2023) develop a Bayesian method to estimate this model. Instead, we apply a Maximum Likelihood filtering method to estimate the model. We assume that the error terms

[12] Including r_t as independent variables in Eqn. (17) directly is infeasible as r_t contains 25 equity portfolios. Therefore, following Bryzgalova et al. (2023), we assume there is one common component in these stock returns, the latent variable X_t (and its lags), that predicts aggregate labor income.

are i.i.d. and normally distributed, and that ε_t and w_t are independent.

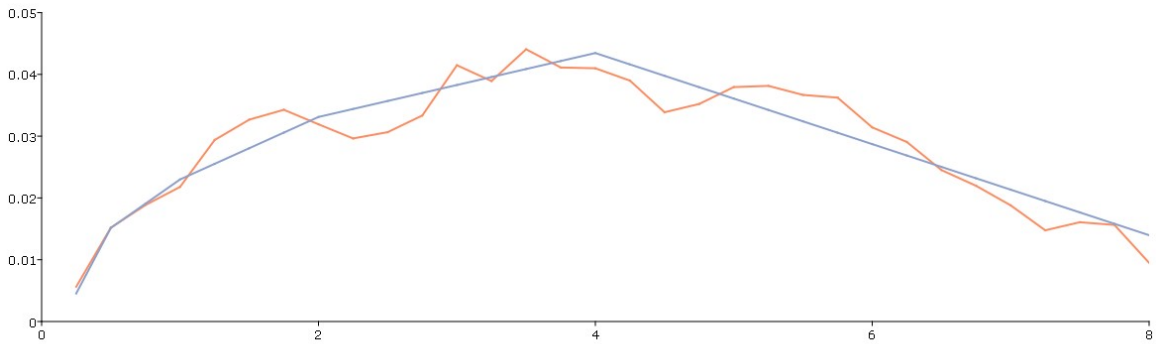

Figure 1. Impulse response of stock returns on labor income growth.
This figure plots the cumulative impulse response $\sum_{s=0}^{h-1} \rho_s$ of aggregate labor income growth $\bar{l}_{t+h} - \bar{l}_t$ to a shock in the common stock return factor X_{t+1} as a function of the time horizon h quarters, estimated using the Bryzgalova et al. (2023) factor model structure given in Eqns. (17) and (18). The blue smooth line plots the same function estimated under the restrictions that $\rho_h = \tilde{\rho}_j$ for $h = 2^{j-1}, \ldots, 2^j - 1$ and $j = 1, \ldots, 5$. The scale on the horizontal axis is in years.

Figure 1 plots the cumulative impulse response function $\sum_{s=0}^{h-1} \rho_s$, i.e., the effect of a common shock in the stock returns X_{t+1} on cumulative aggregate log labor income growth $\bar{l}_{t+h} - \bar{l}_t$ as a function of the horizon h, for $h = 1, \ldots, 32$ quarters. The immediate impact of a shock in the stock returns on labor income growth is close to zero. This is in line with wage rigidity and 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.

The 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 less uncertainty about the labor income growth rate in the short run compared to longer horizons. During the period of wage rigidity, wages are smoother than the marginal product of labor, and hence smoother than output. This can 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 co–movements between wage growth and stock returns at the three–year horizon.

Indeed, several studies find that the frequency of wage setting is about every three to four years.

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 once every three years in their production–based asset pricing model, which helps generate both smooth wages and volatile stock returns.

In sum, this analysis confirms the existence of horizon effects in the dynamic relation between stock returns and labor income growth. At the short horizon, wages are rigid and do not respond to shocks in stock returns. Only at the medium–term horizon, after approximately four years, we see the strongest impact. These results suggest that stock return exposures to labor income risk are likely more pronounced for labor income risk at the medium horizon. Whether and how horizon–specific labor income risk is priced in the cross–section of stock returns is another question, which we address in the next section.

4 Empirical Results

We estimate the asset pricing equation that follows from our model, Eqn. (11), using a standard two–stage cross–sectional regression approach. As discussed in Section 2, we focus on an unconditional asset pricing model with state-independent risk exposures and prices of risk. This way, we can keep the model tractable, while still allowing for horizon–specific prices of labor income risk. As such, we obtain our beta estimates by regressing stock returns on realized labor income growth (strips) at different future horizons using data from the full sample period. This approach is similar to, among others, Parker and Julliard (2005) who regress stock returns on future (three–year ahead) consumption growth.

In the first stage, we obtain the risk exposures (betas) by running ordinary least squares time–series regressions of portfolio i excess returns on the equity market factor and the labor income growth strips:

$$R^e_{i,t+1} = \alpha_{0,i} + \beta_{\mathrm{mkt},i} R^e_{\mathrm{mkt},t+1} + \sum_{j=1}^{J} \beta_i^{(j)} \mathrm{WAGE}_t^{(j)} + \beta_i^{(>J)} \mathrm{WAGE}_t^{(>J)} + \epsilon_{i,t+1}, \tag{19}$$

where $\mathrm{WAGE}_t^{(j)}$ is the labor income growth strip corresponding to horizon j, measured at quarter t. Note that all data used for this time–series regression is at the quarterly frequency. As is common in the literature, we focus on multivariate regressions that include excess stock market returns and the labor income growth strips. The resulting multivariate betas capture the marginal exposures of equity portfolio returns to the labor income growth strips, controlling for any indirect exposure through their market betas. At the same time, the pricing equation that follows from our theoretical model is expressed in terms of univariate betas. Therefore, we will also report and discuss the univariate betas (i.e., based on a time–series regression of excess stock returns on only one labor income growth strip at a time) and corresponding cross–sectional regressions.

In the second stage, we estimate the market prices of risk by running for each time t a cross–sectional regression using the estimated betas from the first stage, i.e.,

$$R^e_{i,t+1} = \lambda_{0,t+1} + \hat{\beta}_{\mathrm{mkt},i} \lambda_{\mathrm{mkt},t+1} + \sum_{j=1}^{J} \hat{\beta}_i^{(j)} \lambda_{l,t+1}^{(j)} + \hat{\beta}_i^{(>J)} \lambda_{l,t+1}^{(>J)} + \eta_{i,t+1}, \tag{20}$$

for $t = 0, \ldots, T-1$. The estimated market prices of stock market and horizon–specific labor income risk are given by their time–series averages, i.e., $\hat{\lambda}_{\mathrm{mkt}} = \frac{1}{T}\sum_{t=1}^{T} \hat{\lambda}_{\mathrm{mkt},t}$ and $\hat{\lambda}_l^{(j)} = \frac{1}{T}\sum_{t=1}^{T} \hat{\lambda}_{l,t}^{(j)}$. Similarly, the estimate of the intercept is given by $\hat{\lambda}_0 = \frac{1}{T}\sum_{t=1}^{T} \hat{\lambda}_{0,t}$. We use standard errors that account for the fact that we use estimated betas in the second–stage regression, following Shanken (1992).

In the full model in Eqn. (20) we set the maximum scale to $J = 5$, corresponding to labor income growth allocated to six different horizons: 1–2 quarters, 3–4 quarters, 1–2 years, 2–4 years, 4–8 years, and more than eight years. We also we assess the performance of parsimonious two–factor specifications that include the equity market return and one labor income growth strip, corresponding to one specific horizon, at a time. In robustness tests in Section 5.5 we vary the maximum scale to $J = 4$ or $J = 6$ and we merge several strips.

Throughout this section, we focus on the combined set of 25 size and book–to–market and 25 size and investment sorted portfolios as test assets. Section 5.1 shows that our results are robust to broader cross–sections of 80 and of 202 different test portfolios.

4.1 Exposures to Labor Income Risk across Different Horizons

We first analyze stock return exposures to labor income growth at different horizons. Table 2 reports the estimated first–stage betas with respect to the wage strips and their corresponding t–statistics for the 25 size and book–to–market portfolios, based on Eqn. (19). Three issues stand out. First, while most individual betas are insignificant, the only exception is for $\text{WAGE}^{(4)}$, i.e., labor income risk at the two– to four–year horizon. We find that 14 out of 25 betas with respect to $\text{WAGE}^{(4)}$ are statistically significant. By sharp contrast, the other strips have very few, if any, significant betas. The Internet Appendix (Table IA.1) reports very similar results for 25 size–investment portfolios[13] and Section 5.1 shows similar results for alternative sets of test portfolios where, by far, most of the significant beta estimates are with respect to $\text{WAGE}^{(4)}$. We also conduct two Wald tests. We first test the hypothesis that all 50 betas (for the combined set of 25 size and book–to–market and 25 size–investment portfolios) with respect to a given strip are jointly equal to zero. Then, we test the null hypothesis that all 50 beta estimates for a given strip are equal to each other. Both hypotheses can be rejected at the 1% or 5% levels in all cases, as shown in the Internet Appendix. While our stylized asset pricing model cannot directly speak to patterns in betas as it takes the exposures as exogenously given, the empirically identified dominant two–to–four year horizon is consistent with the horizon of wage rigidity.

A second observation is that almost all beta estimates with respect to $\text{WAGE}^{(4)}$ are negative. At first sight, this may appear counterintuitive, given the cointegrative relation between wages and dividends shown in Benzoni et al. (2007) and the impulse response analysis in Section 3.1. However, a closer look reveals that the results are aligned. First, recall from Eqn. (9) that quarterly labor income growth equals the sum of all labor income growth strips. Hence, even if stock returns

[13] Note that in total, we estimate 300 labor income risk betas for the 50 test assets. At the 10% significance level, we would expect to find 30 significant betas by chance alone. However, in that case we would not expect the significant betas to cluster for medium–run labor income risk, as our results show.

would have positive exposures to total quarterly labor income growth, exposures to some of the strips can have different signs. Indeed, Table 2 shows that for other horizons, betas are often positive, yet less often statistically significant. Second, to a large extent, the negative betas arise due to the use of multivariate regressions that also include the equity market factor. Stock market returns themselves are highly positively exposed to medium–run labor income risk. In our data, the estimated market's exposure to $\text{WAGE}^{(4)}$ equals 4.25. This is consistent with our impulse response analysis in the previous section and in line with the intuition that especially at the medium– and longer–run horizons, stock market returns and labor income growth positively comove. Correcting for this indirect exposure through the stock market makes many of the marginal exposures (i.e., multivariate betas) negative, despite positive total exposures (i.e., univariate betas).[14] Indeed, most of the univariate betas with respect to $\text{WAGE}^{(4)}$ are positive, as is shown and discussed in more detail in the Internet Appendix, Table IA.2.

A third observation is that the labor risk betas at the medium horizon display important cross–sectional variation in the size, value and investment dimensions. Value stocks have lower beta estimates than growth stocks. Also, except for the smallest stocks, low investment (conservative) stocks have lower betas than high investment (aggressive) stocks and, for the most part, small stocks tend to have lower beta estimates than big stocks. For example, Table 2 shows that on average, across all size quintiles, the medium–term labor beta estimate for value stocks is -5.80, while the average beta estimate for growth stocks is -0.53.[15] This suggests that value stocks are more suitable for traditional labor income risk hedging, but less suitable for keeping up with aggregate labor income growth at the medium–run horizon. At the same time, growth stocks (along with large and high investment stocks) tend to have higher exposures to medium–term labor income risk and are therefore relatively more suitable to keep up with the Joneses and less attractive for traditional labor income risk hedging. One potential micro foundation that is in line with these cross–sectional patterns in labor betas comes from Kogan et al. (2020). In their general equilibrium model, growth

[14] Multivariate betas can be mapped into univariate betas using: $\beta_i^{(4)} = \tilde{\beta}_i^{(4)} - \tilde{\beta}_{\text{mkt}}^{(4)} \beta_{\text{mkt},i}$, where $\tilde{\beta}_i^{(4)}$ is the univariate beta of portfolio i with respect to $\text{WAGE}^{(4)}$, $\beta_i^{(4)}$ and $\beta_{\text{mkt},i}$ are the multivariate betas of portfolio i with respect to $\text{WAGE}^{(4)}$ and excess stock market returns, respectively, and $\tilde{\beta}_{\text{mkt}}^{(4)}$ is the exposure of the excess stock market returns themselves to the fourth labor income strip.

[15] The cross–sectional spread in univariate betas is very similar, as can be seen in Table IA.2.

stocks are more exposed to technological innovation and displacement risk than value stocks, which makes growth stocks attractive for investors with concerns over relative consumption. In line with our medium–term horizon, Kogan et al. (2020) find, both in their model and using annual data, that the negative correlation between the rate of innovation and the value factor HML is more pronounced at the three–year horizon, compared to shorter horizons.[16]

Interestingly, the cross–sectional patterns in betas are opposite for labor income risk at shorter horizons. We find that value stocks have relatively higher exposures to labor income growth at the one quarter up to one year horizon (i.e., $j = 1, 2$) than growth stocks. This suggests that growth stocks are relatively more suitable for hedging short–term labor income risk, in line with Cronqvist et al. (2015), Addoum et al. (2019) and Betermier et al. (2017). However, we also find that at the short horizon, labor betas are mostly insignificant.

4.2 Cross–Sectional Asset Pricing Tests

The results discussed in the previous subsection reveal that, both in terms of economic and statistical significance, labor risk betas peak for $\text{WAGE}^{(4)}$, consistent with the horizon of wage rigidity. This subsection shows that labor income risk labor income growth at this two– to four–year horizon also dominates in terms of asset pricing implications.

4.2.1 The Price of Labor Income Risk across Different Horizons

Table 3 Panel A reports the estimated prices of labor income risk at different horizons resulting from the second–stage cross–sectional regressions of Eqn. (20). All model specifications contain an intercept term and the equity market risk factor. In the full model specification, in which we include labor income risk across all different horizons (i.e., all six strips corresponding to the maximum scale $J = 5$), the 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 $\hat{\lambda}_l^{(4)}$ is -0.0023, which is significant at the 5% level based on error–in–variable (EIV) corrected t–statistics and at the 1% level based on Fama–MacBeth t–statistics. Labor income risk at other horizons does not carry a significant

[16]See also Garleanu et al. (2012) for a link between growth stocks, innovation and displacement risk in an overlapping generations model.

price of risk. As the model is estimated using excess returns, the intercept should be statistically insignificant, which is the case when considering EIV corrected t–statistics. The cross–sectional adjusted R^2 is 70.4% for the combined set of 25 size–BM and 25 size–investment sorted portfolios.

The full model includes all six labor strips plus the equity market return factor. This allows us to let the data speak on which horizon matters most for the pricing of labor income risk. Next, we reduce the number of factors by considering various two–factor specifications that include the equity market risk factor and one labor income strip corresponding to labor income risk at one specific horizon.

The two–factor specifications confirm that labor income risk at the two– to four–year horizon dominates. The price of risk is highly significant and the point estimate is very similar to that in the full model (again -0.0023). By contrast, for all other horizons except for one, labor income risk does not carry a significant price of risk. Only for $\text{WAGE}^{(2)}$ do we find a marginally significant price of risk, but we know from the full model specification that it loses significance once $\text{WAGE}^{(4)}$ is included as well. Further, the adjusted R^2 peaks for the two–factor specification with $\text{WAGE}^{(4)}$ at 61.7%. By comparison, the adjusted R^2s of the other two–factor specifications with labor income risk at different horizons range between -4% ($\text{WAGE}^{(3)}$ and $\text{WAGE}^{(5)}$) and 36% ($\text{WAGE}^{(2)}$). Finally, the estimate of the intercept is insignificant for the specification with $\text{WAGE}^{(4)}$ and the specification with $\text{WAGE}^{(2)}$, but not for the other two–factor specifications. We find that in all specifications, the price of equity market risk is statistically insignificant, which is a well–known result.

We next discuss the cross–sectional regressions based on univariate betas, which is in line with the specification of the asset pricing equation in Section 2 Eqn. (11). Table 3 Panel B shows that the results are very similar to those based on multivariate betas. In the full model specification including all wage strips, only the fourth strip is significantly priced. This remains the case when including only $\text{WAGE}^{(4)}$ together with the market returns. The estimated price of risk is almost identical to that in Panel A (-0.0024 versus -0.0023) and the adjusted R^2 is, by construction, the same. The negative price of risk estimate suggests that the relative wealth preferences outweigh the traditional labor income risk hedging channel at this horizon. Section 4.2.3 analyzes this more deeply by backing out the implied KUJ parameter based on the theoretical model and our empirical estimates.[17]

Based on these results, we continue with the parsimonious two–factor specification of our model that includes the equity market risk factor and $\text{WAGE}^{(4)}$, i.e., the fourth strip that captures labor income risk at the two–to–four year horizon. Next, we compare this preferred specification to a number of alternative asset pricing models, keeping in mind that this specification is selected from the full model specification with all strips.

4.2.2 Comparison to Alternative Models

First, consistent with the literature, we find the cross–sectional fit of the static CAPM to be poor. Table 4 shows that the intercept is significantly positive, the (adjusted) R^2 is very close to zero, and the market price of equity market risk is not significant. The addition of the quarterly aggregate labor income growth factor in the human capital CAPM only marginally improves the cross–sectional fit. The intercept remains positive and statistically significant, the adjusted R^2 increases from -2% to 5.6%, 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 to our preferred specification with $\text{WAGE}^{(4)}$ clearly highlights the effect of taking into account the "right" horizon of labor income risk. Replacing the contemporaneous quarterly labor income growth factor with the fourth strip of labor income growth (which is constructed nonparametrically from the same underlying series of quarterly labor income) drastically improves the adjusted R^2 from 5.6% to 61.7%. Recall from Section 2 that quarterly labor income growth equals the sum of all labor strips. When we separately include the strips in the asset pricing model, we find that only the fourth strip is robustly priced.

[17]Recall that in our theoretical model, the equity market price of risk is independent of the KUJ parameter and is always positive, even in the presence of strong KUJ effects. Indeed, we can see that the estimated market prices of risk are positive in Panel B. The implied expected excess return on the market also incorporates the market's exposure to labor income risk. Given that the market portfolio's estimated exposure to medium–run labor income risk is 4.25, this exposure to negatively priced labor income risk dampens the market risk premium. Nevertheless, when we take into account the estimated intercept, the expected excess return on the equity market portfolio implied by our estimates in Panel B is positive.

Since the other strips are not, they confound the asset pricing effect of medium–run labor income risk when using total quarterly labor income growth as a factor, in line with the well–known poor performance of the standard human capital CAPM.

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 their findings, we find that this specification greatly outperforms the traditional consumption CAPM with an adjusted R^2 of 35.1% as opposed to 3.2%. Also, while quarterly consumption growth is not significantly priced in the cross–section of returns, ultimate consumption growth carries a significant and positive price of risk.

One potential concern is that our medium–term labor income risk factor captures similar risks as ultimate consumption growth, which operates at a comparable horizon. To further analyze this, we estimate an alternative two–factor model with the equity market factor and the fourth strip of consumption growth (denoted by $\mathrm{CONS}^{(4)}$). This is similar to our preferred two–factor specification of the labor–based model, except that we replace the fourth labor income growth strip with the fourth consumption growth strip. Table 4 shows that the corresponding price of risk estimate is positive and marginally significant at the 10% level, based on the error-in-variables adjusted $t-$statistic. Besides, the positive price of risk estimate of $\mathrm{CONS}^{(4)}$ also highlights that the negative price of risk estimate of $\mathrm{WAGE}^{(4)}$ is not due to the HAAR decomposition itself, but rather signals a strong KUJ effect on the pricing of labor income risk. The cross–sectional R^2 is somewhat below what we find for our labor–based model (41.5% compared to 61.7% for $\mathrm{WAGE}^{(4)}$). Next, we add the medium–term consumption risk factors (i.e., ultimate consumption growth and $\mathrm{CONS}^{(4)}$) and quarterly consumption growth to our preferred two–factor labor model with $\mathrm{WAGE}^{(4)}$. The results are reported in the Internet Appendix, Table IA.3. All three consumption factors lose significance, while $\mathrm{WAGE}^{(4)}$ continues to be significantly priced at the 5% level. The point estimate of the price of labor risk is relatively unaffected by the inclusion of the consumption risk factors and the adjusted R^2 remains very similar as well. Combined with the finding that the price of risk estimate of $\mathrm{CONS}^{(4)}$ is positive while that of $\mathrm{WAGE}^{(4)}$ is negative, and given the low correlation between $\mathrm{WAGE}^{(4)}$ and $\mathrm{CONS}^{(4)}$ of 0.002, we conclude that the medium–term labor income risk factor WAGE$^{(4)}$ is not a mere proxy for ultimate consumption risk. The two appear to capture distinct sources of systematic risk.

Next, while our goal is not to run a horse race between the labor–based model and standard return–based multi–factor models, a comparison can be insightful as these models were designed to capture the variation in average returns across portfolios sorted on size, value and investment. We find that while the FF3 and FF5 models have a slightly better cross–sectional fit with adjusted R^2s of 71.4% and 74.9%, the difference with our labor–based model is not large. Our main model specification, which has only one macro factor WAGE$^{(4)}$ besides the equity market return, comes relatively close with an adjusted R^2 of 61.7%.[18]

4.2.3 Backing out the KUJ Parameter

To give an economic interpretation of the sign and magnitude of the estimated price of medium–run labor income risk, we turn to our labor asset pricing model of Section 2. As we estimate the exact pricing equation of the theoretical model, we can use the empirical estimates of the prices of risk to back out deep model parameters. In particular, the negative price of medium–run labor income risk implies that the Keeping–Up–with–the–Joneses preferences are sufficiently strong such that they outweigh the effects of traditional labor income risk hedging at this horizon. Below, we back out the deep model parameter ψ that captures the strength of the relative wealth preferences.

Eqns. (14) and (16) give expressions for the prices of risk in our model when we re–write the pricing equation as a function of the labor income growth strips. A key component of the price of labor income risk is ω_i (see Eqn. (5)). Assume for simplicity that $L_{(h)} \equiv L$. The expression for ω_i then reduces to

$$\omega_i = (\gamma - 1)H^{-1}(1 - i/H - \psi). \tag{21}$$

Recall Eqn. (15) and take $i = 2^j$ for all $2^{j-1} < i \leq 2^j$ such that

$$\zeta_j = 2^j \sum_{i=2^{j-1}+1}^{2^j} \omega_i = 2^{2j-1-J}(\gamma - 1)(1 - 2^{j-J} - \psi), \qquad j = 1, \ldots, J, \tag{22}$$

[18]When we add the FF3 and FF5 factors to our model, WAGE$^{(4)}$ loses significance for the 50 test baseline test portfolios (see Table IA.3), but in unreported results we find that for the 80 and 202 alternative test portfolios WAGE$^{(4)}$ remains significantly priced when we add the FF3 and FF5 factors.

with $\zeta_0 = \omega_1$. This yields model–implied values for $\Omega_j = \sum_{s=0}^{j-1} \zeta_s$, $j = 1, \ldots, J$, and $\Omega_{>J} = \sum_{s=0}^{J} \zeta_s$, given γ and ψ.

At the same time, from Eqns. (14) and (16) we can back out values for Ω_j and $\Omega_{>J}$ that are implied by our empirical estimates:

$$\Omega_j = \lambda_l^{(j)} / \mathrm{Var}\left(\mathrm{WAGE}_t^{(j)}\right), \qquad \Omega_{>J} = \lambda_l^{(>J)} / \mathrm{Var}\left(\mathrm{WAGE}_t^{(>J)}\right). \tag{23}$$

Since the pricing equation is written in terms of univariate betas, we use the price of risk estimates of of $\lambda_l^{(j)}$ and $\lambda_l^{(>J)}$ from Table 3 Panel B to back out the model parameter ψ.

Upon minimizing squared differences between the model–implied values of Ω_j (depending on γ and ψ) and their empirical counterparts using $J = 5$ and $\gamma = 10$, we find $\widehat{\psi} = 0.92$. Keeping in mind that $\psi = 0$ implies no KUJ preferences and $\psi = 1$ corresponds to the habit specification in Abel (1990), our imputed value of 0.92 reveals relatively strong KUJ preferences. This is consistent with the negative price of labor income risk that we find.

The pronounced KUJ effect is in line with Gomez et al. (2009), Gomez et al. (2016) and Kogan et al. (2020). In particular, Gomez et al. (2009) also find strong KUJ preferences, with a KUJ parameter estimate that is typically somewhat below the Abel (1990) specification. In all, strong KUJ effects imply that the desire to hedge the risk of falling behind aggregate labor income growth at the medium–run horizon is strong enough such that stocks with positive exposures to aggregate labor income growth are attractive, on aggregate. These stocks carry a lower risk premium than stocks with lower exposures to aggregate labor income growth. While the traditional labor income risk hedging channel can still be at play, the negative price of labor income risk estimates and high implied KUJ parameter indicate that on aggregate, the relative wealth preferences dominate at the medium–run horizon.

5 Robustness Tests

5.1 Alternative Test Assets

Next to the standard 25 size–BM portfolios and 25 size–investment portfolios of our main analysis, we also consider two additional sets of test assets. First, we add 30 industry portfolios to these 50 test assets. Second, we consider a set of 202 test portfolios discussed in Section 3, which are also used in, among others, Giglio and Xiu (2017) and Dello-Preite et al. (2024).

We start by examining the labor betas of these alternative sets of test assets. Table 5 summarizes the number of beta estimates that are statistically significant at at least the 10% level. The number of significant betas clearly peaks for the fourth wage strip, for each set of test portfolios. Out of the 80 test portfolios, 33 have significant beta estimates with respect to $\text{WAGE}^{(4)}$, while for the other strips, the number of significant betas ranges from 2 ($\text{WAGE}^{(2)}$) to 8 ($\text{WAGE}^{(1)}$). The bottom line reports the number of significant betas for the set of 202 test assets. This number also peaks for $\text{WAGE}^{(4)}$ at 81 significant beta estimates. For the other labor risk strips, the number ranges from 9 ($\text{WAGE}^{(2)}$) to 27 ($\text{WAGE}^{(5)}$).

Table 6 Panel A reports the cross-sectional regression results for the set of 80 portfolios. We again find that labor income risk at the medium horizon dominates: $\text{WAGE}^{(4)}$ is significantly priced, while the other strips are not. Again, the estimated price of risk is negative, in line with KUJ preferences. The cross–sectional fit when the 30 industry equity portfolios are added as test assets decreases somewhat, which is a well–known finding for many asset pricing models. However, the adjusted R^2 of 38.2% still surpasses that of all benchmark models except for the Fama and French (1993) three–factor and Fama and French (2015) five–factor models (see Internet Appendix, Table IA.4).

Table 6 Panel B shows the results for the set of 202 test portfolios. When we include all six labor income risk strips at once and when we include one strip at a time, we find that $\text{WAGE}^{(4)}$ is again significantly negatively priced at the 5% level. Different from the other sets of test portfolios, we now also find (marginally) significant estimates for the price of risk of $\text{WAGE}^{(2)}$ and $\text{WAGE}^{(>5)}$ in the full model. Therefore, we also estimate the corresponding two–factor models with only the stock market returns and these wage strips. While the price of risk estimates remain significant, in both cases the intercept is also statistically significant. Further, the adjusted R^2s are substantially lower than for the two–factor model with WAGE$^{(4)}$. Combined with our finding that WAGE$^{(2)}$ and WAGE$^{(>5)}$ are not significantly priced in the full model for other sets of test assets and that few portfolios have significant exposures to these factors, we conclude that these factors are not robustly priced, and that medium–run labor income risk continues to dominate. The Internet Appendix shows that the benchmark models with consumption have a substantially worse fit for the set of 202 test portfolios and none of the consumption risk factors are significantly priced. The price of risk estimate for the quarterly wage growth factor of the human capital CAPM is marginally significant and positive, but the adjusted R^2 is close to zero. Finally, the FF3 and FF5 models have adjusted R^2s that are only slightly higher than that of the two–factor model with WAGE$^{(4)}$.

5.2 Per Capita versus Per Worker Wage Growth

Our analysis uses per worker labor income as a basis for the labor income risk strips. As aggregate wages can be affected by a composition effect (e.g., Solon et al., 1994) and fluctuations in the size of the workforce may have a confounding effect, we also consider per capita wages for the labor risk strips. Table 7 shows that the results are similar. While the adjusted R^2 is somewhat lower, the price of medium–run labor income risk continues to be negative and highly statistically significant. The intercept is again insignificant.

5.3 Nominal versus Real Labor Income Growth

Next, we decompose nominal labor income growth (which is the basis of our main analysis) into real labor income growth and inflation, using the Personal Consumer Expenditure price deflator as reported by the Bureau of Economic Analysis. Then, we use the fourth HAAR scales of both components in our asset pricing tests, separately and together. Table 7 shows that both components matter: real labor income risk and inflation risk at the two– to four–year horizons are both significantly negatively priced in all specifications. As a benchmark, we perform a similar analysis for the Human capital CAPM and split quarterly nominal wage growth into quarterly real wage growth and inflation (see Internet Appendix Table IA.5). In contrast to the results with medium–

run components of real wage growth and inflation, when we simply take the quarterly rates, the two factors are not significantly priced based on EIV–adjusted $t-$statistics, and the cross–sectional R^2s are low.

5.4 Ultimate Labor Income Growth

We next use an alternative measure for longer–term labor income risk, based on the measure of three–year ahead ultimate consumption growth from Parker and Julliard (2005), but applied to wages. Specifically, we use the 11–quarter ahead growth rate in nominal per worker wages. Note that, different from the labor income growth strips, this measure does not extract a specific frequency but rather captures total wage growth from quarter t to quarter $t+11$. Table 7 shows that, in sharp contrast to WAGE$^{(4)}$, ultimate wage growth is not significantly priced and leads to an adjusted R^2 of only 0.8%. When we add WAGE$^{(4)}$, the adjusted R^2 increases to 60.9% and the price of risk for WAGE$^{(4)}$ is highly significant at -0.0024. These results highlight the important role of fluctuations in wage growth at the two– to four–year horizon. Adding other horizons to the measure of labor income risk, as in the ultimate labor income growth measure, confounds the asset pricing effects.

5.5 Alternative Scale Specifications

Throughout our analysis, we defined the maximum scale to be $J = 5$. As a result, we have six labor strips: five 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, increases the number of factors. 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, as a robustness test we select two alternative maximum scales of $J = 4$ and $J = 6$. The results are reported in Table IA.6 in the Internet Appendix. In both cases, the prices of risk of the $j = 4$ scale component $\text{WAGE}^{(4)}$ are significant, while for other scales it is not. This confirms that our findings are robust to the specification of the maximum scale.

Next, we merge the short–run strips and we also merge the long–run strips, to reduce the number of factors and in order to more directly compare short–, medium– and long–horizon labor income risk. To this end, we sum the first three strips into $\text{WAGE}^{(1:3)} = \text{WAGE}^{(1)} + \text{WAGE}^{(2)} + \text{WAGE}^{(3)}$ and we sum the last two strips into $\text{WAGE}^{(>4)} = \text{WAGE}^{(5)} + \text{WAGE}^{(>5)}$. We keep the fourth strip, $\text{WAGE}^{(4)}$, as is. We now run cross–sectional regressions with these three labor income growth strips combined and one at a time. The results are presented in the Internet Appendix Table IA.7. In short, medium–run labor income risk is the only factor that is consistently priced across all specifications and all test portfolios. The short–run merged strips $\text{WAGE}^{(1:3)}$ are only marginally significantly priced for the set of 50 test portfolios, but including other strips or using different test portfolios leads to insignificant coefficient estimates. The long run strip $\text{WAGE}^{(>4)}$ is significantly priced for the 202 test portfolios only (as we also discussed in Section 5.1), but this result no longer holds when using the other two sets of test assets.

5.6 Sub Sample Analysis

Finally, we re–estimate the model for the post–oil crisis period, using data only as of 1976Q1, following Welch and Goyal (2007). The results are robust: both in the full model and in the two–factor specification, $\text{WAGE}^{(4)}$ is significantly negatively priced and adjusted R^2s remain high. Other labor strips are not significantly priced (See Internet Appendix, Table IA.8).

6 Conclusion

This paper revisits the question: does labor income risk matter for expected stock returns? We bring in a novel perspective by studying horizon effects in labor income risk. Horizon effects are particularly relevant here for two reasons. First, wages are well–known to be sticky, which dampens the exposures of stock returns to short–term labor income risk. Second, different cohorts of investors have different employment horizons, generating horizon–specific portfolio adjustments and hedging demands for labor income risk.

We formalize the intuition in a stylized labor asset pricing model with multiple cohorts of investors. Our empirical results reveal one dominant horizon: labor income risk at the medium two–to–four year horizon. Stock returns are visibly more exposed to medium–run labor income risk, consistent with wage rigidity. Further, medium–run labor income risk is robustly priced across many specifications and test portfolios. By contrast, labor income risk at shorter or longer horizons is not robustly priced. The effect of measuring labor income risk over the medium horizon is strong: when we nonparametrically extract only the component of quarterly labor income growth that corresponds to the medium horizon, the cross–sectional R^2 increases from 6% to 62%, even though both are based on the same underlying data series.

Similar to several existing studies that focus on contemporaneous labor income risk (e.g., Gomez et al., 2009; Gomez et al., 2016), we find that the price of risk of medium–run labor income risk is consistently negative. This is in line with Keeping–Up–with–the–Joneses preferences that we have in our model. When we back out the deep KUJ parameter from our model using our empirical estimates, we find a value of 0.92, which is close to the value of 1 that corresponds to the specification of Abel (1990). The negative price of risk implies that, on aggregate, investors prefer to hold stocks that help hedge against the risk that they fall behind aggregate labor income growth at the medium–run horizon.

An interesting extension for future research is to empirically analyze at a more disaggregated level how the comovements between stock returns and labor income growth vary across stocks, industries, horizons, and possibly also types of labor income. This could deliver relevant further inputs for constructing portfolios that help individual investors hedge their labor income risk or that help them keep up with the labor income growth of their peers.

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Appendix

A. Model Derivations

In this Appendix, we provide the details of the derivations in our theoretical model. First, following Campbell and Viceira (2002), we derive a log–linear approximation of multi–period wealth, which we subsequently use in the portfolio optimization problem. Finally, we aggregate the resulting optimal portfolio demands over cohorts of investors with heterogeneous investment horizons to obtain our equilibrium asset pricing equation.

A.1 Log–Linearization of the Wealth Dynamics

We consider the portfolio choice at time t of an investor with horizon h, initial wealth W_t and current labor income L_t. For notational convenience, we only discuss the case of one risky asset and hence a scalar portfolio weight x_t. The generalization to multiple risky assets and a vector of portfolio weights is straightforward. The investor earns labor income until $t+h$ and her terminal wealth at horizon h can be expressed as

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

given the wealth level W_t at time t, a stream of labor income L_{t+i}, $i = 1, \ldots, h$, and with gross portfolio return in period $t+i$ given by $R_{p,t+i} = R_f + x'_{t+i-1}(R_{t+i} - R_f)$. We assume that the vector of stock returns R_{t+1} is jointly lognormal, cross–sectionally dependent and temporally conditionally uncorrelated, and that nontradable labor income L_t is lognormal as well with horizon–dependent covariance structure. Defining log returns as $r_f = \log(R_f)$ and $r_{t+1} = \log(R_{t+1})$, we can write the one–period portfolio returns as

$$R_{p,t+1} = R_f[1 + x_t(\exp(r_{t+1} - r_f) - 1)]. \tag{A.2}$$

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 $(w_t, l_{t+i}, r_{t+1} - r_f)$.[19] The first derivatives are

$$\begin{aligned} \frac{\partial w_{t+h}}{\partial w_t} &= \frac{(R_{p,t+h} \cdots R_{p,t+1})W_t}{W_{t+h}}, && \text{(A.3)} \\ \frac{\partial w_{t+h}}{\partial l_{t+i}} &= \frac{(R_{p,t+h} \cdots R_{p,t+i+1})L_{t+i}}{W_{t+h}}, && \text{(A.4)} \\ \frac{\partial w_{t+h}}{\partial (r_{t+1} - r_f)} &= \frac{x_t R_{t+1}(R_{p,t+h} \cdots R_{p,t+2})W_t}{W_{t+h}}, && \text{(A.5)} \end{aligned}$$

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

$$\frac{\partial^2 w_{t+h}}{\partial (r_{t+1} - r_f)^2} = \frac{x_t R_{t+1}(R_{p,t+h} \cdots R_{p,t+2})W_t W_{t+h} - (x_t R_{t+1}(R_{p,t+h} \cdots R_{p,t+2})W_t)^2}{W_{t+h}^2}, \quad \text{(A.6)}$$

where we use

$$\frac{\partial R_{p,t+1}}{\partial (r_{t+1} - r_f)} = \frac{\partial^2 R_{p,t+1}}{\partial (r_{t+1} - r_f)^2} = R_f x_t \exp(r_{t+1} - r_f) = x_t R_{t+1}. \quad \text{(A.7)}$$

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 $\bar{W}_{t+h} = R_f^h W_t + \sum_{j=1}^h R_f^{h-j} \mathbb{E}_t[L_{t+j}]$, we find

$$\begin{aligned} \frac{\partial w_{t+h}}{\partial w_t} &= \rho, && \text{(A.8)} \\ \frac{\partial w_{t+h}}{\partial l_{t+i}} &= \rho_i, && \text{(A.9)} \\ \frac{\partial w_{t+h}}{\partial (r_{t+1} - r_f)} &= \rho x_t, && \text{(A.10)} \\ \frac{\partial^2 w_{t+h}}{\partial (r_{t+1} - r_f)^2} &= \rho x_t - (\rho x_t)^2 = \rho x_t(1 - \rho x_t), && \text{(A.11)} \end{aligned}$$

with

$$\rho = \frac{R_f^h W_t}{\bar{W}_{t+h}} = \frac{W_t}{W_t + \sum_{j=1}^h R_f^{-j} \mathbb{E}_t[L_{t+j}]}, \quad \text{(A.12)}$$

[19] 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 x_t.

and

$$\rho_i = \frac{R_f^{h-i}\mathbb{E}_t[L_{t+i}]}{\bar{W}_{t+h}} = \frac{R_f^{-i}\mathbb{E}_t[L_{t+i}]}{W_t + \sum_{j=1}^{h} R_f^{-j}\mathbb{E}_t[L_{t+j}]}. \tag{A.13}$$

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

$$w_{t+h} = k(h) + \rho w_t + \rho x_t(r_{t+1} - r_f) + \frac{1}{2}\rho x_t(1 - \rho x_t)\mathrm{Var}(r_{t+1}) + \sum_{i=1}^{h} \rho_i l_{t+i}. \tag{A.14}$$

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 Eqn. (2) 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 $\bar{l}_{t+h} = \log\left(\bar{L}_{t+h}\right)$,

$$V(w_{t+h} - \psi\bar{l}_{t+h}) = \mathbb{E}_t[w_{t+h} - \psi\bar{l}_{t+h}] + \frac{1}{2}(1-\gamma)\mathrm{Var}_t\left(w_{t+h} - \psi\bar{l}_{t+h}\right). \tag{A.15}$$

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

Using (A.14) and with shorthand notation $\mu = \mathbb{E}_t[r_{t+1}]$ and $\sigma^2 = \mathrm{Var}(r_{t+1})$, the expectation and variance of log wealth minus ψ times labor income growth at horizon h are given by

$$\begin{aligned}\mathbb{E}_t[w_{t+h} - \psi\bar{l}_{t+h}] = k(h) + \rho w_t + \rho x_t(\mu - r_f) + \frac{1}{2}\rho x_t(1 - \rho x_t)\sigma^2 \\ + \sum_{i=1}^{h} \rho_i \mathbb{E}_t[l_{t+i}] - \psi\mathbb{E}_t[\bar{l}_{t+h}],\end{aligned} \tag{A.16}$$

and

$$\mathrm{Var}_t\left(w_{t+h} - \psi \bar{l}_{t+h}\right) = (\rho x_t)^2 \sigma^2$$
$$+ 2\rho x_t \sum_{i=1}^{h} \rho_i \mathrm{Cov}_t(r_{t+1}, l_{t+i}) - 2\rho x_t \psi \mathrm{Cov}_t(r_{t+1}, \bar{l}_{t+h}), \tag{A.17}$$

where we omitted from the expression for the variance all terms that do not depend on x_t. The derivative of the mean–variance utility V defined in (A.15) with respect to x_t then is

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

which can be simplified to

$$0 = \rho\left(\mu - r_f + \frac{1}{2}\sigma^2\right)$$
$$- \gamma\rho^2 x_t \sigma^2 + (1-\gamma)\rho\left[\sum_{i=1}^{h} \rho_i \mathrm{Cov}_t(r_{t+1}, l_{t+i}) - \psi \mathrm{Cov}_t(r_{t+1}, \bar{l}_{t+h})\right]. \tag{A.19}$$

Solving for x_t gives the optimal portfolio weight at time t for an investor with horizon h

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

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

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

With multiple assets, we can write the vector of optimal portfolio weights as

$$x_t = \frac{W_t + hL_t}{W_t}\frac{1}{\gamma}\mathrm{Var}(r_{t+1})^{-1}\left(\mu - r_f + \frac{1}{2}\sigma^2\right) + \left(1 - \frac{1}{\gamma}\right)\left[\psi\frac{W_t + hL_t}{W_t}\mathrm{Cov}_t(r_{t+1}, \bar{l}_{t+h}) - \frac{L_t}{W_t}\sum_{i=1}^{h}\mathrm{Cov}_t(r_{t+1}, l_{t+i})\right], \tag{A.22}$$

where σ^2 now denotes the diagonal of $\mathrm{Var}(r_{t+1})$. Recall that this is the optimal investment portfolio for an investor with horizon h. Hence, the optimal portfolio is a function of the investor's horizon as well as her initial wealth and current labor income, which may differ per cohort. This leads to Eqn. (3) in the main text.

A.3 Equilibrium Pricing

Next, we 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 $h = 1, \ldots, H$, current wealth $W_{t,(h)}$ and current labor income $L_{t,(h)}$. Then, from Eqn. (3), the dollar portfolio demand of cohort h is

$$W_{t,(h)}x_{t,(h)} = (W_{t,(h)} + hL_{t,(h)})\frac{1}{\gamma}\mathrm{Var}(r_{t+1})^{-1}\left(\mu - r_f + \frac{1}{2}\sigma^2\right) + \left(1 - \frac{1}{\gamma}\right)\left[\psi(W_{t,(h)} + hL_{t,(h)})\mathrm{Cov}_t(r_{t+1}, \bar{l}_{t+h}) - L_{t,(h)}\sum_{i=1}^{h}\mathrm{Cov}_t(r_{t+1}, l_{t+i,(h)})\right], \tag{A.23}$$

We 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 for a given horizon, so that

$\mathrm{Cov}_t(r_{t+1}, l_{t+i,(h)}) = \mathrm{Cov}_t(r_{t+1}, \bar{l}_{t+i})$. Furthermore, we assume stationarity which allows us to write

$$\mathrm{Cov}_t(r_{t+1}, \bar{l}_{t+i}) = \mathrm{Cov}_t(r_{t+1}, \bar{l}_{t+i} - \bar{l}_t) = \mathrm{Cov}(r_{t+1}, \bar{l}_{t+i} - \bar{l}_t) \tag{A.24}$$

for all i. The optimal portfolio equation (A.23) is in terms of conditional expectations and variances, given the information at time t. Given the assumption of stationarity, we can now replace all conditional expectations, variances and covariances by their unconditional counterparts. Furthermore, we define $\gamma_i = \mathrm{Cov}(r_{t+1}, \bar{l}_{t+i} - \bar{l}_t)$, $\mathbb{E}[R] = \mathbb{E}[r_{t+1}] + \frac{1}{2}\sigma^2$, and $\Omega = \mathrm{Var}(r_{t+1})$. Then, from Eqn. (A.23), and leaving out the now redundant time subscripts, the dollar portfolio demand of cohort h is

$$\begin{aligned} W_{(h)} x_h = {} & (W_{(h)} + hL_{(h)}) \frac{1}{\gamma} \Omega^{-1} (\mathbb{E}[R] - r_f) \\ & + \left(1 - \frac{1}{\gamma}\right) \Omega^{-1} \left[\psi (W_{(h)} + hL_{(h)}) \gamma_h - L_{(h)} \sum_{i=1}^{h} \gamma_i \right]. \end{aligned} \tag{A.25}$$

Adding this over all cohorts $h = 1, \ldots, H$ and dividing by aggregate wealth gives the aggregate portfolio weight

$$\begin{aligned} x_{\mathrm{mkt}} = {} & \frac{\sum_{h=1}^{H} (W_{(h)} + hL_{(h)})}{\sum_{h=1}^{H} W_{(h)}} \frac{1}{\gamma} \Omega^{-1} (\mathbb{E}[R] - r_f) \\ & + \left(1 - \frac{1}{\gamma}\right) \Omega^{-1} \frac{\sum_{h=1}^{H} \left[\psi (W_{(h)} + hL_{(h)}) \gamma_h - L_{(h)} \sum_{i=1}^{h} \gamma_i \right]}{\sum_{h=1}^{H} W_{(h)}}. \end{aligned} \tag{A.26}$$

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

$$\begin{aligned} \mathbb{E}[R] - r_f = {} & \gamma \frac{\sum_{h=1}^{H} W_{(h)}}{\sum_{h=1}^{H} (W_{(h)} + hL_{(h)})} \Omega x_{\mathrm{mkt}} \\ & + (\gamma - 1) \frac{\sum_{h=1}^{H} \left[L_{(h)} \sum_{i=1}^{h} \gamma_i - \psi (W_{(h)} + hL_{(h)}) \gamma_h \right]}{\sum_{h=1}^{H} (W_{(h)} + hL_{(h)})}. \end{aligned} \tag{A.27}$$

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

$$\begin{aligned}\mathbb{E}[R] - r_f = \gamma \left[\frac{\sum_{h=1}^{H} W_{(h)}}{\sum_{h=1}^{H} (W_{(h)} + hL_{(h)})} \right] \Omega x_{\text{mkt}} \\ + (\gamma - 1) \sum_{i=1}^{H} \left[\frac{\sum_{h=i}^{H} L_{(h)} - \psi(W_{(i)} + iL_{(i)})}{\sum_{h=1}^{H} (W_{(h)} + hL_{(h)})} \right] \gamma_i. \end{aligned} \tag{A.28}$$

Defining the log market portfolio return as $r_{\text{mkt},t+1} = x'_{\text{mkt}} r_{t+1}$ and recalling the definitions $\gamma_i = \text{Cov}(r_{t+1}, \bar{l}_{t+i} - \bar{l}_t)$ and $\Omega = \text{Var}(r_{t+1})$ yields Eqn. (4) in the main text.

B. Re–writing the Asset Pricing Equation in Terms of Labor Income Growth Strips

To express the pricing equation as a function of the labor income growth strips, we proceed as follows. Let $H = 2^J$ and assume that the covariances between stock returns and aggregate labor income growth are the same within each block of length 2^{j-1}, starting at $h = 2^{j-1}$ and ending at $h = 2^j$. Under this assumption, we can rewrite the pricing equation (4) in terms of the covariances between returns and the moving averages

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

with $\zeta_0 = \omega_1$ and $\zeta_j = 2^j \sum_{i=2^{j-1}+1}^{2^j} \omega_i$ for $j = 1, \ldots, J$, where ω_i is as defined in Eqn. (5). Next, we rewrite this equation in terms of the labor income growth strips:

$$\begin{aligned}\mathbb{E}[R] = r_f + \tilde{\gamma} \text{Cov}(r_{t+1}, r_{\text{mkt},t+1}) + \sum_{j=1}^{J} \Omega_j \text{Cov} \left(r_{t+1}, \text{WAGE}_t^{(j)} \right) \\ + \Omega_{>J} \text{Cov} \left(r_{t+1}, \text{WAGE}_t^{(>J)} \right), \end{aligned} \tag{B.2}$$

with $\Omega_j = \sum_{s=0}^{j-1} \zeta_s$ for $j = 1, \ldots, J$ and $\Omega_{>J} = \sum_{s=0}^{J} \zeta_s$.

Tables

Table 1. Correlation between risk factors and labor income growth strips.
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_{mkt}, SMB, HML, RMW, CMA), the quarterly labor income growth factor (WAGE), the quarterly consumption growth factor (C), the ultimate consumption growth at the three–year horizon (C_{ult}), the fourth strip of consumption growth ($\text{CONS}^{(4)}$), and all strips of labor income growth (denoted by $\text{WAGE}^{(j)}$ for scale j). The sample period for stock returns runs from 1963Q3 to 2013Q1 and the sample period for labor income growth (including the longest horizon) runs from 1963Q3 to 2020Q4.

	SMB	HML	RMW	CMA	WAGE	C	C_{ult}	$\text{CONS}^{(4)}$	$\text{WAGE}^{(1)}$	$\text{WAGE}^{(2)}$	$\text{WAGE}^{(3)}$	$\text{WAGE}^{(4)}$	$\text{WAGE}^{(5)}$	$\text{WAGE}^{(>5)}$
R_{mkt}	0.457	–0.301	–0.266	–0.417	–0.018	0.153	0.099	0.197	–0.093	0.036	0.074	0.085	0.056	–0.046
SMB	1.000	–0.118	–0.217	–0.214	0.064	0.096	0.032	0.163	–0.015	0.019	0.052	–0.038	0.119	0.064
HML		1.000	0.053	0.740	0.050	0.004	0.109	–0.035	0.038	0.121	–0.037	–0.142	–0.068	0.070
RMW			1.000	0.029	–0.187	–0.114	–0.075	–0.129	–0.057	–0.020	–0.155	–0.134	0.044	–0.146
CMA				1.000	–0.002	–0.058	0.026	–0.086	0.029	0.057	–0.031	–0.105	–0.082	0.016
WAGE					1.000	0.206	0.140	–0.002	0.642	0.344	0.259	0.323	0.233	0.475
C						1.000	0.346	0.406	0.041	0.096	0.109	–0.142	–0.016	0.280
C_{ult}							1.000	0.279	–0.016	–0.027	–0.036	–0.157	–0.156	0.450
$\text{CONS}^{(4)}$								1.000	–0.002	–0.055	–0.064	0.002	0.059	0.045
$\text{WAGE}^{(1)}$									1.000	–0.048	–0.004	0.083	0.001	–0.004
$\text{WAGE}^{(2)}$										1.000	–0.001	0.016	–0.002	–0.028
$\text{WAGE}^{(3)}$											1.000	0.160	–0.040	–0.063
$\text{WAGE}^{(4)}$												1.000	0.170	–0.104
$\text{WAGE}^{(5)}$													1.000	–0.038
$\text{WAGE}^{(>5)}$														1.000

Table 2. Exposures of 25 size–BM portfolios to labor income risk across different horizons. This table presents the time–series regression betas and t–statistics (in parentheses) of 25 size–BM portfolios based on a multivariate regression of quarterly excess returns on portfolio i on all 6 wage strips (WAGE$^{(j)}$, $j = 1, \ldots, 5$ and $j > 5$) and excess stock market returns. *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively. The sample period runs from 1963Q3 to 2013Q1 for stock returns and from 1963Q3 to 2020Q4 for labor income growth, including the longest horizon.

	Betas					t–statistics				
					Betas w.r.t. WAGE$^{(1)}$					
	Growth	BM2	BM3	BM4	Value	Growth	BM2	BM3	BM4	Value
Small	1.33	1.29	1.46	1.64	1.77*	(0.80)	(1.10)	(1.58)	(1.59)	(1.72)
2	1.00	0.63	0.27	0.79	1.03	(1.07)	(0.78)	(0.40)	(0.97)	(0.98)
3	0.24	0.59	0.64	0.21	0.69	(0.26)	(0.99)	(1.08)	(0.27)	(0.74)
4	0.52	0.30	–0.23	0.04	1.18	(0.57)	(0.50)	(–0.34)	(0.06)	(1.18)
Big	–0.10	0.43	0.16	0.55	0.83	(–0.18)	(0.97)	(0.19)	(0.41)	(0.74)
					Betas w.r.t. WAGE$^{(2)}$					
	Growth	BM2	BM3	BM4	Value	Growth	BM2	BM3	BM4	Value
Small	0.83	1.44	0.37	1.72	1.26	(0.36)	(0.76)	(0.22)	(0.98)	(0.64)
2	–0.52	0.41	1.39	1.18	2.89	(–0.34)	(0.30)	(0.90)	(0.73)	(1.38)
3	–0.94	1.17	1.14	0.79	0.95	(–0.78)	(1.03)	(0.75)	(0.49)	(0.50)
4	–0.21	0.40	0.60	0.51	1.12	(–0.14)	(0.28)	(0.39)	(0.37)	(0.62)
Big	–0.49	0.40	0.38	1.86	2.03	(–0.60)	(0.48)	(0.37)	(0.88)	(1.08)
					Betas w.r.t. WAGE$^{(3)}$					
	Growth	BM2	BM3	BM4	Value	Growth	BM2	BM3	BM4	Value
Small	5.14	5.60**	2.24	2.36	2.47	(1.59)	(1.97)	(0.91)	(0.87)	(0.79)
2	1.52	0.95	–1.37	0.72	0.21	(0.76)	(0.55)	(–0.66)	(0.30)	(0.07)
3	0.00	0.18	–0.43	–0.45	–0.28	(0.00)	(0.12)	(–0.19)	(–0.20)	(–0.10)
4	2.74	–0.79	–1.19	–0.31	0.72	(1.25)	(–0.46)	(–0.60)	(–0.18)	(0.30)
Big	0.15	–1.09	–2.34	–0.69	1.22	(0.13)	(–0.98)	(–1.53)	(–0.28)	(0.43)
					Betas w.r.t. WAGE$^{(4)}$					
	Growth	BM2	BM3	BM4	Value	Growth	BM2	BM3	BM4	Value
Small	–1.54	–4.40	–3.92	–6.69**	–6.69*	(–0.43)	(–1.36)	(–1.22)	(–2.14)	(–1.94)
2	–1.69	–3.88	–5.55**	–6.11**	–7.19**	(–0.64)	(–1.49)	(–2.22)	(–2.45)	(–2.25)
3	–0.91	–3.36*	–6.91***	–5.69**	–6.70**	(–0.43)	(–1.66)	(–3.57)	(–2.52)	(–2.36)
4	–0.18	–3.74**	–3.81**	–4.20*	–4.83*	(–0.10)	(–2.08)	(–2.02)	(–1.82)	(–1.73)
Big	1.66	–0.57	–2.78*	–0.06	–3.57	(1.22)	(–0.43)	(–1.74)	(–0.03)	(–1.53)
					Betas w.r.t. WAGE$^{(5)}$					
	Growth	BM2	BM3	BM4	Value	Growth	BM2	BM3	BM4	Value
Small	5.49	4.63	3.69	4.12	3.98	(1.57)	(1.58)	(1.30)	(1.43)	(1.19)
2	4.05	3.62*	1.09	3.20	1.84	(1.58)	(1.69)	(0.53)	(1.52)	(0.70)
3	2.14	0.32	1.46	–0.47	0.45	(0.96)	(0.18)	(0.89)	(–0.25)	(0.18)
4	0.10	1.12	0.49	–2.52	–0.47	(0.06)	(0.76)	(0.37)	(–1.46)	(–0.21)
Big	–1.92	–0.34	1.62	–1.58	–1.77	(–1.32)	(–0.33)	(1.10)	(–1.13)	(–0.68)
					Betas w.r.t. WAGE$^{(>5)}$					
	Growth	BM2	BM3	BM4	Value	Growth	BM2	BM3	BM4	Value
Small	3.91**	1.85	1.67	1.19	2.05	(2.37)	(1.26)	(1.23)	(0.87)	(1.24)
2	1.61	0.54	0.41	1.09	1.70	(1.23)	(0.46)	(0.41)	(1.04)	(1.21)
3	0.50	–0.07	0.31	0.50	0.36	(0.48)	(–0.09)	(0.41)	(0.55)	(0.27)
4	–0.52	–0.95	0.69	0.83	1.14	(–0.62)	(–1.31)	(0.95)	(1.04)	(0.92)
Big	–0.63	–0.53	–0.72	1.25	0.17	(–1.10)	(–1.03)	(–1.10)	(1.34)	(0.15)

Table 3. Cross–sectional regressions for 50 portfolios (combined 25 size–BM and 25 size–INV portfolios).
This table reports the second–stage cross–sectional regression results for different model specifications using labor income growth strips as factors and 25 size–BM portfolios and 25 size–INV portfolios as test assets, based on Eqn. (20). Panel A reports results where betas are obtained from a multivariate time–series regression of quarterly excess returns of portfolio i on quarterly excess market returns and the labor income growth strips. Panel B reports results based on univariate first–stage betas. 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 (EIV) corrected t–statistics in square brackets, which are based on Shanken (1992) in Panel A and Jagannathan and Wang (1998) in Panel B. The last column reports the cross–sectional R^2 and adjusted–R^2 (in square brackets). *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively, based on the EIV corrected t–statistics. The sample period runs from 1963Q3 to 2013Q1 for stock returns from 1963Q3 to 2020Q4 for labor income growth, including the longest horizon.

Panel A: Cross–sectional regression results using multivariate betas

	λ_0	λ_{mkt}	$\lambda_l^{(1)}$	$\lambda_l^{(2)}$	$\lambda_l^{(3)}$	$\lambda_l^{(4)}$	$\lambda_l^{(5)}$	$\lambda_l^{(>5)}$	R^2
All	0.0157	−0.0010	0.0008	0.0009	0.0009	−0.0023**	−0.0006	−0.0009	0.746
	(2.15)	(−0.11)	(0.76)	(1.77)	(2.15)	(−4.49)	(−1.21)	(−0.11)	[0.704]
	[1.23]	[−0.07]	[0.40]	[1.07]	[1.20]	[−2.26]	[−0.70]	[−0.62]	
$\text{WAGE}^{(1)}$	0.0298*	−0.0095	0.0054						0.138
	(3.70)	(−0.95)	(2.35)						[0.101]
	[1.76]	[−0.55]	[1.35]						
$\text{WAGE}^{(2)}$	0.0159	0.0035		0.0046*					0.386
	(1.79)	(0.32)		(3.71)					[0.360]
	[0.83]	[0.19]		[1.72]					
$\text{WAGE}^{(3)}$	0.0243***	−0.0014			0.0001				0.001
	(3.00)	(−0.13)			(0.25)				[−0.04]
	[3.00]	[−0.13]			[0.25]				
$\text{WAGE}^{(4)}$	0.0139	0.0013				−0.0023**			0.633
	(1.56)	(0.12)				(−3.89)			[0.617]
	[0.92]	[0.08]				[−2.24]			
$\text{WAGE}^{(5)}$	0.0262***	−0.0003					0.0003		0.006
	(3.50)	(−0.35)					(0.61)		[−0.036]
	[3.45]	[−0.35]					[0.60]		
$\text{WAGE}^{(>5)}$	0.0342***	−0.0123						0.0033	0.147
	(3.62)	(−1.14)						(2.14)	[0.111]
	[2.79]	[−0.93]						[1.56]	

Panel B: Cross–sectional regression results using univariate betas

	λ_0	λ_{mkt}	$\lambda_l^{(1)}$	$\lambda_l^{(2)}$	$\lambda_l^{(3)}$	$\lambda_l^{(4)}$	$\lambda_l^{(5)}$	$\lambda_l^{(>5)}$	R^2
All	0.0157	0.0063	0.0015	0.0010	0.0012	−0.0026**	−0.0002	−0.0013	0.746
	(2.15)	(0.64)	(1.33)	(1.87)	(2.92)	(−4.86)	(−0.36)	(−1.55)	[0.704]
	[1.15]	[0.34]	[0.65]	[1.01]	[1.39]	[−2.32]	[−0.20]	[−0.83]	
$\text{WAGE}^{(4)}$	0.0139	0.0011				−0.0024**			0.633
	(1.56)	(0.99)				(−3.78)			[0.617]
	[0.93]	[0.59]				[−2.25]			

Table 4. Cross–sectional regressions for 50 portfolios (combined 25 size–BM and 25 size–INV) - comparison with alternative asset pricing models.

This table evaluates the cross–sectional regression results of benchmark asset pricing models for quarterly excess returns on 25 size–BM and 25 size–INV equity portfolios: 1) the standard CAPM, 2) the human capital CAPM, which augments the CAPM with a quarterly aggregate labor income growth factor, 3) the classic consumption CAPM (CCAPM) with real per capita quarterly consumption growth as a factor, 4) the ultimate consumption CAPM of Parker and Julliard (2005), which uses 11–quarter ahead consumption growth as risk factor, 5) the CAPM augmented with the fourth strip of consumption growth ($\text{CONS}^{(4)}$) as risk factor, 6) the Fama and French (1993) 3–factor model, which we denote by FF3, 7) the Fama and French (2015) 5–factor model, which we denote by FF5. The cross–sectional regressions, based on multivariate betas, are estimated using the Fama and MacBeth (1973) procedure. We report the second–stage cross–sectional regression coefficients and corresponding Fama–MacBeth t–statistics in parentheses and EIV adjusted t–statistics in square brackets. *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively, based on the EIV 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_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	R^2
CAPM	0.0236^{***}	−0.0008							0.000
	(2.76)	(−0.07)							[−0.02]
	[2.76]	[−0.07]							
Human capital CAPM	0.0334^{***}	−0.0108	0.0043						0.095
	(3.76)	(−1.05)	(1.85)						[0.056]
	[2.68]	[−0.83]	[1.57]						
CCAPM	0.0176^{***}			0.0015					0.052
	(3.12)			(0.81)					[0.032]
	[2.92]			[0.76]					
Ultimate CCAPM	0.0105			0.0357^{**}					0.365
	(1.45)			(3.10)					[0.351]
	[0.97]			[2.05]					
$R_{\text{mkt}} + \text{CONS}^{(4)}$	0.0372^{**}	−0.0153		0.0031^{*}					0.438
	(4.13)	(−1.46)		(3.50)					[0.415]
	[2.17]	[−0.86]		[1.73]					
FF3	0.0304^{***}	−0.0138			0.0059	0.0127^{***}			0.732
	(3.77)	(−1.37)			(1.47)	(2.97)			[0.714]
	[3.46]	[−1.30]			[1.46]	[2.95]			
FF5	0.0101	0.0055			0.0072^{*}	0.0107^{**}	0.0070	0.0097^{***}	0.775
	(0.97)	(0.45)			(1.81)	(2.52)	(1.53)	(3.11)	[0.749]
	[0.71]	[0.35]			[1.80]	[2.48]	[1.34]	[3.01]	

Table 5. Number of significant betas.
This table presents, for each wage strip, the number of test portfolios that have significant exposures with respect to that factor. For each portfolio, the betas are estimated in one multivariate time–series regression including excess stock market returns and all six labor income growth strips. Each column presents the number of portfolios within a certain set that have a significant beta estimate with respect to that particular strip, at least at the 10% level. We consider the following ten sets of portfolios, all based on data from Kenneth French's website: 25 size and book–to–market sorted portfolios (25 SizeBM), 25 size–investment (25 SizeInv), 30 industry (30 Ind), 17 industries (17 Ind), 25 operating profitability–investment (25 OpInv), 25 size–accruals (25 SizeAccrual), 25 size–market beta (25 SizeBeta), 25 size–variance (25 SizeVar), 35 size–net share issuance (35 SizeNetIss) and 25 size–momentum (25 SizeMom) sorted portfolios. The bottom three rows report the total number of significant betas for three sets of test portfolios that we use in the cross-sectional regressions. The 202 test portfolios include 25 SizeBM, 17 Ind, 25 OpInv, 25 SizeAccrual, 25 SizeBeta, 25 SizeVar, 35 SizeNetIss and 25 SizeMom. The sample period for stock returns runs from 1963Q3 to 2013Q1 and the sample period for labor income growth (including the longest horizon) runs from 1963Q3 to 2020Q4.

	Number of significant betas with respect to each labor risk factor					
Portfolios	$\text{WAGE}^{(1)}$	$\text{WAGE}^{(2)}$	$\text{WAGE}^{(3)}$	$\text{WAGE}^{(4)}$	$\text{WAGE}^{(5)}$	$\text{WAGE}^{(>5)}$
25 SizeBM	1	0	1	14	1	1
25 SizeInv	2	0	1	14	4	3
30 Ind	5	2	3	5	2	0
17 Ind	3	0	3	3	2	1
25 OpInv	1	5	4	7	2	4
25 SizeAccrual	3	1	2	5	4	3
25 SizeBeta	1	2	2	13	1	2
25 SizeVar	1	0	0	16	6	4
35 SizeNetIss	3	1	2	13	8	5
25 SizeMom	1	0	2	10	3	3
25 SizeBM & 25 SizeInv	3	0	2	28	5	4
25 SizeBM & 25 SizeInv & 30 Ind	8	2	5	33	7	4
202 test portfolios	14	9	16	81	27	23

Table 6. Cross–sectional regressions for alternative test portfolios.
This table reports the second–stage cross–sectional regression results for different model specifications using aggregate labor income growth strips as factors, in addition to excess market returns. We use two alternative sets of test portfolios. Panel A reports results for the combined set of 25 size–BM, 25 size–INV and 30 industry portfolios. Panel B reports results for a combination of 202 portfolios from Kenneth French's website as test assets. This includes 25 size book–to–market, 25 operating profitability–investment, 25 size–momentum, 25 size–beta, 35 size–net issuance, 25 size–accruals, 25 size–variance and 17 industry portfolios. 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 (EIV) adjusted t–statistics in square brackets. The last column reports the cross–sectional R^2 and adjusted–R^2 (in square brackets). *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively, based on the EIV adjusted t–statistics.

Panel A: Cross–sectional regression results for 80 test portfolios

	λ_0	λ_{mkt}	$\lambda_l^{(1)}$	$\lambda_l^{(2)}$	$\lambda_l^{(3)}$	$\lambda_l^{(4)}$	$\lambda_l^{(5)}$	$\lambda_l^{(>5)}$	R^2
All	0.0200**	−0.0028	−0.0013	0.0008	0.0001	−0.0014**	0.0003	0.0004	0.457
	(2.89)	(−0.31)	(−1.39)	(1.01)	(0.13)	(−3.03)	(0.83)	(0.44)	[0.405]
	[2.07]	[−0.26]	[−0.97]	[0.64]	[0.08]	[−2.05]	[0.60]	[0.33]	
WAGE$^{(4)}$	0.0165*	0.0006				−0.0016**			0.397
	(2.22)	(0.06)				(−3.43)			[0.382]
	[1.65]	[0.05]				[−2.52]			

Panel B: Cross–sectional regression results for 202 test portfolios

	λ_0	λ_{mkt}	$\lambda_l^{(1)}$	$\lambda_l^{(2)}$	$\lambda_l^{(3)}$	$\lambda_l^{(4)}$	$\lambda_l^{(5)}$	$\lambda_l^{(>5)}$	R^2
All	0.0197**	−0.0029	−0.0024	0.0010*	−0.0001	−0.0015**	0.0001	0.0026**	0.506
	(3.71)	(−0.36)	(−2.79)	(2.77)	(−0.29)	(−4.03)	(0.36)	(3.80)	[0.489]
	[2.26]	[−0.27]	[−1.62]	[1.67]	[−0.17]	[−2.28]	[0.23]	[2.43]	
WAGE$^{(2)}$	0.0209**	−0.0004		0.0022***					0.106
	(3.26)	(−0.54)		(3.94)					[0.097]
	[2.37]	[−0.05]		[2.95]					
WAGE$^{(4)}$	0.0146	0.0018				−0.0019**			0.381
	(2.14)	(0.19)				(−3.87)			[0.375]
	[1.47]	[0.15]				[−2.53]			
WAGE$^{(>5)}$	0.0297***	−0.0095						0.0041**	0.244
	(5.07)	(−1.12)						(3.73)	[0.237]
	[3.50]	[−0.89]						[2.48]	

Table 7. Cross–sectional regressions using alternative definitions of medium–run labor income risk. This table reports the second–stage cross–sectional regression results for different model specifications using various risk factors and 25 size–BM portfolios and 25 size–INV portfolios as test assets. In particular, we consider for each time $t = 0, 1, \ldots, T-1$ the following specification (and subsets thereof):

$$R^e_{i,t+1} = \lambda_{0,t+1} + \hat{\beta}_{\text{mkt},i}\lambda_{\text{mkt},t+1} + \hat{\beta}_{l,i}\lambda_{l,t+1} + \hat{\beta}^{(4)}_i\lambda^{(4)}_{l,t+1} + \hat{\beta}^{(4)}_{\text{infl},i}\lambda^{(4)}_{\text{infl},t+1} + \eta_{i,t+1}.$$

Here $\hat{\beta}_{\text{mkt},i}$, $\hat{\beta}_{l,i}$, $\hat{\beta}^{(4)}_i$ and $\hat{\beta}^{(4)}_{\text{infl},i}$ 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, a labor income risk factor, the fourth strip of labor income growth and the fourth strip of inflation (or subsets thereof). 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 (EIV) corrected t–statistics, based on Shanken (1992), in square brackets. The last column reports the cross–sectional R^2 and adjusted–R^2 (in square brackets). *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively, based on the EIV corrected t–statistics. The sample period for stock returns runs from 1963Q3 to 2013Q1 and the sample period for labor income growth (including the longest horizon) runs from 1963Q3 to 2020Q4.

	λ_0	λ_{mkt}	λ_l	$\lambda^{(4)}_l$	$\lambda^{(4)}_{\text{infl}}$	R^2
WAGE$^{(4)}$	0.0139	0.0013		-0.0023^{**}		0.633
	(1.56)	(0.12)		(-3.98)		[0.617]
	[0.92]	[0.08]		[-2.24]		
WAGE PER CAPITA$^{(4)}$	0.0163	0.0008		-0.0041^{**}		0.319
	(1.90)	(0.08)		(-3.92)		[0.291]
	[1.17]	[0.05]		[-2.30]		
REALWAGE$^{(4)}$	0.0124	0.0074		-0.0026^{**}		0.272
	(1.41)	(0.67)		(-3.42)		[0.241]
	[0.81]	[0.42]		[-2.32]		
INFLATION$^{(4)}$	0.0249^{*}	-0.0058			-0.0031^{**}	0.309
	(2.91)	(-0.56)			(-3.67)	[0.279]
	[1.71]	[-0.37]			[-2.12]	
REALWAGE$^{(4)}$, INFLATION$^{(4)}$	0.0125	0.0027		-0.0011^{*}	-0.0012^{*}	0.639
	(1.44)	(0.25)		(-2.00)	(-2.10)	[0.615]
	[1.29]	[0.24]		[-1.84]	[-1.88]	
Ultimate labor income growth	0.0316^{***}	-0.0089	0.0244			0.048
	(3.38)	(-0.84)	(1.37)			[0.008]
	[3.03]	[-0.77]	[1.23]			
Ultimate labor income growth + WAGE$^{(4)}$	0.0136	0.0017	-0.0103	-0.0024^{**}		0.633
	(1.64)	(0.16)	(-0.75)	(-4.45)		[0.609]
	[0.91]	[0.11]	[-0.43]	[-2.39]		

Internet Appendix for

Labor Income Risk across Horizons

This Internet Appendix discusses the comparison of univariate and multivariate labor betas in more detail. Further, the document reports the following additional results: (1) exposures of 25 size–investment sorted portfolios to the labor income growth strips, (2) a comparison of univariate and multivariate labor income growth betas, and various robustness tests of the cross–sectional asset pricing analysis, including (3) adding WAGE$^{(4)}$ to the benchmark models as an additional factor, (4) estimating benchmark models for different sets of test portfolios, and cross–sectional regression results when (5) decomposing quarterly nominal wage growth into quarterly real wage growth and inflation, (6) using different maximum scales J, (7) merging several labor income growth strips, and (8) using a different sub sample period. This Internet Appendix also shows figures with the different frequency components of wage growth.

Univariate versus multivariate betas

To show the link between multivariate and univariate betas explicitly, we focus on a two–factor version of the model, where we include the excess market returns and WAGE$^{(4)}$. This is consistent with the cross–sectional asset pricing regressions, where we consider this parsimonious version of the model as our preferred specification. First, we re–estimate the multivariate betas for this two–factor model. As the labor income strips are by construction not highly correlated (see Table 1 in the paper), the resulting multivariate beta estimates with respect to WAGE$^{(4)}$ are very similar to those in Table 2. Panels A and B in Table IA.2 report the results.

Multivariate betas can be mapped into univariate betas using the following well–known linear relationship:

$$\beta_i^{(4)} = \tilde{\beta}_i^{(4)} - \tilde{\beta}_{\text{mkt}}^{(4)} \beta_{\text{mkt},i}, \qquad \text{(ia.1)}$$

where $\tilde{\beta}_i^{(4)}$ is the univariate beta of portfolio i with respect to WAGE$^{(4)}$, $\beta_i^{(4)}$ and $\beta_{\text{mkt},i}$ are the multivariate betas of portfolio i with respect to WAGE$^{(4)}$ and excess stock market returns, respectively, and $\tilde{\beta}^{(4)}_{\text{mkt}}$ is the exposure of the excess stock market returns themselves to the fourth labor income strip:

$$\tilde{\beta}^{(4)}_{\text{mkt}} = \text{Cov}(R^e_{\text{mkt},t+1}, \text{WAGE}^{(4)}_t)/\text{Var}(\text{WAGE}^{(4)}_t). \tag{ia.2}$$

In our data, the estimated $\tilde{\beta}^{(4)}_{\text{mkt}}$ is large and positive at 4.25. Given that the market betas are positive as well, the second term on the right–hand side of Eqn. (ia.1) can lead to negative multivariate labor betas, even if univariate labor betas are positive. Indeed, we see in Panels C and D of Table IA.2 that most of the univariate betas with respect to $\text{WAGE}^{(4)}$ are positive. Note that the univariate betas are individually less often statistically significant. However, Panel E shows that they are still jointly significantly different from zero and from each other. Also, the cross–sectional asset pricing results are very similar for univariate and multivariate betas, as discussed in Section 4.2 of the paper.

Table IA.1 Exposures of 25 size–INV portfolios to labor income risk across different horizons. Panel A presents the time–series regression betas and t–statistics (in parentheses) of 25 size–investment sorted portfolios based on a multivariate regression of quarterly excess returns on portfolio i on all 6 wage strips (WAGE$^{(j)}$, $j = 1, ..., 5$ and $j > 5$) and excess stock market returns. *,**,*** indicate significance at the 10%, 5%, and 1% levels. Panel B reports the p–values of two Wald tests on the joint significance of the joint set of 50 betas (for the 25 Size–BM and 25 Size–INV portfolios) per factor. The sample period runs from 1963Q3 to 2013Q1 for stock returns and from 1963Q3 to 2020Q4 for labor income growth, including the longest horizon.

Panel A: 25 size–INV portfolios

	Betas					t–statistics				
Betas w.r.t. WAGE$^{(1)}$										
	INV1	INV2	INV3	INV4	INV5	INV1	INV2	INV3	INV4	INV5
Small	1.57	1.36*	1.71*	1.39	1.53	(1.08)	(1.71)	(1.78)	(1.59)	(1.34)
2	0.90	0.39	0.81	0.64	0.96	(1.27)	(0.54)	(1.20)	(1.02)	(1.10)
3	–0.19	0.61	0.13	0.48	0.62	(–0.28)	(0.92)	(0.22)	(0.81)	(0.92)
4	0.59	0.00	0.11	0.13	0.34	(1.07)	(0.00)	(0.22)	(0.20)	(0.41)
Big	–0.49	0.47	–0.15	–0.39	–0.26	(–0.82)	(0.85)	(–0.28)	(–1.15)	(–0.29)
Betas w.r.t. WAGE$^{(2)}$										
	INV1	INV2	INV3	INV4	INV5	INV1	INV2	INV3	INV4	INV5
Small	2.76	1.51	0.36	1.45	–0.11	(1.28)	(0.92)	(0.20)	(0.86)	(–0.62)
2	1.90	1.53	2.09	1.58	–0.60	(1.37)	(1.10)	(1.32)	(1.05)	(–0.43)
3	1.46	1.42	–0.20	0.72	–0.44	(1.14)	(1.11)	(–0.15)	(0.62)	(–0.38)
4	0.22	0.51	–0.10	1.29	–0.93	(0.17)	(0.39)	(–0.09)	(1.07)	(–0.60)
Big	–0.05	–0.03	1.15	0.26	–1.32	(–0.04)	(–0.03)	(1.55)	(0.49)	(–1.16)
Betas w.r.t. WAGE$^{(3)}$										
	INV1	INV2	INV3	INV4	INV5	INV1	INV2	INV3	INV4	INV5
Small	6.83**	1.58	1.31	2.52	1.83	(2.08)	(0.60)	(0.49)	(1.05)	(0.69)
2	0.60	–0.01	0.84	–1.25	0.84	(0.30)	(–0.00)	(0.40)	(–0.60)	(0.46)
3	0.70	0.08	–0.44	0.32	–0.71	(0.32)	(0.04)	(–0.25)	(0.22)	(–0.41)
4	0.57	–2.00	0.42	1.87	2.77	(0.29)	(–1.27)	(0.34)	(1.45)	(1.13)
Big	–0.83	–0.31	–1.20	0.11	0.28	(–0.53)	(–0.26)	(–1.32)	(0.11)	(0.19)
Betas w.r.t. WAGE$^{(4)}$										
	INV1	INV2	INV3	INV4	INV5	INV1	INV2	INV3	INV4	INV5
Small	–3.83	–5.01*	–5.63*	–5.73*	–4.59	(–1.03)	(–1.68)	(–1.86)	(–1.95)	(–1.33)
2	–4.62*	–4.34*	–4.70*	–5.83**	–2.59	(–1.79)	(–1.83)	(–1.86)	(–2.40)	(–1.04)
3	–5.28***	–4.51**	–4.84**	–4.04**	–1.92	(–2.68)	(–2.25)	(–2.46)	(–2.10)	(–0.90)
4	–2.80	–2.67	–3.56**	–4.03**	–1.41	(–1.64)	(–1.44)	(–2.08)	(–2.30)	(–0.70)
Big	–0.61	–0.95	–0.49	0.88	2.85*	(–0.39)	(–0.78)	(–0.49)	(0.87)	(1.83)
Betas w.r.t. WAGE$^{(5)}$										
	INV1	INV2	INV3	INV4	INV5	INV1	INV2	INV3	INV4	INV5
Small	2.78	3.90	4.35	5.76**	6.05**	(0.74)	(1.35)	(1.64)	(2.03)	(1.96)
2	1.12	1.63	2.01	2.66	4.83**	(0.45)	(0.78)	(0.97)	(1.35)	(2.14)
3	0.85	0.19	–0.45	1.44	1.93	(0.37)	(0.10)	(–0.29)	(0.89)	(0.96)
4	–0.47	–0.81	0.41	–0.36	0.55	(–0.27)	(–0.53)	(0.30)	(–0.28)	(0.35)
Big	–0.03	–0.75	–0.55	–1.73*	–0.72	(–0.02)	(–0.62)	(–0.56)	(–1.94)	(–0.48)
Betas w.r.t. WAGE$^{(>5)}$										
	INV1	INV2	INV3	INV4	INV5	INV1	INV2	INV3	INV4	INV5
Small	2.45	1.34	1.08	2.16	2.94*	(1.51)	(1.01)	(0.78)	(1.58)	(1.89)
2	1.59	0.51	0.27	0.45	2.09*	(1.34)	(0.51)	(0.26)	(0.44)	(1.69)
3	0.59	0.87	–0.43	0.41	0.29	(0.58)	(1.02)	(–0.57)	(0.49)	(0.29)
4	0.39	–0.26	–0.06	–0.27	0.12	(0.48)	(–0.35)	(–0.10)	(–0.47)	(0.14)
Big	–0.38	–0.35	–0.76*	–0.40	0.31	(–0.50)	(–0.58)	(–1.85)	(–0.84)	(0.47)

Panel B: Wald tests of joint significance of all 50 betas for size–BM and size–INV portfolios

	R_{mkt}	WAGE$^{(1)}$	WAGE$^{(2)}$	WAGE$^{(3)}$	WAGE$^{(4)}$	WAGE$^{(5)}$	WAGE$^{(>5)}$
H_0: all betas are zero	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)
H_0: all betas are equal	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.038)	(0.000)

Table IA.2 Comparing multivariate and univariate betas.
Panels A and B report estimated multivariate betas w.r.t. the excess market returns $R^e_{\mathrm{mkt},t+1}$ and medium–run labor income risk $\mathrm{WAGE}^{(4)}_t$ based on the following two–factor regression for portfolio i:

$$R^e_{i,t+1} = \alpha_{0,i} + \beta_{\mathrm{mkt},i} R^e_{\mathrm{mkt},t+1} + \beta^{(4)}_i \mathrm{WAGE}^{(4)}_t + \epsilon_{i,t+1}.$$

Panel A reports results for 25 size–BM portfolios and Panel B for 25 size–INV portfolios. Panels C and D report estimated univariate betas and corresponding t–statistics w.r.t. $\mathrm{WAGE}^{(4)}_t$. t–statistics are given in parentheses. *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively. Panel E reports the p–values of two Wald tests on the joint significance of the 50 univariate betas. The sample period for stock returns runs from 1963Q3 to 2013Q1 and for labor income growth (including the longest horizon) it runs from 1963Q3 to 2020Q4.

	Betas					t–statistics				
	Panel A: multivariate betas of 25 size–BM portfolios based on 2–factor model									
	Multivariate beta w.r.t. R^e_{mkt}									
	Growth	BM2	BM3	BM4	Value	Growth	BM2	BM3	BM4	Value
Small	1.60***	1.37***	1.23***	1.14***	1.22***	(21.28)	(19.93)	(19.42)	(18.22)	(16.12)
2	1.49***	1.27***	1.14***	1.07***	1.16***	(26.43)	(24.53)	(22.02)	(21.19)	(17.08)
3	1.38***	1.17***	1.03***	1.03***	1.05***	(31.45)	(29.96)	(22.62)	(20.24)	(15.60)
4	1.27***	1.09***	1.00***	1.01***	1.10***	(31.05)	(29.07)	(22.05)	(22.47)	(16.95)
Big	0.99***	0.90***	0.80***	0.88***	0.90***	(36.25)	(32.68)	(22.34)	(16.00)	(14.64)
	Multivariate beta w.r.t. $\mathrm{WAGE}^{(4)}$									
	Growth	BM2	BM3	BM4	Value	Growth	BM2	BM3	BM4	Value
Small	–0.34	–2.79	–2.97	−5.47*	−5.65*	(–0.10)	(–0.92)	(–1.03)	(–1.94)	(–1.78)
2	–0.93	–3.11	−5.61**	−5.51**	−6.94**	(–0.36)	(–1.27)	(–2.45)	(–2.35)	(–2.40)
3	–0.65	–3.09	−6.65***	−5.89***	−6.57**	(–0.31)	(–1.63)	(–3.54)	(–2.78)	(–2.45)
4	0.55	−3.40**	−4.14**	−4.81**	−4.72*	(0.30)	(–2.03)	(–2.24)	(–2.18)	(–1.77)
Big	1.49	–0.58	−2.72*	–0.53	–3.43	(1.14)	(–0.45)	(–1.78)	(–0.28)	(–1.56)

	Panel B: multivariate betas of 25 size–INV portfolios based on 2–factor model									
	Multivariate beta w.r.t. R^e_{mkt}									
	INV1	INV2	INV3	INV4	INV5	INV1	INV2	INV3	INV4	INV5
Small	1.44***	1.17***	1.12***	1.19***	1.49***	(18.21)	(18.10)	(16.64)	(18.99)	(20.73)
2	1.29***	1.07***	1.07***	1.19***	1.47***	(23.16)	(23.37)	(21.51)	(23.59)	(25.63)
3	1.15***	1.00***	1.02***	1.16***	1.38***	(21.81)	(23.03)	(25.40)	(27.37)	(31.55)
4	1.10***	0.98***	0.99***	1.08***	1.36***	(26.99)	(25.23)	(30.44)	(36.12)	(29.52)
Big	0.91***	0.79***	0.86***	0.94***	1.12***	(23.69)	(28.07)	(39.24)	(40.52)	(34.51)
	Multivariate beta w.r.t. $\mathrm{WAGE}^{(4)}$									
	INV1	INV2	INV3	INV4	INV5	INV1	INV2	INV3	INV4	INV5
Small	–2.33	–4.06	–4.54	−4.52*	–3.62	(–0.69)	(–1.52)	(–1.62)	(–1.67)	(–1.12)
2	−4.44*	−4.07*	−4.06*	−5.54**	–1.94	(–1.92)	(–1.88)	(–1.77)	(–2.51)	(–0.80)
3	−5.18***	−4.49**	−4.86***	−3.72**	–1.66	(–2.81)	(–2.39)	(–2.60)	(–2.01)	(–0.80)
4	−2.71*	−3.07*	−3.53**	−3.64**	–0.81	(–1.68)	(–1.73)	(–2.18)	(–2.21)	(–0.42)
Big	–0.79	–0.92	–0.63	0.63	2.62*	(–0.52)	(–0.77)	(–0.60)	(0.63)	(1.66)

Table IA.2 Comparing multivariate and univariate betas (ctd).

Panel C: univariate betas of 25 size–BM portfolios w.r.t. WAGE$^{(4)}$

	Betas					t–statistics				
	Growth	BM2	BM3	BM4	Value	Growth	BM2	BM3	BM4	Value
Small	6.48	3.03	2.25	–0.61	–0.47	(1.07)	(0.59)	(0.48)	(–0.14)	(–0.10)
2	5.41	2.27	–0.77	–0.98	–1.99	(0.98)	(0.50)	(–0.19)	(–0.24)	(–0.43)
3	5.23	1.89	–2.28	–1.53	–2.10	(1.03)	(0.44)	(–0.60)	(–0.40)	(–0.52)
4	5.94	1.23	0.12	–0.53	–0.05	(1.29)	(0.33)	(0.03)	(–0.14)	(–0.01)
Big	5.68*	3.26	0.67	3.20	0.38	(1.67)	(1.06)	(0.23)	(0.95)	(0.11)

Panel D: univariate betas of 25 size–INV portfolios w.r.t. WAGE$^{(4)}$

	Betas					t–statistics				
	INV1	INV2	INV3	INV4	INV5	INV1	INV2	INV3	INV4	INV5
Small	3.78	0.90	0.21	0.54	2.69	(0.68)	(0.21)	(0.05)	(0.12)	(0.48)
2	1.03	0.49	0.48	–0.48	4.30	(0.22)	(0.12)	(0.12)	(–0.11)	(0.81)
3	–0.29	–0.24	–0.53	1.21	4.19	(–0.07)	(–0.07)	(–0.15)	(0.29)	(0.82)
4	1.99	1.10	0.69	0.93	4.99	(0.55)	(0.31)	(0.20)	(0.24)	(1.05)
Big	3.06	2.42	3.02	4.64	7.39*	(1.03)	(0.91)	(1.08)	(1.44)	(1.87)

Panel E: Wald tests of joint significance of all 50 univariate betas for size–BM and size–INV portfolios

	WAGE$^{(4)}$
H_0: all betas are zero	(0.000)
H_0: all betas are equal	(0.000)

Table IA.3 Cross–sectional regressions for 50 portfolios (combined 25 size–BM and 25 size–INV) - adding WAGE$^{(4)}$ to alternative asset pricing models.

This table evaluates the cross–sectional regression results of benchmark asset pricing models for quarterly excess returns on 25 size–BM and 25 size–INV equity portfolios by adding WAGE$^{(4)}$ (i.e., the fourth labor income growth strip) to the following benchmark models: 1) the standard CAPM, 2) the human capital CAPM, which augments the CAPM with a quarterly aggregate labor income growth factor, 3) the classic consumption CAPM (CCAPM) with real per capita quarterly consumption growth as a factor, 4) the ultimate consumption CAPM of Parker and Julliard (2005), which uses 11–quarter ahead consumption growth as risk factor, 5) the CAPM augmented with the fourth strip of consumption growth (CONS$^{(4)}$) as risk factor, 6) the Fama and French (1993) 3–factor model, which we denote by FF3, 7) the Fama and French (2015) 5–factor model, which we denote by FF5. The cross–sectional regressions, based on multivariate betas, are estimated using the Fama and MacBeth (1973) procedure. We report the second–stage cross–sectional regression coefficients and corresponding Fama–MacBeth t–statistics in parentheses and EIV adjusted t–statistics in square brackets. *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively, based on the EIV 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_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	$\lambda_l^{(4)}$	R^2
WAGE$^{(4)}$ + R_{mkt}	0.0139	0.0013							−0.0023**	0.633
	(1.56)	(0.12)							(−3.89)	[0.617]
	[0.92]	[0.08]							[−2.24]	
WAGE$^{(4)}$ + Human capital CAPM	0.0199	−0.0045	−0.00006						−0.0021**	0.663
	(2.46)	(−0.44)	(−0.34)						(−4.08)	[0.641]
	[1.45]	[−0.30]	[−0.21]						[−2.37]	
WAGE$^{(4)}$ + CCAPM	0.0184*			0.0031					−0.0023**	0.662
	(3.26)			(1.63)					(−3.88)	[0.648]
	[1.75]			[0.83]					[−2.08]	
WAGE$^{(4)}$ + ultimate CCAPM	0.0189**			0.0225					−0.0018**	0.621
	(3.09)			(2.09)					(−3.18)	[0.605]
	[1.97]			[1.30]					[−2.12]	
WAGE$^{(4)}$ + R_{mkt} + CONS$^{(4)}$	0.0228	−0.0062		0.0015					−0.0019**	0.706
	(2.72)	(−0.61)		(2.33)					(−3.65)	[0.687]
	[1.64]	[−0.41]		[1.39]					[−2.18]	
WAGE$^{(4)}$ + FF3	0.0277***	−0.0118			0.0064	0.0122***			−0.0007	0.744
	(3.33)	(−1.15)			(1.61)	(2.84)			(−1.33)	[0.722]
	[2.81]	[−1.03]			[1.60]	[2.81]			[−1.07]	
WAGE$^{(4)}$ + FF5	0.0114	0.0039			0.0072*	0.0105**	0.0065	0.0097***	−0.0005	0.778
	(1.19)	(0.35)			(1.83)	(2.47)	(1.48)	(3.11)	(−1.01)	[0.747]
	[0.83]	[0.26]			[1.82]	[2.41]	[1.27]	[2.99]	[−0.88]	

Table IA.4 Cross–sectional regressions for alternative test portfolios – comparison with benchmark asset pricing models. This table reports the second–stage cross–sectional regression results for different benchmark asset pricing models using two alternative sets of test portfolios. Panel A reports results for the combined set of 25 size–BM, 25 size–INV and 30 industry portfolios. Panel B reports results for a combination of 202 portfolios from Kenneth French's website as test assets. This includes 25 size book–to–market, 25 operating profitability–investment, 25 size–momentum, 25 size–beta, 35 size–net issuance, 25 size–accruals, 25 size–variance and 17 industry portfolios. The benchmark models include the classic human capital CAPM, the consumption CAPM, the ultimate consumption CAPM of Parker and Julliard (2005), the CAPM augmented with the fourth strip of consumption growth (CONS$^{(4)}$), 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 (EIV) adjusted t–statistics in square brackets. The last column reports the cross–sectional R^2 and adjusted–R^2 (in square brackets). *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively, based on the EIV adjusted t–statistics.

Panel A: Cross–sectional regression results for 80 test portfolios

	λ_0	λ_{mkt}	λ_l	λ_c	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	R^2
CAPM	0.0195***	0.0018							0.00
	(2.64)	(0.18)							[−0.009]
	[2.64]	[0.18]							
human capital CAPM	0.0214***	−0.0002	0.0008						0.010
	(2.73)	(−0.02)	(0.48)						[−0.016]
	[2.70]	[−0.02]	[0.48]						
CCAPM	0.0195***			0.0006					0.013
	(3.71)			(0.40)					[0.000]
	[3.67]			[0.40]					
Ultimate CCAPM	0.0185***			0.0091					0.068
	(2.97)			(1.24)					[0.056]
	[2.82]			[1.17]					
R_{mkt} + CONS$^{(4)}$	0.0256***	−0.0042		0.0010**					0.099
	(3.59)	(−0.45)		(2.32)					[0.076]
	[3.19]	[−0.42]		[2.07]					
FF3	0.0322***	−0.0154*			0.0062	0.0094**			0.498
	(4.83)	(−1.73)			(1.52)	(2.13)			[0.478]
	[4.52]	[−1.68]			[1.52]	[2.11]			
FF5	0.0252***	−0.0090			0.0069*	0.0073	0.0031	0.0080**	0.530
	(3.68)	(−0.98)			(1.72)	(1.67)	(0.74)	(2.13)	[0.498]
	[3.33]	[−0.92]			[1.72]	[1.63]	[0.70]	[2.05]	

Table IA.4 Cross–sectional regressions for alternative test portfolios – comparison with benchmark asset pricing models (ctd).

Panel B: Cross–sectional regression results for 202 test portfolios									
	λ_0	λ_{mkt}	λ_l	λ_c	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	R^2
CAPM	0.0202***	0.0010							0.001
	(3.14)	(0.11)							[−0.004]
	[3.14]	[0.11]							
human capital CAPM	0.0265***	−0.0054	0.0029*						0.046
	(4.77)	(−0.65)	(1.83)						[0.036]
	[3.96]	[−0.59]	[1.68]						
CCAPM	0.0147***			0.0020					0.083
	(2.85)			(1.25)					[0.079]
	[2.57]			[1.12]					
Ultimate CCAPM	0.0205***			0.0031					0.134
	(2.96)			(1.61)					[0.130]
	[2.53]			[1.38]					
R_{mkt} + CONS$^{(4)}$	0.0217***	−0.0006		0.0004					0.008
	(3.68)	(−0.70)		(0.78)					[−0.002]
	[3.62]	[−0.07]		[0.76]					
FF3	0.0369***	−0.0020**			0.0073*	0.0065			0.409
	(6.05)	(−2.32)			(1.79)	(1.40)			[0.400]
	[5.76]	[−2.27]			[1.78]	[1.38]			
FF5	0.0197***	−0.0039			0.0094**	0.0003	0.0089**	0.0109***	0.564
	(3.57)	(−0.47)			(2.33)	(0.07)	(2.53)	(3.36)	[0.553]
	[3.07]	[−0.43]			[2.31]	[0.07]	[2.47]	[3.29]	

Table IA.5 The Human capital CAPM with real labor income growth and inflation.
This table reports the second–stage cross–sectional regression results for the Human capital CAPM where we split up quarterly nominal labor income growth into quarterly real labor income growth and inflation. The results are based on 25 size–BM portfolios and 25 size–INV portfolios as test assets. In particular, we consider for each time $t = 0, 1, \ldots, T-1$ the following specification (and subsets thereof):

$$R^e_{i,t+1} = \lambda_{0,t+1} + \hat{\beta}_{\mathrm{mkt},i}\lambda_{\mathrm{mkt},t+1} + \hat{\beta}_{l,i}\lambda_{l,t+1} + \hat{\beta}_{\mathrm{infl},i}\lambda_{\mathrm{infl},t+1} + \eta_{i,t+1}.$$

Here $\hat{\beta}_{\mathrm{mkt},i}$, $\hat{\beta}_{l,i}$ and $\hat{\beta}_{\mathrm{infl},i}$ are the estimated first–stage betas obtained from a multivariate time–series regression of quarterly excess returns of portfolio i on quarterly excess market returns, quarterly real labor income growth and quarterly inflation (or subsets thereof). 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 (EIV) corrected t–statistics, based on Shanken (1992), in square brackets. The last column reports the cross–sectional R^2 and adjusted–R^2 (in square brackets). *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively, based on the EIV corrected t–statistics. The sample period runs from 1963Q3 to 2013Q1.

	λ_0	λ_{mkt}	λ_l	λ_{infl}	R^2
REALWAGE	0.0231***	−0.0003	−0.0004		0.001
	(2.90)	(−0.03)	(−0.29)		[−0.041]
	[2.89]	[−0.03]	[−0.28]		
INFLATION	0.0355**	−0.0150		0.0078	0.232
	(3.73)	(−1.37)		(2.75)	[0.200]
	[2.36]	[−0.95]		[1.57]	
REAL WAGE, INFLATION	0.0364**	−0.0158	−0.0027	0.0077	0.234
	(3.86)	(−1.45)	(−1.74)	(2.83)	[0.184]
	[2.32]	[−0.97]	[−0.92]	[1.44]	

Table IA.6 Cross–sectional regressions using different maximum scales J.
This table reports the second–stage cross–sectional regression results for different model specifications using aggregate labor income growth strips as factors and the combined 25 size–BM and size–INV portfolios as test assets. In particular, we consider for each time $t = 0, 1, \dots, T-1$ the following specification (and subsets thereof):

$$R^e_{i,t+1} = \lambda_{0,t+1} + \hat{\beta}_{\text{mkt},i}\lambda_{\text{mkt},t+1} + \sum_{j=1}^{J} \hat{\beta}_i^{(j)} \lambda_{l,t+1}^{(j)} + \hat{\beta}_i^{(>J)} \lambda_{l,t+1}^{(>J)} + \eta_{i,t+1}.$$

Here $\hat{\beta}_{\text{mkt},i}$, $\hat{\beta}_i^{(j)}$, and $\hat{\beta}_i^{(>J)}$ are the estimated first–stage betas obtained from a multivariate time–series regression of quarterly excess returns of portfolio i on quarterly excess market returns and the strips of labor income growth (using $j = 1, \dots, J, > J$). Panel A reports the results for $J = 4$ and Panel B 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 (EIV) adjusted t–statistics in square brackets. The last column reports the cross–sectional R^2 and adjusted–R^2 (in square brackets). *,**,*** indicate significance at the 10%, 5%, and 1% levels based on the EIV adjusted t–statistics. The sample period for stock returns runs from 1963Q3 until 2013Q1 for $J = 4$ and from 1963Q3 until 2005Q1 for $J = 6$. The sample period for labor income growth (including the longest horizon) runs from 1963Q3 to 2020Q4.

	λ_0	λ_{mkt}	$\lambda_l^{(1)}$	$\lambda_l^{(2)}$	$\lambda_l^{(3)}$	$\lambda_l^{(4)}$	$\lambda_l^{(5)}$	$\lambda_l^{(6)}$	$\lambda_l^{(>4)}$	$\lambda_l^{(>6)}$	R^2
Panel A: $J = 4$											
All	0.0156	−0.0009	0.0009	0.0008	0.0009	−0.0023**			−0.0015		0.746
	(1.98)	(−0.09)	(0.78)	(1.69)	(2.20)	(−4.55)			(−1.76)		[0.711]
	[1.14]	[−0.06]	[0.39]	[1.04]	[1.25]	[−2.34]			[−1.06]		
$\text{WAGE}^{(4)} + \text{WAGE}^{(>4)}$	0.0141	0.0016				−0.0023**			0.0002		0.633
	(1.71)	(0.11)				(−4.41)			(0.17)		[0.609]
	[0.99]	[0.08]				[−2.47]			[0.10]		
$\text{WAGE}^{(>4)}$	0.0355***	−0.0134							0.0031		0.126
	(3.71)	(−1.24)							(1.96)		[0.089]
	[3.02]	[−1.07]							[1.57]		
Panel B: $J = 6$											
All	0.0189*	−0.0036	−0.0013	0.0008	0.0009	−0.0014*	0.0002	−0.0001		−0.0010	0.821
	(2.57)	(−0.36)	(−1.73)	(1.82)	(2.51)	(−3.56)	(0.36)	(−0.41)		(−1.50)	[0.786]
	[1.67]	[−0.27]	[−1.15]	[1.22]	[1.36]	[−1.86]	[0.24]	[−0.29]		[−0.98]	
$\text{WAGE}^{(4)} + \text{WAGE}^{(>6)}$	0.0036	0.0106				−0.0017**				−0.0010	0.726
	(0.37)	(0.91)				(−3.67)				(−1.57)	[0.708]
	[0.25]	[0.66]				[−2.50]				[−1.15]	
$\text{WAGE}^{(>6)}$	0.0321***	−0.0085								0.0010	0.020
	(3.40)	(−0.76)								(1.16)	[−0.022]
	[3.20]	[−0.74]								[1.10]	

Table IA.7 Cross–sectional regressions with merged strips.
This table reports the second–stage cross–sectional regression results for an alternative specification of labor income growth strips. Specifically, we sum the first three labor income growth strips $\text{WAGE}^{(1:3)} = \text{WAGE}^{(1)} + \text{WAGE}^{(2)} + \text{WAGE}^{(3)}$ and we sum the last two strips $\text{WAGE}^{(>4)} = \text{WAGE}^{(5)} + \text{WAGE}^{(>5)}$. We keep the fourth strip, $\text{WAGE}^{(4)}$, as is. In particular, we consider for each time $t = 0, 1, \ldots, T-1$ the following specification (and subsets thereof):

$$R^e_{i,t+1} = \lambda_{0,t+1} + \hat{\beta}_{\text{mkt},i}\lambda_{\text{mkt},t+1} + \hat{\beta}_i^{(1:3)}\lambda_{l,t+1}^{(1:3)} + \hat{\beta}_i^{(4)}\lambda_{l,t+1}^{(4)} + \hat{\beta}_i^{(>4)}\lambda_{l,t+1}^{(>4)} + \eta_{i,t+1}.$$

Here all betas are the estimated first–stage betas obtained from a multivariate time–series regression of quarterly excess returns of portfolio i on quarterly excess market returns and the (merged) strips of labor income growth. Panel A reports the results for the 25 size–INV and 25 size–BM portfolios, Panel B reports the results for 80 test portfolios where the 30 industry equity portfolios have been added to the original set of 50 portfolios. Panel C reports results for 202 test portfolios, including 25 size–BM, 25 operating profitability–investment, 25 size–momentum, 25 size–beta, 35 size–net issuance, 25 size–accruals, 25 size–variance and 17 industry portfolios. 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 (EIV) adjusted t–statistics in square brackets. The last column reports the cross–sectional R^2 and adjusted–R^2 (in square brackets). *,**,*** indicate significance at the 10%, 5%, and 1% levels based on the EIV adjusted t–statistics. The sample period for stock returns runs from 1963Q3 until 2013Q1 for $J = 4$ and from 1963Q3 until 2005Q1 for $J = 6$. The sample period for labor income growth (including the longest horizon) runs from 1963Q3 to 2020Q4.

	λ_0	λ_{mkt}	$\lambda_l^{(1:3)}$	$\lambda_l^{(4)}$	$\lambda_l^{(>4)}$	R^2
Panel A: 50 test portfolios						
All	0.0128	0.0017	0.0042	-0.0021^{**}	-0.0019	0.732
	(1.56)	(0.16)	(3.10)	(-4.03)	(-2.20)	[0.708]
	[0.84]	[0.10]	[1.63]	[-2.19]	[-1.23]	
$\text{WAGE}^{(1:3)}$	0.0313^{*}	-0.0103	0.0064^{*}			0.246
	(3.72)	(-1.02)	(2.92)			[0.214]
	[1.87]	[-0.61]	[1.67]			
$\text{WAGE}^{(4)}$	0.0139	0.0013		-0.0023^{**}		0.633
	(1.56)	(0.12)		(-3.89)		[0.617]
	[0.92]	[0.08]		[-2.24]		
$\text{WAGE}^{(>4)}$	0.0355^{***}	-0.0134			0.0031	0.126
	(3.71)	(-1.24)			(1.96)	[0.089]
	[3.02]	[-1.07]			[1.57]	

Table IA.7 Cross–sectional regressions with merged strips (ctd).

	λ_0	λ_{mkt}	$\lambda_l^{(1:3)}$	$\lambda_l^{(4)}$	$\lambda_l^{(>4)}$	R^2
Panel B: 80 test portfolios						
All	0.0205^{**}	-0.0034	-0.0001	-0.0015^{**}	0.0009	0.417
	(2.85)	(-0.37)	(-0.12)	(-3.41)	(0.86)	[0.386]
	[2.15]	[-0.31]	[-0.09]	[-2.56]	[0.62]	
$\text{WAGE}^{(1:3)}$	0.0214^{***}	-0.0003	0.0010			0.020
	(2.77)	(-0.03)	(0.77)			[-0.005]
	[2.71]	[-0.03]	[0.76]			
$\text{WAGE}^{(4)}$	0.0165^{*}	0.0006		-0.0016^{**}		0.397
	(2.22)	(0.06)		(-3.43)		[0.382]
	[1.65]	[0.05]		[-2.52]		
$\text{WAGE}^{(>4)}$	0.0264^{***}	-0.0055			0.0020	0.073
	(3.76)	(-0.61)			(1.73)	[0.049]
	[3.43]	[-0.57]			[1.57]	
Panel C: 202 test portfolios						
All	0.0215^{***}	-0.0047	-0.0010	-0.0015^{**}	0.0026^{**}	0.461
	(3.90)	(-0.57)	(-1.07)	(-3.63)	(3.10)	[0.450]
	[2.67]	[-0.46]	[-0.71]	[-2.39]	[2.10]	
$\text{WAGE}^{(1:3)}$	0.0231^{***}	-0.0021	0.0015			0.016
	(4.00)	(-0.25)	(1.23)			[0.006]
	[3.69]	[-0.24]	[1.16]			
$\text{WAGE}^{(4)}$	0.0146	0.0018		-0.0019^{**}		0.381
	(2.14)	(0.19)		(-3.87)		[0.375]
	[1.47]	[0.15]		[-2.53]		
$\text{WAGE}^{(>4)}$	0.0301^{***}	-0.0099			0.0041^{**}	0.255
	(5.19)	(-1.19)			(3.51)	[0.248]
	[3.85]	[-1.00]			[2.50]	

Table IA.8 Sub sample analysis.
This table reports the second–stage cross–sectional regression results for a sub sample period that starts later, in 1976Q1. Here, stock returns are used from 1976Q1 to 2013Q1 and labor income growth (including the longest horizon) runs from 1976Q1 to 2020Q4. The table reports results using aggregate labor income growth strips as factors and 25 size–BM portfolios and 25 size–INV portfolios as test assets. In particular, we consider for each time $t = 0, 1, \ldots, T-1$ the following specification (and subsets thereof):

$$R^e_{i,t+1} = \lambda_{0,t+1} + \hat{\beta}_{\text{mkt},i}\lambda_{\text{mkt},t+1} + \sum_{j=1}^{5} \hat{\beta}_i^{(j)} \lambda_{l,t+1}^{(j)} + \hat{\beta}_i^{(>5)} \lambda_{l,t+1}^{(>5)} + \eta_{i,t+1}.$$

Here $\hat{\beta}_{\text{mkt},i}$, $\hat{\beta}_i^{(j)}$, and $\hat{\beta}_i^{(>5)}$ 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 labor income growth strips. 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 (EIV) corrected t–statistics, based on Shanken (1992), in square brackets. The last column reports the cross–sectional R^2 and adjusted–R^2 (in square brackets). *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively, based on the EIV corrected t–statistics.

	λ_0	λ_{mkt}	$\lambda_l^{(1)}$	$\lambda_l^{(2)}$	$\lambda_l^{(3)}$	$\lambda_l^{(4)}$	$\lambda_l^{(5)}$	$\lambda_l^{(>5)}$	R^2
All	0.017	0.001	0.001	−0.000	0.001	-0.002^{**}	−0.001	−0.001	0.735
	(2.37)	(0.14)	(0.78)	(−0.07)	(1.59)	(−4.74)	(−1.69)	(−2.47)	[0.691]
	[1.29]	[0.09]	[0.42]	[−0.04]	[0.95]	[−2.50]	[−0.91]	[−1.40]	
WAGE$^{(4)}$	0.017	0.002				-0.002^{**}			0.652
	(1.67)	(0.17)				(−3.26)			[0.637]
	[1.11]	[0.12]				[−2.16]			

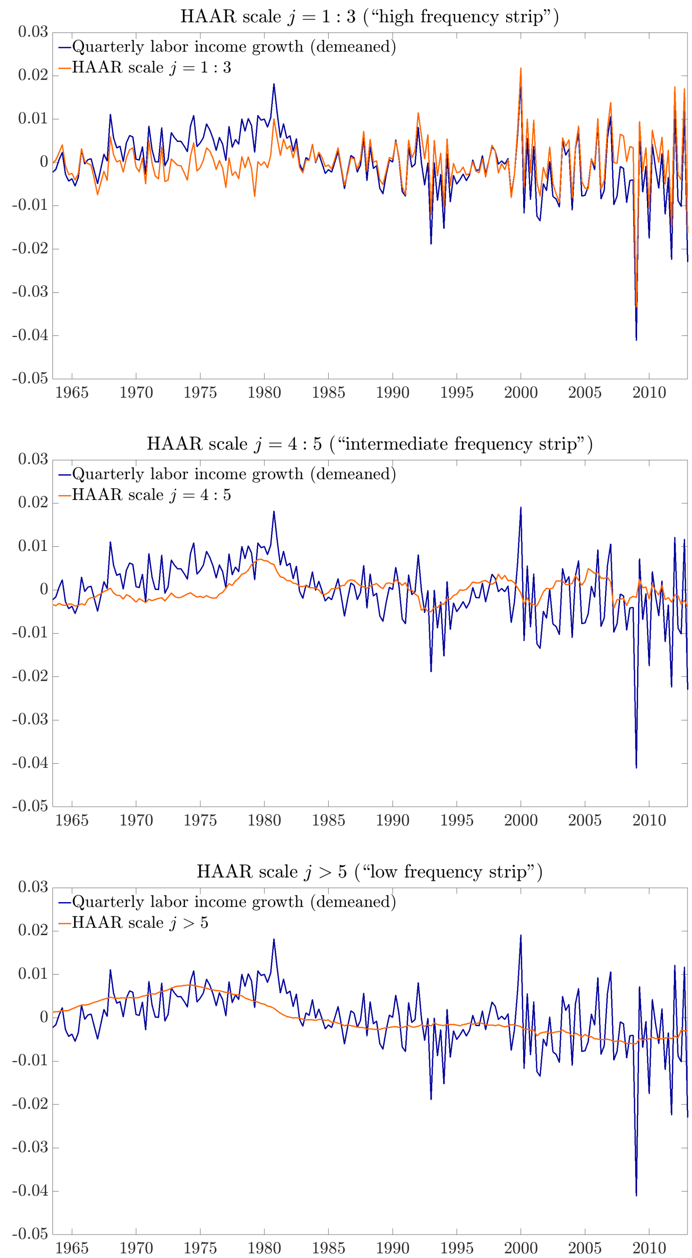

Figure IA.1 Aggregate labor income growth decomposed into different frequency components. This figure plots the quarterly (demeaned) aggregate labor income growth series against its high, intermediate, and low frequency components. The high frequency component is defined as the sum of the labor income growth strips for scales $j = 1, 2, 3$, and contains fluctuations with a half–life of less than 2 years. The intermediate frequency component is defined as the sum of the strips with 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 strips with scales > 5, and contains fluctuations with a half–life of more than 8 years. The sample period for labor income growth (including the lowest frequency component) used in these plots runs from 1963Q3 to 2020Q4. Due to the forward–looking definition of the labor income growth strips this results in an effective sample period from 1963Q3 to 2013Q1.