Internet Appendix to "In Search of Preference Shock Risks: Evidence from Longevity Risks and Momentum Profits"

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Abstract

This appendix provides supplementary materials to the paper *In Search of Preference Shock Risks: Evidence from Longevity Risks and Momentum Profits* (to appear at Journal of Financial Economics).

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Appendices

For Online Publication

A. Data description

The U.S. data of population, exposure, and mortality rates are obtained from the Human Mortality Database (HMD). Due to its accessibility, reliability and consistency over time, it has been widely used in demographic and actuarial research. HMD uses the official population estimates available from the Census Bureau. However, there are several issues with the primary data source. First, the population definition changes over time, for example, with the inclusion or exclusion of armed forces overseas and the nonresident population.[1] Second, for many years, the estimates are provided for single year of age up to 85 only.[2] In addition, the counts for age 85 and above are grouped together, making it difficult to compute single-age death rates at older ages. Third, the frequency of estimates varies over time. This is unamenable to the calculation of exposure. HMD adjusts the population estimates to exclude the military population. This helps not only to remove the mortality component that is unrelated to the underlying longevity trend but also to match the exposure to the death counts.[3] Furthermore HMD distributes the population in the open age interval into a single year of age[4] and reestimates the population as of January 1 for each year.

The death data are published in the National Vital Statistics Reports by the National Center for Health Statistics (NCHS).[5] Before 1959, the data are available only in five-year

[1] Armed forces overseas are included for the period from $1940-1979$. Nonresidents are included before 1970. Residents of Alaska and Hawaii are included beginning in 1950.

[2] The years include $1940-1979$ and $2000-2009$. Before 1940, only ages up to 75 are provided. Ages up to 100 are provided for $1980-1999$ and 2010–present.

[3] The principle of correspondence states that for mortality rates to be valid, the deaths must come from those who are counted in the exposure. When there is a mismatch, the exposure is usually adjusted to match the deaths. The official death counts include only residents within the U.S. territory.

[4] This is achieved by the methods of extinct cohort (Kannisto, 1994) and survival ratio (Thatcher et al., 2002). Members of the population with unknown ages are then distributed proportionately over each age.

[5] The responsible agency has changed over time. The task was first given to the Census Bureau in 1902 and was subsequently transferred to the Public Health Service in 1946. Since 1960, after the merger with

age groups except for children below age 5.[6] HMD distributes the death counts into a single year of age using cubic spline and then deaths of unknown ages into each age category. Note that 1933 is the first year that mortality rates are deemed reliable and thus included in the HMD complete series.[7]

For the purpose of our analysis, we use the mortality series from $1963-2014$. The age range we consider is $0-99$, as the number of deaths for age 100 and beyond is very volatile and the data are not as reliable.[8]

B. Alternative GMM estimation

As a toolbox, GMM often generates results sensitive to the specifications. In particular, the weighting matrix often turns out to be important for the estimates. Although there is some statistical evidence suggesting the optimal choice of a weighting matrix, the results are often sensitive in small samples. Moreover, Ludvigson (2013) argues that in many asset pricing applications, it is inappropriate to use the optimal weight matrix suggested in Hansen (1982). In this section, we extensively evaluate various GMM estimations by comparing different GMM estimation procedures and different corrections for heteroskedasticity and autocorrelation.

We first compare two different GMM estimation procedures: two-step GMM and iterative GMM. Two-step GMM builds upon one-step GMM and puts different weights on different moment conditions based on statistical considerations, which is similar to GLS in linear regressions. Like two-step GMM, iterative GMM keeps using the estimation results from the previous step until the results converge. Asymptotically, no improvement can be achieved by such iterations in iterative GMM, but some Monte-Carlo simulations show that finite-sample properties of this estimator are slightly better (Ferson and Foerster, 1994). Table

National Health Survey, it has been under the purview of NCHS.

[6]The breakdowns for seniors above age 85 start in 1951.

[7]Registration areas were completed in 1933 with the admission of Texas.

[8]Given the small exposure at such ages, their impact on the longevity estimates will be negligible.

B.1 presents results from iterative GMM with Newey-West one-lag adjustment. Comparing the results with those in Table 2, we see that two-step GMM and iterative GMM generate similar estimates. The estimated coefficients in Panel A, implied prices of risks in Panel B, and implied parameters in Panel C are very close. The main differences are in the goodness of fit in Panel D. We find that iterative GMM presents much larger pricing errors ($RMSE$) and lower R^2. Taking the consumption-based three-factor model (2) as an example, we see that two-step GMM has an R^2 of 0.91 and an $RMSE$ of 1.06%, while iterative GMM has an R^2 of -0.35 and an $RMSE$ of 8.65%. This suggests that iterative GMM performs much worse than two-step GMM.[9]

Next, we consider the impacts of corrections for heteroskedasticity and autocorrelation during two-step GMM. We use different numbers of lags in Newey-West adjustment. Whereas Table 2 uses the one-lag Newey-West adjustment, Tables B.2, B.3, and B.4 report estimation results from two-lag, six-lag, and optimal (17-lag) Newey-West adjustment, respectively. Comparing results in Tables 2, B.2, B.3, and B.4, we see that they are very close. The main differences emerge in t-statistics and the Hansen's J-test of overidentification. The t-statistics and p-values of the J-test increase with the number of lags used in corrections for heteroskedasticity and autocorrelation. However, the pricing errors are similar. Taking the consumption-based three-factor model (2) as an example, we see that the one-lag Newey-West adjustment in Table 2 reports an $RMSE$ of 1.06% and a p-value of 0.41, while the six-lag Newey-West adjustment in Table B.3 has an $RMSE$ of 1.01% and a p-value of 1.00. Although we cannot compare different models based on Hansen's overidentification test, because different models use different weighting matrices, the similar pricing errors give us a warning about the number of lags used in Newey-West adjustment. The results suggest that adding more lags to Newey-West adjustment artificially blows up the weighting matrix (so that we see a small Hansen's J-statistic and a high p-value), but this does not improve the pricing errors.

[9] We also consider various lags in the Newey-West adjustment when comparing two-step GMM and iterative GMM. The untabulated results reach similar conclusions.

To summarize, we find that two-step GMM estimation produces much smaller pricing errors than iterative GMM. We also show that increasing the number of lags in Newey-West adjustment does not improve the pricing errors. It does artificially blow up the weighting matrix, which leads to a high p-value of Hansen's overidentification test. Therefore, to be conservative, we report two-step GMM with Newey-West one-lag adjustment as our main results in Table 2.

C. Cross-sectional regressions: using orthogonalized factors or PLS predictor scores

In this section, we consider the potential multicollinearity issue arising from regressing against the market factor, the mimicking consumption portfolio, and the longevity portfolio simultaneously. First, we follow Menkhoff et al. (2012) to use the orthogonalized component of consumption factor in the regressions. Specifically, we project the mimicking consumption portfolio on the market factor and the mimicking longevity portfolio and then use the residuals, the orthogonalized component of consumption factor, in the regressions. Column (2) of Table C.1 shows the full-sample Fama-MacBeth regression results. We see that the orthogonalized component of consumption factor is no longer significant. This implies the mimicking consumption portfolio is largely subsumed by the market factor and the mimicking longevity portfolio. The prices of the market factor and the longevity risk are similar to those in Column (1). Column (2) shows an insignificant intercept of 0.04% per month (t-statistic=0.71) only. This indicates that the marginally significant intercept in Column (1) may be due to the multicollinearity issue.

Second, we perform the partial least square (PLS) regressions. PLS regressions consider correlation with the dependent variables when extracting the key components from predictors (Kelly and Pruitt, 2013, 2015). We extract two predictor scores from the three factors, e.g., the market factor,the mimicking consumption portfolio, and the mimicking longevity portfolio. Column (3) of Table C.1 shows the Fama-MacBeth regression results, using the two predictor scores estimated from PLS. We see that the first predictor score is positively priced (a risk price of 0.93% per month, t-statistic=5.09) while the second predictor score is negatively priced (a risk price of -0.85% per month, t-statistic=-4.46). Examining the loadings of these two predictor scores on the three factors, we see the first (second) predictor score is positively related to the consumption (longevity) factor. Column (3) shows an insignificant intercept of 0.03% per month (t-statistic=0.52) only.

Overall, Table C.1 shows that the pricing errors become insignificant once we control for the multicollinearity issue.

D. Factor loadings on longevity risk: two alternative models

In this section, we report the full-sample time-series regression results from the consumption-based three-factor model (in Table D.1) and the consumption-based two-factor model (in Table D.2).

Examining the loadings on the longevity factor, we see that losers (winners) have positive (negative) loadings and such loadings monotonically decrease from the losers to the winners portfolio in Tables D.1 and D.2. The magnitudes of these factor loadings are close to those found in Table 4. Turning to the market factor and the consumption factor, we find that winners have lower loadings on the market factor and consumption factor than losers. Therefore, the market factor and the consumption factor cannot explain the momentum returns. Compared with the Fama-French model augmented with the longevity factor, the consumption-based three-factor model and the two-factor model demonstrate much larger residuals and lower R^2.

E. Measuring longevity risk as the growth rates

Our main measure of longevity risk is computed as the first-order difference of the weighted average period life expectancy. However, Eq. (14) and (16) suggest that we might measure longevity shocks as the longevity growth rates, as follows:

$$dE_t = ln\left(\frac{E_t}{E_{t-1}}\right). \tag{E.1}$$

In this section, we compare these two measures of longevity risk. Table E.1 reports the Fama-MacBeth regression results, using both measure. Roughly speaking, these two measures differ by a scaling factor, which is the average life expectancy over the sample period. Therefore, we see that their results are quite similar. But, for easy interpretations, we use the first-order difference of the weighted average period life expectancy as our main measure, as this tells us the price of a one-year increase in longevity during GMM estimations.

F. Estimating the PLC model

The log likelihood function is

$$\ln L = \sum_x \sum_t -m_{x,t}E_{x,t} + d_{x,t}\ln m_{x,t} + constant, \tag{F.2}$$

where $d_{x,t}$ is the realized value of $D_{x,t}$. We use the Newton-Raphson method to maximize the log likelihood function. The parameters a_x, b_x and k_t are estimated iteratively. We set the initial values of the parameters as follows:

$$\hat{a}_x^{(0)} = \frac{1}{T}\sum_t \hat{m}_{x,t}^{(0)}, \tag{F.3}$$

$$\hat{b}_x^{(0)} = 0, \tag{F.4}$$

$$\hat{k}_t^{(0)} = \frac{1}{N}, \tag{F.5}$$

where $\hat{m}_{x,t}^{(0)}$ is the crude death rate given by $d_{x,t}/E_{x,t}$, and T and N are the number of years and ages, respectively. At the j^{th} iteration, the estimate of a_x is updated as follows:

$$\hat{a}_x^{(j)} = \hat{a}_x^{(j-1)} + \frac{\partial l/\partial a_x}{\partial^2 l/\partial a_x^2}\Big|_{a_x=\hat{a}_x^{(j-1)}}. \tag{F.6}$$

$\hat{k}_t^{(j)}$ and $\hat{b}_x^{(j)}$ are updated in a similar way. Note that the model is under-identified. To ensure identifiability, we follow the literature and impose two restrictions: $\sum_x b_x = 0$ and $\sum_t k_t = 1$. This helps to normalize the values of $\hat{b}_x$ and $\hat{k}_t$ and ensures that they converge.[10]

G. Mortality risk

The mortality index is estimated via a full sample of data. Fig. G.1 plots the time series of mortality risk (dK) estimated from the PLC model with a full sample over $1963 - 2014$. We find that mortality risk (dK) is highly correlated with the longevity risk (dE), with a correlation of -0.99. Mortality risk (dK) is also positively correlated with the momentum factor, with a correlation of 0.31. Next, we construct a mimicking mortality portfolio, similar to the mimicking longevity portfolio in Eq. (30) and (32). The mimicking portfolio returns of mortality risk are estimated via ordinary least squares with a full sample of data. For example, the normalized weights are $\widetilde{\kappa}_x = [-0.39, 0.53, -0.06, 0.18, 0.48, -0.38, 0.66]'$. The mimicking mortality portfolio tracks the mortality risk very well. We find that the correlation between the annual mortality risk and its mimicking portfolio returns is 0.36. We see that mortality risk is positively correlated with the momentum factor, while its correlation with the size and book-to-market factors is less clear. The correlation between the mortality risk and momentum profits is apparent in Fig. G.2. Echoing this correlation, Fig. G.3 plots the annual momentum factor (MOM) and the mimicking portfolio returns of mortality risk (PL). We see that PL closely tracks the annual momentum profits, including the huge

[10]Normalization is applied after each update.

momentum crash in 2009.

Panels A and B of Table G.1 reports the summary statistics of mortality risk and its mimicking portfolio returns. Mortality risk (dK_t) has a mean of -1.30 (corresponding to an increase of 0.14 years in life expectancy), a standard deviation of 1.31, and a negative first-order autocorrelation of -0.13. The mimicking mortality portfolio has an annual return of 9.29% and a standard deviation of 12.28%. This mimicking mortality portfolio is highly correlated with the momentum factor, with a correlation of 0.87.

In preliminary tests, Panel C of Table G.1 regresses the mimicking mortality factor against the benchmark Fama-French three factors or the Fama-French three factors plus the momentum factor. Model (1) shows that the Fama-French three factors explain little of the mimicking mortality risk. The R^2 is as low as 0.08, and there is a large alpha of 0.72% per month. Adding the momentum factor to the Fama-French three-factor model, Model (2) shows that the momentum factor captures a significant part of mortality risk. Model (2) produces a much higher R^2 of 0.89 and a smaller alpha of 0.12, though the alpha is still statistically significant at the 1% level. In summary, Panel C of Table G.1 suggests that mortality risk is unlikely to be captured by the Fama-French three factors and is highly correlated with the momentum factor.

H. Estimate equity duration

To measure firm-level equity duration (DUR), we follow Dechow et al. (2004) except that we adapt it to a quarterly frequency. It is essentially a Macaulay type of duration, computed as the weighted average time of future cash flows, as follows:

$$DUR = \frac{\sum_{t=1}^{\infty} t * CF_t/(1+r)^t}{ME}, \tag{H.7}$$

where ME is the market equity at time 0, CF_t is the net cash flow to equity holders at time t, and r is the expected return on equity. To simplify, Dechow et al. (2004) assume that we can forecast the stream of cash flows up to horizon T and the remaining cash flows beyond T are to be a perpetuity. Thus,

$$DUR = \frac{\sum_{t=1}^{T} t * CF_t/(1+r)^t}{ME} + \left(T + \frac{1+r}{r}\right) \frac{\sum_{s=T+1}^{\infty} CF_s/(1+r)^s}{ME}. \tag{H.8}$$

To estimate duration, we need to forecast cash flows for the immediate T periods. Cash flows are computed from the accounting identity $BE_t = BE_{t-1} + E_t - CF_t$, where BE_t is the book equity at time t, and E_t is the same period earnings. Earnings can be computed by book equity and return on equity (ROE). Dechow et al. (2004) assume that book equity grows at the rate of sales growth (SGR). They further assume that SGR and ROE follow two separate first-order autoregressive (AR(1)) processes.

As in Dechow et al. (2004), we estimate two separate first-order autoregressive processes for sales growth (SGR) and return on equity (ROE). To avoid the seasonality issue, we use pooled COMPUSTAT annual data from 1963 to 2014 and then convert the estimates into the quarterly frequency. SGR is defined as the percentage change in net sales (SALE), while ROE is the ratio of earnings before extraordinary items (IB) over book value of common equity (CEQ).[11] These processes are assumed to converge to a long-run mean of 6% for sales growth and 12% for return on equity.[12] Thus, we estimate the AR(1) coefficients to be 0.21 and 0.56 for SGR and ROE, respectively. Next, we adjust the annual estimates to a quarterly frequency. We do so by scaling the long-run mean to one-fourth of the annual counterpart and the AR(1) coefficient to root four of the annual estimate. That is, SGR and ROE evolve as follows:

$$SGR_t = 0.33 * 6\%/4 + 0.67 * SGR_{t-1}, \tag{H.9}$$

$$ROE_t = 0.14 * 12\%/4 + 0.86 * ROE_{t-1}, \tag{H.10}$$

[11] We also used total shareholder book equity minus deferred tax and investment tax credit, plus book value of preferred equity. The results are similar.

[12] These are the long-run average estimates of GDP growth rate and equity return from Ibbotson Associates (1999).

where t represents a quarter.

SGR and ROE are projected for the next $T = 40$ quarters to forecast cash flows. Other data are from quarterly COMPUSTAT. We obtain quarterly sales (SALEQ), earnings (IBQ), book value of common equity (CEQQ), and market value of common equity (PRCCQ*CSHOQ) at the end of each fiscal quarter in the sample period. Using the cash flow forecasts, we compute duration (in quarters) from Eq. (H.8). Note that the appropriate discount rate r is 3%. We trim the duration estimates at 0 and 100 years.

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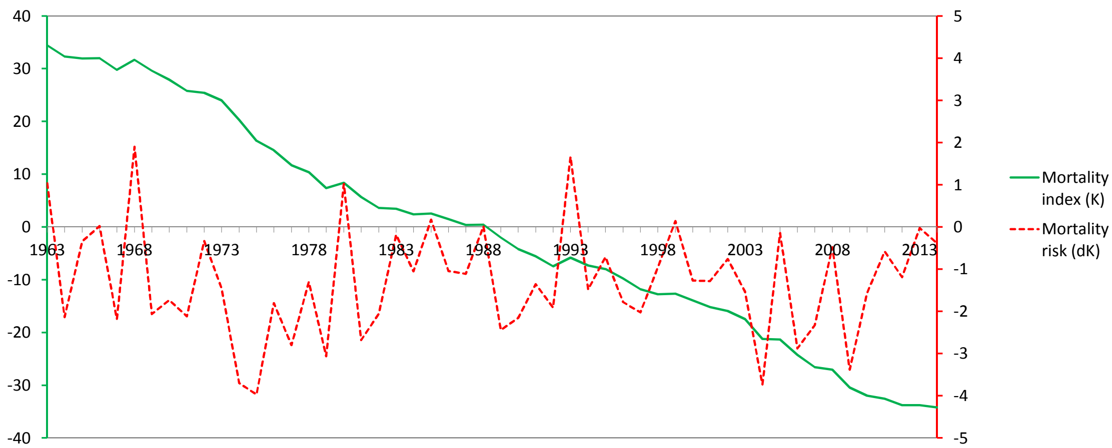

Fig. G.1. Annual mortality index and mortality risk

This figure plots the annual mortality index (K_t, shown in the left axis) and innovations in the mortality index (dK_t, shown in the right axis), i.e., the mortality risk. The mortality index is computed as in Brouhns et al. (2002). The sample data are from 1963 to 2014.

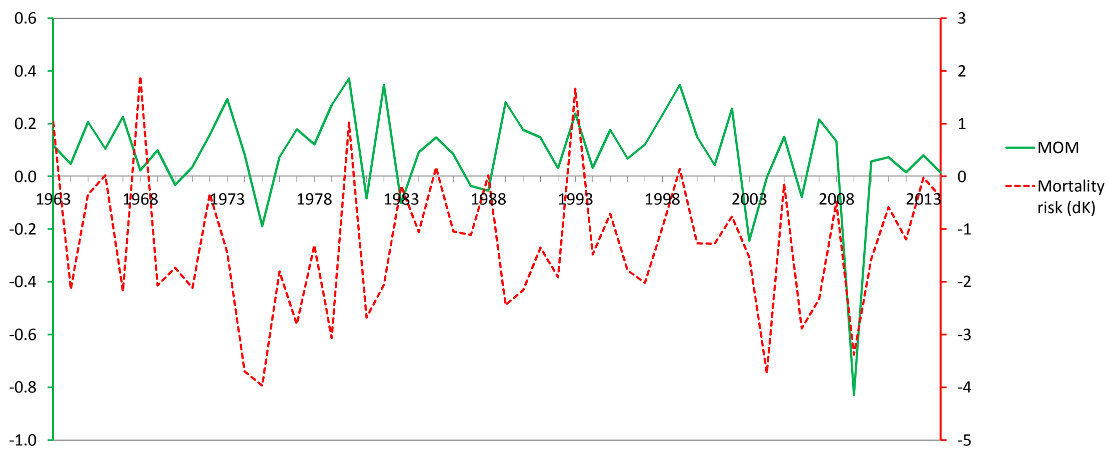

Fig. G.2. Annual momentum factor and mortality risk

This figure plots the annual momentum factor (MOM, shown in the left axis) and innovations in the mortality index (dK, shown in the right axis), i.e., the mortality risk. The mortality index is computed as in Brouhns et al. (2002). An unexpected decrease in the mortality index implies an unexpected increase in longevity. The sample data are from 1963 to 2014.

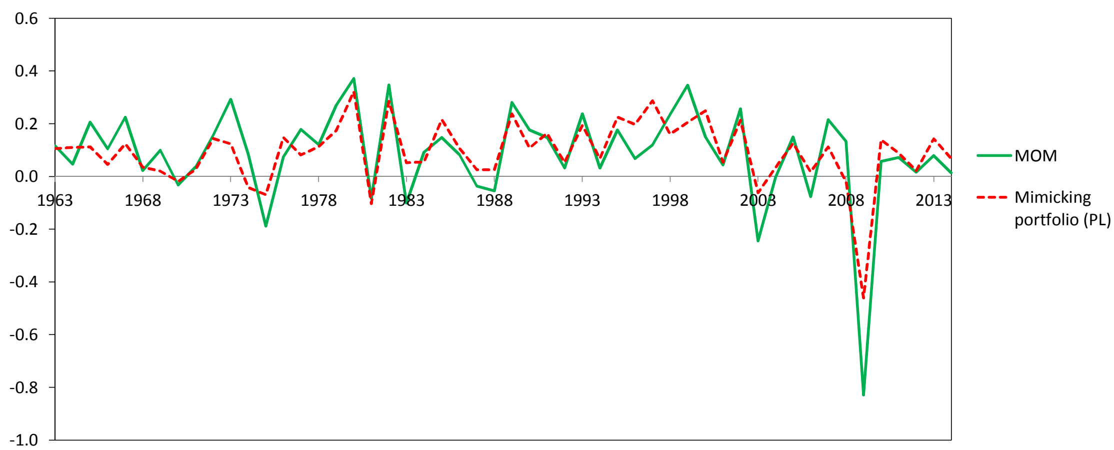

Fig. G.3. Annual momentum factor and the mimicking factor of mortality risk

This figure plots the annual momentum factor (MOM) and the mimicking portfolio returns of mortality risk (PL). The sample data are from 1963 to 2014.

Table B.1
Estimating consumption-based models, CAPM, and the Fama-French model: Iterative GMM with Newey-West one-lag adjustment

This table presents the iterative GMM estimation with one-lag Newey-West adjustment of consumption-based CAPM (see Eq. (28)). Factors include shocks to the time preferences, consumption growth rate, and the market portfolio. The unfiltered consumption data on nondurable goods and services are from Kroencke (2017). The shocks to time preferences are measured as the first-order difference of the weighted average period life expectancy. Test assets include six size and book-to-market sorted portfolios, six size and investment sorted portfolios, six size and operating profitability sorted portfolios, and six size and momentum sorted portfolios. Stock returns are adjusted by the Consumption Price Index to convert into real returns when necessary. Column (1) presents estimates from a power utility, while Column (2) presents results from the Epstein-Zin recursive preferences. For comparison, Columns (3) and (4) present GMM estimates from CAPM and the Fama-French three-factor model. Panel A shows the coefficients (b) from the GMM estimation, and their t-statistics are in parentheses. * indicates that the coefficient is restricted by the model, not by the estimation. Panel B reports the implied price of risk (λ) for each factor, based on estimates in Panel A. Panel C presents the implied parameters, i.e., relative risk aversion (γ) and the elasticity of intertemporal substitution (ψ). Panel D provides statistics of goodness of fit, including R^2, root-mean-square errors ($RMSE$), and Hansen's J-test of overidentification. R^2 is defined as one minus the ratio of the cross-sectional variance of the pricing errors to the cross-sectional variance of realized average portfolio returns, following Campbell and Vuolteenaho (2004). The annual data from 1964 to 2014 are used.

	Consumption CAPM		CAPM	Fama-French model
	Power utility	Recursive preferences		
	(1)	(2)	(3)	(4)
Panel A: Coefficients				
Longevity (b_L)	-1	-1.93		
	(*)	(-3.28)		
Consumption (b_C)	25.57	31.21		
	(7.52)	(3.75)		
Market (b_M)		-0.93	1.97	5.33
		(*)	(2.49)	(4.91)
SMB (b_{SMB})				1.58
				(3.20)
HML (b_{HML})				5.74
				(7.80)
Panel B: Implied price of risk				
Longevity ($\lambda_L, \%$)	-4.63	-6.94		
Consumption ($\lambda_C, \%$)	1.84	2.19		
Market ($\lambda_M, \%$)		1.41	6.57	15.18
SMB ($\lambda_{SMB}, \%$)				6.61
HML ($\lambda_{HML}, \%$)				7.32
Panel C: Implied parameters				
γ	25.57	30.28		
ψ		0.06		
Panel D: Goodness of fit				
R^2	-0.07	-0.35	-0.11	-0.98
RMSE (%)	6.29	8.65	3.98	9.47
p-value (J)	0.44	0.41	0.42	0.30

Table B.2
Estimating consumption-based models, CAPM, and the Fama-French model: Two-step GMM with Newey-West two-lag adjustment

This table presents the two-step GMM estimation with two-lag Newey-West adjustment of consumption-based CAPM (see Eq. (28)). Factors include shocks to the time preferences, consumption growth rate, and the market portfolio. The unfiltered consumption data on nondurable goods and services are from Kroencke (2017). The shocks to time preferences are measured as the first-order difference of the weighted average period life expectancy. Test assets include six size and book-to-market sorted portfolios, six size and investment sorted portfolios, six size and operating profitability sorted portfolios, and six size and momentum sorted portfolios. Stock returns are adjusted by the Consumption Price Index to convert into real returns when necessary. Column (1) presents estimates from a power utility, while Column (2) presents results from the Epstein-Zin recursive preferences. For comparison, Columns (3) and (4) present GMM estimates from CAPM and the Fama-French three-factor model. Panel A shows the coefficients (b) from the GMM estimation, and their t-statistics are in parentheses. * indicates that the coefficient is restricted by the model, not by the estimation. Panel B reports the implied price of risk (λ) for each factor, based on estimates in Panel A. Panel C presents the implied parameters, i.e., relative risk aversion (γ) and the elasticity of intertemporal substitution (ψ). Panel D provides statistics of goodness of fit, including R^2, root-mean-square errors ($RMSE$), and Hansen's J-test of overidentification. R^2 is defined as one minus the ratio of the cross-sectional variance of the pricing errors to the cross-sectional variance of realized average portfolio returns, following Campbell and Vuolteenaho (2004). The annual data from 1964 to 2014 are used.

	Consumption CAPM		CAPM	Fama-French model
	Power utility	Recursive preferences		
	(1)	(2)	(3)	(4)
Panel A: Coefficients				
Longevity (b_L)	-1	-1.24		
	(*)	(-7.99)		
Consumption (b_C)	22.67	24.11		
	(13.47)	(13.71)		
Market (b_M)		-0.24	2.47	2.37
		(*)	(5.90)	(4.27)
SMB (b_{SMB})				0.41
				(0.67)
HML (b_{HML})				3.48
				(7.19)
Panel B: Implied price of risk				
Longevity ($\lambda_L, \%$)	-4.34	-4.95		
Consumption ($\lambda_C, \%$)	1.64	1.72		
Market ($\lambda_M, \%$)		2.61	8.22	6.00
SMB ($\lambda_{SMB}, \%$)				2.38
HML ($\lambda_{HML}, \%$)				4.97
Panel C: Implied parameters				
γ	22.67	23.87		
ψ		0.05		
Panel D: Goodness of fit				
R^2	0.91	0.91	0.01	0.49
RMSE (%)	1.06	1.03	3.12	2.33
p-value (J)	0.84	0.81	0.82	0.71

Table B.3
Estimating consumption-based models, CAPM, and the Fama-French model: Two-step GMM with Newey-West six-lag adjustment

This table presents the two-step GMM estimation with six-lag Newey-West adjustment of consumption-based CAPM (see Eq. (28)). Factors include shocks to the time preferences, consumption growth rate, and the market portfolio. The unfiltered consumption data on nondurable goods and services are from Kroencke (2017). The shocks to time preferences are measured as the first-order difference of the weighted average period life expectancy. Test assets include six size and book-to-market sorted portfolios, six size and investment sorted portfolios, six size and operating profitability sorted portfolios, and six size and momentum sorted portfolios. Stock returns are adjusted by the Consumption Price Index to convert into real returns when necessary. Column (1) presents estimates from a power utility, while Column (2) presents results from the Epstein-Zin recursive preferences. For comparison, Columns (3) and (4) present GMM estimates from CAPM and the Fama-French three-factor model. Panel A shows the coefficients (b) from the GMM estimation, and their t-statistics are in parentheses. * indicates that the coefficient is restricted by the model, not by the estimation. Panel B reports the implied price of risk (λ) for each factor, based on estimates in Panel A. Panel C presents the implied parameters, i.e., relative risk aversion (γ) and the elasticity of intertemporal substitution (ψ). Panel D provides statistics of goodness of fit, including R^2, root-mean-square errors ($RMSE$), and Hansen's J-test of overidentification. R^2 is defined as one minus the ratio of the cross-sectional variance of the pricing errors to the cross-sectional variance of realized average portfolio returns, following Campbell and Vuolteenaho (2004). The annual data from 1964 to 2014 are used.

	Consumption CAPM		CAPM	Fama-French model
	Power utility	Recursive preferences		
	(1)	(2)	(3)	(4)
Panel A: Coefficients				
Longevity (b_L)	-1	-1.19		
	(*)	(-10.62)		
Consumption (b_C)	21.35	22.80		
	(20.38)	(21.90)		
Market (b_M)		-0.19	2.40	2.32
		(*)	(9.27)	(8.68)
SMB (b_{SMB})				0.47
				(1.22)
HML (b_{HML})				3.45
				(11.40)
Panel B: Implied price of risk				
Longevity ($\lambda_L, \%$)	-4.22	-4.73		
Consumption ($\lambda_C, \%$)	1.55	1.64		
Market ($\lambda_M, \%$)		2.59	7.99	5.88
SMB ($\lambda_{SMB}, \%$)				2.46
HML ($\lambda_{HML}, \%$)				4.96
Panel C: Implied parameters				
γ	21.35	22.61		
ψ		0.05		
Panel D: Goodness of fit				
R^2	0.91	0.91	0.02	0.50
RMSE (%)	1.06	1.01	3.10	2.32
p-value (J)	1.00	1.00	1.00	1.00

Table B.4
Estimating consumption-based models, CAPM, and the Fama-French model: Two-step GMM with optimal (17-lag) Newey-West adjustment

This table presents the two-step GMM estimation with optimal (17-lag) Newey-West adjustment of consumption-based CAPM (see Eq. (28)). Factors include shocks to the time preferences, consumption growth rate, and the market portfolio. The unfiltered consumption data on nondurable goods and services are from Kroencke (2017). The shocks to time preferences are measured as the first-order difference of the weighted average period life expectancy. Test assets include six size and book-to-market sorted portfolios, six size and investment sorted portfolios, six size and operating profitability sorted portfolios, and six size and momentum sorted portfolios. Stock returns are adjusted by the Consumption Price Index to convert into real returns when necessary. Column (1) presents estimates from a power utility, while Column (2) presents results from the Epstein-Zin recursive preferences. For comparison, Columns (3) and (4) present GMM estimates from CAPM and the Fama-French three-factor model. Panel A shows the coefficients (b) from the GMM estimation, and their t-statistics are in parentheses. * indicates that the coefficient is restricted by the model, not by the estimation. Panel B reports the implied price of risk (λ) for each factor, based on estimates in Panel A. Panel C presents the implied parameters, i.e., relative risk aversion (γ) and the elasticity of intertemporal substitution (ψ). Panel D provides statistics of goodness of fit, including R^2, root-mean-square errors ($RMSE$), and Hansen's J-test of overidentification. R^2 is defined as one minus the ratio of the cross-sectional variance of the pricing errors to the cross-sectional variance of realized average portfolio returns, following Campbell and Vuolteenaho (2004). The annual data from 1964 to 2014 are used.

	Consumption CAPM		CAPM	Fama-French model
	Power utility	Recursive preferences		
	(1)	(2)	(3)	(4)
Panel A: Coefficients				
Longevity (b_L)	-1	-1.20		
	(*)	(-16.42)		
Consumption (b_C)	21.26	22.46		
	(37.50)	(36.83)		
Market (b_M)		-0.20	2.37	2.32
		(*)	(11.63)	(10.18)
SMB (b_{SMB})				0.50
				(1.91)
HML (b_{HML})				3.44
				(19.50)
Panel B: Implied price of risk				
Longevity ($\lambda_L, \%$)	-4.21	-4.70		
Consumption ($\lambda_C, \%$)	1.54	1.62		
Market ($\lambda_M, \%$)		2.53	7.88	5.91
SMB ($\lambda_{SMB}, \%$)				2.51
HML ($\lambda_{HML}, \%$)				4.94
Panel C: Implied parameters				
γ	21.26	22.26		
ψ		0.05		
Panel D: Goodness of fit				
R^2	0.91	0.92	0.03	0.49
RMSE (%)	1.06	1.01	3.10	2.32
p-value (J)	1.00	1.00	1.00	1.00

Table C.1
Cross-sectional regressions: Using orthogonalized factors or PLS predictor scores

This table presents Fama-MacBeth regressions using the excess returns of 25 portfolios sorted by size and momentum. Factors include the Fama-French three factors, the mimicking portfolio for longevity factor (PL), the mimicking portfolio for consumption factor (PC), the orthogonalized component of consumption factor (C^{Orth}), or the two predictor scores from the partial least square regressions ($s1$ and $s2$). The orthogonalized component of consumption factor (PC^{Orth}) is the residuals from projecting the mimicking consumption portfolio on the market factor and the mimicking longevity portfolio. The factor betas, which are the independent variables in the regressions, are computed over the full sample. All coefficients are multiplied by 100. The t-statistics are in parentheses and adjusted for errors in variables, following Shanken (1992). The adjusted R^2 follows Jagannathan and Wang (1996). The 5th and 95th percentiles of the adjusted R^2 distribution from a bootstrap simulation of 10,000 times are reported in brackets. The sample period is from July 1963 to December 2014.

	(1)	(2)	(3)
γ_0	0.09	0.04	0.03
	(1.92)	(0.71)	(0.52)
γ_M	0.66	0.70	
	(3.50)	(3.73)	
γ_{PC}	0.73		
	(4.49)		
γ_{PC}^{Orth}		0.02	
		(0.13)	
γ_{PL}	-0.83	-0.81	
	(-6.50)	(-6.30)	
γ_{s1}			0.93
			(5.09)
γ_{s2}			-0.85
			(-4.46)
R^2	0.80	0.82	0.80
	[0.63, 0.88]	[0.66, 0.88]	[0.62, 0.88]

Table D.1
Time-series regressions of the three-factor model

This table reports the intercepts (in % per month) and factor loadings from full-sample time-series regressions of 25 portfolios sorted by size and momentum. Factors include the market factor, the mimicking consumption portfolio, and the mimicking longevity portfolio. The standard errors of residuals ($s(e)$) are reported in percentages. The Newey-West t-statistics with six lags are provided. The sample period is from July 1963 to December 2014.

	Losers	2	3	4	Winners		Losers	2	3	4	Winners	
			α			*diff*			t-statistic			*diff*
Small	0.20	0.40	0.47	0.55	0.83	0.62	0.96	2.70	3.14	3.27	3.93	4.11
2	0.21	0.35	0.29	0.42	0.57	0.36	1.26	2.89	2.51	3.46	3.64	2.10
3	0.33	0.24	0.20	0.09	0.46	0.13	2.27	2.42	2.15	0.88	3.53	0.82
4	0.23	0.19	0.10	0.08	0.23	0.01	1.71	2.25	1.15	1.10	2.04	0.05
Large	0.09	0.19	-0.12	-0.17	-0.06	-0.15	0.60	2.13	-1.46	-2.50	-0.73	-0.87
			β_M			*diff*			t-statistic			*diff*
Small	1.65	1.11	0.99	1.01	1.31	-0.34	26.83	17.29	18.09	19.92	18.39	-7.64
2	1.71	1.17	1.01	1.04	1.36	-0.35	28.06	20.35	19.71	23.57	21.06	-6.16
3	1.59	1.12	0.98	0.92	1.26	-0.32	32.53	24.78	19.56	22.43	23.49	-5.51
4	1.52	1.10	0.93	0.90	1.14	-0.38	33.00	20.97	20.61	25.05	27.50	-6.58
Large	1.36	0.94	0.84	0.78	0.96	-0.40	29.54	22.82	23.94	27.55	30.09	-7.01
			β_{PC}			*diff*			t-statistic			*diff*
Small	-0.23	0.09	0.11	-0.03	-0.42	-0.19	-2.17	0.89	1.36	-0.28	-2.75	-2.27
2	-0.19	0.10	0.13	0.03	-0.46	-0.27	-2.30	1.30	1.86	0.49	-3.18	-2.48
3	-0.08	0.19	0.24	0.21	-0.39	-0.31	-1.17	2.99	3.86	3.93	-3.42	-2.35
4	0.06	0.29	0.31	0.22	-0.28	-0.34	0.89	3.51	4.06	3.27	-2.87	-2.47
Large	0.18	0.30	0.24	0.19	-0.16	-0.34	2.16	4.29	4.08	3.05	-3.63	-3.78
			β_{PL}			*diff*			t-statistic			*diff*
Small	1.01	0.48	0.23	-0.02	-0.41	-1.42	7.96	5.24	3.03	-0.28	-3.36	-14.96
2	0.97	0.50	0.15	-0.04	-0.55	-1.52	7.50	6.07	2.29	-0.64	-4.81	-12.68
3	1.02	0.49	0.29	-0.04	-0.62	-1.63	14.77	9.25	4.80	-0.62	-7.26	-18.05
4	1.12	0.57	0.29	-0.04	-0.65	-1.77	16.11	8.80	5.47	-0.80	-9.63	-19.36
Large	1.03	0.65	0.20	-0.18	-0.67	-1.69	13.86	10.32	3.37	-3.16	-14.16	-20.47
			R^2						$s(e)$			
Small	0.74	0.68	0.67	0.67	0.68		4.08	3.31	3.12	3.19	3.86	
2	0.83	0.77	0.77	0.76	0.78		3.22	2.81	2.54	2.65	3.18	
3	0.85	0.84	0.82	0.82	0.82		2.83	2.22	2.13	2.10	2.69	
4	0.86	0.87	0.87	0.88	0.84		2.72	2.00	1.73	1.65	2.33	
Large	0.83	0.85	0.87	0.88	0.87		2.83	1.92	1.58	1.50	1.89	

Table D.2
Time-series regressions of the two-factor model

This table reports the intercepts (in % per month) and factor loadings from full-sample time-series regressions of 25 portfolios sorted by size and momentum. Factors include the mimicking consumption portfolio and the mimicking longevity portfolio. The standard errors of residuals ($s(e)$) are reported in percentages. The Newey-West t-statistics with six lags are provided. The sample period is from July 1963 to December 2014.

	Losers	2	3	4	Winners		Losers	2	3	4	Winners	
			α			*diff*			t-statistic			*diff*
Small	-0.13	0.17	0.27	0.34	0.56	0.69	-0.29	0.57	0.96	1.13	1.47	4.03
2	-0.14	0.11	0.08	0.21	0.29	0.43	-0.33	0.40	0.33	0.80	0.91	2.27
3	0.00	0.02	0.01	-0.10	0.20	0.20	0.01	0.07	0.03	-0.46	0.73	1.10
4	-0.08	-0.03	-0.09	-0.10	0.00	0.09	-0.24	-0.13	-0.42	-0.51	0.02	0.48
Large	-0.19	0.00	-0.29	-0.33	-0.26	-0.07	-0.60	-0.02	-1.58	-2.08	-1.33	-0.34
			β_{PC}			*diff*			t-statistic			*diff*
Small	0.90	0.85	0.79	0.67	0.47	-0.43	2.91	3.95	4.18	3.32	1.63	-6.04
2	0.98	0.91	0.82	0.75	0.48	-0.51	3.36	4.65	4.80	3.96	1.62	-6.39
3	1.01	0.95	0.91	0.84	0.48	-0.53	4.55	6.27	6.21	6.43	1.90	-5.99
4	1.11	1.04	0.95	0.84	0.51	-0.60	5.43	8.28	9.33	8.07	2.25	-6.79
Large	1.11	0.94	0.82	0.72	0.50	-0.61	6.22	8.74	7.66	7.63	3.33	-10.19
			β_{PL}			*diff*			t-statistic			*diff*
Small	0.94	0.43	0.19	-0.06	-0.46	-1.40	2.61	1.90	0.98	-0.31	-1.56	-11.97
2	0.90	0.45	0.10	-0.08	-0.60	-1.50	2.48	1.95	0.56	-0.42	-2.01	-11.19
3	0.95	0.44	0.25	-0.07	-0.67	-1.62	3.33	2.37	1.39	-0.46	-2.62	-16.87
4	1.06	0.53	0.25	-0.08	-0.69	-1.75	3.96	3.05	1.85	-0.58	-3.13	-17.44
Large	0.97	0.61	0.17	-0.21	-0.71	-1.68	4.61	4.45	1.21	-1.64	-4.02	-20.78
			R^2						$s(e)$			
Small	0.14	0.18	0.20	0.18	0.14		7.46	5.34	4.88	4.99	6.28	
2	0.15	0.20	0.24	0.24	0.19		7.23	5.26	4.58	4.73	6.06	
3	0.19	0.25	0.29	0.34	0.25		6.64	4.78	4.27	4.07	5.49	
4	0.23	0.30	0.35	0.37	0.31		6.37	4.62	3.93	3.80	4.91	
Large	0.25	0.32	0.34	0.42	0.39		5.88	4.03	3.56	3.30	4.11	

Table E.1
Cross-sectional regressions: Measuring longevity risk as the growth rate of life expectancy

This table presents Fama-MacBeth regressions using the excess returns of 25 portfolios sorted by size and momentum. Factors include the Fama-French three factors, the mimicking portfolio for consumption factor (PC), and the mimicking portfolio for longevity factor (PL). In Panel A, longevity risk is measured as the first-order difference of the weighted average period life expectancy. In Panel B, longevity risk is measured as the growth rate of the weighted average period life expectancy. The factor betas, which are the independent variables in the regressions, are computed over the full sample. All coefficients are multiplied by 100. The t-statistics are in parentheses and adjusted for errors in variables, following Shanken (1992). The adjusted R^2 follows Jagannathan and Wang (1996). The 5th and 95th percentiles of the adjusted R^2 distribution from a bootstrap simulation of 10,000 times are reported in brackets. The sample period is from July 1963 to December 2014.

		Panel A			Panel B		
	(1)	(2)	(3)	(4)			
γ_0	0.74	0.09	0.18	0.02	0.10	0.19	0.02
	(5.85)	(1.92)	(1.44)	(0.49)	(1.98)	(1.45)	(0.60)
γ_M	-0.09	0.66		0.56	0.66		0.55
	(-0.42)	(3.50)		(3.04)	(3.48)		(3.01)
γ_{SMB}	0.24			0.24			0.24
	(1.80)			(1.80)			(1.82)
γ_{HML}	-0.46			0.36			0.35
	(-2.39)			(2.61)			(2.52)
γ_{PC}		0.73	0.80		0.72	0.78	
		(4.49)	(4.55)		(4.38)	(4.39)	
γ_{PL}		-0.83	-0.84	-0.80	-0.84	-0.85	-0.81
		(-6.50)	(-6.54)	(-6.17)	(-6.54)	(-6.58)	(-6.19)
R^2	0.07	0.80	0.81	0.91	0.79	0.80	0.91
	[-0.07, 0.34]	[0.63, 0.88]	[0.55, 0.88]	[0.81, 0.94]	[0.62, 0.88]	[0.55, 0.87]	[0.81, 0.94]

Table G.1
Mortality risk: Descriptive statistics and relations with other factors

Panel A summarizes the annual statistics of mortality risk (dK), the mimicking portfolio returns of mortality risk (PL, in %), and the mimicking portfolio returns of consumption risk (PC, in %). The full-sample data are used in estimating the mimicking portfolio returns. $AR(1)$ denotes the first-order autocorrelation of each series. Panel B reports the sample means, standard deviation, Sharpe ratio, and correlations for the Fama-French three factors, momentum factor (MOM), the mimicking portfolio for mortality risk (PL), and the mimicking portfolio for consumption risk (PC), using annual data. Panel C reports the time-series regressions of the mortality factor against the Fama-French three-factor model or the Fama-French three-factor model augmented with the momentum factor, using monthly data. The Newey-West t-statistics with six lags are in parentheses. The sample data are from 1963 to 2014.

Panel A: Descriptive statistics								
	Mean	Median	Std. Dev.	Min	Max	AR(1)		
dK	-1.30	-1.33	1.31	-3.97	1.90	-0.13		
PL(%)	9.29	10.75	12.28	-46.07	32.18	0.01		
PC(%)	13.15	15.18	14.22	-17.50	45.72	0.09		
Panel B: Factor means, volatilities, and correlations								
Factor	Mean (%)	Std. Dev. (%)	Sharpe Ratio	SMB	HML	MOM	PL	PC
R_M	6.84	17.82	0.38	0.28	-0.27	-0.17	0.15	0.44
SMB	3.44	13.89	0.25		-0.01	-0.12	-0.11	-0.05
HML	5.07	13.59	0.37			-0.19	-0.10	0.60
MOM	8.57	18.28	0.47				0.87	0.05
PL	9.29	12.28	0.76					0.40
PC	13.15	14.22	0.92					
Panel C: Time-series regressions								
$PL_t = \alpha + \beta_M R_{Mt} + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \epsilon_t$								
	α(%)	β_M	β_{SMB}	β_{HML}	β_{MOM}	R^2		
Model (1)	0.72	0.16	-0.12	-0.12		0.08		
	(7.04)	(2.82)	(-1.66)	(-1.12)				
Model (2)	0.12	0.28	-0.13	0.09	0.67	0.89		
	(2.98)	(20.57)	(-5.42)	(2.60)	(42.21)			