Wage Growth and Equity Risk Premia *

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Abstract

We develop a simple three-factor consumption-based asset pricing model that includes wage growth as a risk factor, and evaluate whether the model explains six major CAPM anomalies: book-to-market, investment, operating profitability, long-term return reversal, net share issues, and residual variance. Wage growth arises in the pricing kernel by using a non-separable utility over consumption and leisure, and represents the growth in the opportunity cost of enjoying leisure hours. In the model, wage growth earns a negative price of risk, that is, higher wage growth leads to a decline in leisure demand, which increases the marginal utility of consumption for an investor with risk aversion above one. The empirical cross-sectional tests show that the model explains around 50% of the cross-sectional dispersion in average returns of the joint six CAPM anomalies (160 equity portfolios). Further, the proposed model compares favorably with alternative return-based multifactor models widely used in the literature. The risk price estimates for wage growth are significantly negative, while the implied preference parameter (share of leisure) estimates are economically plausible in most cases. Overall, our results suggest that aggregate wage growth can help explaining cross-sectional equity risk premia.

Keywords: Asset pricing; Consumption-based asset pricing model; Leisure; Wage growth; Cross-section of stock returns; Stock market anomalies

JEL classification: E21; E44; G11; G12

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1 Introduction

Given the failure of the baseline Consumption-CAPM (CCAPM) of Lucas (1978) and Breeden (1979) when it comes to explaining equity risk premia (e.g., Breeden, Gibbons, and Litzenberger (1989), Lettau and Ludvigson (2001), Brav, Constantinidies, and Geczy (2002), Jacobs and Wang (2004), among others), a large body of the macro finance literature aims at improving the empirical performance of the baseline model. In particular, several studies have focused on deriving and estimating multifactor macroeconomic asset pricing models that contain other macro variables as risk factors in addition to the standard consumption (non-durables and services) growth factor (e.g., Lettau and Ludvigson (2001), Lustig and Van Nieuwerburgh (2005), Yogo (2006), Gomes, Kogan, and Yogo (2009), Lioui and Maio (2014), Delikouras (2017), Chen and Lu (2018), among others).[1] The current paper contributes to this literature by proposing a new macroeconomic model to price a rich cross-section of average stock returns.

Specifically, we derive a three-factor macro model in which the factors are the standard real consumption growth employed in the baseline CCAPM; the standard market return (or return on total wealth) factor employed in the CAPM of Sharpe (1964) and Lintner (1965); and aggregate wage growth. This model is denoted by Consumption-Wage CAPM (CW-CAPM). The underlying theoretical framework assumes an intertemporal utility of the recursive form (Epstein and Zin (1989, 1991) and Weil (1989)), combined with an intra-temporal utility that depends on both real consumption and the services provided by leisure (with a Cobb-Douglas specification). By using the intraperiod equilibrium condition relating the marginal rate of substitution (between leisure and consumption) and the respective relative price of leisure (real wage), we are able to substitute the growth in hours of leisure by the wage growth rate in the pricing kernel that prices assets. In the model, the wage rate represents the opportunity cost of leisure, i.e., the foregone income by providing one hour less of work. There are three preference parameters in the model: the coefficient of relative risk aversion, the share of leisure over utility and total expenditure, and the elasticity of intertemporal substitution. This allows us to obtain a one-to-one correspondence between the factor risk prices of the linear model and the underlying structural parameters. Given the assumption of a positive share of leisure, the wage risk price should be negative as long as the risk aversion parameter is above one (more risk averse than an investor with log utility). In other words, higher wage growth decreases the demand for leisure services and thus increases the marginal utility of consumption ("bad times").

A restricted version of CW-CAPM (denoted by CW-CAPM*) contains consumption

[1] Other studies have estimated the single-factor model by employing alternative measures of consumption growth (e.g., Ait-Sahalia, Parker, and Yogo (2004), Parker and Julliard (2005), Jagannathan and Wang (2007), Malloy, Moskowitz, and Vissing-Jorgensen (2009), Savov (2011), and Kroencke (2017)).

growth and wage growth as the two risk factors. This nested model is derived by assuming that the risk aversion parameter is the reciprocal of the elasticity of intertemporal substitution, that is, we are back to the standard power utility function. Further, the three-factor model also nests the baseline CCAPM and CAPM models as well as the two-factor model of Epstein and Zin (1991) (which contains consumption growth and the market return as risk factors) as special cases.

We estimate a linear version of the three-factor macro model (in expected return-covariance representation) by first-stage Generalized Method of Moments (GMM) using a rich cross-section of stock returns. Specifically, we use portfolios sorted on size and each of six prominent stock characteristics: book-to-market ratio; asset growth; net share issues; long-term return reversal; operating profitability; and residual stock variance. These portfolios are associated with some of the most important market anomalies, that is, they produce significant cross-sectional spreads in average returns that are not explained by the baseline CAPM. We use quarterly data from 1963 to 2017 in our empirical cross-sectional asset pricing tests.

Overall, the empirical results provide a strong support for the linear three-factor macro model, and also suggest that the wage factor helps pricing cross-sectional equity risk premia. Specifically, in the augmented cross-sectional test with the joint six portfolio groups (160 portfolios in total) both versions of the consumption-wage model explain around 50% of the cross-sectional dispersion in average returns of the 160 portfolios. Critically, the wage risk price estimates are negative and strongly statistically significant, and thus consistent with the theoretical model. The implied estimates of the leisure share are also economically plausible and in line with the macro literature. Wage growth is the key factor in terms of driving the performance of the consumption-wage CAPM, as the dispersion in the respective risk premium (price of risk times quantity of risk) drives to a large degree the dispersion in raw portfolio equity risk premia that we seek to explain. Indeed, value stocks, stocks that invest less, stocks with low equity issuance, past long-term losers, more profitable stocks, and stocks with lower idiosyncratic risk, earn higher average returns relative to stocks with the opposite characteristics because the former stocks have higher labor income risk, that is, these stocks load more negatively on the wage growth factor (which earns a negative risk price).

The performance of both CW-CAPM and CW-CAPM* survives several robustness checks: employing an alternative definition of the wage factor; including the market factor in the menu of testing assets; using alternative stock variance portfolios; estimating the model by second-stage GMM; and estimating the model in its beta representation. Notably, both macro models containing the wage factor compare favorably with the workhorse factor models employed in the empirical asset pricing literature: the three-factor model of Fama and French (1993), the four-factor models of Carhart (1997), Pástor and Stambaugh (2003), and Hou, Xue, and Zhang (2015), and the five-factor model of Fama and French (2015). However, the

Consumption-Wage CAPM cannot price portfolios sorted on momentum or accruals. This result is not totally surprising as it is not likely that a single factor (wage growth) explains cross-sectional dispersion in risk premia associated with portfolio groups that are weakly (or even negatively) correlated (e.g., momentum, operating profitability, and asset growth portfolios). In comparison, the multifactor models described above employ several factors to achieve that goal.

Our work is directly related to other studies that estimate linear factor models containing factors directly or indirectly associated with the growth in labor income to price the cross-section of expected stock returns (e.g., Campbell (1996), Jagannathan and Wang (1996), Lettau and Ludvigson (2001), Santos and Veronesi (2006), and Eiling (2013)). We differentiate from these papers in two major dimensions. On the theoretical side, contrary to those studies, our model is an equilibrium consumption-based model in which the factor risk prices are linked to the underlying preference parameters. On the empirical side, we conduct asset pricing tests that use a significantly broader cross-section of stock returns than in those studies (which mainly focus on size/book-to-market portfolios), a procedure that is in line with the recent empirical asset pricing literature.

The rest of the paper is organized as follows. Section 2 presents the theoretical background. Section 3 describes the data and econometric methodology. Section 4 presents the main empirical results. Section 5 provides a sensitivity analysis for the main results. Finally, Section 6 concludes.

2 The Consumption-Wage Asset Pricing Model

In this section, we derive the Consumption-Wage CAPM.

2.1 Euler Equations

Consider an economy in which a representative agent maximizes its expected utility determined by the recursive preferences of Epstein and Zin (1989, 1991) and Weil (1989):

$$U_t = \left\{(1-\delta)V_t^{1-1/\psi} + \delta\left(E_t\left[U_{t+1}^{1-\gamma}\right]\right)^{1/\theta}\right\}^{\frac{1}{1-1/\psi}}, \tag{1}$$

where V_t denotes the intratemporal utility; $0 < \delta < 1$ is the subjective time discount factor; γ is the relative risk aversion coefficient (RRA); ψ denotes the elasticity of intertemporal substitution (EIS) parameter; and θ is an auxiliary parameter defined as $\theta \equiv (1-\gamma)/(1-1/\psi)$. This specification for preference has the desirable feature of allowing to separate ψ and γ, contrary to the standard power utility function widely used in the macro-finance literature in which ψ is the reciprocal of γ ($\gamma = 1/\psi$).

In each period, the representative agent consumes units of consumption goods, and enjoys the service delivered by leisure. Utility is non-separable across consumption and leisure, which represents a specification that is widely used in the macroeconomics literature (e.g., King and Rebelo (1999)). This brings a simple and natural transmission mechanism of macroeconomic shocks (such as unemployment rate shocks) to asset prices, by affecting the marginal utility of consumption. Specifically, the agent has the following intraperiod Cobb-Douglas utility function,

$$V_t = C_t^{1-\eta} \left(H - N_t \right)^{\eta}, \tag{2}$$

in which C_t is aggregate consumption goods; H represents the endowment of "hours" that the representative agent allocates between labor and leisure; N_t denotes the hours of work supplied by the household to the production sector; and $0 < \eta < 1$ can be interpreted as the share of leisure services. This Cobb-Douglas utility over consumption and leisure has been used in Eichenbaum, Hansen, and Singleton (1988), as well as in a large number of economic growth and business cycle models. It implies an intraperiod elasticity of substitution between consumption and leisure of one.[2]

The representative agent faces the following standard intertemporal budget constraint,

$$B_{t+1} = R_{m,t+1} \left[B_t - C_t - W_t \left(H - N_t \right) \right] \tag{3}$$

$$R_{m,t+1} = \sum_{i=1}^{N} \omega_{i,t} \left(R_{i,t+1} - R_{f,t+1} \right) + R_{f,t+1}, \tag{4}$$

where B_{t+1} denotes the aggregate wealth at the end of period $t+1$; $R_{m,t+1}$ is the (gross) return on aggregate wealth; $\omega_{i,t}$ represents the portfolio weight associated with risky asset i; $R_{i,t+1}$ is the corresponding (gross) return; and $R_{f,t+1}$ is the gross risk-free rate from t to $t+1$, which is known at the beginning of the period. W_t denotes the wage for hours worked, and represents the relative price of the services enjoyed from leisure, measured in terms of consumption. In simple terms, the budget constraint postulates that the investable (or net) wealth at the end of t enjoys the one-period gross return of $R_{m,t+1}$ in order to accumulate to the total wealth at the end of $t+1$.

The first-order conditions for the dynamic consumption and portfolio choice problem deliver intertemporal and intratemporal marginal rates of substitution. The intertemporal

[2] As emphasized by Kydland (1995), this is the only value consistent with the long-term stability of labor hours (within the general class of constant elasticity of substitution utility functions).

marginal rate of substitution (pricing kernel) is given by

$$M_{t+1} = \delta^{\theta} \left(\frac{C_{t+1}}{C_t}\right)^{\frac{\theta}{\psi}(\eta-1)-\eta\theta} \left(\frac{H-N_{t+1}}{H-N_t}\right)^{\eta(1-\gamma)} R_{m,t+1}^{\theta-1}. \tag{5}$$

The pricing kernel depends on the leisure growth, which arises from the non-separability between consumption and leisure in the utility function. Notice that the pricing kernel is a decreasing function of leisure growth as long as $\gamma > 1$, that is when the investor is more risk averse than an household with log utility.[3] Hence, periods in which leisure is low represent periods of high marginal utility of consumption (bad times), in which consumption is more valuable.

To estimate and evaluate the asset pricing implication of Equation (5), accurate data on hours of leisure (or equivalently, hours worked) are required. It is well documented, however, that hours allocated to leisure are difficult to measure in practice. Perhaps, hours of work data suffer from measurement error even more than do consumption data.[4] In order to circumvent the measurement error of hours of leisure/work data, we focus on an equivalent representation of the pricing kernel as a function of wages, which are likely to be more accurately measured. We bring out wages into the pricing kernel by exploiting the following intraperiod equilibrium relationship between consumption, leisure, and the wage earned from supplying labor to productive activities:

$$\frac{\eta}{1-\eta}\frac{C_t}{H-N_t} = W_t. \tag{6}$$

This equation states that the intratemporal marginal rate of substitution between consumption and leisure (left hand side) should be equal to the relative price of the service enjoyed from leisure (the opportunity cost of leisure), measured in terms of consumption (right hand side). Since we follow the convention of normalizing the price of consumption to one, W_t represents both the absolute and relative price of leisure.

Rearranging the equation above shows that η can be interpreted as the share of leisure over the total expenditure on consumption and leisure:

$$\eta = \frac{(H-N_t)W_t}{C_t + (H-N_t)W_t}. \tag{7}$$

[3]More specifically, we have:

$$\frac{\partial M_{t+1}}{\partial\left(\frac{H-N_{t+1}}{H-N_t}\right)} = \eta(1-\gamma)\delta^{\theta} \left(\frac{C_{t+1}}{C_t}\right)^{\frac{\theta}{\psi}(\eta-1)-\eta\theta} \left(\frac{H-N_{t+1}}{H-N_t}\right)^{\eta(1-\gamma)-1} R_{m,t+1}^{\theta-1}.$$

This expression is negative if $\gamma > 1$.

[4]Aggregate consumption data suffer from measurement error (e.g., Wilcox (1992)).

By using Equation (6) into the pricing kernel above, we can express the intertemporal marginal rate of substitution directly as a function of wage growth,

$$M_{t+1} = \delta^{\theta} \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{\theta}{\psi}} \left(\frac{W_{t+1}}{W_t} \right)^{-\eta(1-\gamma)} R_{m,t+1}^{\theta-1}. \tag{8}$$

Compared to the pricing kernel implied from the standard model of Epstein and Zin (1991), we introduce wage growth as a new risk factor that helps pricing risk premia. The parameter η measures the weight of wage growth in pricing assets: A larger value of η suggests that wage growth (and implicitly, leisure) plays a relatively more important role for asset pricing than the standard consumption factor. Indeed, when $\eta = 0$, that is, there is no role for leisure in the utility of the representative investor, we obtain the Epstein–Zin model as a special case:

$$M_{t+1} = \delta^{\theta} \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{\theta}{\psi}} R_{m,t+1}^{\theta-1}. \tag{9}$$

A full derivation of the pricing kernel presented above is provided in Appendix A. The first-order derivative of the SDF with respect to wage growth is given by

$$\frac{\partial M_{t+1}}{\partial \left(\frac{W_{t+1}}{W_t} \right)} = -\eta(1-\gamma)\delta^{\theta} \left(\frac{C_{t+1}}{C_t} \right)^{-\frac{\theta}{\psi}} \left(\frac{W_{t+1}}{W_t} \right)^{-\eta(1-\gamma)-1} R_{m,t+1}^{\theta-1}. \tag{10}$$

This expression is positive for $\gamma > 1$. Intuitively, a higher wage rate (the opportunity cost of leisure) decreases the demand for leisure (since households tend to allocate more time on labor hours when facing higher opportunity cost of enjoying leisure), which leads to an increase in the marginal utility of consumption.

2.2 Linear Factor Model

Following Yogo (2006), we use a log-linear approximation of the pricing kernel to obtain a linear factor model. The main advantage of the linear factor model representation is that it shows how the risk exposures to each factor (covariances or betas) are paired with expected returns across assets. Thereby, we can understand which factor(s) contribute most in terms of explaining the cross-sectional dispersion in average returns. Further, it allows us to directly compare our results with the extensive empirical asset pricing literature that mostly rely on linear factor models.

The general expected return-covariance representation in unconditional form is as follows

$$E\left(R_{i,t+1}^{e}\right) = -Cov\left(m_{t+1}, R_{i,t+1}^{e}\right), \tag{11}$$

where $m_{t+1} \equiv \ln(M_{t+1})$ denotes the log pricing kernel, and $R^e_{i,t+1}$ is the excess return (relative to the risk-free rate) on the ith risky asset.

By applying the general pricing Equation (11) to the pricing kernel in Equation (9), we obtain the expected return-covariance representation of the consumption-wage asset pricing model (CW-CAPM),

$$E\left(R^e_{i,t+1}\right) = \gamma_c Cov\left(\Delta c_{t+1}, R^e_{i,t+1}\right) + \gamma_w Cov\left(\Delta w_{t+1}, R^e_{i,t+1}\right) + \gamma_m Cov\left(r_{m,t+1}, R^e_{i,t+1}\right), \quad (12)$$

where $\Delta c_{t+1} \equiv \ln(C_{t+1}) - \ln(C_t)$ and $\Delta w_{t+1} \equiv \ln(W_{t+1}) - \ln(W_t)$ denote the log growth of consumption and wage, respectively. $r_{m,t+1} \equiv \ln(R_{m,t+1})$ represents the log return on total wealth or log market return.

In the above pricing equation, the covariance risk prices $(\gamma_c, \gamma_w, \gamma_m)$ are related to the preference parameters as follows:

$$\begin{bmatrix} \gamma_c \\ \gamma_w \\ \gamma_m \end{bmatrix} = \begin{bmatrix} \frac{\theta}{\psi} = \frac{1-\gamma}{\psi-1} \\ \eta(1-\gamma) \\ 1-\theta \end{bmatrix}. \quad (13)$$

Given the above relations, the implied preference parameters can be backed up as follows:

$$\begin{bmatrix} \gamma \\ \psi \\ \eta \end{bmatrix} = \begin{bmatrix} \gamma_c + \gamma_m \\ (1-\gamma_m)/\gamma_c \\ \gamma_w/\left(1-\gamma_c-\gamma_m\right) \end{bmatrix}. \quad (14)$$

According to the CW-CAPM in Equation (12), differences in expected returns across assets are determined by the covariances (betas) of returns with the log consumption growth (Δc_{t+1}), the log wage growth (Δw_{t+1}), and the log return on the wealth portfolio $(r_{m,t+1})$. One benefit of consumption-based asset pricing models is that the sign and magnitude of the risk prices are linked with the underlying preference parameters. Suppose that $\gamma > 1$ and $\psi < 1$ is the relevant empirical case, as shown in the related literature (e.g., Yogo (2006) and Lioui and Maio (2014)), as well as in this paper (as will be shown below). The first term in the right hand side of Equation (12) is familiar from the models based on power utility: the risk is associated with aggregate consumption growth, and its price of risk is positive. The second term is the risk associated with wage growth, and it arises as a result of non-separable consumption and leisure in the utility of the average investor. Since $\eta > 0$ by definition, the risk price for wage growth is negative, given the positive correlation between wage growth and the pricing kernel discussed above. Therefore, an asset with a negative loading on wage growth earns a higher risk premium (relative to an asset with a zero or positive loading on the same factor), since it delivers a low payoff when the marginal utility of consumption is high (bad times). Finally, the third term is obtained as a result of $\theta \neq 1$. The risk is associated with the return on the wealth portfolio, and its price of risk is positive as long as $\theta < 1$, or equivalently, the RRA parameter is lower than the inverse of the EIS parameter, $\gamma < 1/\psi$.

The proposed model, CW-CAPM, in Equation (12) represents a rich specification in the sense that it nests the following asset pricing models as special cases. First, the two-factor nonseparable expected utility model (denoted by CW-CAPM*) is obtained when the EIS is the inverse of risk aversion (i.e., $\theta = 1$):[5]

$$E\left(R^e_{i,t+1}\right) = \gamma Cov\left(\Delta c_{t+1}, R^e_{i,t+1}\right) + \eta(1-\gamma)Cov\left(\Delta w_{t+1}, R^e_{i,t+1}\right). \tag{15}$$

If the market return has little explanatory power for cross-sectional equity risk premia, the performance of CW-CAPM* will be similar to that of CW-CAPM.

Second, the two-factor recursive utility model of Epstein and Zin (1989) is obtained when both consumption and leisure are additively separable in the utility function, that is, there is no role for leisure in the intertemporal marginal rate of substitution (i.e., $\eta = 0$):

$$E\left(R^e_{i,t+1}\right) = \frac{\theta}{\psi}Cov\left(\Delta c_{t+1}, R^e_{i,t+1}\right) + (1-\theta)Cov\left(r_{m,t+1}, R^e_{i,t+1}\right). \tag{16}$$

Third, the standard CCAPM based on power utility developed by Lucas (1978) and Breeden (1979) is obtained by imposing both $\eta = 0$ and $\psi = 1/\gamma$:

$$E\left(R^e_{i,t+1}\right) = \gamma Cov\left(\Delta c_{t+1}, R^e_{i,t+1}\right). \tag{17}$$

Finally, the CAPM of Sharpe (1964) and Lintner (1965) is obtained by imposing both $\eta = 0$ and $\psi \to \infty$:

$$E\left(R^e_{i,t+1}\right) = \gamma Cov\left(r_{m,t+1}, R^e_{i,t+1}\right). \tag{18}$$

These nested asset pricing models will be compared against the CW-CAPM or CW-CAPM* models. The proposed macro models with wage growth will improve the explanatory power of the Epstein-Zin model, CCAPM, or CAPM in explaining the cross-section of average returns, if the dispersion in the covariances (betas) associated with the wage growth factor, $Cov\left(\Delta w_{t+1}, R^e_{i,t+1}\right)$, captures the corresponding dispersion in average returns of the testing assets, $E\left(R^e_{i,t+1}\right)$.

[5] Eichenbaum, Hansen, and Singleton (1988) use this utility specification to derive an SDF that depends on both consumption and leisure.

3 Data and Econometric Methodology

In this section, we describe the data and empirical method employed in the following sections.

3.1 Data

We use quarterly data for the 1963:Q3 to 2017:Q4 period, where the beginning date is restricted by the data availability on some of the testing portfolios employed in the asset pricing tests. Consumption and wage data are obtained from the National Income and Product Account (NIPA) database. In line with the macro-finance literature, consumption is the sum of personal expenditure on nondurable goods and services, and wage is the sum of wage and salary disbursements. We deflate consumption and wage by both total population and the Consumer Price Index (CPI) in order to compute per capital real consumption and per capita real wage. We use the standard "end-of-period" timing assumption, in which the consumption growth over the period from t and $t+1$ is matched with asset returns calculated over the same time interval. Following Epstein and Zin (1991), Yogo (2006), Lioui and Maio (2014), among others, we use the return on the value-weighted stock market portfolio from CRSP as the proxy for the return on the wealth portfolio. We compute the real stock market return by deflating the nominal return by the CPI index. To be consistent with the theoretical model derived in the last section, the factors in the CW-CAPM represent log growth rates in both quarterly real consumption and real wage, as well as the quarterly log real market return.

The testing assets used in the asset pricing tests include value-weighted portfolios formed on both firm size (market capitalization) and each of six major anomaly variables: book-to-market ratio (SBM25), investment (SINV25), operating profitability (SOP25), long-term return reversal (SREV25), net share issues (SNSI35), and residual stock return variance (SRVAR25). These firm characteristics represent some of the most important CAPM anomalies that are examined by many prior studies. These portfolios show significant cross-sectional spreads in average returns, and are widely adopted as test assets in the empirical asset pricing literature (e.g., Fama and French (2015, 2016), Hou, Xue, and Zhang (2015), Dittmar and Lundblad (2017), Cooper and Maio (2018a)). Moreover, they enable to control for the connection between size and each of these characteristics, as there is evidence that those anomalies are stronger among small caps (see, for example, Fama and French (2008) and Hou, Xue, and Zhang (2018)). Each portfolio group contains 25 portfolios, with the exception of SNSI35, in which case there are 35 portfolios (see Fama and French (2016) for details on the portfolio construction).

The value-growth anomaly comes from the evidence that value stocks (stocks with a high book-to-market ratio) have higher average returns than growth stocks (stocks with low book-to-market) (see Basu (1983) and Fama and French (1992)). The investment or asset growth anomaly represents a pattern in which firms that invest more earn lower average returns than firms that invest less (Titman, Wei, and Xie (2004), Cooper, Gulen, and Schill (2008), Fama and French (2006, 2015)). The operating profitability anomaly stems from the evidence that firms with high operating profitability enjoy higher average returns than firms with low profitability (Novy-Marx (2013), Fama and French (2006, 2015)). The long-term return reversal effect refers to a pattern in which stocks with low past returns over the last two to five years outperform stocks with high past returns (De Bondt and Thaler (1985, 1987)). The net share issues effect postulates that firms with high net share issues exhibit lower returns going forward than firms with low net share issues (Ikenberry, Lakonishok, and Vermaelen (1995) and Loughran and Ritter (1995)). The residual variance anomaly describes a cross-sectional pattern in which stocks with high residual variance (idiosyncratic volatility) earn lower average returns than stocks with low residual variance (Ang, Hodrick, Xing, and Zhang (2006) and Fama and French (2016)).

We compound the monthly returns to obtain the quarterly portfolio returns. We subtract the return on the three-month T-bill to obtain the quarterly portfolio excess returns. All portfolio return data are obtained from Kenneth French's website. The return on the three-month T-bill and CPI inflation rates are obtained from the FRED database (St. Louis FED).

Table 1 reports descriptive statistics for the three factors associated with the benchmark three-factor macro model. Log wage growth (Δw) is considerably more volatile than log consumption growth (Δc), having standard deviations of 1.27% and 0.76% per quarter, respectively. Figure 1 plots the time-series of the consumption and wage growth factors. The figure illustrates that the volatility of consumption growth and, in particular, wage growth sharply increases around recessionary periods. This pattern is especially notorious around the recent Global Financial Crisis. The figure also suggests that wage growth is pro-cyclical. Indeed, by regressing wage growth on the NBER business cycle dummy (which assumes the value of one in economic booms), we obtain the following results (Newey and West (1987) t-ratios in parentheses),

$$\begin{aligned} \Delta w_t &= -0.006 + 0.013 NBER_t, R^2 = 0.13, \\ &\quad (-2.39)(4.93), \end{aligned}$$

which confirms that the growth rate in aggregate wages tends to rise during economic expansions. We can also see that all the three factors in the CW-CAPM are not persistent, as the first-order autocorrelation coefficient estimates are around or below 0.20. The correlations reported in Panel B of Table 1 show that wage growth is weakly correlated with consumption growth (correlation of 0.42), while being uncorrelated with the market factor. On the other hand, Δc and r_m show a modest positive correlation (0.22).

Table 2 presents the descriptive statistics for the returns spreads associated with the six market anomalies enumerated above. Within each quintile of the anomaly variable, the average portfolio return across the five size quintiles are computed. The average portfolios associated with the highest and lowest rank of a given characteristic are defined as "high" and "low" portfolios, respectively. For the SBM25 portfolio as an example, the return on the "high" portfolio is defined as the average of the returns corresponding to the S1BM5, S2BM5, S3BM5, S4BM5, and S5BM5 original portfolios. The return on the "Low" portfolio is similarly defined as the average of the returns on the S1BM1, S2BM1, S3BM1, S4BM1, and S5BM1 portfolios. The return spreads are then calculated as the difference between the returns of the "high" and "low" portfolios.

The results show that the "high-minus-low" return spreads are all statistically significant at the 5% or higher significance level.[6] All six anomalies are economically significant as well, since the magnitudes of the average return spreads are all above 0.90% per quarter (in absolute value). The anomaly with the largest average return is NSI with an average gap in returns of 1.75% (in magnitude), followed by RVAR with an average return spread of 1.44% (in magnitude). The anomaly showing the lowest average return is OP with an average gap of 0.94%, followed by INV (average of 1.01% in magnitude). RVAR is clearly associated with the most volatile return spread (standard deviation of 9.80% per quarter), followed by the BM return spread (6.87%). At the other end of the spectrum, both INV and OP are the least volatile return spreads, with standard deviation below 5% per quarter. The six return spreads are not serially correlated as indicated by the first-order autoregressive coefficients below 0.20 (in magnitude) in all cases.

3.2 Econometric Methodology

We estimate factor prices of risk and evaluate linear factor models by applying first-stage GMM (Hansen (1982) and Cochrane (1996, 2005)). As Cochrane (2005) notes, the first-stage GMM estimation using equally-weighted sample moments is equivalent to an OLS cross-sectional regression of average excess returns on factor covariances (or equivalently, single-regression betas), which is widely employed in the literature (e.g., Black, Jensen, and Scholes (1972), Jagannathan and Wang (1998), Kan, Robotti, and Shanken (2013), among others).[7] Critically, the first-stage GMM estimation allows one to evaluate whether an asset

[6]The t-ratios are associated with the intercept estimate of a regression of the return spread containing only the intercept.

[7]The Fama-MacBeth method (Fama and MacBeth (1973)) is also equivalent if the covariances (betas) are estimated from the full sample.

pricing model can explain a chosen set of economically interesting portfolios. In contrast, although it provides most efficient estimates of the factor risk prices, the second-stage GMM with an estimated weighting matrix uses a linear combination (often with extreme positive and negative weights) of these original test portfolios. Hence, these "transformed" testing portfolios may be difficult to interpret economically (see Lettau and Ludvigson (2001) and Cochrane (2005) for further discussion). Since we want to evaluate whether the CW-CAPM can explain several CAPM anomalies (portfolios formed on economically interesting characteristics), we focus on the first-stage GMM estimation in our main results.

Let $\boldsymbol{R^e_{t+1}} = (R_{1,t+1} - R_{f,t+1}, \ldots, R_{N,t+1} - R_{f,t+1})'$ and $\boldsymbol{f_{t+1}}$ be the observation of the vector of N excess returns on test assets at time $t+1$, and the vector of K factors, respectively.[8] The GMM system has $N + K$ moment conditions, where the first N sample moments correspond to the pricing errors for each of the N test portfolios:

$$\begin{bmatrix} \boldsymbol{R^e_{t+1}} - \boldsymbol{R^e_{t+1}} \left(\boldsymbol{f_{t+1}} - \boldsymbol{\mu_f}\right)' \boldsymbol{\gamma} \\ \boldsymbol{f_{t+1}} - \boldsymbol{\mu_f} \end{bmatrix} = \mathbf{0}. \tag{19}$$

$\boldsymbol{\gamma}$ denotes the vector of factor prices of risk and $\boldsymbol{\mu_f}$ denotes the vector of factor means. The last K moment conditions in the system above allow us to estimate the factor means; thus the estimated factor risk prices $\boldsymbol{\gamma}$ take into account for the estimation error in the factor means, as in Cochrane (2005), Yogo (2006), Maio and Santa-Clara (2012), and Maio (2013a). The GMM-based t-ratios associated with the risk price estimates are based on standard errors constructed with the VARHAC procedure (see Den Haan and Levin (1997)). Given that the signs of the risk price estimates are constrained by theory, we use single-sided p-values in evaluating the respective statistical significance.

The over-identifying restrictions of the model can be tested using the following χ^2-statistic,

$$\hat{\boldsymbol{\alpha}}' \mathrm{Var}\left(\hat{\boldsymbol{\alpha}}\right)^{\dagger} \hat{\boldsymbol{\alpha}} \sim \chi^2(N-K), \tag{20}$$

where $\hat{\boldsymbol{\alpha}}$ denotes the vector of the pricing errors associated with the N test assets and † denotes a pseudo inverse. The degree of over-identification is $N - K$ ($N + K$ moments and $2K$ parameters to estimate).

The χ^2-statistic evaluates the null hypothesis that the pricing errors across the N testing assets are jointly equal to zero. This test is conceptually similar to the GRS test (Gibbons, Ross, and Shanken (1989)), since the test statistic is a quadratic form in the vector of pricing errors (Cochrane (2005)). This statistic, however, can be problematic due to several biases. In some cases, the covariance matrix of the pricing errors can be close to singular, causing problems in inverting it, which misleads toward a rejection of a model even with

[8] For instance, the vector of factors in the CW-CAPM is $\boldsymbol{f_{t+1}} = (\Delta c_{t+1}, \Delta w_{t+1}, r_{m,t+1})'$.

small magnitudes of pricing errors. In other cases, the inverse of the covariance matrix can be underestimated, misleading to the non-rejection of a model even with large magnitudes of pricing errors.

Acknowledging these limitations of the χ^2-statistic, we also present two simpler and more robust goodness-of-fit measures to evaluate the fit of the model, which are widely used in the related literature. The first measure is the cross-sectional OLS R^2,

$$R^2_{OLS} = 1 - \frac{\text{Var}_N(\widehat{\alpha}_i)}{\text{Var}_N(\bar{R}_i)}, \tag{21}$$

where $\text{Var}_N(\cdot)$ stands for the cross-sectional variance and $\bar{R}_i$ is the average excess return on asset i. The cross-sectional R^2_{OLS} measures the percentage of the cross-sectional variance of average excess returns explained by the fitted model. This measure can have a negative value for poorly fitting models estimated under the constraint that the zero-beta rate equals the risk-free rate, that is, when the pricing equation does not include an intercept (Campbell and Vuolteenaho (2004), Yogo (2006), among others).

An alternative measure is the mean absolute pricing error (MAE):

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |\hat{\alpha}_i|. \tag{22}$$

This metric is also widely employed in the empirical asset pricing literature (e.g., Yogo (2006), Lustig and Verdelhan (2007), Da, Yang, and Yun (2016), among others). However, unlike R^2_{OLS}, MAE does not enable a comparison between the average pricing error and the average excess return that we want to price.

4 Main Results

In this section, we discuss the main results associated with the asset pricing tests of the macro models presented in Section 2, with particular focus on the macro models containing wage growth as a risk factor.

4.1 Factor Risk Prices and Pricing Errors

The estimation and evaluation results for the five linear factor models presented above are displayed in Table 3. The testing assets represent each of the six portfolio groups presented in the last section. In the case of the baseline CAPM, the cross-sectional R^2 estimates are either negative (estimation with SBM25, SINV25, SNSI35, or SRVAR25 portfolios) or very close to zero (estimation with SOP25 or SREV25). A negative R^2 in this case means that the model performs even worse than a trivial model containing solely an intercept as the risk factor (see, for example, Campbell and Vuolteenaho (2004) and Maio and Santa-Clara (2017)). The CAPM is formally rejected by the specification test as the corresponding p-values are around zero in all cases. These results are in line with previous evidence showing that the CAPM fails completely in terms of pricing these cross-sectional patterns in average stock returns. Hence, we have the usual designation of "market anomalies" for the stock characteristics on which those portfolios are sorted.

The C-CAPM seems to outperform considerably the CAPM when it comes to explaining the dispersion in average returns among the SBM25, SINV25, SNSI35, and (to a lower extent) SOP25 portfolios, with R^2 estimates in the 12-18% range. In contrast, the C-CAPM does even worse than the CAPM when it comes to pricing the SREV25 portfolios, as indicated by the negative explanatory ratio (-9%). In the estimation with the SRVAR25 portfolios the explanatory ratio is zero, yet this estimate is significantly better than the very negative fit obtained for the CAPM (-72%). The C-CAPM is not rejected (at the 5% level) when the testing assets are SOP25 or SREV25. Yet, in the latter case the OLS R^2 is negative, which means that the model does worse than the cross-sectional average risk premium in terms of explaining dispersion in average portfolio returns. This shows how misleading the χ^2-statistic can be, that is, validating a model with very large pricing errors. Overall, while providing an improvement relative to the CAPM, the C-CAPM still performs modestly in terms of explaining cross-sectional risk premia, since at most only 18% of the dispersion in average returns is explained by the single-factor model. These results are in line with previous evidence showing that the model performs rather modestly in terms of pricing several CAPM anomalies (e.g., Yogo (2006), Lioui and Maio (2014), Maio and Silva (2018), among others).

We see that the two-factor macro model containing wage growth as a risk factor (CW-CAPM*) clearly outperforms the C-CAPM in terms of explaining the six anomalies: The explanatory ratios vary between 39% (test with the SREV25 portfolios) and 60% (SOP25). These estimates are substantially above the corresponding fit obtained for the C-CAPM, with positive spreads between 30 (from 15% to 45%, estimation with the SBM25 portfolios) and 58 (from 0% to 58%, SRVAR25) percentage points. The average pricing error estimates vary between 0.29% (SOP25) and 0.44% (SRVAR25), which are substantially below the corresponding estimates associated with the consumption model. Hence, the inclusion of the wage growth factor seems to play a large role in terms of driving the relative performance of CW-CAPM* versus C-CAPM. Despite the good global fit, the two-factor model is rejected (at the 5% level) in the estimation with SBM25, SINV25, SREV25, or SNSI35. In part, this rejection arises from a problematic inversion of the covariance matrix of the pricing errors, which magnifies the value of the χ^2-statistic.

Turning to the risk price estimates within CW-CAPM*, it turns out that the estimates for γ_w are negative in all cases, with statistical significance at the 5% or 1% level. These negative estimates are thus consistent with the theoretical model derived in Section 2 for realistic structural parameter values. Indeed, most of the implied estimates of η represent plausible values, varying between 46% (estimation with SREV25) and 76% (SOP25).[9] The exception is in the estimation with the SRVAR25 portfolios, in which case the estimate for the share of leisure in utility is unrealistically above one (1.43). On the other hand, the two-factor model tends to produce lower implied estimates of the risk-aversion parameter than the C-CAPM, the exceptions being the estimation with either SBM25 or SNSI35 (in which cases, both models produce a similar estimate for γ).

The fit of the benchmark macro model (CW-CAPM) is similar to that registered for the two-factor model when the testing assets are SOP25, SREV25, and SNSI35, as both the R^2 and MAE estimates are almost identical in both models. The three-factor model generates a modest rise in the explanatory ratio (about 10 percentage points) when it comes to pricing either the SBM25 or SINV25 portfolios. This suggests that the inclusion of the market return factor has a relatively minor effect in the performance of the CW-CAPM. The exception to this pattern is in the estimation with the SRVAR25 portfolios, in which case the OLS R^2 increases by about 23 percentage points relative to the CW-CAPM* (from 0.58 to 0.81), while the average pricing error declines from 0.44% to 0.32% per quarter. A notable difference relative to the two-factor model relies on the fact that the CW-CAPM is not rejected by the specification test in the estimation with either SBM25 or SINV25 groups, with p-values above 5%. Hence, small pricing errors are aligned with the macro model passing the formal test for four of the six portfolio groups.

Similarly to the comparison between CW-CAPM* and C-CAPM, we can assess the incremental explanatory power driven by the wage growth factor (in the three-factor model) by comparing the performance against the Epstein–Zin model: The gains in the cross-sectional R^2 are always above 30 percentage points, varying between 31 points (estimation with SREV25) and 65 points (SRVAR25). This represents another signal of the economic significance associated with the wage factor within the benchmark macro model.

In terms of risk price estimates within the three-factor model, it turns out that the estimates of γ_w are negative and strongly statistically significant (5% or 1% level) in most cases. The only exception is in the estimation with SBM25, in which case the wage risk price is only marginally significant (10% level). Except in the case of SREV25, the implied estimates of η have smaller magnitudes than the corresponding estimates within CW-CAPM*. This is especially notable when the testing portfolios are SRVAR25, in which case the share of leisure declines from 1.48 to a plausible value of 0.78. On the other hand, with the exception of the

[9] Eichenbaum, Hansen, and Singleton (1988) obtain shares of leisure above 80% by estimating an Euler equation containing the risk-free rate. On the other hand, Jacobs (2007) obtains shares of leisure above 50% by estimating Euler equations with individual household data.

estimation with SREV25, the implied estimates of γ tend to be larger than the corresponding estimates in the restricted macro model. Again, this pattern is especially relevant when the testing assets are the size–variance portfolios. Hence, these results suggest a trade-off in the preference parameter estimates within the macro model, that is, the lower estimates of the leisure share within the three-factor model come at the cost of higher risk aversion estimates. On the other hand, large estimates of the RRA parameter are inescapable in cross-sectional tests of macro asset pricing models containing aggregate consumption growth as a risk factor (e.g., Yogo (2006), Savov (2011), Lioui and Maio (2014), Chen and Lu (2018), Maio and Silva (2018), among others).

We can also see that the estimates for the market price of risk are implausibly negative in most cross-sectional tests, the sole exception being the case of the SREV25 portfolios. However, all the estimates of γ_m are largely non-significant even at the 10% level, including the estimation with SRVAR25. Hence, the market factor induces incremental explanatory power in the case of the variance portfolios only indirectly by affecting the consumption and wage risk price estimates. The implied estimates of the elasticity of substitution parameter are very close to zero in all cases, which is in line with previous studies conducting asset pricing tests of models based on recursive preferences (e.g., Yogo (2006), Lioui and Maio (2014), Chen and Lu (2018), and Maio and Silva (2018)).

Table 4 displays the results for the augmented asset pricing test containing simultaneously the six portfolio groups, for a total of 160 portfolios. The joint estimation with the six anomalies is the most challenging and relevant asset pricing test: It forces the model to price a large cross-section of returns, and avoids the possibility of unstable risk price estimates across different portfolio groups, as documented above.

The results indicate that the C-CAPM shows a rather poor performance in terms of pricing the six anomalies, with a R^2 of only 8% and an average pricing error of 0.50% per quarter. On the other hand, the two-factor macro model shows a substantial improvement in fit relative to the consumption model, as indicated by the explanatory ratio around 50% and the MAE of 0.36% per quarter. The three-factor model shows only a marginal gain in performance relative to CW-CAPM*, with an explanatory ratio of 55% and the same average pricing error estimate as in the two-factor model. To assess the value added by the wage growth factor, it follows that the CW-CAPM produces a rise in R^2 of 46 percentage points against the Epstein–Zin model, while the increase in fit of CW-CAPM* relative to the baseline consumption model has a similar magnitude (41 percentage points). Not surprisingly, both macro models are rejected by the specification test given the large number of testing portfolios involved, which causes serious problems in inverting the covariance matrix of the pricing errors.

In terms of risk price estimates, the estimate of γ_m within the benchmark macro model is negative, although highly insignificant. On the other hand, both estimates for the wage risk price are negative and strongly significant (1% level). This implies estimates of the share of leisure of 0.57 and 0.70 in the benchmark and two-factor models, respectively. The implied estimate of the risk aversion parameter in the benchmark model is substantially higher than the corresponding estimate associated with CW-CAPM* (238 versus 175). This represents another signal of the trade-off associated with the magnitudes of these two preference parameters in the consumption–wage CAPM. We also see that the CW-CAPM* generates lower estimates of γ than both C-CAPM and EZ models, although the same does not occur for CW-CAPM.

4.2 Return Decomposition

To gain further insight in the performance of CW-CAPM, we conduct a decomposition of portfolio risk premia for each portfolio group. Specifically, the total risk premium associated with a given portfolio from the three-factor macro model is decomposed in the corresponding partial factor risk premiums (risk price times beta), one for each factor in the model.[10] We are interested in establishing which of the three factor risk premiums within the CW-CAPM drive the original portfolio average return, that is, which factors help the model in explaining risk premia. Since our goal is to capture how the model succeeds in explaining cross-sectional dispersion in risk premium, we look at the gap in risk premia of the extreme high-minus-low portfolios within each anomaly.

Table 5 displays the return decomposition for each of the six anomalies or portfolio groups. The spreads high-minus-low associated with each stock characteristic (BM, INV, OP, REV, NSI, or RVAR) are computed within each size quintile. This enables to assess the performance of the model in explaining a given anomaly (e.g., operating profitability) conditional on size. The raw spreads in average returns are positive for all size quintiles in the cases of the SBM25 and SOP25 portfolios in light of the positive correlations between these two characteristics (book-to-market and operating profitability) and average stock returns. For the wage factor to have a relevant contribution in terms of driving the dispersion in average returns of those two portfolio groups, it turns out that the corresponding gaps in risk premia should be also positive. This is indeed true for the first three size quintiles (small and mid caps). In the cases of the upper two size quintiles (large caps), we obtain negative gaps in the wage risk premium, yet the magnitudes are relatively modest. Turning to the other four portfolio groups (SINV25, SREV25, SNSI35, and SRVAR25), we observe negative spreads in raw risk premia in light of the negative correlation between these characteristics (INV, REV, NSI, and RVAR) with average stock returns. These negative return spreads are matched by

[10] A similar analysis is conducted in Maio (2013b) and Maio and Philip (2018).

corresponding gaps in the wage risk premium with the same sign for the vast majority of the cases. The very few exceptions occur for the fourth size quintile within the SNSI35 and SRVAR25 groups and the last size quintile within SRVAR25.

Regarding the consumption factor, it turns out that the corresponding gaps in risk premia assume much more frequently the wrong sign in comparison to the wage growth factor. This is especially true when the testing portfolios are SINV25, SREV25, or SRVAR25. Further, the magnitudes of the risk premia spreads associated with wage growth tend to be larger than the corresponding estimates associated with consumption growth. Therefore, the wage factor is quantitatively more important than the consumption factor in terms of explaining the six CAPM anomalies.

The dispersion in risk premium associated with the market factor tends to be substantially smaller (in magnitude) in comparison to the other two factors. This implies that the market factor plays a relatively minor role in terms of pricing these anomalies, as suggested above. The main exception is in the estimation with the SRVAR25 portfolios, in which case the magnitudes of the gaps in market risk premia gaps are greater than for the other two factors in the model.

Overall, the results from Table 5 largely confirm the evidence from the last subsection that the wage factor is the key driving force of the three-factor model when it comes to explaining the cross-section of stock returns.

4.3 Factor loadings

The results above clearly suggest that there is a relevant dispersion in the loadings on the wage factor. Moreover, such dispersion in betas has the correct sign, that is, the factor loadings are aligned with the raw portfolio risk premia that we seek to explain.

The estimated loadings on the wage factor are displayed in Table 6. Each panel corresponds to a different portfolio group, similarly to Table 5. The last column represents the low-minus-high spread of the wage betas within each size quintile in the cases of SINV25, SREV25, SNSI35, and SRVAR25 groups. In the cases of SBM25 and SOP25, we report the high-minus-low spreads in betas. For each anomaly, it turns out that the spread in wage betas is negative within most size quintiles. The few exceptions occur for the upper two size quintiles corresponding to the SBM25, SOP25, and SRVAR25 portfolio classes. Hence, the negative spread in wage betas is more significantly negative within small and mid caps, at least for some anomalies. More importantly, such negative gap in betas, multiplied by the negative price of risk associated with the wage factor, as discussed above, generates the positive gaps in risk premia that are necessary to explain the raw anomalies. This represents the main mechanism by which wage growth helps explaining cross-sectional dispersion in equity risk premia.

Therefore, value stocks, stocks that invest less, stocks with low equity issuance, past long-term losers, more profitable stocks, and stocks with lower idiosyncratic risk, earn higher average returns relative to stocks with the opposite characteristics because the former groups of stocks have higher labor income risk, that is, these stocks load more negatively on the wage growth factor.

Why do we observe such cross-sectional dispersion in wage betas? One conjecture relies on the possibility that many of the value and past loser firms are financially constrained as a consequence of a series of past negative shocks in their cash-flows (see Fama and French (1993, 1996)). Therefore, these firms will be more negatively impacted by an upwards shock in wage growth.[11] This mechanism will be especially relevant for firms with a production process that is relatively more dependent on labor. On the other hand, firms that invest less and have lower equity issuance are also likely firms that are more financially constrained. Hence, such firms will also be more negatively affected by rises in wages. Many of the stocks with a low idiosyncratic variance (relative to the Fama-French three-factor model) are likely small stocks given that the size factor is included in the benchmark model. Typically, small stocks are more financially constrained than mid caps, and hence their cash-flows will be more impacted by rising wages. In addition to the financial constraints channel, the dependence on the labor force might represent another channel that explains the pattern in wage betas. Hence, many of the more profitable firms might be highly dependent on labor force in their production function, in particular high-skill workers. When the average wage in the economy rises, it becomes more costly for these firms to maintain or replace their skilled labor force (see Belo, Li, Lin, and Zhao (2017)). Therefore, those firms will also be significantly negatively affected by an increase in the wage costs.

4.4 Alternative Factor Models

In this subsection, we compare the performance of the macro model with alternative multi-factor models widely used in the empirical asset pricing literature.

The first model that we estimate is the Fama and French (1993, 1996) three-factor model (henceforth FF3), in which the expected return-covariance representation is given by

$$\mathrm{E}(R^e_{i,t+1}) = \gamma_M Cov(R^e_{i,t+1}, R_{m,t+1}) + \gamma_{SMB} Cov(R^e_{i,t+1}, SMB_{t+1}) + \gamma_{HML} Cov(R^e_{i,t+1}, HML_{t+1}). \tag{23}$$

R_m represents the excess market return (in levels), while SMB and HML denote the size and value factors, respectively.

[11] This is consistent with the Credit Channel Mechanism theory proposed in Bernanke and Gertler (1989, 1990, 1995), which works either through a balance sheet channel or a bank lending channel.

The second model is the four-factor model of Carhart (1997) (C4),

$$\mathrm{E}(R^e_{i,t+1}) = \gamma_M Cov(R^e_{i,t+1}, R_{m,t+1}) + \gamma_{SMB} Cov(R^e_{i,t+1}, SMB_{t+1}) + \gamma_{HML} Cov(R^e_{i,t+1}, HML_{t+1}) + \gamma_{UMD} Cov(R^e_{i,t+1}, UMD_{t+1}), \quad (24)$$

in which the difference relative to FF3 is the inclusion of a momentum factor (UMD).

The third model is the four-factor model of Pástor and Stambaugh (2003) (PS4), which adds a stock liquidity factor (LIQ) to FF3:

$$\mathrm{E}(R^e_{i,t+1}) = \gamma_M Cov(R^e_{i,t+1}, R_{m,t+1}) + \gamma_{SMB} Cov(R^e_{i,t+1}, SMB_{t+1}) + \gamma_{HML} Cov(R^e_{i,t+1}, HML_{t+1}) + \gamma_{LIQ} Cov(R^e_{i,t+1}, LIQ_{t+1}). \quad (25)$$

The fourth model is the four-factor model of Hou, Xue, and Zhang (2015) and Hou, Mo, Xue, and Zhang (2019) (HXZ4). In addition to the usual market factor, this model contains a size factor (ME), an investment factor (IA), and a net profitability factor (ROE):

$$\mathrm{E}(R^e_{i,t+1}) = \gamma_M Cov(R^e_{i,t+1}, R_{m,t+1}) + \gamma_{ME} Cov(R^e_{i,t+1}, ME_{t+1}) + \gamma_{IA} Cov(R^e_{i,t+1}, IA_{t+1}) + \gamma_{ROE} Cov(R^e_{i,t+1}, ROE_{t+1}). \quad (26)$$

Finally, we estimate the five-factor model of Fama and French (2015, 2016) (FF5). This model augments FF3 with an investment (CMA) and an operating profitability (RMW) factor:

$$\mathrm{E}(R^e_{i,t+1}) = \gamma_M Cov(R^e_{i,t+1}, R_{m,t+1}) + \gamma_{SMB} Cov(R^e_{i,t+1}, SMB_{t+1}) + \gamma_{HML} Cov(R^e_{i,t+1}, HML_{t+1}) + \gamma_{CMA} Cov(R^e_{i,t+1}, CMA_{t+1}) + \gamma_{RMW} Cov(R^e_{i,t+1}, RMW_{t+1}). \quad (27)$$

The monthly data on the ME, IA, and ROE factors are obtained from Lu Zhang, while the data on LIQ are from Robert Stambaugh's webpage. The data on the remaining factors are from Kenneth French's data library. The quarterly factors are obtained by compounding the corresponding monthly factors.

Since all the factors in these models represent excess returns, the factor risk price estimates of the equivalent beta representations should be equal to the corresponding factor means. Therefore, following Maio and Santa-Clara (2017) and Cooper and Maio (2018b) (see also Lewellen, Nagel, and Shanken (2010)), we compute the "constrained" cross-sectional R^2:

$$R^2_C = 1 - \frac{\mathrm{Var}_N(\hat{\alpha}_{i,C})}{\mathrm{Var}_N(\bar{R}_i)}. \quad (28)$$

This metric is similar to the OLS R^2 presented above, but employs pricing errors ($\hat{\alpha}_{i,C}$)

from a "constrained regression" in which the beta risk prices are equal to the respective factor means, rather than being freely estimated from an OLS cross-sectional regression, or equivalently, first-stage GMM (see Maio and Santa-Clara (2017) and Cooper and Maio (2018b) for details). It is important to note that this measure can only be used to evaluate factor models in which all the factors are traded, hence, it can not be applied to our macro model.

The estimation results for the alternative factor models are presented in Table 7. To save space, we only report results for the augmented test containing simultaneously the six portfolio groups. We can see that the CW-CAPM has similar or higher OLS R^2 estimates than the FF3, C4, and PS4 models. Moreover, CW-CAPM* dominates both FF3 and PS4. At a first glance, both macro models seem to be dominated by both HXZ4 and FF5, as indicated by the higher explanatory ratios of the empirical models (around or above 70%). However, the higher OLS R^2 for these two models are obtained at the cost of implausible covariance and beta risk price estimates. When we impose the constraint on the beta risk price estimates, it follows that the fit of these models declines substantially: the R^2_C estimates are around 25% in both cases, which represents about a third of the magnitude of the corresponding OLS explanatory ratios. This level of fit is about half of the fit registered for both macro models that contain the wage growth factor.

Therefore, if anything, the evidence from Table 7 is that both macro models compare favorably with the alternative multifactor models in terms of pricing jointly the six anomalies. This result is especially notable as some of these models were designed specifically to price some of the testing portfolios employed here (e.g., the case of HML in pricing the SBM25 portfolios, both IA and CMA when it comes to pricing SINV25, or RMW in explaining the SOP25 portfolios). The size factors are also mechanically related with all the six groups of portfolios. In other words, there is a high mechanical correlation between some of the traded factors and some of the testing assets, which is absent in the case of the macro models.

5 Additional Results

In this section, we report some additional results and conduct a sensitivity analysis to the main results reported in the previous section.

5.1 Second-Stage GMM

We estimate the CW-CAPM by second-stage or efficient GMM in which the moments in Equation (19) are weighted by the inverse of the spectral density matrix. The second-stage GMM estimation is equivalent to a Generalized Least Squares (GLS) cross-sectional regression of average returns on factor covariances, and provides the most efficient estimates of parameters (i.e., lowest standard errors).

When estimating the model by efficient GMM, we calculate the Weighted Least Squares (WLS) R^2 as a goodness-of-fit metric:

$$R^2_{WLS} = 1 - \frac{\hat{\boldsymbol{\alpha}}' \hat{\boldsymbol{S}^*}_N^{-1} \hat{\boldsymbol{\alpha}}}{\bar{\boldsymbol{R}}' \hat{\boldsymbol{S}^*}_N^{-1} \bar{\boldsymbol{R}}}. \tag{29}$$

$\hat{\boldsymbol{\alpha}}$ denotes the vector of pricing errors from second-stage GMM; $\hat{\boldsymbol{S}^*}_N$ represents a diagonal matrix corresponding to the block of the spectral density matrix associated with the pricing errors of the N test assets; and $\bar{\boldsymbol{R}}$ denotes the vector of (cross-sectionally) demeaned average excess returns. The R^2_{WLS} assigns less weight to the pricing errors with larger standard errors (e.g., Ferson and Harvey (1999) and Shanken and Zhou (2007)).

Lewellen, Nagel, and Shanken (2010) argue that a GLS or WLS cross-sectional regression (or equivalently, second-stage GMM) has some advantages over an OLS cross-sectional regression (or equivalently, first-stage GMM). In particular, the GLS/WLS R^2 has an useful economic interpretation, that is, it measures how far a linear combination of the factors (or the factors' mimicking portfolios in the case of macro factors) is close to the mean-variance frontier generated from the testing assets. Put differently, GLS/WLS R^2 represents a measure of how well a model explains the risk-return opportunities available in the market. Further, there is a more rigorous hurdle to attain a high GLS/WLS R^2 than a high OLS R^2. This is because a model can yield a high OLS R^2 even though it cannot explain the maximum Sharpe ratio constructed from the testing assets. Cochrane (2005) and Lettau and Ludvigson (2001), however, point out that in the GLS/WLS regression a model is forced to explain "re-packaged" portfolios, which sometimes represent extreme linear combination of the original test portfolios, as stressed above. As such, the GLS/WLS regression approach loses the economic content of the original testing portfolios that are of direct interest.

Table 8 presents results for the second-stage GMM estimation that includes the six market anomalies simultaneously (i.e., 160 portfolios in total). Consistent with previous evidence, the baseline CAPM cannot price the transformed portfolios as indicated by the very negative explanatory ratio (−79%). The C-CAPM improves the CAPM by a big margin, with a WLS R^2 of 66%. However, the CW-CAPM* performs even better, with an explanatory ratio as large as 85%, indicating that a linear combination of the factors' mimicking portfolios is close to the mean-variance frontier, that is, the model explains well the available risk-return opportunities. That estimate is also significantly above the OLS counterpart (49%), which suggests that the two-factor model does a better job in pricing the transformed portfolios than the original portfolios. The benchmark macro model achieves essentially the same fit as the CW-CAPM* (86%), thus suggesting that the market factor does not add relevant explanatory power for the transformed cross-sectional risk premia.

As in the benchmark case with first-stage GMM, the wage risk price estimates are negative and strongly significant (1% level) in both models. Further, the implied estimates of η are very similar to the first-stage counterpart estimates. On the other hand, we obtain substantially smaller magnitudes for the consumption risk price estimates than in the benchmark case, which in turn implies lower estimates for the risk aversion parameter (below 125). Therefore, we obtain more economically plausible estimates for the implied preference parameters than in the estimation with first-stage GMM.

5.2 Beta Representation

We test the CW-CAPM in expected return-beta representation by using the time-series/cross-sectional regression approach employed in Black, Jensen, and Scholes (1972), Jagannathan and Wang (1998), and Brennan, Wang, and Xia (2004) (or, equivalently the Fama and MacBeth (1973) two-pass methodology). In the first step, we estimate multivariate time-series regressions to obtain the factor betas for each test asset,

$$R^e_{i,t+1} = \delta_i + \boldsymbol{\beta_i'} \boldsymbol{f_{t+1}} + \epsilon_{i,t+1}, \tag{30}$$

where $\boldsymbol{\beta_i}$ denotes the vector of factor betas for asset i.

In the second step, we run an OLS cross-sectional regression of (time-series) average excess returns on the factor betas to estimate the factor risk premiums $\boldsymbol{\lambda}$,

$$\bar{R}_i = \boldsymbol{\lambda}' \boldsymbol{\beta_i} + \alpha_i, \tag{31}$$

where $\bar{R}_i$ denotes the sample average excess return for asset i and α_i denotes the pricing error. To impose the economic restriction that zero-beta rate equals the risk-free rate, we do not include an intercept in the regression. The critical difference between the first-stage GMM estimation and the two-step regression approach is that the betas from GMM estimation are single-regression betas rather than multiple-regression betas. The later take into account correlation among the factors (see Cochrane (2005) and Kan, Robotti, and Shanken (2013)). Both approaches, however, produce the same pricing error estimates, and thus the same fit. In calculating the t-statistics for the beta factor risk prices, we use the Shanken's correction (Shanken (1992)) for the errors-in-variables bias.

Table 9 reports the results for the augmented estimation with the six anomalies. As expected, the explanatory power of the CW-CAPM is the same in the estimation of the beta representation. The point estimates for the risk price associated with wage growth are negative and significant (at the 5% level) in both models, while those associated with consumption growth are positive and significant only in the case of the CW-CAPM. Interestingly, the market price of risk estimates are significantly positive within the EZ and CW-CAPM models, in contrast to the respective covariance risk price estimates. This shows that the risk price estimates can flip sign between the covariance and (multivariate) beta representations of a given model due to the correlations among the factors.

Next, we re-estimate the beta equation of each factor model by including an intercept in the cross-sectional regression. If the model is correctly specified, the estimated intercept in the regression should be indistinguishable from zero. The estimates for the excess zero-beta rate are small and largely insignificant in the models that contain the wage growth factor. Further, the estimates for factor risk prices and R^2_{OLS} are quite similar in magnitude to the corresponding estimates in the benchmark regression without intercept. In sharp contrast, in the case of the alternative factor models (CAPM, C-CAPM, and EZ) the estimates for the intercept are sizable, varying between 1.02% (C-CAPM) and 2.43% (CAPM), being statistically significant in all three cases. Further, for these three models, the R^2_{OLS} estimates significantly increase due to the presence of the intercept in the regression, especially in the cases of CAPM and EZ models. These results suggest that the models containing the wage growth factor can match the zero-beta rate and are not misspecified when they are forced to price multiple anomalies. On the other hand, there are relevant missing risk factors in the alternative linear factor models.

Overall, the estimation results from the beta representation of the CW-CAPM and CW-CAPM* are consistent with those from the covariance representation, and reveal that the wage growth factor is important to meet the economic restriction on average risk premia (i.e., matching the zero-beta rate).

5.3 Sensitivity Analysis

We perform several robustness checks on the results presented in the previous section. The results are reported in the appendix. First, we use an alternative measure of wage. The benchmark measure uses "wages and salaries", which has two components, "private industries" and "government". The alternative measure of wage relies only on the "private industries" component, thus excluding the "government" component. The rationale is that wages and salaries from private industries reflect more effectively changes in broad economic conditions. The results associated with the new version of the macro models are quite similar to the benchmark results, as indicated by the explanatory ratios of 50% and 55% for CW-CAPM* and CW-CAPM, respectively. This suggests that the choice of wage data in constructing the wage growth factor has a negligible impact in the performance of our macro models.

Second, we add the market factor in the menu of testing assets. Lewellen, Nagel, and Shanken (2010) suggest that the traded factors (in the form of portfolio excess returns) in a model (the market factor in our case) should be included as a testing asset. We therefore force the models to price the excess market return, in additional to the six portfolio groups. The results are very similar to the benchmark case. Specifically, the CW-CAPM delivers a R^2_{OLS} of 55% and an average pricing error of 0.36% per quarter, essentially the same as in our benchmark test. Thus, the inclusion of the market factor in the set of testing assets does not affect our results.

Third, we use the portfolios sorted on total variance, instead of residual variance. Ang, Hodrick, Xing, and Zhang (2006) show that stocks with higher variance earn lower average returns, irrespective of whether variance is computed as the variance of daily returns or as the variance of residual returns associated with the FF3 model. In our benchmark test, we use the portfolios formed by size and residual variance (SRVAR25). As a robustness check, we replace this portfolio group with portfolios sorted by size and total variance (SVAR25), which are also obtained from Kenneth French's data library. The results show that both the risk price estimates and R^2_{OLS} are similar to the corresponding values in the benchmark asset pricing test. Specifically, the explanatory ratios decline only marginally to 42% and 48% in the cases of CW-CAPM* and CW-CAPM, respectively, while the average pricing error in both models is basically the same as in the benchmark estimation (0.37% versus 0.36%).

Finally, we examine whether CW-CAPM explains the momentum and accrual anomalies. Price momentum refers to a cross-sectional pattern by which stocks with high prior short-term returns outperform stocks with low prior returns (Jegadeesh and Titman (1993) and Fama and French (1996)). The accruals anomaly represents the evidence that stocks of firms with low accruals enjoy higher average returns than stocks of firms with high accruals (Sloan (1996) and Richardson, Sloan, Soliman, and Tuna (2005)). We employ double-sorted portfolios on size and either prior returns (SM25) or accruals (SACC25). The portfolio return data are retrieved from Kenneth French's data library.

The results show that both models containing the wage growth factor fail to successfully explain both CAPM anomalies in a way that is consistent with the theoretical framework developed in Section 2. For instance, in the estimation with SM25, both CW-CAPM* and CW-CAPM produce a large fit (R^2_{OLS} around 70%) and are not rejected by the specification test. However, most of the factor risk price estimates are insignificant at the 10% level. Critically, the wage risk price estimates are implausibly positive in both models, which leads to negative implied estimates for η. In the estimation with the accruals portfolios, the fit of CW-CAPM* is rather modest, with an explanatory ratio close to zero (6%). In comparison, the benchmark model produces a better performance (33%). Yet, as in the estimation with the SM25 portfolios, the estimates for γ_w are positive in both cases, with marginal significance in the case of CW-CAPM. Hence, the corresponding estimates of γ and η in the three-factor model are -5.60 and 8.23, respectively, which are inconsistent with the theoretical model.

Therefore, the seemingly positive fit of the three-factor model comes at the cost of implausible preference parameter estimates.

The failure of the CW-CAPM in explaining the momentum and accrual anomalies represents a limitation of the model. However, these results are not totally surprising. Indeed, the results above indicate that the wage growth factor drives the explanatory power of both macro models. Yet, it is not likely that a single factor explains cross-sectional dispersion in risk premia associated with portfolio groups that are weakly (or even negatively) correlated (e.g., momentum, operating profitability, and asset growth portfolios). For example, the recent multifactor models of Hou, Xue, and Zhang (2015) and Fama and French (2015) employ several factors to achieve that goal.

6 Conclusions

We propose a new macroeconomic model to price a broad cross-section of average stock returns. Specifically, we derive a three-factor macro model in which the factors are the standard real consumption growth factor, the standard market return factor, and aggregate wage growth. This model is denoted by Consumption-Wage CAPM (CW-CAPM). The underlying theoretical framework assumes an intertemporal utility of the recursive form, combined with an intra-temporal utility that depends on both real consumption and the services provided by leisure (with a Cobb-Douglas specification). By using the intraperiod equilibrium condition relating the marginal rate of substitution (between leisure and consumption) and the respective relative price of leisure, we are able to substitute hours of leisure by wage growth in the pricing kernel that prices assets. There are three preference parameters in the model: the coefficient of relative risk aversion, the share of leisure over utility, and the elasticity of intertemporal substitution. Given the assumption of a positive share of leisure, the wage risk price should be negative as long as the risk aversion parameter is above one (more risk averse than an investor with log utility). In other words, higher wage growth decrease the demand of leisure services and thus increase the marginal utility of consumption ("bad times").

A restricted version of CW-CAPM (denoted by CW-CAPM*) contains consumption growth and wage growth as the two risk factors. This nested model is derived by assuming that the risk aversion parameter is the reciprocal of the elasticity of intertemporal substitution. Further, the three-factor model also nests the baseline CCAPM and the two-factor model of Epstein and Zin (1991) (which contains consumption growth and the market return as risk factors) as special cases.

We estimate a linear version of the three-factor macro model (in expected return-covariance representation) by first-stage GMM with a broad cross-section of stock returns. Specifically, we use portfolios sorted on size and each of six stock characteristics: book-to-market ratio; asset growth; net share issues; long-term return reversal; operating profitability; and residual stock variance.

Overall, the empirical results provide a strong support for the linear three-factor macro model, and also suggest that the wage factor helps pricing cross-sectional equity risk premia. Specifically, in the augmented cross-sectional test with the joint six portfolio groups (160 portfolios in total) both versions of the consumption-wage model explain around 50% of the cross-section dispersion in average returns of the 160 portfolios. Critically, the wage risk price estimates are negative and strongly significant, and thus consistent with the theoretical model. The implied estimates of the leisure share over utility are also economically plausible. Wage growth is the key factor in terms of driving the performance of the consumption-wage CAPM, as the dispersion in the respective risk premium (price of risk X quantity of risk) drives to a large degree the dispersion in equity risk premia. Indeed, value stocks, stocks that invest less, stocks with low equity issuance, past long-term losers, more profitable stocks, and stocks with lower idiosyncratic risk, earn higher average returns relative to other stocks because they have higher labor income risk, that is, these stocks load more negatively on the wage growth factor.

Notably, both macro models containing the wage factor compare favorably with the workhorses employed in the empirical asset pricing literature: the three-factor model of Fama and French (1993), the four-factor models of Carhart (1997), Pástor and Stambaugh (2003), and Hou, Xue, and Zhang (2015), and the five-factor model of Fama and French (2015). However, the Consumption-Wage CAPM cannot price portfolios sorted on momentum or accruals.

References

Ait-Sahalia, Y., J. A. Parker, and M. Yogo. 2004. "Luxury Goods and the Equity Premium." *Journal of Finance* 59, 2959–3004.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang. 2006. "The Cross-Section of Volatility and Expected Returns." *Journal of Finance* 61, 259–300.

Basu, S. 1983. "The Relationship Between Earnings Yield, Market Value, and Return for NYSE Common Stocks: Further Evidence." *Journal of Financial Economics* 12, 129–156.

Belo, F., J. Li, X. Lin, and X. Zhao. 2017. "Labor-Force Heterogeneity and Asset Prices: The Importance of Skilled Labor." *Review of Financial Studies* 30, 3669–3709.

Bernanke, B.S., and M. Gertler. 1989. "Agency Costs, Net Worth, and Business Fluctuations." *American Economic Review* 79, 14–31.

Bernanke, B.S., and M. Gertler. 1990. "Financial Fragility and Economic Performance." *Quarterly Journal of Economics* 105, 87–114.

Bernanke, B.S., and M. Gertler. 1995. "Inside the Black Box: The Credit Channel of Monetary Policy Transmission." *Journal of Economic Perspectives* 9, 27–48.

Black, F., M. C. Jensen, and M. Scholes. 1972. "The Capital Asset Pricing Model: Some Empirical Tests." In *Studies in the Theory of Capital Markets*, M. C. Jensen, ed. New York, NY: Praeger.

Brav, A., G. M. Constantinidies, and C. C. Geczy. 2002. "Asset Pricing with Heterogeneous Consumers and Limited Participation: Empirical Evidence." *Journal of Political Economy* 110, 793–824.

Breeden, D. T. 1979. "An Intertemporal Asset Pricing Model with Stochastic Consumption and Investment Opportunities." *Journal of Financial Economics* 7, 265–296.

Breeden, D. T., M. R. Gibbons, and R. Litzenberger. 1989. "Empirical Tests of the Consumption-Oriented CAPM." *Journal of Finance* 44, 231–262.

Brennan, M., A. Wang, and Yihong Xia. 2004. "Estimation and Test of a Simple Model of Intertemporal Capital Asset Pricing." *Journal of Finance* 59, 1743–1775.

Campbell, J. Y. 1996. "Understanding Risk and Return." *Journal of Political Economy* 104, 298–345.

Campbell, J. Y., and T. Vuolteenaho. 2004. "Bad Beta, Good Beta." *American Economic Review* 94, 1249–1275.

Carhart, M. M. 1997. "On Persistence in Mutual Fund Performance." *Journal of Finance* 52, 57–82.

Chen, Z., and A. Lu. 2018. "Seeing the Unobservable from the Invisible: The Role of CO2 in Measuring Consumption Risk." *Review of Finance* 22, 977–1009.

Cochrane, J. H. 1996. "A Cross-Sectional Test of an Investment-Based Asset Pricing Model." *Journal of Political Economy* 104, 572–621.

Cochrane, J. H. 2005. *Asset Pricing*. Princeton, NJ: Princeton University Press.

Cooper, I., and P. Maio. 2018a. "Asset Growth, Profitability, and Investment Opportunities." *Management Science*, forthcoming.

Cooper, I., and P. Maio. 2018b. "New Evidence on Conditional Factor Models." *Journal of Financial and Quantitative Analysis*, forthcoming.

Cooper, M. J., H. Gulen, and M. J. Schill. 2008. "Asset Growth and the Cross-Section of Stock Returns." *Journal of Finance* 63, 1609–1652.

Da, Z., W. Yang, and H. Yun. 2016. "Household Production and Asset Prices." *Management Science* 62, 387–409.

De Bondt, W. F. M., and R. H. Thaler. 1985. "Does the Stock Market Overreact?" *Journal of Finance* 40, 793–805.

De Bondt, W. F. M., and R. H. Thaler. 1987. "Further Evidence on Investor Overreaction and Stock Market Seasonality." *Journal of Finance* 42, 557–581.

Delikouras, S. 2017. "Where's the Kink? Disappointment Events in Consumption Growth and Equilibrium Asset Prices." *Review of Financial Studies* 30, 2851–2889.

Den Haan, W. J., and A. T. Levin. 1997. "A Practitioner's Guide to Robust Covariance Matrix Estimation." In *Handbook of Statistics*, G. S. Maddala and C. R. Rao, eds. Amsterdam: North Holland, vol. 15, 299–342.

Dittmar, R. F., and C. T. Lundblad. 2017. "Firm Characteristics, Consumption Risk, and Firm-Level Risk Exposures." *Journal of Financial Economics* 125, 326–343.

Eichenbaum, M., L. P. Hansen, and K. J. Singleton. 1988. “A Time-Series Analysis of Representative Agent Models of Consumption and Leisure Choice under Uncertainty.” *Quarterly Journal of Economics* 103, 51–78.

Eiling, E. 2013. “Industry-Specific Human Capital, Idiosyncratic Risk, and the Cross-Section of Expected Stock Returns. *Journal of Finance* 68, 43–84.

Epstein, L. G., and S. E. Zin. 1989. “Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework.” *Econometrica* 57, 937–968.

Epstein, L. G., and S. E. Zin. 1991. “Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: An Empirical Analysis.” *Journal of Political Economy* 99, 263–286.

Fama, E. F., and K. R. French. 1992. “The Cross-Section of Expected Stock Returns.” *Journal of Finance* 47, 427–465.

Fama, E. F., and K. R. French. 1993. “Common Risk Factors in the Returns on Stocks and Bonds.” *Journal of Financial Economics* 33, 3–56.

Fama, E. F., and K. R. French. 1996. “Multifactor Explanations of Asset Pricing Anomalies.” *Journal of Finance* 51, 55–84.

Fama, E. F., and K. R. French. 2006. “Profitability, Investment, and Average Returns.” *Journal of Financial Economics* 82, 491–518.

Fama, E.F., and K.R. French. 2008. “Dissecting Anomalies.” *Journal of Finance* 63, 1653–1678.

Fama, E. F., and K. R. French. 2015. “A Five-Factor Asset Pricing Model.” *Journal of Financial Economics* 116, 1–22.

Fama, E. F., and K. R. French. 2016. “Dissecting Anomalies with a Five-Factor Model.” *Review of Financial Studies* 29, 69–103.

Fama, E., and J. MacBeth. 1973. “Risk, Return, and Equilibrium: Empirical Tests.” *Journal of Political Economy* 81, 607–636.

Ferson, W. E., and C. R. Harvey. 1999. “Conditioning Variables and the Cross Section of Stock Returns.” *Journal of Finance* 54, 1325–1360.

Gibbons, M. R., S. A. Ross, and J. Shanken. 1989. “A Test of the Efficiency of a Given Portfolio.” *Econometrica* 57, 1121–1152.

Gomes, J., L. Kogan, and M. Yogo. 2009. "Durability of Output and Expected Stock Returns." *Journal of Political Economy* 117, 941–986.

Hansen, L. P. 1982. "Large Sample Properties of Generalized Methods of Moments Estimators." *Econometrica* 50, 1029–1054.

Hou, K., H. Mo, C. Xue, and L. Zhang. 2019. "Which Factors?" *Review of Finance* 23, 1–35.

Hou, K., C. Xue, and L. Zhang. 2015. "Digesting Anomalies: An Investment Approach." *Review of Financial Studies* 28, 650–705.

Hou, K., C. Xue, and L. Zhang. 2018. Replicating Anomalies. *Review of Financial Studies*, forthcoming.

Ikenberry, D., J. Lakonishok, and T. Vermaelen. 1995. "Market Underreaction to Open Market Share Repurchases." *Journal of Financial Economics* 39, 181–208.

Jacobs, K. 2007. "Consumption-Leisure Nonseparabilities in Asset Market Participants' Preferences." *Journal of Monetary Economics* 54, 2131–2138.

Jacobs, K., and K. Q. Wang. 2004. "Idiosyncratic Consumption Risk and the Cross Section of Asset Returns." *Journal of Finance* 59, 2211–2252.

Jagannathan, R., and Y. Wang. 2007. "Lazy Investors, Discretionary Consumption, and the Cross-Section of Stock Returns." *Journal of Finance* 62, 1623–1661.

Jagannathan, R., and Z. Wang. 1996. "The Conditional CAPM and the Cross-Section of Expected Returns." *Journal of Finance* 51, 3–53.

Jagannathan, R., and Z. Wang. 1998. "An Asymptotic Theory for Estimating Beta-Pricing Models Using Cross-Sectional Regressions." *Journal of Finance* 53, 1285–1309.

Jegadeesh, N., and S. Titman. 1993. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance* 48, 65–91.

Kan, R., C. Robotti, and J. Shanken. 2013. "Pricing Model Performance and the Two-Pass Cross-Sectional Regression Methodology." *Journal of Finance* 68, 2617–2649.

King, R. G., and S. T. Rebelo. 1999. "Resuscitating Real Business Cycles." In *Handbook of Macroeconomics*, J. B. Taylor and M. Woodford, eds. Amsterdam: North-Holland.

Kroencke, T. A. 2017. "Asset Pricing without Garbage." *Journal of Finance* 72, 47–98.

Kydland. 1995. "Business Cycles and Aggregate Labor Market Fluctuations." In *Frontiers of Business Cycle Research*, T. F. Cooley, ed. Princeton, NJ: Princeton University Press.

Lettau, M., and S. Ludvigson. 2001. "Resurrecting the (C)CAPM: A Cross-Sectional Test when Risk Premia are Time-Varying." *Journal of Political Economy* 109, 1238–1287.

Lewellen, J., S. Nagel, and J. Shanken. 2010. "A Skeptical Appraisal of Asset-Pricing Tests." *Journal of Financial Economics* 96, 175–194.

Lintner, J. 1965. "Security Prices, Risk, and Maximal Gains from Diversification." *Journal of Finance* 20, 587–615.

Lioui, A., and P. Maio. 2014. "Interest Rate Risk and the Cross-Section of Stock Returns." *Journal of Financial and Quantitative Analysis* 49, 483–511.

Loughran, T., and J. R. Ritter. 1995. "The New Issues Puzzle." *Journal of Finance* 50, 23–51.

Lucas, R. 1978. "Asset Prices in an Exchange Economy." *Econometrica* 46, 1429–1445.

Lustig, H., and S. Van Nieuwerburgh. 2005. "Housing Collateral, Consumption Insurance, and Risk Premia: An Empirical Perspective." *Journal of Finance* 60, 1167–1219.

Lustig, H., and A. Verdelhan. 2007. "The Cross-Section of Foreign Currency Risk Premia and Consumption Growth Risk." *American Economic Review* 97, 89-–117.

Maio, P. 2013a. "Intertemporal CAPM with Conditioning Variables." *Management Science* 59, 122–141.

Maio, P. 2013b. "Return Decomposition and the Intertemporal CAPM." *Journal of Banking and Finance* 37, 4958–4972.

Maio, P., and D. Philip. 2018. "Economic Activity and Momentum Profits: Further Evidence." *Journal of Banking and Finance* 88, 466–482.

Maio, P., and P. Santa-Clara. 2012. "Multifactor Models and Their Consistency with the ICAPM." *Journal of Financial Economics* 106, 586–613.

Maio, P., and P. Santa-Clara. 2017. "Short-Term Interest Rates and Stock Market Anomalies." *Journal of Financial and Quantitative Analysis* 52, 927–961.

Maio, P., and A. C. Silva. 2018. "Asset Pricing Implications of Money: New Evidence." Working Paper, Hanken School of Economics.

Malloy, C., T. Moskowitz, and A. Vissing-Jorgensen. 2009. "Long-Run Stockholder Consumption Risk and Asset Returns." *Journal of Finance* 64, 2427–2479.

Newey, W.K., and K.D. West. 1987. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica* 55, 703–708.

Novy-Marx, R. 2013. "The Other Side of Value: The Gross Profitability Premium." *Journal of Financial Economics* 108, 1–28.

Parker, J. A., and C. Julliard. 2005. "Consumption Risk and the Cross-Section of Expected Returns." *Journal of Political Economy* 113, 185–222.

Pástor, L., and R. F. Stambaugh. 2003. "Liquidity Risk and Expected Stock Returns." *Journal of Political Economy* 111, 642–684.

Richardson, S. A., R. G. Sloan, M. T. Soliman, and I. Tuna. 2005. "Accrual Reliability, Earnings Persistence and Stock Prices." *Journal of Accounting and Economics* 39, 437–485.

Santos, T., and P. Veronesi. 2006. "Labor Income and Predictable Stock Returns." *Review of Financial Studies* 19, 1–44.

Savov, A. 2011. "Asset Pricing with Garbage." *Journal of Finance* 66, 177–201.

Shanken, J. 1992. "On the Estimation of Beta Pricing Models." *Review of Financial Studies* 5, 1–34.

Shanken, J., and G. Zhou. 2007. "Estimating and Testing Beta Pricing Models: Alternative Methods and Their Performance in Simulations." *Journal of Financial Economics* 84, 40–86.

Sharpe, W. F. 1964. "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk." *Journal of Finance* 19, 425–442.

Sloan, R. G. 1996. "Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?" *Accounting Review* 71, 289–315.

Titman, S., K. C. J. Wei, and F. Xie. 2004. "Capital Investments and Stock Returns." *Journal of Financial and Quantitative Analysis* 39, 677–700.

Weil, P. 1989. "The Equity Premium Puzzle and the Risk-Free Rate Puzzle." *Journal of Monetary Economics* 24, 401–421.

Wilcox, D. W. 1992. "The Construction of U.S. Consumption Data: Some Facts and Their Implications For Empirical Work." *American Economic Review* 82, 922–941.

Yogo, M. 2006. "A Consumption-Based Explanation of Expected Stock Returns." *Journal of Finance* 61, 539–580.

A Derivation of the Euler Equations

The investor's intertemporal problem is given by

$$\max_{C_t, L_t, \{\omega_{i,t}\}_{i=1}^N} U_t = \left\{(1-\delta)\left[C_t^{1-\eta}\left(H-N_t\right)^{\eta}\right]^{1-1/\psi} + \delta\left(E_t\left[U_{t+1}^{1-\gamma}\right]\right)^{1/\theta}\right\}^{\frac{1}{1-1/\psi}}$$

$$s.t.\ B_{t+1} = R_{m,t+1}\left[B_t - C_t - W_t\left(H-N_t\right)\right],$$

$$R_{m,t+1} = \sum_{i=1}^N \omega_{i,t}\left(R_{i,t+1}-R_{f,t+1}\right) + R_{f,t+1}.$$

This problem can be represented in a dynamic programming setting as

$$J(B_t) \equiv \max_{C_t, L_t, \{\omega_{i,t}\}_{i=1}^N} \left\{(1-\delta)\left[C_t^{1-\eta}\left(H-N_t\right)^{\eta}\right]^{\frac{1-\gamma}{\theta}} + \delta\left(E_t\left[J\left(B_{t+1}\right)^{1-\gamma}\right]\right)^{1/\theta}\right\}^{\frac{\theta}{1-\gamma}} \tag{A.1}$$

$$s.t.\ B_{t+1} = R_{m,t+1}\left[B_t - C_t - W_t\left(H-N_t\right)\right], \tag{A.2}$$

$$R_{m,t+1} = \sum_{i=1}^N \omega_{i,t}\left(R_{i,t+1}-R_{f,t+1}\right) + R_{f,t+1}. \tag{A.3}$$

The first-order conditions relative to C_t and $(H-N_t)$ are given respectively by

$$(1-\eta)C_t^{\frac{1-\gamma}{\theta}(1-\eta)-1}\left(H-N_t\right)^{\frac{1-\gamma}{\theta}\eta} = \frac{\delta}{1-\delta}\left(E_t\left[J\left(B_{t+1}\right)^{1-\gamma}\right]\right)^{\frac{1}{\theta}-1} E_t\left[J\left(B_{t+1}\right)^{-\gamma} J_B\left(B_{t+1}\right) R_{m,t+1}\right], \tag{A.4}$$

and

$$\eta C_t^{\frac{1-\gamma}{\theta}(1-\eta)}\left(H-N_t\right)^{\frac{1-\gamma}{\theta}(\eta-1)}\frac{1}{W_t} = \frac{\delta}{1-\delta}\left(E_t\left[J\left(B_{t+1}\right)^{1-\gamma}\right]\right)^{\frac{1}{\theta}-1} E_t\left[J\left(B_{t+1}\right)^{-\gamma} J_B\left(B_{t+1}\right) R_{m,t+1}\right]. \tag{A.5}$$

By combining the two first-order conditions, we obtain the intratemporal equilibrium condition:

$$\left(\frac{\eta}{1-\eta}\right)\left(\frac{C_t}{H-N_t}\right) = W_t. \tag{A.6}$$

By using the homogeneity of the optimization problem, the value function is proportional to wealth,

$$J\left(B_t\right) = \phi_t B_t. \tag{A.7}$$

By substituting (A.7) in (A.4), using both the law of iterated expectations and the intertemporal budget constraint (A.2), and rearranging, we have:

$$C_t^{\frac{1-\gamma}{\theta}(1-\eta)-1}\left(H-N_t\right)^{\frac{1-\gamma}{\theta}\eta} = \frac{\delta}{1-\delta}\left(E_t\left[J\left(B_{t+1}\right)^{1-\gamma}\right]\right)^{\frac{1}{\theta}}\left[B_t - C_t - W_t\left(H-N_t\right)\right]^{-1}. \tag{A.8}$$

On the other hand, the value function in (A.1) can be rearranged as follows:

$$J\left(B_{t+1}\right)^{\frac{1-\gamma}{\theta}} - (1-\delta)\left[C_t^{1-\eta}\left(H-N_t\right)^{\eta}\right]^{\frac{1-\gamma}{\theta}} = \delta\left(E_t\left[J\left(B_{t+1}\right)^{1-\gamma}\right]\right)^{\frac{1}{\theta}}. \tag{A.9}$$

By substituting (A.9) in (A.8), and after some tedious algebra, we obtain the explicit functional form for the value function,

$$J\left(B_t\right) = (1-\delta)^{\frac{\theta}{1-\gamma}}(1-\eta)^{\frac{\theta}{1-\gamma}}\left(\frac{C_t}{B_t}\right)^{1-\frac{\theta}{1-\gamma}}\left(\frac{H-N_t}{C_t}\right)^{\eta} B_t = \phi_t B_t, \tag{A.10}$$

$$\phi_t \equiv (1-\delta)^{\frac{\theta}{1-\gamma}}(1-\eta)^{\frac{\theta}{1-\gamma}}\left(\frac{C_t}{B_t}\right)^{1-\frac{\theta}{1-\gamma}}\left(\frac{H-N_t}{C_t}\right)^{\eta}, \tag{A.11}$$

which confirms the previous guess.

By substituting (A.10) in (A.8), we derive the Euler equation for the return on the aggregate wealth portfolio,

$$E_t\left\{\delta^{\theta}\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}}\left[\frac{\left(H-N_{t+1}\right)/C_{t+1}}{\left(H-N_t\right)/C_t}\right]^{\eta\theta\left(1-\frac{1}{\psi}\right)}\left[\frac{B_{t+1}}{B_t-C_t-W_t\left(H-N_t\right)}\right]^{\theta}\right\} = 1 \Leftrightarrow \tag{A.12}$$

$$E_t\left\{\delta^{\theta}\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}}\left[\frac{\left(H-N_{t+1}\right)/C_{t+1}}{\left(H-N_t\right)/C_t}\right]^{\eta\theta\left(1-\frac{1}{\psi}\right)} R_{m,t+1}^{\theta}\right\} = 1, \tag{A.13}$$

which implies that the pricing kernel is given by

$$M_{t+1} = \delta^{\theta}\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{\theta}{\psi}}\left[\frac{\left(H-N_{t+1}\right)/C_{t+1}}{\left(H-N_t\right)/C_t}\right]^{\eta\theta\left(1-\frac{1}{\psi}\right)} R_{m,t+1}^{\theta-1}. \tag{A.14}$$

Table 1: Descriptive statistics for risk factors

This table reports descriptive statistics for the risk factors in the CW-CAPM. The factors are the log consumption growth (Δc), log wage growth (Δw), and the log market return (r_m). The sample period is from 1963:Q3 to 2017:Q4. ϕ denotes the first order autocorrelation. Panel B reports the correlations between the factors.

			Panel A		
	Mean (%)	Stdev. (%)	Min. (%)	Max. (%)	ϕ
Δc	0.45	0.76	–2.25	2.67	0.07
Δw	0.50	1.27	–3.50	5.70	0.21
r_m	1.45	8.45	–30.43	20.04	0.07
			Panel B		
	Δc	Δw	r_m		
Δc	1.00	0.42	0.22		
Δw		1.00	0.04		
r_m			1.00		

Table 2: Descriptive statistics for return spreads

This table reports descriptive statistics for the "high-minus-low" spreads in returns associated with various market anomalies. The portfolios are formed on firm size and each of the six anomaly variables: book-to-market (SBM25), investment (SINV25), operating profitability (SOP25), long-term return reversals (SREV25), net share issues (SNSI35), and residual variance (SRVAR25). Within each quintile of the anomaly variable, the average portfolio returns across the size quintiles are computed. The average portfolios associated with the highest and lowest rank of a given characteristic are denoted as "high" and "low" portfolios. The return spreads are then calculated as the difference between the returns of the "high" and "low" portfolios. The sample period is from 1963:Q3 to 2017:Q4. ϕ denotes the first order autocorrelation.

	Mean (%)	Stdev. (%)	t-value	Min. (%)	Max. (%)	ϕ
BM	1.30	6.87	2.80	–28.76	30.42	0.16
INV	–1.01	4.55	–3.27	–16.20	12.50	0.02
OP	0.94	4.80	2.90	–18.34	27.56	0.19
REV	–1.09	5.80	–2.77	–23.83	14.70	–0.07
NSI	–1.75	5.24	–4.93	–33.42	21.90	0.09
RVAR	–1.44	9.80	–2.17	–40.23	40.78	0.08

Table 3: Factor risk premia for single anomalies

This table presents the estimation and evaluation results for the CW-CAPM:

$$E\left(R^e_{i,t+1}\right) = \gamma_c Cov\left(\Delta c_{t+1}, R^e_{i,t+1}\right) + \gamma_w Cov\left(\Delta w_{t+1}, R^e_{i,t+1}\right) + \gamma_m Cov\left(r_{m,t+1}, R^e_{i,t+1}\right).$$

Its nested models are also estimated and reported. Test assets are portfolios formed on firm size and each of the six anomaly variables: book-to-market (SBM25), investment (SINV25), operating profitability (SOP25), long-term return reversals (SREV25), net share issues (SNSI35), and residual variance (SRVAR25). The model is estimated by first-stage GMM with equally-weighted moments. Each Panel reports the estimation results for each anomaly portfolio group. The first line associated with each asset pricing test reports the estimates for covariance risk price and the second line reports their GMM-based t-statistics (in parentheses). γ, ψ, and η represent the estimates for implied preference parameter. The column χ^2 presents the level and its corresponding p-value (in parentheses) for the χ^2 statistic. R^2_{OLS} denotes the OLS cross-sectional R^2, and MAE(%) is the average absolute pricing error. The sample period is from 1963:Q3 to 2017:Q4. t-ratios marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	γ_c	γ_w	γ_m	χ^2	R^2_{OLS}	MAE (%)	γ	ψ	η
				Panel A (SBM25)					
CAPM			2.79	70.51	–0.48	0.58			
			(2.82***)	(0.00)					
C-CAPM	181.51			45.81	0.15	0.44	181.51		
	(1.78**)			(0.00)					
EZ	250.17		–1.10	32.59	0.21	0.44	249.07	0.01	
	(1.80**)		(−0.42)	(0.09)					
CW-CAPM*	181.96	–106.70		39.45	0.45	0.36	181.96		0.59
	(1.82**)	(−2.00**)		(0.02)					
CW-CAPM	282.14	–117.83	–1.60	29.68	0.56	0.36	280.54	0.01	0.42
	(2.10**)	(−1.55*)	(−0.59)	(0.13)					
				Panel B (SINV25)					
CAPM			2.80	77.81	–0.42	0.54			
			(2.85***)	(0.00)					
C-CAPM	182.76			41.59	0.16	0.42	182.76		
	(1.79**)			(0.01)					
EZ	209.99		–0.43	34.32	0.17	0.41	209.56	0.01	
	(2.06**)		(−0.21)	(0.06)					
CW-CAPM*	179.74	–109.06		43.30	0.55	0.31	179.74		0.61
	(1.79**)	(−2.49***)		(0.01)					
CW-CAPM	255.21	–121.81	–1.20	32.35	0.63	0.27	254.01	0.01	0.48
	(2.47***)	(−2.31**)	(−0.52)	(0.07)					

Table 3 (Continued)
Factor risk premia for single anomalies

	γ_c	γ_w	γ_m	χ^2	R^2_{OLS}	MAE (%)	γ	ψ	η
Panel C (SOP25)									
CAPM			2.72	42.56	0.05	0.45			
			(2.79***)	(0.01)					
C-CAPM	176.48			31.43	0.18	0.40	176.48		
	(1.76**)			(0.14)					
EZ	116.94		0.93	41.79	0.23	0.41	117.87	0.00	
	(1.72**)		(0.66)	(0.01)					
CW-CAPM*	166.44	–125.13		29.50	0.60	0.29	166.44		0.76
	(1.58*)	(–2.17**)		(0.16)					
CW-CAPM	200.58	–137.15	–0.55	27.35	0.62	0.28	200.03	0.01	0.69
	(1.71**)	(–1.92**)	(–0.22)	(0.20)					
Panel D (SREV25)									
CAPM			3.07	52.40	0.07	0.42			
			(3.06***)	(0.00)					
C-CAPM	207.85			27.80	–0.09	0.45	207.85		
	(1.68**)			(0.27)					
EZ	70.35		2.05	48.71	0.10	0.42	72.40	–0.01	
	(1.62*)		(1.60*)	(0.00)					
CW-CAPM*	189.66	–87.48		38.59	0.39	0.34	189.66		0.46
	(1.93**)	(–2.12**)		(0.02)					
CW-CAPM	145.07	–78.79	0.69	44.62	0.41	0.34	145.76	0.00	0.54
	(1.93**)	(–2.00**)	(0.36)	(0.00)					
Panel E (SNSI35)									
CAPM			2.65	97.15	–0.24	0.60			
			(2.73***)	(0.00)					
C-CAPM	178.76			82.66	0.12	0.49	178.76		
	(1.74**)			(0.00)					
EZ	150.09		0.45	90.25	0.13	0.49	150.53	0.00	
	(2.37***)		(0.30)	(0.00)					
CW-CAPM*	178.20	–121.20		60.47	0.52	0.37	178.20		0.68
	(1.64*)	(–2.49***)		(0.00)					
CW-CAPM	193.10	–124.47	–0.23	58.24	0.52	0.38	192.86	0.01	0.65
	(2.62***)	(–2.83***)	(–0.12)	(0.00)					
Panel F (SRVAR25)									
CAPM			2.48	84.29	–0.72	0.96			
			(2.59***)	(0.00)					
C-CAPM	194.05			43.19	0.00	0.73	194.05		
	(1.56*)			(0.01)					
EZ	321.23		–1.80	22.45	0.16	0.70	319.43	0.01	
	(2.09**)		(–0.54)	(0.49)					
CW-CAPM*	158.31	–225.61		19.68	0.58	0.44	158.31		1.43
	(0.78)	(–2.72***)		(0.66)					
CW-CAPM	316.76	–243.46	–2.25	13.45	0.81	0.32	314.51	0.01	0.78
	(1.96**)	(–2.14**)	(–0.54)	(0.92)					

Table 4: Factor risk premia for multiple anomalies

This table presents the estimation and evaluation results for the CW-CAPM:

$$E\left(R^e_{i,t+1}\right) = \gamma_c Cov\left(\Delta c_{t+1}, R^e_{i,t+1}\right) + \gamma_w Cov\left(\Delta w_{t+1}, R^e_{i,t+1}\right) + \gamma_m Cov\left(r_{m,t+1}, R^e_{i,t+1}\right).$$

Its nested models are also estimated and reported. Test assets include all portfolios groups formed on firm size and each of the six anomaly variables: book-to-market (SBM25), investment (SINV25), operating profitability (SOP25), long-term return reversals (SREV25), net share issues (SNSI35), and residual variance (SRVAR25). The model is estimated by first-stage GMM with equally-weighted moments. The first line reports the estimates for covariance risk price and the second line reports their GMM-based t-statistics (in parentheses). γ, ψ, and η represent the estimates for implied preference parameter. The column χ^2 presents the level and its corresponding p-value (in parentheses) for the χ^2 statistic. R^2_{OLS} denotes the OLS cross-sectional R^2, and MAE(%) is the average absolute pricing error. The sample period is from 1963:Q3 to 2017:Q4. t-ratios marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	γ_c	γ_w	γ_m	χ^2	R^2_{OLS}	MAE (%)	γ	ψ	η
CAPM			2.74	191.23	–0.41	0.60			
			(2.80***)	(0.04)					
C-CAPM	182.74			202.09	0.08	0.50	182.74		
	(1.76**)			(0.01)					
EZ	193.50		–0.17	200.48	0.09	0.49	193.33	0.01	
	(2.63***)		(−0.09)	(0.01)					
CW-CAPM*	174.94	–121.50		200.07	0.49	0.36	174.94		0.70
	(1.63*)	(−2.98***)		(0.01)					
CW-CAPM	239.15	–134.28	–1.02	199.13	0.55	0.36	238.13	0.01	0.57
	(2.92***)	(−2.92***)	(−0.45)	(0.01)					

Table 5: Accounting of risk premia

This table reports the risk premium (beta times risk price) for each factor from the CW-CAPM for the "high-minus-low" return spread within each size quintile. Test assets are portfolios formed on firm size and each of the six anomaly variables: book-to-market (SBM25), investment (SINV25), operating profitability (SOP25), long-term return reversals (SREV25), net share issues (SNSI35), and residual variance (SRVAR25). $\bar{R}$ and $\bar{\alpha}$ denote the average returns and average pricing errors for the return spreads. $E[R]_{\Delta c}$, $E[R]_{\Delta w}$, and $E[R]_{r_m}$ represent the risk premiums for the consumption growth, wage growth, and market return, respectively. The sample period is from 1963:Q3 to 2017:Q4.

	$\bar{R}$	$E[R]$	$E[R]_{\Delta c}$	$E[R]_{\Delta w}$	$E[R]_{r_m}$	$\bar{\alpha}$
Panel A (SBM25)						
S1	2.44	1.04	0.04	0.57	0.44	1.40
S2	1.39	1.33	0.73	0.22	0.38	0.06
S3	1.52	1.54	0.67	0.51	0.36	–0.02
S4	0.67	1.04	0.96	–0.09	0.17	–0.37
S5	0.50	–0.63	–0.59	–0.12	0.07	1.13
Panel B (SINV25)						
S1	–1.72	–0.32	0.48	–0.76	–0.04	–1.40
S2	–1.11	–1.08	–0.28	–0.65	–0.15	–0.03
S3	–1.01	–0.98	–0.13	–0.66	–0.19	–0.03
S4	–0.57	–0.86	–0.28	–0.35	–0.22	0.29
S5	–0.64	–0.86	0.62	–1.29	–0.19	0.22
Panel C (SOP25)						
S1	0.89	1.34	0.50	0.81	0.02	–0.45
S2	1.11	0.28	–0.64	0.87	0.05	0.83
S3	1.24	0.27	–0.46	0.69	0.04	0.97
S4	0.77	0.25	0.40	–0.18	0.03	0.52
S5	0.70	0.08	0.53	–0.52	0.07	0.62
Panel D (SREV25)						
S1	–1.65	0.12	0.66	–0.50	–0.04	–1.77
S2	–1.25	–1.10	–0.38	–0.70	–0.02	–0.15
S3	–0.79	–0.49	–0.13	–0.42	0.06	–0.31
S4	–0.94	–0.72	0.24	–1.04	0.08	–0.22
S5	–0.80	–0.55	–0.17	–0.39	0.02	–0.26
Panel E (SNSI35)						
S1	–2.26	–0.62	–0.16	–0.39	–0.07	–1.64
S2	–1.65	–1.10	–0.25	–0.78	–0.06	–0.56
S3	–1.90	–0.78	–0.24	–0.49	–0.05	–1.12
S4	–1.73	–0.36	–0.40	0.08	–0.04	–1.37
S5	–1.20	–1.16	–1.09	–0.04	–0.03	–0.04
Panel F (SRVAR25)						
S1	–3.35	–2.45	0.30	–1.39	–1.37	–0.90
S2	–1.98	–1.95	–0.06	–0.52	–1.37	–0.02
S3	–1.09	–0.90	0.73	–0.35	–1.28	–0.19
S4	–0.82	–0.19	0.20	0.82	–1.21	–0.63
S5	0.04	–0.96	–0.20	0.12	–0.88	1.00

Table 6: Betas for the wage growth factor

This table reports the beta estimates for the wage growth factor (Δw). Test assets are portfolios formed on firm size and each of the six anomaly variables: book-to-market (SBM25), investment (SINV25), operating profitability (SOP25), long-term return reversals (SREV25), net share issues (SNSI35), and residual variance (SRVAR25). The sample period is from 1963:Q3 to 2017:Q4. The last column reports the spread in factor loadings between the two extreme anomaly quintiles portfolios.

			Panel A (SBM25)			
	BM1	BM2	BM3	BM4	BM5	BM5 – BM1
S1	0.35	0.32	0.25	0.11	0.05	–0.30
S2	–0.03	–0.22	–0.10	0.08	–0.15	–0.12
S3	0.06	0.01	0.01	–0.26	–0.21	–0.27
S4	–0.05	–0.14	–0.28	–0.42	–0.01	0.05
S5	0.21	–0.05	0.07	–0.25	0.27	0.06
			Panel B (SINV25)			
	INV1	INV2	INV3	INV4	INV5	INV1 – INV5
S1	–0.01	0.03	–0.01	0.28	0.37	–0.39
S2	–0.33	–0.07	0.07	–0.17	0.01	–0.33
S3	–0.33	0.07	–0.16	0.05	0.01	–0.34
S4	–0.25	–0.29	–0.22	–0.06	–0.07	–0.18
S5	–0.39	0.13	0.14	0.05	0.26	–0.66
			Panel C (SOP25)			
	OP1	OP2	OP3	OP4	OP5	OP5 – OP1
S1	0.23	0.12	–0.02	–0.04	–0.14	–0.37
S2	0.07	–0.10	–0.03	–0.52	–0.32	–0.40
S3	0.07	–0.02	–0.17	–0.14	–0.25	–0.32
S4	–0.10	–0.25	–0.37	–0.17	–0.02	0.08
S5	–0.08	0.14	0.05	0.02	0.16	0.24
			Panel D (SREV25)			
	REV1	REV2	REV3	REV4	REV5	REV1 – REV5
S1	–0.17	–0.04	0.08	–0.18	0.23	–0.39
S2	–0.72	0.02	–0.21	–0.01	–0.16	–0.55
S3	–0.34	–0.16	–0.29	–0.19	–0.01	–0.33
S4	–0.99	–0.51	–0.20	–0.04	–0.16	–0.82
S5	–0.10	–0.09	–0.11	0.05	0.21	–0.31
			Panel E (SNSI35)			
	NSI1	NSI2	NSI3	NSI4	NSI5	NSI1 – NSI5
S1	0.17	–0.17	0.06	0.29	0.25	–0.08
S2	–0.15	–0.25	–0.15	0.04	0.20	–0.35
S3	–0.48	–0.23	0.02	0.01	0.19	–0.67
S4	–0.55	–0.17	–0.21	0.31	–0.21	–0.34
S5	–0.02	0.00	–0.10	0.15	0.09	–0.11
			Panel F (SRVAR25)			
	RVAR1	RVAR2	RVAR3	RVAR4	RVAR5	RVAR1 – RVAR5
S1	–0.07	–0.08	–0.37	–0.15	0.28	–0.35
S2	0.02	–0.14	–0.37	–0.44	0.16	–0.13
S3	–0.08	–0.21	–0.33	–0.38	0.01	–0.09
S4	–0.05	–0.27	–0.24	–0.24	–0.26	0.21
S5	0.14	0.02	–0.09	0.05	0.11	0.03

Table 7: Factor risk premia for alternative return-based multifactor models

This table reports the estimation and evaluation results for alternative return-based multifactor models, including the Fama-French 3-factor model (FF3), Carhart 4-factor model (C4), Pastor-Stambaugh 4-factor model (PS4), Hou-Xue-Zhang 4-factor model (HXZ4), and Fama-French 5-factor model (FF5). γ_M, γ_{SMB}, γ_{HML}, γ_{UMD}, and γ_{LIQ} represent the covariance risk price estimates for the market, size, value, momentum, and liquidity factors. γ_{ME}, γ_{IA}, and γ_{ROE} represent the covariance risk price estimates for the Hou-Xue-Zhang size, investment, and profitabiity factors. γ_{RMW} and γ_{CMA} represent the covariance risk price estimates for the Fama-French profitability and investment factors. Test assets include all portfolios groups formed on firm size and each of the six anomaly variables: book-to-market (SBM25), investment (SINV25), operating profitability (SOP25), long-term return reversals (SREV25), net share issues (SNSI35), and residual variance (SRVAR25). The model is estimated by first-stage GMM with equally-weighted moments. Below the covariance risk price estimates are displayed GMM-based t-statistics (in parentheses). The column χ^2 presents the level and its corresponding p-value (in parentheses) for the χ^2 statistic. R^2_{OLS} denotes the OLS cross-sectional R^2, and MAE(%) is the average absolute pricing error. The sample period is from 1963:Q3 to 2017:Q4. t-ratios marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	γ_M	γ_{SMB}	γ_{HML}	γ_{UMD}	γ_{LIQ}	γ_{ME}	γ_{IA}	γ_{ROE}	γ_{RMW}	γ_{CMA}	χ^2	R^2_{OLS}	R^2_C
FF3	4.18	–0.92	7.73								196.46	0.44	0.34
	(3.21***)	(–0.61)	(4.61***)								(0.02)		
C4	5.68	1.23	9.77	7.46							198.91	0.55	0.43
	(3.62***)	(0.76)	(4.65***)	(2.69***)							(0.01)		
PS4	4.26	–1.81	7.62		0.15						188.59	0.37	0.35
	(3.18***)	(–1.12)	(4.45***)		(0.06)						(0.04)		
HXZ4	5.20					3.35	13.53	8.86			193.18	0.74	0.25
	(3.51***)					(1.88**)	(3.28***)	(2.65***)			(0.02)		
FF5	5.01	1.42	–0.77						8.34	10.86	194.85	0.71	0.25
	(3.93***)	(0.94)	(–0.32)						(2.88***)	(3.14***)	(0.02)		

Table 8: Factor risk premia for multiple anomalies: Second-stage GMM

This table presents the estimation and evaluation results for the CW-CAPM:

$$E\left(R^e_{i,t+1}\right) = \gamma_c Cov\left(\Delta c_{t+1}, R^e_{i,t+1}\right) + \gamma_w Cov\left(\Delta w_{t+1}, R^e_{i,t+1}\right) + \gamma_m Cov\left(r_{m,t+1}, R^e_{i,t+1}\right).$$

Its nested models are also estimated and reported. Test assets include all portfolios groups formed on firm size and each of the six anomaly variables: book-to-market (SBM25), investment (SINV25), operating profitability (SOP25), long-term return reversals (SREV25), net share issues (SNSI35), and residual variance (SRVAR25). The model is estimated by second-stage GMM. The first line reports the estimates for covariance risk price and the second line reports their GMM-based t-statistics (in parentheses). γ, ψ, and η represent the estimates for implied preference parameter. The column J-test presents the level and its corresponding p-value (in parentheses) for the Hansen's (1982) J-test. R^2_{WLS} denotes the WLS cross-sectional R^2. The sample period is from 1963:Q3 to 2017:Q4. t-ratios marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	γ_c	γ_w	γ_m	J-test	R^2_{WLS}	γ	ψ	η
CAPM			4.71	195.10	–0.79			
			(6.73***)	(0.03)				
C-CAPM	110.06			207.90	0.66	110.06		
	(17.82***)			(0.01)				
EZ	113.42		–0.33	207.70	0.68	113.09	0.01	
	(17.58***)		(−0.84)	(0.00)				
CW-CAPM*	101.91	–68.94		205.49	0.85	101.91		0.68
	(17.91***)	(−16.48***)		(0.01)				
CW-CAPM	124.74	–69.78	–1.05	203.80	0.86	123.70	0.02	0.57
	(17.29***)	(−15.09***)	(−2.57***)	(0.01)				

Table 9: Factor risk premia for multiple anomalies: Expected Return-Beta Representation

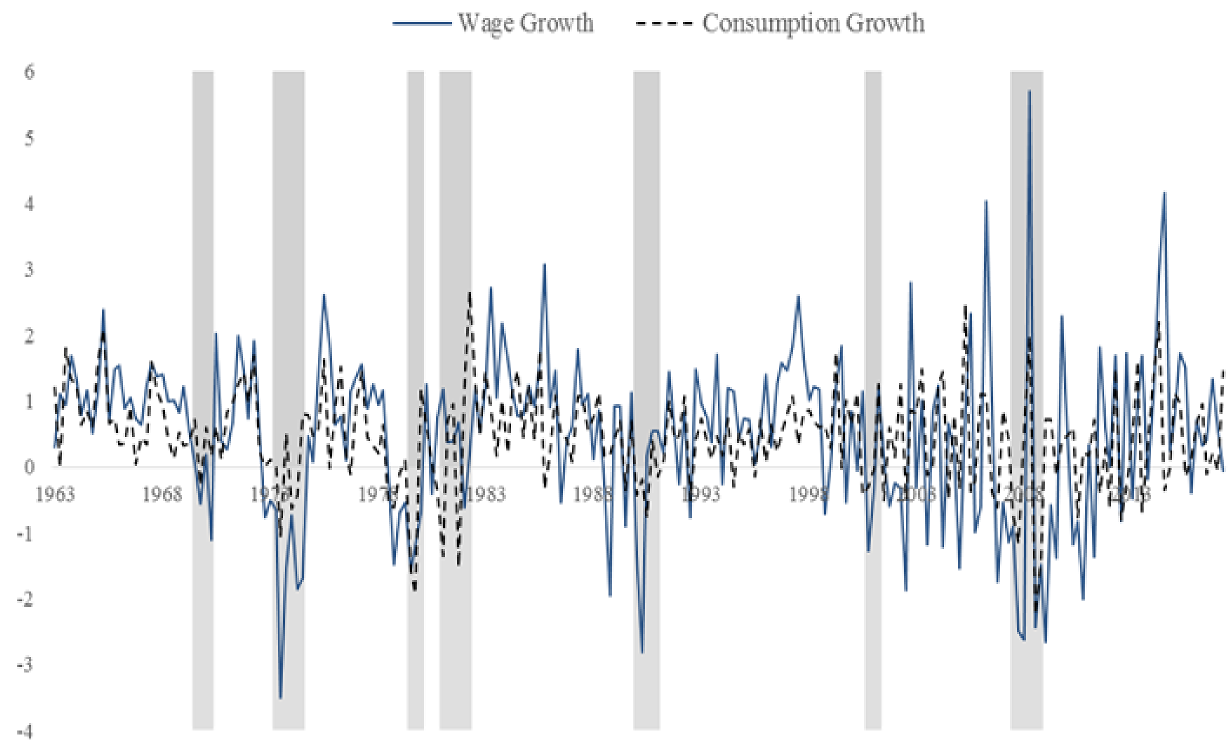
This table presents the estimation results for the CW-CAPM in expected return-beta representation:

$$E\left(R^e_{i,t+1}\right) = \lambda_0 + \lambda_c\beta_{i,c} + \lambda_w\beta_{i,w} + \lambda_m\beta_{i,m}.$$

Its nested models are also estimated and reported. Test assets include all portfolios groups formed on firm size and each of the six anomaly variables: book-to-market (SBM25), investment (SINV25), operating profitability (SOP25), long-term return reversals (SREV25), net share issues (SNSI35), and residual variance (SRVAR25). The estimation procedure is the time-series/cross-sectional regression approach. The first line reports the estimates for beta risk price (in %) and the second line reports the t-statistics using Shanken's correction for the errors-in-variables bias (in parentheses). R^2_{OLS} denotes the OLS cross-sectional R^2, and MAE (%) is the average absolute pricing error. The sample period is from 1963:Q3 to 2017:Q4. t-ratios marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	λ_0	λ_c	λ_w	λ_m	R^2_{OLS}	MAE (%)
CAPM				1.90	–0.41	0.60
				(3.16***)		
	2.43			–0.18	0.00	0.54
	(3.62***)			(−0.19)		
C-CAPM		1.06			0.08	0.49
		(1.92**)				
	1.02	0.59			0.15	0.48
	(1.40*)	(1.47*)				
EZ		1.08		2.59	0.08	0.49
		(3.45***)		(3.46***)		
	1.65	0.76		0.96	0.22	0.47
	(1.46*)	(2.30**)		(0.65)		
CW-CAPM*		0.52	–1.25		0.49	0.36
		(1.00)	(−2.31**)			
	0.01	0.51	–1.25		0.49	0.36
	(0.01)	(0.90)	(−2.31**)			
CW-CAPM		0.81	–1.21	2.02	0.55	0.36
		(2.49***)	(−2.06**)	(2.53***)		
	0.68	0.70	–1.14	1.39	0.57	0.35
	(0.42)	(1.58*)	(−2.31**)	(0.68)		

Figure 1: **Time-series of consumption and wage growths**



This figure plots the time-series for the log consumption growth and log wage growth. The sample period is from 1963:Q3 to 2017:Q4. The shaded regions are NBER recessions.

Table A.1: Alternative wage factor

This table presents the estimation and evaluation results for the CW-CAPM:

$$E\left(R^e_{i,t+1}\right) = \gamma_c Cov\left(\Delta c_{t+1}, R^e_{i,t+1}\right) + \gamma_w Cov\left(\Delta w_{t+1}, R^e_{i,t+1}\right) + \gamma_m Cov\left(r_{m,t+1}, R^e_{i,t+1}\right).$$

Its nested model (CW-CAPM*) ia also estimated and reported. Test assets include all portfolios groups formed on firm size and each of the six anomaly variables: book-to-market (SBM25), investment (SINV25), operating profitability (SOP25), long-term return reversals (SREV25), net share issues (SNSI35), and residual variance (SRVAR25). The model is estimated by first-stage GMM with equally-weighted moments. The first line reports the estimates for covariance risk price and the second line reports their GMM-based t-statistics (in parentheses). γ, ψ, and η represent the estimates for implied preference parameter. The column χ^2 presents the level and its corresponding p-value (in parentheses) for the χ^2 statistic. R^2_{OLS} denotes the OLS cross-sectional R^2, and MAE(%) is the average absolute pricing error. The sample period is from 1963:Q3 to 2017:Q4. t-ratios marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	γ_c	γ_w	γ_m	χ^2	R^2_{OLS}	MAE (%)	γ	ψ	η
CW-CAPM*	172.21	–110.10		199.95	0.50	0.35	172.21		0.64
	(1.69**)	(−3.16***)		(0.01)					
CW-CAPM	236.92	–121.85	–1.03	198.12	0.55	0.35	235.89	0.01	0.52
	(2.97***)	(−2.98***)	(−0.47)	(0.01)					

Table A.2: Adding the market factor in the testing assets

This table presents the estimation and evaluation results for the CW-CAPM:

$$E\left(R_{i,t+1}^{e}\right) = \gamma_c Cov\left(\Delta c_{t+1}, R_{i,t+1}^{e}\right) + \gamma_w Cov\left(\Delta w_{t+1}, R_{i,t+1}^{e}\right) + \gamma_m Cov\left(r_{m,t+1}, R_{i,t+1}^{e}\right).$$

Its nested models are also estimated and reported. Test assets include all portfolios groups formed on firm size and each of the six anomaly variables: book-to-market (SBM25), investment (SINV25), operating profitability (SOP25), long-term return reversals (SREV25), net share issues (SNSI35), and residual variance (SRVAR25). The excess market return is included in the set of testing assets. The model is estimated by first-stage GMM with equally-weighted moments. The first line reports the estimates for covariance risk price and the second line reports their GMM-based t-statistics (in parentheses). γ, ψ, and η represent the estimates for implied preference parameter. The column χ^2 presents the level and its corresponding p-value (in parentheses) for the χ^2 statistic. R^2_{OLS} denotes the OLS cross-sectional R^2, and MAE(%) is the average absolute pricing error. The sample period is from 1963:Q3 to 2017:Q4. t-ratios marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	γ_c	γ_w	γ_m	χ^2	R^2_{OLS}	MAE (%)	γ	ψ	η
CAPM			2.74	191.42	–0.40	0.60			
			(2.80***)	(0.05)					
C-CAPM	182.59			202.39	0.09	0.49	182.59		
	(1.76**)			(0.01)					
EZ	193.36		–0.17	200.80	0.09	0.49	193.19	0.01	
	(2.63***)		(−0.09)	(0.01)					
CW-CAPM*	174.87	–121.61		200.06	0.49	0.36	174.87		0.70
	(1.63*)	(−2.98***)		(0.02)					
CW-CAPM	239.13	–134.38	–1.02	200.04	0.55	0.36	238.12	0.01	0.57
	(2.92***)	(−2.92***)	(−0.45)	(0.01)					

Table A.3: Using SVAR25 rather than SRVAR25

This table presents the estimation and evaluation results for the CW-CAPM:

$$E\left(R^e_{i,t+1}\right) = \gamma_c Cov\left(\Delta c_{t+1}, R^e_{i,t+1}\right) + \gamma_w Cov\left(\Delta w_{t+1}, R^e_{i,t+1}\right) + \gamma_m Cov\left(r_{m,t+1}, R^e_{i,t+1}\right).$$

Its nested models are also estimated and reported. Test assets include all portfolios groups formed on firm size and each of the six anomaly variables: book-to-market (SBM25), investment (SINV25), operating profitability (SOP25), long-term return reversals (SREV25), net share issues (SNSI35), and variance (SVAR25). The model is estimated by first-stage GMM with equally-weighted moments. The first line reports the estimates for covariance risk price and the second line reports their GMM-based t-statistics (in parentheses). γ, ψ, and η represent the estimates for implied preference parameter. The column χ^2 presents the level and its corresponding p-value (in parentheses) for the χ^2 statistic. R^2_{OLS} denotes the OLS cross-sectional R^2, and MAE(%) is the average absolute pricing error. The sample period is from 1963:Q3 to 2017:Q4. t-ratios marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	γ_c	γ_w	γ_m	χ^2	R^2_{OLS}	MAE (%)	γ	ψ	η
CAPM			2.73	193.68	–0.43	0.60			
			(2.80***)	(0.03)					
C-CAPM	182.05			206.94	0.04	0.50	182.05		
	(1.76**)			(0.01)					
EZ	192.33		–0.16	206.32	0.04	0.50	192.17	0.01	
	(2.66***)		(−0.09)	(0.01)					
CW-CAPM*	174.16	–117.32		204.34	0.42	0.37	174.16		0.68
	(1.66**)	(−2.89***)		(0.01)					
CW-CAPM	243.92	–132.18	–1.11	203.57	0.48	0.37	242.81	0.01	0.55
	(2.92***)	(−2.85***)	(−0.49)	(0.01)					

Table A.4: Pricing momentum and accruals portfolios

This table presents the estimation and evaluation results for the CW-CAPM:

$$E\left(R^e_{i,t+1}\right) = \gamma_c Cov\left(\Delta c_{t+1}, R^e_{i,t+1}\right) + \gamma_w Cov\left(\Delta w_{t+1}, R^e_{i,t+1}\right) + \gamma_m Cov\left(r_{m,t+1}, R^e_{i,t+1}\right).$$

Its nested models are also estimated and reported. Test assets include portfolios groups formed on firm size and each of two anomaly variables: momentum (SM25) and accruals (SACC25). The model is estimated by first-stage GMM with equally-weighted moments. The first line associated with each asset pricing test reports the estimates for covariance risk price and the second line reports their GMM-based t-statistics (in parentheses). γ, ψ, and η represent the estimates for implied preference parameter. The column χ^2 presents the level and its corresponding p-value (in parentheses) for the χ^2 statistic. R^2_{OLS} denotes the OLS cross-sectional R^2, and MAE(%) is the average absolute pricing error. The sample period is from 1963:Q3 to 2017:Q4. t-ratios marked with *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	γ_c	γ_w	γ_m	χ^2	R^2_{OLS}	MAE (%)	γ	ψ	η
				Panel A (SM25)					
CAPM			2.50	73.82	–0.28	0.89			
			(2.60***)	(0.00)					
C-CAPM	207.29			23.04	0.54	0.50	207.29		
	(1.52*)			(0.52)					
EZ	354.89		–2.01	9.95	0.72	0.41	352.87	0.01	
	(1.52*)		(–0.43)	(0.99)					
CW-CAPM*	220.74	90.15		16.38	0.68	0.44	220.74		–0.41
	(1.14)	(0.53)		(0.84)					
CW-CAPM	323.30	43.30	–1.49	10.45	0.74	0.39	321.81	0.01	–0.13
	(1.53*)	(0.50)	(–0.33)	(0.98)					
				Panel B (SACC25)					
CAPM			2.65	62.46	0.24	0.32			
			(2.73***)	(0.00)					
C-CAPM	186.22			30.63	0.05	0.40	186.22		
	(1.68**)			(0.16)					
EZ	24.74		2.31	59.24	0.24	0.32	27.05	–0.05	
	(0.66)		(2.06**)	(0.00)					
CW-CAPM*	187.82	20.14		25.22	0.06	0.39	187.82		–0.11
	(1.55*)	(0.38)		(0.34)					
CW-CAPM	–8.44	54.32	2.84	46.97	0.33	0.32	–5.60	0.22	8.23
	(–0.16)	(1.58*)	(2.00**)	(0.00)					