



Time varying consumption covariance and dynamics of the equity premium: Evidence from the G7 countries[☆]

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ABSTRACT

We examine implications of time-varying correlation and covariance between excess equity returns and consumption growth for the equity premium of the G7 countries. We find that the correlation and covariance are higher when there is a negative shock to labor income and a positive shock to returns. The combined effect is that the correlation and covariance are countercyclical and so is the equity premium. We test asset pricing models with time-varying consumption risk and find that the conditional price of risk is generally positive. These results survive several robustness checks. Our results highlight the importance of labor income for understanding dynamics of the equity premium.

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Economists have long sought to understand time-series evidence that the equity premium EP is countercyclical (Fama and French, 1989; Ferson and Harvey, 1991). Since the EP should be proportional to the covariance of returns with consumption growth, countercyclical variation in the conditional covariance may result in similar variation in the EP ¹. Indeed, on theoretical grounds, we expect the covariance to be counter-cyclical. For example, Santos and Veronesi (2006) show theoretically that, if investors have dividend and labor income that grow stochastically over time, then the ratio of labor income to aggregate consumption (LIC from now on) predicts the EP . When LIC increases, consumption is driven mainly by labor income, decreasing the covariance between consumption growth and returns, and lowering EP . Conversely, during recessions, LIC decreases, forecasting higher covariance and EP . Hence, the covariance is countercyclical. In Appendix B, we discuss a number of other asset pricing models with the implication that the covariance is countercyclical.

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¹ Other explanations for time variation in the EP include time-varying risk aversion (Constantinides, 1990; Campbell and Cochrane, 1999; Barberis et al. 2001), and consumption commitments or transactions costs that must be paid to change consumption (Chetty and Szeidl, 2003).

The available empirical evidence, however, does not clearly establish whether the conditional covariance and correlation are countercyclical or not.² Santos and Veronesi (2006) find empirically that expected returns are negatively related to *LIC* at horizons from 1 to 4 years. Although this result is consistent with a countercyclical covariance, they do not directly examine the empirical relation between *LIC* and the covariance. Moreover, Duffee (2005) shows that the covariance and correlation increase with the ratio of aggregate stock market wealth to consumption (*MEC* from now on), and infers that the covariance and correlation are procyclical. Establishing the cyclical properties of the covariance is important for asset pricing because pro-cyclical covariance and counter-cyclical *EP* are difficult to reconcile theoretically.

In this paper, we reconcile the conflicting empirical evidence regarding the conditional covariance and correlation by combining information on labor income and stock returns, and assessing the implications for asset pricing models. During recessions, *MEC* is low and predicts lower covariance; however, *LIC* is also low and forecasts increased covariance. We examine the combined effect of *MEC* and *LIC* on the covariance and the *EP*. Since U.S. data has been mined extensively in previous research, we provide fresh evidence by extending our results to the G7 countries. Finally, we examine whether the price of consumption risk varies as predicted by asset pricing models, after conditioning on stock return and labor income shocks.

For estimation, we use a Vector Autoregression (VAR) framework to characterize the first moments and a bivariate GARCH specification to generate second moments of stock returns and consumption growth. Consistent with the literature, we show that the conditional correlation decreases with *LIC* and increases with *MEC*. A new result is that the correlation and covariance are unambiguously higher during recessions even under the combined effect of *LIC* and *MEC*. The time-variation in the correlation and covariance is large: in U.S. quarterly data, for example, the correlation varies from 0.70 in recessions to 0.20 in expansions. We further find that the conditional equity premium *EP*, implied by the correlation, increases during recessions.

Our results extend to the G7 countries. We reject the assumption of constant correlation in all countries, except France and Italy,³ and find evidence supporting countercyclical variation in the correlation and *EP*. The evidence is strongest for Canada, Germany, and the UK, countries with relatively large shares of stock market capitalization to GDP.

Are the conditional covariance and the *EP* positively related in the time series after incorporating information on labor income? To examine implications for asset pricing, we test models of time-varying consumption risk. We show that the conditional price of risk is positive in most quarters and the average price of risk is positive for all countries except Italy. Also, the price of consumption risk varies with proxies such as surplus consumption (Campbell and Cochrane, 1999), with signs as predicted by theory. However, as our estimates imply a large average price of risk, we fail to explain the “equity premium puzzle” (Mehra and Prescott, 1985).

We implement several robustness checks. Ameriks et al. (2004) and Reis (2003) examine the consequences of infrequent updating and monitoring of spending decisions by consumers; an implication of their results (as discussed in Appendix B) is that the correlation should increase with large negative income shocks (e.g. due to higher unemployment). Thus, we use changes in the unemployment growth *UG* as a recession proxy, and find that the correlation is higher after periods with rising unemployment, compared to periods of falling unemployment. Lettau and Ludvigson (2001a) find that higher values of *CAY*, or fluctuations in the aggregate consumption wealth ratio, predict higher expected returns. We use *CAY* as another recession proxy and find that higher values of *CAY* predict higher conditional correlation. These results are consistent with countercyclical variations in the correlation. Our results continue to hold after we control for the decline in consumption volatility after 1990. Finally, since seasonal adjustment of consumption may induce a “forward-looking bias,” we use a moving average of non-seasonally adjusted consumption. Again, our results remain valid after making these adjustments.

We contribute to the literature by reconciling the qualitatively different implications of labor income (i.e. *LIC* and *UG*) and returns (i.e. *MEC* and *RR*) for equity return dynamics. While the former implies countercyclical and the latter implies pro-cyclical dynamics, respectively, we show that the effect of labor dynamics dominates so that consumption risk is countercyclical. We further contribute to the literature by providing evidence for the G7 countries. These results illustrate the prominent role of labor income in explaining the dynamics of the equity premium.⁴

Of related papers, Santos and Veronesi (2006) show that *LIC* predicts stock returns in the time-series and further, that *LIC* performs well as a conditioning variable in cross-sectional tests. Unlike us, they do not use *LIC* or return shocks to predict the covariance. Yogo (2006) finds that durable consumption growth is high relative to nondurable consumption growth during recessions and that stock returns decrease (increase) with durable (nondurable) consumption growth, implying countercyclical variation in the *EP*. In contrast, we obtain countercyclical variation in the equity premium through time-varying correlation of returns with nondurable consumption growth. Different from these papers, we relate the correlation to macro indicators, and estimate the price of consumption risk. Duffee (2005) finds that the correlation is positively related to *MEC* but he does not combine information on *MEC* with labor income. While all of the papers discussed above study US data only, we also study the remaining G7 countries.

The remainder of this paper is as follows. In Sections 1 and 2, we describe the VAR-GARCH framework and the data, and present descriptive statistics. U.S. results are in Sections 3 and 4, and results for other G7 countries are in Section 5. In Section 6, we develop the GARCH-IN-MEAN framework and test asset pricing models. Section 7 concludes.

² Harvey (1989) shows that the conditional covariance is high in January, but not enough to explain the January premium in stock returns. The correlation has also been studied empirically as it is more intuitive. In cross-sectional evidence, Lettau and Ludvigson (2001b) find that value stocks earn higher average returns than growth stocks because of higher consumption correlation during bad times.

³ Previously, the hypothesis of constant conditional covariance was rejected in U.S. data by Schwert and Seguin (1990) and Harvey (1989) and for U.S., UK, and Japanese data by Cumby (1990).

⁴ Jagannathan and Wang (1996), Lettau and Ludvigson (2001a,b) and Santos and Veronesi (2006), among others, show the predictive power of labor income in the time series and the cross-section of stock returns.

1. Empirical methodology

Consumption-based asset pricing models predict that expected asset returns should be proportional to the covariance between returns and some function of real consumption, such as expected consumption growth (Hansen and Singleton, 1983). If the covariance is positive, then assets have high returns when consumption is high (i.e. marginal utility is low), and require a higher risk premium. However, the risk-aversion implied by the model is too high in all G7 countries (between 50 and 162 in our sample). An important reason for the model's failure is the low (and even negative) value of the unconditional correlation (Cochrane and Hansen, 1992).

Recent literature has focused on the conditional EP. Given power utility and lognormally distributed consumption growth, the conditional EP is approximately (Cochrane, 2001):

$$E_t(ER_{t+1}) \approx \gamma \sigma_t(CGRO_{t+1}) \sigma_t(ER_{t+1}) \rho_t(CGRO_{t+1}, ER_{t+1}) \quad (1)$$

where γ is the risk-aversion, ρ is the correlation, σ is the standard deviation, $CGRO$ is the log consumption growth, ER is the excess equity return and E_t is an expectation conditional on information at time t .

From Eq. (1), predictable variation in EP may arise from variations in γ , ρ or σ . In this paper, we focus on the conditional correlation ρ . In Appendix B, we discuss several asset pricing models to motivate the idea that time-variation in the correlation and the covariance is economically meaningful and intuitive. Further, sample evidence for the G7 countries shows time-variation in the mean and volatility of returns and consumption growth, as well as in the correlation and covariance between the two.

A natural way to model the above features of the data is to combine a VAR model for means with a GARCH model for second moments. Initially, we model time-variation in ρ and then draw implications for time-variation in the covariance; in Section 6, we estimate time-variation in the covariance directly via a GARCH-IN-MEAN model.

We now describe the VAR-GARCH process and economic factors driving time-variation in the correlation. Let R_t be a vector of consumption growth and excess returns, and define:

$$\begin{aligned} R_t &= m_{t-1} + e_t \\ m_{t-1} &= E(R_t | \Omega_{t-1}) \\ e_t | \Omega_{t-1} &\sim N(0, H_t) \end{aligned} \quad (2)$$

where Ω_{t-1} is the information set at time $t-1$. e_t is a vector of innovations, assumed conditionally normal with a conditional covariance matrix H_t . Elements of H_t are h_{ijt} , $i \neq j$, (off-diagonal terms, or conditional covariance) and h_{iit} (diagonal terms, or conditional variances).

We model the means of consumption growth $CGRO$ and excess returns ER as a VAR, augmented with one-period lagged values of exogenous prediction variables:

$$R_{it} = \alpha_{i0} + \sum_{j=1}^2 \sum_{\tau=1}^L \alpha_{j\tau} R_{jt-\tau} + \sum_{j=1}^P \beta_{ij} z_{j,t-1} + e_{it} \quad (3)$$

where $i=1$ ($CGRO$), or 2 (ER). L is the order of the VAR, chosen according to various information criteria. $z_{j,t-1}$, $j=1, \dots, P$ is the j -th exogenous prediction variable. The VAR model assumes that consumers can predict consumption growth and returns. Evidence of predictability is relatively weak for consumption growth and somewhat stronger for returns.⁵

We use a GARCH(1,1) model to estimate conditional second moments of the VAR innovations.

$$h_{iit} = a_i + b_i e_{it}^2 + c_i h_{iit-1} \quad i = 1, 2 \quad (4)$$

where b_i represents the ARCH effect while c_i represents the GARCH effect. Note that Eq. (4) omits $z_{j,t-1}$ as high-dimensional GARCH models are difficult to estimate. We test whether the covariance h_{ijt} , $i \neq j$ varies over time by introducing lagged exogenous variables:

$$h_{ijt} = (Int + r_1 X_{t-1}) \sqrt{h_{iit}} \sqrt{h_{jtt}} \quad i \neq j \quad (5)$$

where Int is the intercept and X is an exogenous variable evaluated at time $t-1$. A special case is when the conditional correlation is assumed to be constant and so $r_1 = 0$ (Bollerslev, 1990).

The exogenous variables X are LIC , MEC , the (negative of) unemployment growth $-UG$ and RR , the stock return residual e_2 from the VAR. We use the negative of UG for consistency of interpretation with LIC , so that lower values indicate worse employment conditions. The correlation is expected to be related negatively with LIC , as per Santos and Veronesi (2006), and

⁵ Campbell and Mankiw (1989) find that, for the G7 countries, consumption growth is predicted by its lags and by the term structure. Motivated by habit persistence models, Deaton (1987) estimates a regression of consumption growth on its lags. Kandel and Stambaugh (1990) regress consumption growth on the dividend yield, the default spread and the term spread. For U.S. quarterly returns, Fama and French (1989) document that the Baa-Aa corporate bond yield, the S&P 500 dividend yield and the term spread predict returns. Whitelaw (1994) uses similar variables to predict monthly and quarterly U.S. returns. Time-averaging of consumption may also explain why consumption growth is explained by its lag (Christiano et al., 1991).

positively with *MEC*, consistent with [Duffee \(2005\)](#). The correlation is expected to increase with *UG* due to more frequent updating and monitoring of spending decisions by consumers ([Ameriks et al., 2004](#) and [Reis, 2003](#)) when labor income falls substantially (as in periods of high unemployment). Since consumption has low time-variation, changes in *MEC* are most likely due to return variations, and so *RR* may be viewed as another proxy for changes in the stock market wealth. Accordingly, we expect a positive relation between the correlation and *RR*.

The tests for US data are specified in both indicator and continuous forms. For non-US data, we do not have *LIC* and *MEC* data. Moreover, for the sake of brevity, we only report results for the continuous specification for *UG* and *RR*; the results for the indicator specification are available from the authors.⁶ For the continuous specification, we standardize *X* by subtracting the sample mean and dividing by the sample standard deviation. When there are two exogenous variables, this allows us to compare the marginal effects of each on the correlation. For the indicator specification, we define indicator variable $I_{X,t}$ for time t , as:

$$I_{X,t} = 1 \text{ if } X_t > E(X), \text{ and } I_{X,t} = 0 \text{ otherwise.} \quad (6)$$

where the indicator variable is defined with respect to the full sample mean $E(X)$.⁷

An advantage of the dummy variable framework is that it provides a robustness check, to the extent that alternative specifications of the exogenous variables provide consistent results. Such a framework has previously been used by [Glosten et al. \(1993\)](#) and [Longin and Solnik \(1995\)](#). Plots of the sample correlation for non-overlapping 2 year periods (not shown) indicate that discretization of the correlation is a reasonable approximation to its actual behavior over time. For example, in U.S. monthly data, there are five values of the correlation between 0.1 and 0.2, eight values between 0.2 and 0.3, and five values between 0.4 and 0.5. The correlations are significantly different from zero and generally statistically different from one another, as further discussed below in [Section 2.2](#).

Thus far, we have considered the separate effect of exogenous variables on the conditional correlation. However, our main interest lies in assessing the combined effect of macro and stock return information. For example, what is the net effect of *LIC* and *MEC* on the conditional correlation? If the net effect is positive, this has adverse consequences for asset pricing models, as discussed in [Duffee \(2005\)](#). We combine the effects of continuous variables X_1 and X_2 as follows:

$$h_{ijt} = (Int + r_1 X_{1,t-1} + r_2 X_{2,t-1}) \sqrt{h_{iit}} \sqrt{h_{jtt}} \quad i \neq j \quad (7)$$

X_1 is either $-UG$ or *LIC* and X_2 is either *RR* or *MEC*. We also combine X_1 and X_2 when specified as indicators:

$$h_{ijt} = (Int + r_1 I_{X1,t-1} + r_2 I_{X2,t-1}) \sqrt{h_{iit}} \sqrt{h_{jtt}} \quad i \neq j \quad (8)$$

We implement Wald tests of the restrictions $r_1 = r_2 = 0$ (i.e. the conditional correlation is constant) and $r_1 + r_2 = 0$ (whether the effect of X_1 is larger than the effect of X_2). For the latter test, we report one-sided p values. Therefore, a rejection of $r_1 + r_2 = 0$ also implies rejection of $r_1 + r_2 \geq 0$.

We jointly estimate the VAR-GARCH system (3), (4) and (6) when the correlation varies with a single exogenous variable or (3), (4) and either (7) or (8) when the correlation varies with both macro and financial factors. If x is the vector of all parameters to be estimated and T is the sample size, then the conditional log-likelihood function can be expressed as:

$$Lik(x) = -\frac{1}{2} \sum_{t=1}^T \left[\ln(2\pi) + \ln |H_t| + e_t' (H_t)^{-1} e_t \right] \quad (9)$$

$Lik(x)$ is maximized by the BFGS Quasi-Newton method with a mixed quadratic and cubic line search procedure. We initialize conditional variances to their unconditional values, and use the Simplex method for a few iterations to “straighten out” the initial conditions.

2. Data and descriptive statistics

2.1. Data

A complete description of data sources and sample dates is in the Appendix A. The sample starts in the 1960s for the U.S., UK and Canada, in 1970 for others, and ends 2003 Q1 or Q2. We use monthly data for the U.S., and quarterly data for G7 countries. Per capita consumption is the sum of seasonally adjusted expenditures on nondurables and services, or aggregate expenditures where

⁶ For estimation of non-US country data, we occasionally obtain non-positive estimates of the conditional variances. We use an exponential transformation to ensure positive variance.

⁷ We have also calculated the mean using data until time t for each X_t . The results are similar to those reported here.

disaggregated data is unavailable, divided by the population. Consumption growth is the log difference in current and one-period lagged per capita consumption.⁸ Excess returns are the total return (capital gains plus dividend yield) minus the local 3-month Treasury bill rate. We use the MSCI stock index except for the U.S., UK and Canada, where we use a local stock index to match the longer history of consumption data in those countries. For labor income (the numerator of *LIC*), we use employees' compensation from the NIPA tables. Nominal data are converted to real terms using the local Consumer Price Index.

We use lagged values of *DEF*, the default spread, *DIVY*, the dividend yield, *TERM*, the 10-year note yield minus the 3-month bill rate and *PE*, the price–earnings ratio, to predict the equity premium and consumption growth. For non-U.S. G7 countries, other than Canada, *DEF* is the corporate bond yield minus the long-term Treasury yield since separate data for high-risk and low-risk corporate bonds is unavailable.⁹ For Canada, we use the corporate bond yield minus the 3-month prime corporate paper rate. For the U.S., we use the Baa minus Aa corporate bond yield, and the S&P 500 dividend yield.

2.2. Descriptive statistics for consumption growth and stock returns

Campbell (2002) reports a small or negative unconditional correlation in the quarterly data for most countries. He notes that the ratio of stock market capitalization to GDP (*Mgdp*) may be a reasonable proxy of the stock market claim to total consumption. We first discuss the sample correlation of consumption growth and stock returns, and relate it to the capitalization of the stock market (*Mcap*). To examine the in-sample variation in the correlation, we then compare the correlation for different calendar periods and macro conditions.

We calculate the sample correlation (*SCORR*) of consumption growth *CGRO* and the excess equity returns. The U.S. has the highest correlation (0.24 for monthly and 0.34 for quarterly data). Canada has double-digit correlation, but the other countries have small or negative correlation. The correlation is weakly associated with *Mcap* and *Mgdp*. Thus, while the U.S. and Canada have relatively large stock markets and moderate correlation, Japan and the UK have large stock markets and negative correlation.¹⁰ The mean annualized *CGRO* is around 2% for most countries but, compared to the U.S., the volatility of *CGRO* is higher for the other G7 countries. The mean excess return is high in all countries relative to the consumption volatility, implying (based on the Euler equation) a large risk-aversion coefficient.

We now examine whether the correlation varies with calendar time. Plots of the correlation indicate substantial calendar time-variation over 2-year, 5-year and 10-year horizons in *SCORR*, primarily reflecting similar variation in the covariance (these figures are not shown). We use Fisher's z-statistic to compare correlations for different time periods and find evidence of statistically significant time-variation. For example, we find that *SCORR* is significantly lower in the early 1960s and early 1990s and significantly higher in the early 1980s for the US. For the non-US G7 countries, *SCORR* is significantly lower in the early to mid-1970s for Germany, Italy and Canada and in the mid-1990s for Japan; it is significantly higher in the early to mid-1980s for UK, France and Canada.

Next, we estimate the correlation conditional on whether, in the previous period, $D_1 = 1$ (i.e. *UG* is above average which implies rising unemployment since the mean of *UG* is virtually zero) or $D_1 = 0$ (unemployment is stable/decreasing). Table 1 shows that the correlation is generally higher in times of higher unemployment. The difference is statistically insignificant in most cases except for U.S. monthly data, where *SCORR* is 0.33 (0.19) following months when unemployment growth is high (low), and the difference is statistically significant.

In summary, the correlation varies over time, and is typically higher when unemployment is increasing. The volatility of returns and consumption growth also varies over time. We now estimate conditional moments of consumption and returns, and characterize how the correlation varies with labor and stock market conditions.

3. VAR-GARCH(1,1) results for U.S. quarterly data

In this section, we describe results from estimating the VAR-GARCH(1,1) model for U.S. data. Consumers may better forecast returns and consumption growth by conditioning on variables such as the dividend yield. However, our results for the conditional correlation are not sensitive to inclusion of the forecasting variables in the mean equation. Therefore, we summarize results for the mean (VAR) equations only briefly without reporting results (which are available from the authors). Instead, we focus mainly on describing the GARCH(1,1) results when the correlation varies with labor income and return shocks.

In the data, *CGRO* and excess returns *ER* are most correlated with lagged values of *TERM*, while *ER* also shows moderate correlation with lagged *DY* and lagged *DEF*. The VAR results show that lagged *TERM* is positively related to *CGRO* and *ER*, while lagged *DY* and the lagged *PE* ratio are positively related to *ER*; these relations are all statistically significant. We calculate

⁸ We assume that consumption is measured at the end of a period. If consumption is assumed to be measured at the beginning of a period, consumption growth would be defined relative to next period's consumption, resulting in higher contemporaneous correlation with returns, especially at quarterly horizons (Campbell, 2002).

⁹ Kandel and Stambaugh (1990) use the difference between Aaa and the Treasury bill rates. We use long-term rather than short-term Treasury rates to match the corporate bond maturities more closely.

¹⁰ Data issues may complicate cross-country comparisons of the correlation. For example, the consumption data for some countries do not separate out nondurables and services expenditures. In addition, the aggregation bias in consumption data reduces the variance of consumption changes whereas asset returns data do not have this bias. Differences in the size of this bias across countries may affect the comparability of the correlations.

Table 1

Sample correlation for periods of increasing and non-increasing unemployment: G7 data.

	$D_1 = 1$	$D_1 = 0$	$D_1 = 1$	$D_1 = 0$	$D_1 = 1$	$D_1 = 0$	$D_1 = 1$	$D_1 = 0$
	USM		USQ		Canada		U.K.	
OBS	188	345	59	117	63	85	59	92
SCORR	0.33*	0.19*	0.46	0.24	0.18	0.02	−0.03	−0.01
	(0.10)	(0.10)	(0.12)	(0.13)	(0.51)	(0.27)	(0.82)	(0.99)
COV	6.68	3.36	13.70	3.49	6.63	0.62	−1.66	−0.32
σ ER	13.42	11.43	17.84	13.53	16.23	17.81	19.66	20.28
σ CGRO	1.52	1.57	1.67	1.06	2.29	1.43	2.45	2.01
Mean ER	8.54	1.72	4.22	4.02	3.42	−0.20	19.12	0.71
Mean CGRO	2.11	1.90	1.00	2.42	1.29	2.32	2.08	2.24
	Italy		Japan		France		Germany	
OBS	47	44	72	59	57	72	86	46
SCORR	0.03	0.05	0.08	−0.11	−0.17	0.10	0.02	−0.19
	(0.87)	(0.93)	(0.27)	(0.30)	(0.14)	(0.14)	(0.18)	(0.33)
COV	1.09	1.85	3.96	−11.99	−7.13	4.93	5.37	−63.65
σ ER	27.09	26.53	23.88	25.98	26.72	24.55	22.11	24.80
σ CGRO	1.23	1.41	2.13	4.02	1.60	2.01	13.01	13.30
Mean ER	0.71	2.61	12.57	1.87	6.51	7.51	10.25	4.85
Mean CGRO	2.50	2.10	2.59	1.60	1.15	2.68	1.03	2.92

The table shows the sample correlation (SCORR) and covariance (COV) between per capita log consumption growth (CGRO) and the excess equity returns (ER), and the mean and standard deviation (σ) of CGRO and ER for U.S. monthly (USM) and quarterly (USQ) data and non-U.S. G7 quarterly data. ER is the difference between total stock returns (in local currencies) and the local short-term Treasury rate. We show SCORR when, in the previous quarter or month, $D_1 = 1$ or when $D_2 = 1$. For period t , we define $D_{1,t} = 1$ if $UG_t > E(UG)$ and $D_{1,t} = 0$ otherwise. UG is the change in the unemployment rate and $E(UG)$ is the sample mean of UG . p values (in parenthesis) correspond to a test of the null hypothesis that SCORR, conditional on $D_1 = 1$, is equal to SCORR, conditional on $D_1 = 0$. ** (*) indicates significance at the 5 (10) percent level or less. All data are converted to real terms using the local Consumer Price Index, and annualized. Data sources and sample dates are in Appendix A.

F -statistics for CGRO (ER) to test the null hypothesis that the coefficients of lagged values of CGRO (ER) are jointly zero in the regressions. They show that lagged consumption growth explains variations in CGRO, consistent with Flavin (1981) and Reis (2003). Lagged consumption growth and lagged returns are not significant in predicting ER. Finally, we cannot reject the null hypothesis of zero autocorrelation of the VAR innovations for up to 8 lags.

Table 2 presents estimates of conditional variances and the conditional correlation (CCORR) from the GARCH(1,1) model. Panel A shows results when CCORR is restricted to be constant. Both the ARCH and GARCH coefficients for CGRO and ER are significant. CCORR is 0.34 for U.S. quarterly data and statistically significant at the 5% level. The estimate is similar to the sample value.¹¹

Next, we test for time-variation in the conditional correlation CCORR. In Panel B of Table 2, we show results when CCORR varies either with the macro factors (LIC and $-UG$) or with the stock market factors (MEC and RR). We find that the correlation decreases with LIC and $-UG$. From column LIC Continuous, the estimated r_1 is -0.19 and significant at the 1% level. From column $-UG$ Continuous, the estimated r_1 is -0.72 and significant at the 1% level. The implied correlation is about 0.35 at the sample average values of LIC and UG and about 0.72 at the minimum (maximum) values of LIC and UG . The result also holds in the indicator specifications (columns labeled LIC Indicator and $-UG$ Indicator) as the correlation is lower when $LIC > E(LIC)$ or when $-UG > E(-UG)$. These results imply that returns are more correlated with consumption for negative shocks to labor income; moreover, there is large variation in the correlation between positive and negative labor shocks.

We further find that the correlation increases with MEC and RR and the correlation difference between periods of positive and negative return shocks is considerable. Consider the results in column MEC Continuous, of Table 2 Panel B. The estimated r_1 is 0.13 and significant at the 1% level. The implied correlation is 0.34 at the sample average value of MEC and it is 0.81 at the maximum value of MEC . The result also holds in the MEC Indicator case as the correlation is higher when $MEC > E(MEC)$. In addition, the correlation increases with return shocks RR when specified in indicator form. In column RR Indicator, CCORR is 0.24 when return shocks are at or below average (i.e. for non-negative return shocks, since the mean of RR is essentially zero) and 0.49 (i.e. $0.24 + 0.25$) for positive return shocks. The estimated r_1 is positive in the RR Continuous case but not significant.

The results so far agree with the prior literature on the individual effects of labor income shocks (i.e. negative) and return shocks (i.e. positive) on the correlation. The results using LIC is consistent with Santos and Veronesi (2006) who predict a negative relation between the covariance and LIC . The results using unemployment growth are consistent with infrequent updating and monitoring of spending decisions by consumers (Ameriks et al., 2004 and Reis, 2003), resulting in higher correlation during recessions. The correlation is also higher with MEC and positive return shocks, consistent with the composition effect (Duffee, 2005) or increased stock market participation (Mankiw and Zeldes, 1991; Vissing-Jorgensen, 2002).

¹¹ A potential concern is the relatively small value of the Arch coefficients, implying a standard error for the Garch coefficients that is too low relative to the true one (Ma et al. (2007)). Following Ma et al. (2007), we fit a ARCH(3) model to the VAR residuals. We find that the first-order autocorrelation of the conditional variances estimated from the ARCH(3) model are close to the GARCH(1,1) coefficient reported in Table 2. This alleviates the concern that we have misestimated the GARCH coefficient.

Table 2

VAR-GARCH(1,1) results: U.S. quarterly data.

Panel A: Constant correlation model

	CGRO		EP	
<i>Int</i> (a_i)	0.31** (4.91)		82.77** (15.15)	
<i>Arch</i> (b_i)	0.39** (3.01)		−0.05** (−2.45)	
<i>Garch</i> (c_i)	−0.19** (−3.18)		−0.46** (−5.28)	
CCORR (r_{ij})			0.34** (6.08)	

Panel B: Varying correlation, macro or stock return factors separately

	Estimate	<i>t</i> -stat	Estimate	<i>t</i> -stat	Estimate	<i>t</i> -stat	Estimate	<i>t</i> -stat
	<i>LIC Continuous</i>		<i>LIC Indicator</i>		− <i>UG Continuous</i>		− <i>UG Indicator</i>	
<i>Int</i>	0.34**	4.92	0.24**	7.76	0.36**	9.51	0.26**	2.88
r_1	−0.19**	−3.30	−0.17**	−4.76	−0.72**	−5.63	−0.27**	−2.20
	<i>MEC Continuous</i>		<i>MEC Indicator</i>		<i>RR Continuous</i>		<i>RR Indicator</i>	
<i>Int</i>	0.33**	5.78	0.27**	8.76	0.37**	6.98	0.24**	3.30
r_1	0.13**	3.55	0.24**	4.04	0.06	1.04	0.25**	2.39

Panel C: Varying correlation, macro and stock returns combined

	Estimate	<i>t</i> -stat	Estimate	<i>t</i> -stat	Estimate	<i>t</i> -stat	Estimate	<i>t</i> -stat
	<i>LIC + MEC Continuous</i>		<i>LIC + MEC Indicator</i>		− <i>UG + RR Continuous</i>		− <i>UG + RR Indicator</i>	
<i>Int</i>	0.36**	8.07	0.19**	3.91	0.38**	7.74	0.17**	3.02
r_1	−0.21**	−4.61	−0.23**	−3.40	−0.18**	−3.50	−0.18**	−2.61
r_2	0.05*	1.92	0.17*	2.55	0.06**	14.04	0.17*	1.85
$r_1 = r_2 = 0$								
<i>Chi-sq</i>		24.89		18.07		21.36		19.34
<i>p</i>		0.00		0.00		0.00		0.00
$r_1 + r_2 = 0$								
<i>Chi-sq</i>		4.19		−		5.58		−
<i>p</i>		0.04		−		0.02		−

The table presents results for the following VAR-GARCH(1,1) model using U.S. quarterly (USQ) data. Panels A and B present estimates from the following model:

$$R_{it} = \alpha_{i0} + \sum_{j=1}^2 \sum_{\tau=1}^3 \alpha_{j\tau} R_{jt-\tau} + \sum_{j=1}^2 \beta_{ij} z_{j,t-1} + e_{it}$$

$$h_{iit} = a_i + b_i e_{it}^2 + c_i h_{iit-1} \quad i = 1, 2$$

$$h_{ijt} = (Int + r_1 X_{t-1}) \sqrt{h_{iit}} \sqrt{h_{jtt}} \quad i \neq j$$

where $i = 1$ (log consumption growth *CGRO*) or 2 (excess equity returns *ER*), *Int* is the intercept, h_{iit} is the conditional variance, and h_{ijt} is the conditional covariance for $i \neq j$. *ER* is the difference between total stock returns (in local currencies) and the local short-term Treasury rate. a_i is the intercept term, b_i is the *Arch* coefficient, and c_i is the *Garch* coefficient. z_{jt} is the j -th exogenous prediction variable where $j = \{DY, TERM, DEF, PE\}$. *DY* is the S&P 500 dividend yield, *TERM* is the constant maturity 10-year Treasury note yield minus the 3-month Treasury bill rate, *PE* is the price–earnings ratio, and *DEF* is Moody's BAA minus AA corporate bond yields.

Panel A presents the GARCH estimates when the conditional correlation CCORR is restricted to be constant ($r_1 = 0$). In Panel B, CCORR varies with X_{t-1} , an exogenous variable from the set $\{LIC, MEC, -UG \text{ and } RR\}$. *LIC* is the ratio of labor income to consumption and *MEC* is the ratio of stock market wealth to consumption. *UG* is the change in the unemployment rate, *RR* is the return residual e_2 from the VAR. For the continuous specification, we standardize X_{t-1} by subtracting the sample mean and dividing by the sample standard deviation. For the indicator specification, the indicator variable I_X is defined as follows:

$$I_{X,t} = 1 \text{ if } X_t > E(X), \text{ and } I_{X,t} = 0 \text{ otherwise.}$$

where $E(X)$ is the sample mean of X . The column headings identify the various specifications.

In Panel C, the specification $X1 + X2$, *Continuous* is as follows:

$$h_{ijt} = (Int + r_1 X1_{t-1} + r_2 X2_{t-1}) \sqrt{h_{iit}} \sqrt{h_{jtt}} \quad i \neq j$$

where $X1 = -UG$ or *LIC* and $X2 = RR$ or *MEC*. The $X1 + X2$, *Indicator* specification is as follows:

$$h_{ijt} = (Int + r_1 I_{X1,t-1} + r_2 I_{X2,t-1}) \sqrt{h_{iit}} \sqrt{h_{jtt}} \quad i \neq j$$

In Panel C, we report results of Wald tests of the following coefficient restrictions $r_1 = r_2 = 0$ and $r_1 + r_2 = 0$. For the latter test, we report one-sided p values. The intercept in Panel A is multiplied by 10,000 for easier reading. Estimates significant at the 5 (10) percent level or less are marked by ** (*). All data are converted to real terms using the local Consumer Price Index. Data sources and sample dates are in Appendix A. Note that the *MEC* series ends 2002 Q2, one year earlier than the remaining data.

What is the *combined* effect of *both* types of shocks? In panel C of Table 2, we combine labor income and stock market factors. The specifications $LIC + MEC$ and $-UG + RR$ (in continuous and indicator forms) show that r_1 is negative and significant and r_2 is positive and significant. Thus, the correlation increases with lower labor income and higher unemployment and it also increases when stock prices rise. The Wald tests decisively reject the null hypothesis of a constant conditional correlation ($r_1 = r_2 = 0$). Further, the estimated $r_1 + r_2 < 0$ and the null of $r_1 + r_2 = 0$ is rejected using the one-sided p values for continuous specifications. Hence, the countercyclical effects of LIC and UG on the correlation exceed the procyclical effects of MEC and RR implying that the correlation increases over recessions and decreases over expansions.

To illustrate the business cycle properties of the correlation, we plot the time series of the correlation against NBER recession periods for the $LIC + MEC$ specification (Fig. 1). We find that the conditional correlation $CCORR$ (dashed line) is generally countercyclical as it peaks in recession periods (shaded area) or just after. To focus on the cyclical properties of the correlation, we average the correlation over expansions and recessions (solid line, labeled $CCORR_BC$). The correlation rises in every recession except for the recessions of 1970 and 1980. There is also a secular increase in the correlation in the 1980s and 1990s, perhaps reflecting the strong increase in the stock market capitalization during this time. To control for the trend, we estimate a regression of the correlation on an intercept, a time trend, and one lag of LIC . The estimated coefficient of LIC is -1.95 and significant at the 1% level, indicating a counter-cyclical correlation.

Fig. 1 also shows the correlation averaged over expansions and recessions for the $UG + RR$ specification. For this specification, we do not observe the secular increase in the correlation observed in the $LIC + MEC$ specification. The reason is that, while there was a secular increase in stock market capitalization (reflected in MEC), there was not a similar trend in *unexpected* returns RR (i.e. returns in excess of that predicted by the VAR model). However, we find that the correlation remains countercyclical: indeed, $CCORR_BC$ is higher in every recession in the post-WWII period, compared to expansion periods.

In summary, we find that the correlation varies substantially over time and in counter-cyclical fashion. This indicates that the increase in the correlation during recessions due to a negative shock to labor income (i.e. rising unemployment or declining LIC) offsets the decrease in the correlation due to decreasing returns and lower MEC . This result is reassuring because a pro-cyclical correlation is inconsistent with standard asset pricing models.

4. Additional investigations for U.S. data

Previously, we found that the correlation is higher for negative labor income shocks and positive stock return shocks. In this section, we check the sensitivity of our results to different specifications for the correlation (section A). Stock and Watson (2002) show that the consumption growth variance is lower in the 1990s. Lettau et al. (2008) show that this shift is associated with higher stock prices. Thus, in section B, we re-estimate our model after controlling for the decline in consumption volatility in the post-1990 period. Finally, standard seasonal adjustment of consumption uses a forward-looking filter, so that consumption may not be a valid predetermined instrument. Accordingly, in section C, we repeat our tests using non-seasonally adjusted consumption and a backward-looking filter. The results in this section are not reported but available from the authors.

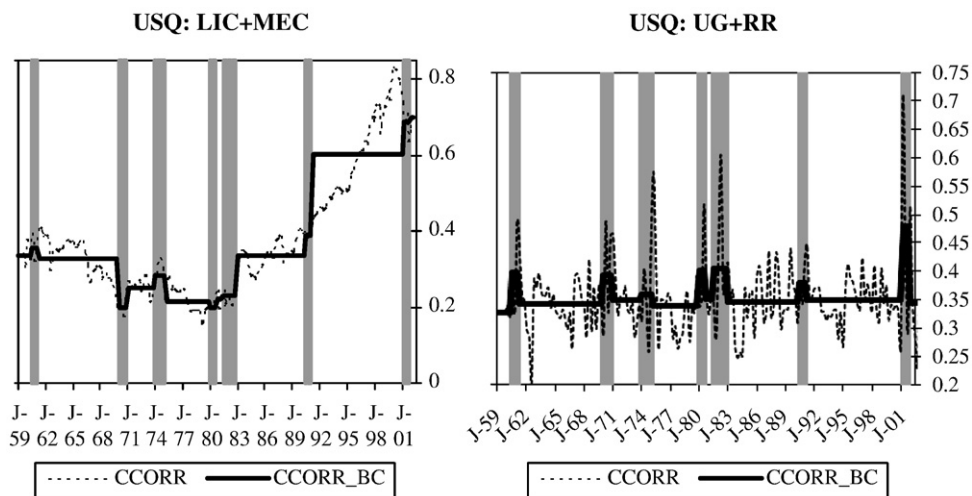


Fig. 1. Conditional correlation: U.S. Quarterly Data. For U.S. quarterly data, we plot the conditional correlation $CCORR$. Estimates are obtained from the VAR-GARCH (1,1) model. In the specification $LIC + MEC$, the conditional correlation $CCORR$ is estimated as a function of the ratio of labor income to aggregate consumption, LIC , and the ratio of stock market wealth to aggregate consumption, MEC . In the specification $UG + RR$, $CCORR$ is estimated as a function of stock return shocks, RR , and changes in the unemployment rate, UG . “ $CCORR_BC$ ” indicates that the correlation is averaged over expansion (post-trough to peak) and recession (post-peak to trough) quarters. Shaded areas indicate NBER-dated recession quarters. The x-axis variable is in J-yy format, where “J” indicates January and yy indicates the year, respectively.

4.1. Alternative specifications for the correlation

Lettau and Ludvigson (2001a, 2003) find that *CAY* predicts the mean and volatility of returns. Thus, we allow the conditional moments to depend on a one-quarter lag of *CAY*.¹² In the VAR, lagged *CAY* is related negatively to *CGRO* and positively to *ER*, and both effects are significant, consistent with Lettau and Ludvigson (2001a). The GARCH results show that *CAY* is negatively related to the return variance, consistent with Lettau and Ludvigson (2003), and the correlation increases with *CAY*, and both relations are significant. Since a high value of *CAY* predicts high returns, the result implies that the correlation is countercyclical. The results also indicate that both *CAY* and *UG* are informative of the correlation.

Gabaix and Laibson (2001) predict that the correlation is higher for larger return shocks. We define a “large” return shock to mean that *ARR*, the absolute value of *RR*, is greater than its mean $E(RR)$ plus standard deviation $\sigma(RR)$. Then, the relevant indicator variable is:

$$I_{ARR,t} = 1 \text{ if } ARR_t > E(RR) + \sigma(RR), \text{ and } I_{ARR,t} = 0 \text{ otherwise.} \quad (10)$$

The results show that *CCORR* is significantly greater for large shocks than for small shocks, indicating that it increases with *ARR*, consistent with Gabaix and Laibson (2001).

4.2. Reduction in consumption volatility in the post-1990 period

To detect shifts in the conditional variance and correlation, we include a dummy variable for the post-1990 period in the GARCH equations. We find that the conditional variance of consumption growth is significantly lower and the conditional correlation is significantly higher in the 1990s. However, the remaining results do not change qualitatively.

4.3. Using non-seasonally adjusted consumption expenditures

We repeat our estimations using a four-quarter moving average of non-seasonally adjusted consumption expenditures *CGRO_NSA* for US quarterly data. The sample correlation between *ER* and *CGRO_NSA* is only 0.05. However, the conditional correlation is 0.18 and significant when *RR* is positive, and statistically zero when *RR* is non-positive. Hence, there is evidence of time-varying correlation with seasonally unadjusted consumption.

5. VAR-GARCH(1,1) results for ex-U.S. G7 data

For U.S. data, we have shown that the conditional correlation *CCORR* increases with proxies for recessions and stock market wealth. Do the results also hold for non-U.S. G7 countries? Cross-country variations in the duration of unemployment insurance (Tatsiramos, 2004) and in the size of the equity market may lead to cross-country differences in how *CCORR* reacts to changes in unemployment and stock market wealth. We describe VAR results followed by the GARCH estimates.

The mean values of prediction variables are broadly comparable across G7 countries.¹³ VAR estimates (not reported to save space) show some evidence of predictability for *CGRO* but little evidence of predictability for returns. The prediction variables generally have low correlation with *CGRO* and *ER*.¹⁴

In Table 3, we show estimates of the conditional correlation *CCORR* for ex-U.S. G7 countries. In the constant correlation model (Panel A), the Arch and Garch effects for *ER* and *CGRO* are positive in all countries, except for the Arch effect in *ER* for Japan. These effects are also generally statistically significant. *CCORR* is statistically zero for all countries and even negative (but not significant) for Japan and France.

In panel B of Table 3, we show results when *CCORR* varies with (the negative of) unemployment growth $-UG$ (in columns labeled $-UG$). Italy is excluded since it has no unemployment data before 1980. The results show that, for Canada, Germany, and Japan, the estimate of r_1 is negative implying that *CCORR* is significantly higher when $-UG$ decreases. The effect of unemployment on the correlation is substantial. For Canada, the *CCORR* is higher by 0.27 when *UG* is at its maximum level. The corresponding numbers for Germany and Japan is 0.60 and 0.08. Hence, for three of five countries considered, the conditional correlation is higher when unemployment growth is above average, consistent with the U.S. evidence. Exceptions are the U.K. and France, where we find no significant variation in the correlation with respect to *UG*.

When we combine $-UG$ and *RR* (in columns $-UG + RR$), the coefficient of *RR* (r_2) is generally not significant, except for Japan where the coefficient is negative and significant. The lack of significance for the returns dummy may be due to more limited

¹² We omit *CAY* from the consumption variance equation since we find that it does not affect the latter significantly. Another concern may be our use of *CAY* as a predetermined variable, in light of the debate on calculating *CAY* as a cointegrating vector residual using the full sample. Without taking a stand on this debate, we simply note that we use *CAY* as an additional recession proxy, and our key results remain valid when using different recession proxies.

¹³ The mean default spread is around 1% for Canada and the UK and 0.51% or below for other countries (compared to 0.71% for the U.S.). The mean dividend yield is between 3% and 4.5% for most countries (compared to 3.34% for the U.S.). The *PE* ratio is around 20 for most countries (compared to 18.68 for the U.S.). The term spread is between 1.24% and 2% for most countries (compared to 1.39% for the U.S.).

¹⁴ *DY* is positively correlated with returns in Canada and the UK. *PE* is positively correlated with returns in the UK and negatively correlated with *CGRO* in Japan and France. *TERM* is positively correlated with returns in Canada and France, and with *CGRO* in Germany. The *F*-statistics indicate that the autoregressive model does poorly in predicting returns, but has moderate ability in predicting *CGRO*. As in U.S. data, *CGRO* is generally negatively autocorrelated at short lags and positively autocorrelated at longer lags. However, as the inclusion of durable consumption in non-U.S. data biases the autocorrelation downward, comparison with U.S. data is problematic.

Table 3

VAR-GARCH(1,1) estimation results: G7 (ex-U.S.) data.

Panel A: Constant correlation model

	Canada		UK		Italy		Japan		France		Germany	
	CGRO	EP	CGRO	EP	CGRO	EP	CGRO	EP	CGRO	EP	CGRO	EP
a_i	0.03** (3.61)	15.57** (4.85)	0.82** (6.61)	13.31** (5.77)	0.25** (7.08)	54.26** (6.34)	0.59** (4.78)	135.96** (9.62)	0.27** (4.43)	117.03** (7.89)	0.14** (6.09)	5.95** (2.78)
b_i	0.04** (9.94)	0.12** (5.78)	0.12** (3.26)	0.15** (7.49)	0.31 (0.39)	0.10** (3.86)	0.98** (3.38)	−0.06 (−1.58)	0.98 (0.24)	0.06** (7.96)	0.48 (0.17)	0.20 (0.24)
c_i	0.92** (2.26)	0.63** (6.58)	0.06** (2.08)	0.70** (4.72)	0.14** (2.44)	0.59** (3.47)	0.01** (2.08)	0.07** (5.50)	0.01 (0.08)	0.12** (2.31)	0.01 (0.44)	0.77** (4.67)
r_{ij}		0.06 (0.74)		0.08 (1.15)		0.03 (0.33)		−0.10 (−1.26)		−0.06 (−0.74)		0.04 (0.40)

Panel B: Correlation varying with UG and RR

	Canada		UK		Japan		France		Germany	
	− UG	− $UG + RR$	− UG	− $UG + RR$	− UG	− $UG + RR$	− UG	− $UG + RR$	− UG	− $UG + RR$
$Int.$	0.02 (0.91)	0.02 (0.90)	0.05 (0.75)	0.05 (0.66)	−0.03 (−1.31)	−0.02 (−0.88)	−0.08 (−1.13)	−0.08 (−0.95)	0.05 (0.52)	0.02 (0.18)
r_1	−0.08** (−6.00)	−0.08** (−6.12)	−0.00 (−0.02)	−0.02 (−0.19)	−0.03** (−2.29)	−0.04** (−3.38)	0.07* (1.88)	0.08 (1.59)	−0.12** (−2.01)	−0.12* (−1.84)
r_2	−	−0.01 (−0.98)	−	−0.03 (−0.39)	−	−0.08** (−5.83)	−	0.63 (0.22)	−	−0.09 (−0.64)

Wald tests of coefficient restrictions

$$r_1 = r_2 = 0$$

Chi-sq	37.56	0.01	36.82	0.04	2.72
p	0.00	0.96	0.00	0.84	0.10

$$r_1 + r_2 = 0$$

Chi-sq	24.90	0.11	33.73	0.06	2.58
p	0.00	0.75	0.00	0.80	0.10

Panel C: Correlation varying with GG and RR

	Canada		UK		Italy		Japan		France		Germany	
	GG	$GG + RR$	GG	$GG + RR$	GG	$GG + RR$	GG	$GG + RR$	GG	$GG + RR$	GG	$GG + RR$
$Int.$	0.04 (1.45)	0.04 (1.47)	0.02 (0.31)	0.02 (0.32)	−0.04 (−0.62)	0.01 (0.06)	−0.03 (−1.12)	−0.03 (−1.21)	−0.05 (−0.60)	−0.08 (−0.91)	0.03 (0.26)	0.01 (0.04)
r_1	−0.06** (−3.77)	−0.05** (3.65)	−0.16** (−2.50)	−0.16* (−2.69)	0.03 (0.40)	0.02 (0.30)	−0.00 (−0.50)	−0.02* (−1.92)	0.06 (0.90)	0.04 (0.58)	0.09 (0.74)	0.08 (0.74)
r_2	−	−0.01 (−1.26)	−	−0.00 (−0.06)	−	−0.01 (−0.02)	−	−0.07** (−5.12)	−	−1.01 (−0.33)	---	−0.13 (−1.26)

Wald tests of coefficient restrictions

$$r_1 = r_2 = 0$$

Chi-sq	16.66	2.72	0.03	26.25	0.12	2.12
p	0.00	0.10	0.86	0.00	0.73	0.15

$$r_1 + r_2 = 0$$

Chi-sq	16.50	3.50	0.03	22.63	0.10	0.09
p	0.00	0.06	0.87	0.00	0.76	0.77

The table presents results for the VAR-GARCH(1,1) model using non-U.S. G7 quarterly data. Panels A and B present estimates from the following model:

$$R_{it} = \alpha_{i0} + \sum_{j=1}^2 \sum_{\tau=1}^L \alpha_{j\tau} R_{jt-\tau} + \sum_{j=1}^4 \beta_{ij} z_{jt-1} + e_{it}$$

$$h_{iit} = a_i + b_i e_{it}^2 + c_i h_{iit-1} \quad i = 1, 2$$

$$h_{ijt} = (Int + r_1 X_{t-1} + r_2 X_{t-1}) \sqrt{h_{iit} h_{jtt}} \quad i \neq j$$

where $i = 1$ (log per capita log consumption growth $CGRO$) or 2 (excess equity returns ER), L is the number of lags, Int is the intercept, h_{iit} is the conditional variance, and h_{ijt} is the conditional covariance. ER is the difference between total stock returns (in local currencies) and the local short-term Treasury rate. a_i is the intercept term, b_i is the Arch coefficient, and c_i is the Garch coefficient. z_{jt} is the j -th exogenous prediction variable where $j = \{DY, TERM, DEF, PE\}$. DY is the dividend yield, $TERM$ is the 10-year Treasury note yield minus the 3-month Treasury bill rate, PE is the price-earnings ratio, and DEF is the corporate bond yield minus the long-term Treasury yield. Panel A presents GARCH estimates when the conditional correlation $CCORR$ is restricted to be constant ($r_1 = 0$). In Panels B and C, $CCORR$ varies with X_{t-1} an exogenous variable from the set $\{-UG, GG$ and $RR\}$. UG is the change in the unemployment rate, GG is the real GDP growth rate, and RR is the return residual e_2 from the VAR. We standardize X_{t-1} by subtracting the sample mean and dividing by the sample standard deviation. The specification $X1 + X2$ is as follows:

$$h_{ijt} = (Int + r_1 X1_{t-1} + r_2 X2_{t-1}) \sqrt{h_{iit} h_{jtt}} \quad i \neq j$$

where $X1 = -UG$ or GG and $X2 = RR$. The column headings identify the various specifications.

We report results of Wald tests of the following coefficient restrictions $r_1 = r_2 = 0$ and $r_1 + r_2 = 0$. For the latter test, we report one-sided p values.

Estimates significant at the 5 (10) percent level or less are marked by ** (*). All data are converted to real terms using the local Consumer Price Index. Data sources and sample dates are in Appendix A. The intercept in Panel A is multiplied by 10,000 for easier reading.

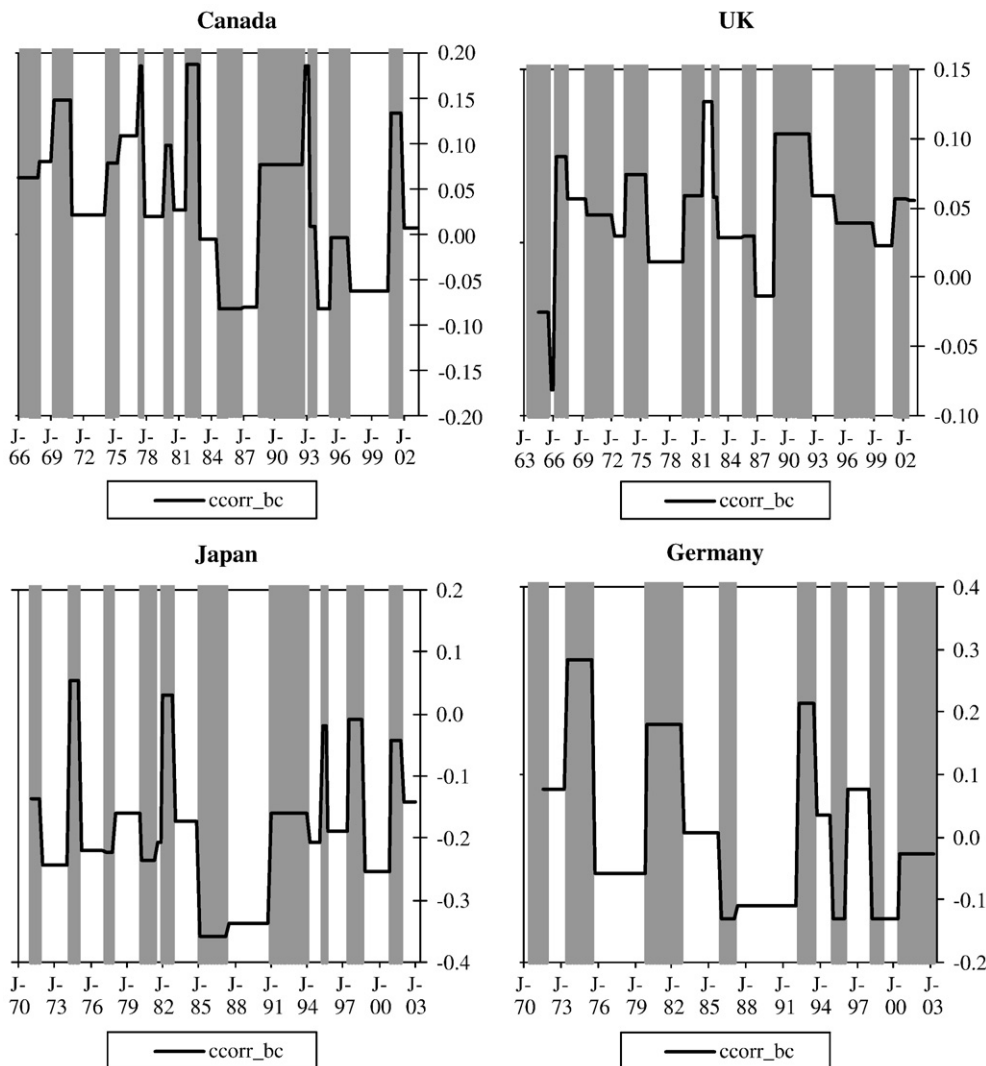


Fig. 2. For ex-U.S. G7 quarterly data, we plot the conditional correlation obtained from a VAR-GARCH(1,1) model where the correlation varies with stock return shocks and changes in the unemployment rate. France and Italy are excluded since we cannot reject the constant correlation model for these countries. “CCORR_BC” indicates that the correlation is averaged over expansion (post-trough to peak) and recession quarters. Shaded areas indicate OECD-dated major recessions (post-peak to trough quarters). The x-axis variable is in J-yy format, where “J” indicates January and yy indicates the year, respectively.

participation in the stock market by non-U.S. investors during our sample period (leading to a lower proportion of consumer wealth tied up in the stock market). The estimated coefficient of RR is negative for all countries except France. Thus, for these countries, the correlation is lower when stock returns are high, the opposite of what is predicted by the composition effect. The Wald tests reject the constant correlation model for Canada, Germany and Japan. Finally, the estimated $r_1 + r_2 < 0$ for all countries except France and the null of $r_1 + r_2 = 0$ is rejected using the one-sided p values for Canada, Germany and Japan.

When aggregate labor income is low, aggregate output may also be expected to be low. Accordingly, we allow the correlation to depend on changes in real GDP GG (columns GG in panel C of Table 3).¹⁵ We find that for Canada and the UK, $CCORR$ is significantly lower when GG is higher. This is also true for Japan when the correlation depends on GG and RR as the coefficient of $r_1 < 0$ in column $GG + RR$. However, for Italy, France and Germany, the coefficient r_1 is positively related to GG although it is not significant.

When we add RR (columns $GG + RR$ of Table 3 Panel C), the sign and significance of r_1 remain unchanged, but the coefficient of RR is negative for every country and statistically significant for Japan. The Wald tests reject the constant correlation model and the null hypothesis of $r_1 + r_2 = 0$ for Canada, UK and Japan.

To illustrate the combined effects of unemployment and returns on the correlation, we plot estimates of the conditional correlation over business cycles dated by the OECD for all countries except France and Italy (since for these countries we cannot

¹⁵ In U.S. data, the correlation is only weakly related to either GG or the growth in real industrial production, suggesting that output measures are less informative than income measures in predicting U.S. correlation.

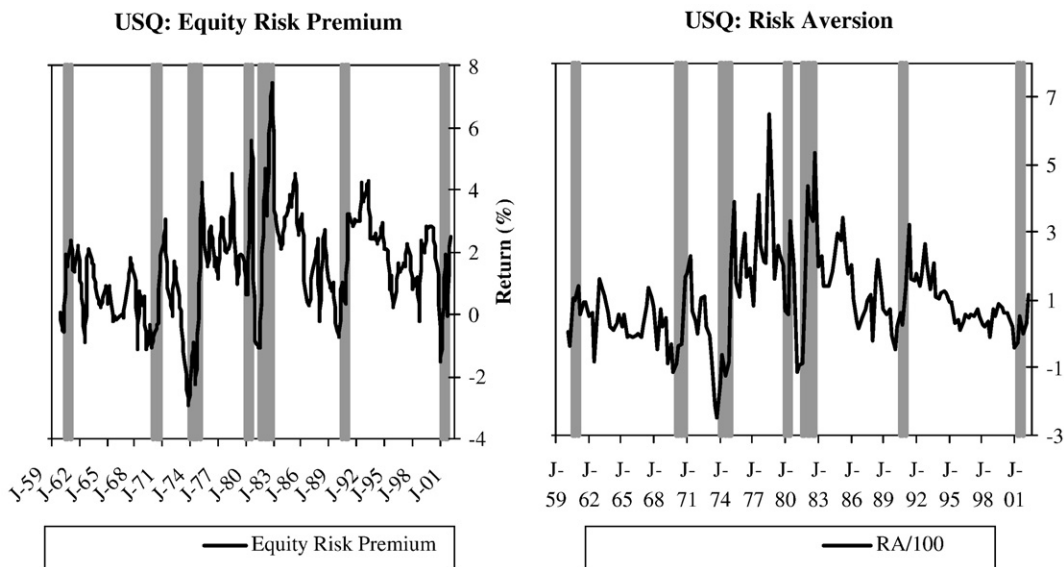


Fig. 3. Equity premium and risk-aversion: U.S. Quarterly Data. For U.S. quarterly data, we plot the risk-aversion RA . Estimates are obtained from the VAR-GARCH (1,1) model, where the conditional correlation is estimated as a function of the ratio of labor income to aggregate consumption, LIC , and the ratio of stock market wealth to aggregate consumption, MEC . The RA is obtained from:

$$RA_t = \frac{E_t(ER_t + 1)}{\sigma_t(CGRO_t + 1)\sigma_t(ER_t + 1)\rho_t(CGRO_t + 1, ER_t + 1)}$$

where E_t is an expectation conditional on information at time t , $CGRO$ is the log consumption growth, ER is the equity risk premium and ρ_t is the conditional correlation. RA is divided by 100. Shaded areas indicate NBER-dated recessions (post-peak to trough quarters). The x-axis variable is in J-yy format, where “J” indicates January and yy indicates the year, respectively.

reject the constant correlation model). We omit cycles denoted “minor” by the OECD, since the models discussed in Appendix B mostly applies to large income shocks. We plot estimates from the $UG + RR$ model. Fig. 2 shows that the correlation is generally countercyclical in all four countries. The fact that the cyclical pattern of the correlation is robust for a number of countries with different labor and stock market structures lends further credence to our results.

In summary, the constant correlation model is rejected for four of six countries (France and Italy are exceptions). Similar to the U.S. results, the conditional correlation varies substantially over time. While the unconditional correlation is mostly zero or negative, the conditional correlation is positive and has moderate value during economic contractions (i.e. when unemployment growth is high or GDP growth is low). We find less evidence in favor of the composition effect compared to the U.S., perhaps because of lower stock market participation in non-U.S. countries or because returns measure the composition effect poorly.

6. Asset pricing tests

The previous literature has shown that the CCAPM does a poor job of fitting the cross-section of equity returns (Soderlind, 2006). In this section, we examine whether, after incorporating labor income information, the estimated time series of conditional moments are consistent with asset pricing models. As a first approximation, we estimate the equity risk premium $E_t(ER_t + 1)$ and the risk aversion RA assuming power utility and lognormal distributions, using estimates from the VAR-GARCH system as data:

$$RA_t = \frac{E_t(ER_t + 1)}{\sigma_t(CGRO_t + 1)\sigma_t(ER_t + 1)\rho_t(CGRO_t + 1, ER_t + 1)} \quad (11)$$

In Fig. 3, we plot the equity risk premium and the risk aversion divided by 100 for U.S. quarterly data. The equity premium generally rises during recessions, consistent with prior evidence. RA also tends to increase in recessions and shows substantial time-variation, indicating that the unconditional CCAPM model may not be valid. To allow for general risk factors, we follow a modified version of Duffee (2005)¹⁶ and estimate the regression:

$$AEP_t = \text{Intercept} + a_1 E_{t-1}(COV_t) + a_2 RISK_{t-1} + a_3 RISK_{t-1} * E_{t-1}(COV_t) + \varepsilon_t \quad (12)$$

$AEP_t = r_{2t} + (0.5)E_{t-1}(VAR_t)$ where r_{2t} is the excess equity return ER , VAR is the return variance, COV is the covariance between $CGRO$ and ER and $RISK$ is an observable proxy for consumption risk.

¹⁶ Duffee (2005) does not separately control for the risk factor, possibly leading to an omitted error bias.

Table 4

GARCH-IN-MEAN(1,1) results: G7 quarterly data.

Panel A: Tests for USQ data										
	CCAPM		LIC		–UG		SCON		CAY	
γ_1	16.26**	(2.04)	11.19**	(5.32)	10.91**	(2.89)	4.71**	(2.41)	6.94**	(9.83)
γ_2	–132.57	(–0.05)	56.17**	(3.94)	6.25**	(9.98)	199.67**	(4.69)	33.37**	(2.45)
γ_3	–		–0.01**	(–4.12)	0.00	(0.90)	–0.06**	(–5.52)	0.01**	(2.94)
γ_4	–		–35.96**	(–4.39)	–340.13**	(–3.33)	–219.70**	(–4.33)	27.89*	(1.89)
a_{12}	0.00	(0.29)	0.00**	(7.51)	0.00**	(9.08)	0.00**	(4.90)	0.00**	(4.34)
b_{12}	0.00	(0.06)	0.02**	(3.42)	–0.02**	(3.37)	–0.06**	(–4.93)	0.03**	(2.38)
c_{12}	–0.52	(–0.10)	0.03	(0.20)	0.40**	(2.88)	0.00	(–0.12)	–0.01**	(–3.93)
Wald tests of coefficient restrictions($\gamma_3 = \gamma_4 = 0$)										
Chi-sq			45.71**		65.31**		35.46**		58.41**	
p			0.00		0.00		0.00		0.00	
Panel B: Tests for ex-US G7 data										
	Canada		UK		Japan		Germany		France	
	Ccapm	–UG	Ccapm	–UG	Ccapm	–UG	Ccapm	–UG	Ccapm	–UG
γ_1	–24.26	–16.82*	–3.99**	–1.66	13.10**	14.92**	30.22**	0.53	–26.34**	–177.27*
	(–1.40)	(–1.81)	(–3.49)	(–0.65)	(4.00)	(3.76)	(4.00)	(0.38)	(–5.50)	(–5.84)
γ_2	–45.48	89.18**	–671.85**	17.74	27.65	81.46**	–2.12	12.85**	448.75**	–338.73
	(–1.13)	(5.59)	(–3.66)	(0.09)	(1.45)	(4.22)	(–0.27)	(2.46)	(5.53)	(–0.64)
γ_3	–	0.13	–	0.24	–	0.10**	–	–0.12*	–	–0.13*
		(0.77)		(1.03)		(2.34)		(–1.67)		(1.84)
γ_4	–	–522.79**	–	–1845.33	–	–28.43**	–	–161.87**	–	–536.08
		(–2.70)		(1.13)		(–4.47)		(5.16)		(0.76)
a_{12}	0.00	–0.00	0.00**	0.00	0.00	0.00	0.00*	0.00*	0.00	0.00
	(–0.06)	(–0.14)	(3.32)	(0.28)	(0.72)	(1.31)	(1.87)	(1.83)	(1.59)	(0.93)
b_{12}	0.24*	0.24	0.00	0.00	0.30**	0.13**	–0.18**	0.06**	0.01	0.00
	(1.67)	(1.57)	(1.36)	(0.05)	(3.63)	(7.15)	(–2.36)	(4.94)	(1.21)	(0.40)
c_{12}	0.19	0.33	0.30**	0.85**	–0.15	0.71*	0.56**	0.24**	–0.92**	0.99**
	(0.73)	(1.24)	(4.76)	(2.54)	(–0.41)	(1.98)	(4.07)	(7.85)	(–9.65)	(3.15)
Chi-sq	–	7.89**	–	1.38	–	7.67**	–	31.05**	–	4.72*
p	–	0.02	–	0.50	–	0.02	–	0.00	–	0.10

The table presents results from a GARCH-IN-MEAN(1,1) model:

$$R_{1t} = \alpha_{10} + e_{1t}$$

$$R_{2t} = \alpha_{20} - 0.5\gamma_1 h_{22,t} + \gamma_2 h_{12,t} + \gamma_3 RISK_{t-1} + \gamma_4 h_{12,t} RISK_{t-1} + e_{2t}$$

$$h_{iit} = a_{ii} + b_{ii} e_{it}^2 + c_{ii} h_{iit-1} \quad i = 1, 2$$

$$h_{12t} = a_{12} + b_{12} e_{1t-1} e_{2t-1} + c_{12} h_{12t-1}$$

where $i = 1$ (per capita log consumption growth $CGRO$) or 2 (excess equity returns ER), h_{11t} is the conditional variance of $CGRO$, h_{22t} is the conditional variance of ER , and h_{12t} is the conditional covariance. $RISK$ is an observable proxy of consumption risk (times 100). The proxies for $RISK$ are $-UG$, the (negative of) unemployment growth, $SCON$, the surplus consumption ratio, CAY , the aggregate consumption–wealth ratio, and LIC , the ratio of labor income to aggregate consumption. We report results of Wald tests of the coefficient restriction $g_3 = g_4 = 0$. Estimates significant at the 5 (10) percent level or less are marked by ** (*). Data sources and sample dates are in Appendix A.

Asset pricing models predict that the price of risk, which is $a_1 + a_3 RISK_{t-1}$, is positive. $a_2 = a_3 = 0$ implies the unconditional CCAPM case, with consumption growth the only risk factor and a constant risk aversion given by the estimate of a_1 . When $a_2 \neq 0$ and $a_3 \neq 0$, we specify proxies for $RISK$ that are based on labor income. For USQ data, these are $-UG$, LIC , $SCON$ and CAY . For ex-US G7 countries, we use $-UG$ as the risk factor; as before, we omit Italy for lack of unemployment data and because we cannot reject the constant correlation model for Italy. $SCON$ is consumption relative to habit, a slow-moving average of past consumption (Campbell and Cochrane, 1999). Surplus consumption is measured as in Wachter (2006), and the data is from Duffee's web site. High values of CAY and low values of $-UG$, LIC and $SCON$ indicate a high price of risk, and so we expect $a_3 > 0$ when $RISK = CAY$ but $a_3 < 0$ when $RISK = -UG$, LIC or $SCON$.

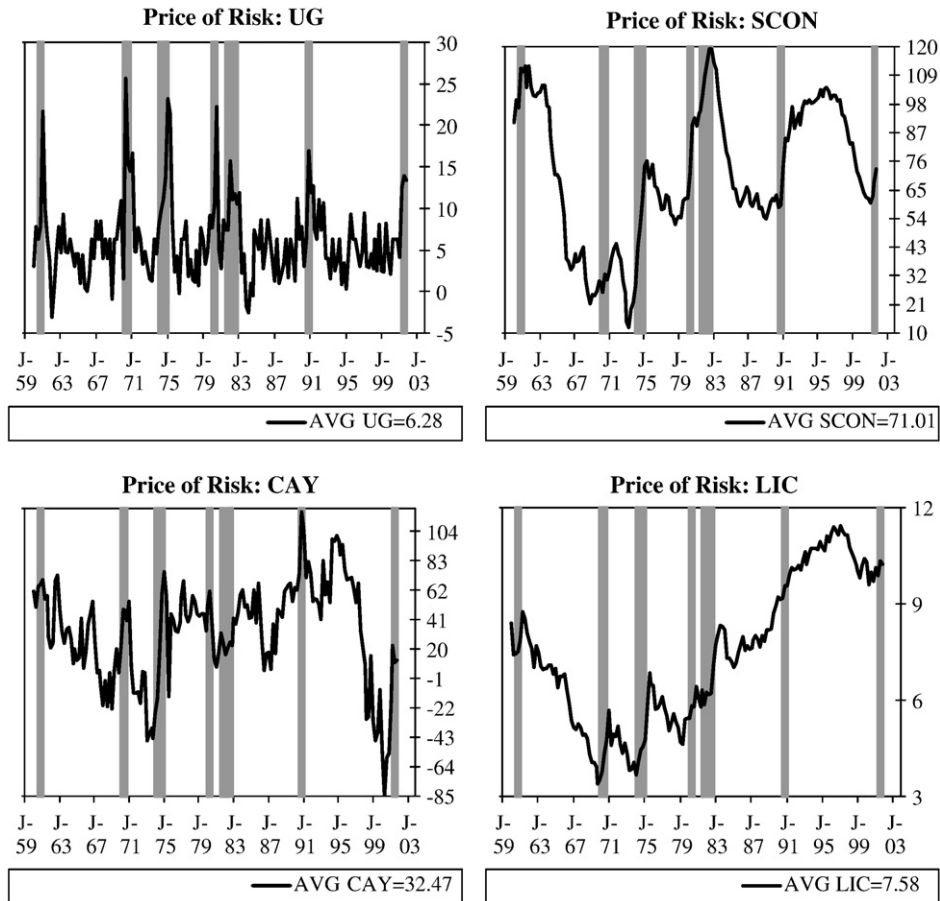


Fig. 4. Conditional price of risk for US quarterly data. For U.S. quarterly data, we plot the conditional price of risk and show the average price of risk in the legend. The price of risk at time t is $PRISK_t = \gamma_2 + \gamma_4 RISK_{t-1}$, where proxies for $RISK$ are UG , the change in the unemployment rate, $SCON$, the surplus consumption ratio, CAY , the aggregate consumption–wealth ratio and LIC , the ratio of labor income to aggregate consumption. Estimates for γ_2 and γ_3 are obtained from a GARCH-IN-MEAN(1,1) model:

$$R_{1t} = \alpha_{10} + e_{1t}$$

$$R_{2t} = \alpha_{20} - 0.5\gamma_1 h_{22,t} + \gamma_2 h_{12,t} + \gamma_3 RISK_{t-1} + \gamma_4 h_{12,t} RISK_{t-1} + e_{2t}$$

$$h_{iit} = a_{ii} + b_{ii} e_{it}^2 - 1 + c_{ii} h_{iit-1} \quad i = 1, 2$$

$$h_{12t} = a_{12} + b_{12} e_{1t-1} e_{2t-1} + c_{12} h_{12t-1}$$

where $i = 1$ (per capita log consumption growth $CGRO$) or 2 (excess equity returns ER), h_{11t} is the conditional variance of $CGRO$, h_{22t} is the conditional variance of ER , and h_{12t} is the conditional covariance. “AVG $RISK$ ” indicates the mean of $PRISK_t$ from the GARCH-IN-MEAN model, where $RISK = \{DY, SCON, CAY, LIC\}$. Shaded areas indicate NBER-dated major recessions (post-trough to peak quarters). The x-axis variable is in J-yy format, where “J” indicates January and yy indicates the year, respectively.

Initially, we adopt a two-stage approach to testing the asset pricing relation (12). We first obtain the conditional moment estimates from the VAR-GARCH model, which are then used as data to estimate (12). The regression is estimated by OLS with t -statistics corrected for heteroskedasticity and autocorrelation using the Newey–West procedure.¹⁷ The results (not reported here) show that the coefficient of $RISK$ is significant in all cases with the predicted signs (i.e. negative for $SCON$ and LIC and positive for CAY and UG). However, there is no reliable evidence that any of the risk factors are priced in U.S. data as the estimated coefficients of $CCOV * RISK$ are generally not significant. Although the average price of risk is positive (except for France and Japan), it has large magnitude (well over 100) for most G7 countries.

¹⁷ We use four truncation lags in the Newey–West procedure. To take into account persistence in the conditional covariance, we estimated the regression with lagged terms of these variables. The results were similar.

The lack of evidence of priced risk factors may be due to problems with the two-stage estimation approach. The independent variables in the regression are estimated with error and, moreover, may be persistent. Second, the variables used to estimate the conditional correlation are different from those used to explain the *EP*. A weak relation between the two sets of variables may result in a weak relation between *CCOV* and *EP*. Finally, since the VAR-GARCH model characterizes the conditional correlation rather than the covariance, variances may change to offset the change in correlations, weakening the relation between *CCOV* and *EP*. To address these concerns, we characterize (in section A) the covariance instead of the correlation and estimate (12) jointly with the conditional variance and covariance equations as a GARCH-IN-MEAN system.

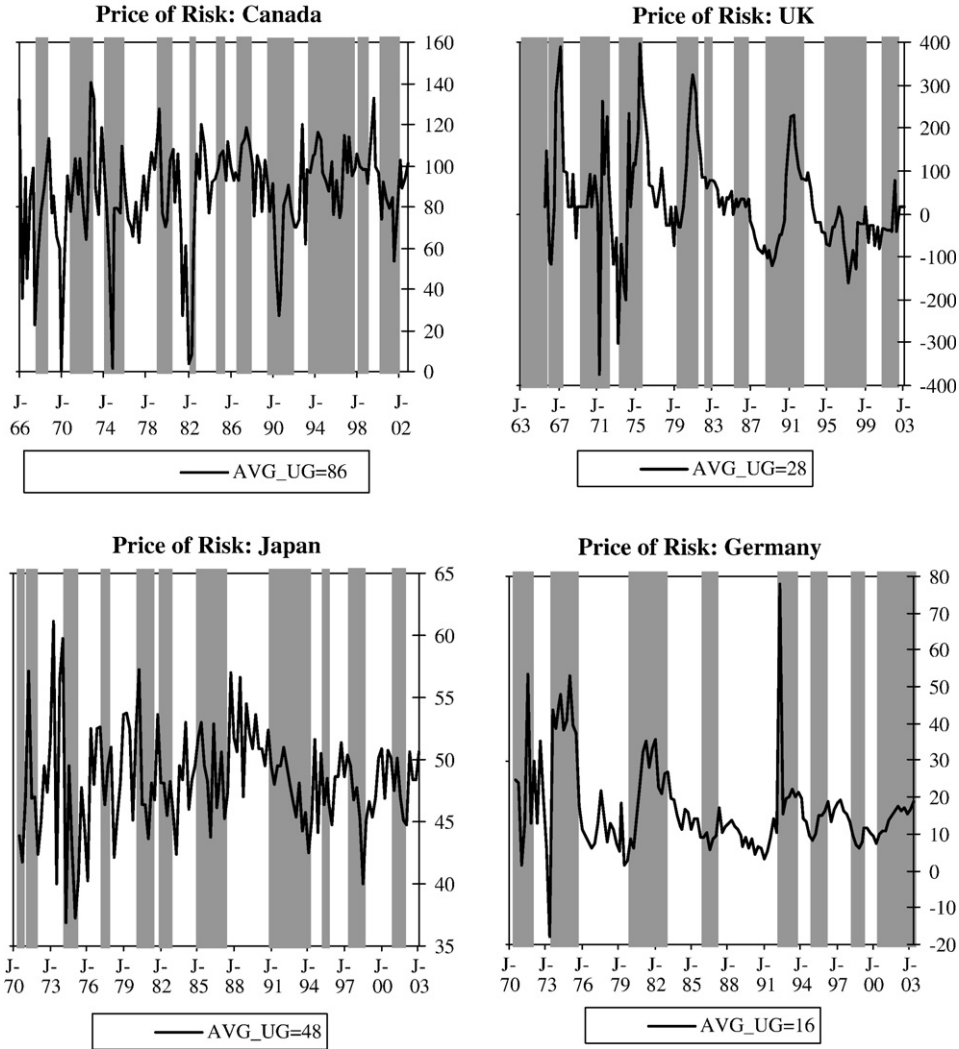


Fig. 5. Conditional price of risk for ex-U.S. G7 Countries. For ex-U.S. G7 quarterly data, we plot the conditional price of risk and show the average price of risk. The price of risk at time t is $PRISK_t = \gamma_2 + \gamma_4 RISK_{t-1}$, where the proxy for *RISK* is *UG*, the change in the unemployment rate. Estimates for γ_2 and γ_3 are obtained from a GARCH-IN-MEAN(1,1) model:

$$R_{1t} = \alpha_{10} + e_{1t}$$

$$R_{2t} = \alpha_{20} - 0.5\gamma_1 h_{22,t} + \gamma_2 h_{12,t} + \gamma_3 RISK_{t-1} + \gamma_4 h_{12,t} RISK_{t-1} + e_{2t}$$

$$h_{iit} = a_{ii} + b_{ii} e_{it}^2 + c_{ii} h_{iit-1} \quad i = 1, 2$$

$$h_{12t} = a_{12} + b_{12} e_{1t-1} e_{2t-1} + c_{12} h_{12t-1}$$

where $i = 1$ (per capita log consumption growth *CGRO*) or 2 (excess equity returns *ER*), $h_{11,t}$ is the conditional variance of *CGRO*, $h_{22,t}$ is the conditional variance of *ER*, and $h_{12,t}$ is the conditional covariance. "AVG UG" indicates the mean of $PRISK_t$ when estimates are from the GARCH-IN-MEAN model. Shaded areas indicate OECD-dated major recessions (post-trough to peak quarters). The x-axis variable is in J-yy format, where "J" indicates January and yy indicates the year, respectively.

6.1. Results from the GARCH-IN-MEAN specification

Previously, we found that the risk factors are generally not priced, but this result may be questioned due to shortcomings in the two-stage approach, as discussed earlier. Thus, we now estimate the asset pricing relation directly using a GARCH-IN-MEAN model:

$$\begin{aligned} R_{1t} &= \alpha_{10} + e_{1t} \\ R_{2t} &= \alpha_{20} - 0.5\gamma_1 h_{22,t} + \gamma_2 h_{12,t} + \gamma_3 RISK_{t-1} + \gamma_4 h_{12,t} RISK_{t-1} + e_{2t} \\ h_{iit} &= a_{ii} + b_{ii} e_{it}^2 + c_{ii} h_{iit-1} \quad i = 1, 2 \\ h_{12t} &= a_{12} + b_{12} e_{1t-1} e_{2t-1} + c_{12} h_{12t-1} \end{aligned} \quad (13)$$

where $i = 1$ (CGRO) or 2 (ER), h_{11t} is the conditional variance of CGRO, h_{22t} is the conditional variance of returns, and h_{12t} is the conditional covariance. In contrast to the previous GARCH model, the asset pricing relation directly enters the mean equation for returns, and the conditional covariance (rather than the correlation) follows a GARCH process. To reduce the dimensionality of the system, autoregressive terms and prediction variables are omitted from the mean equations. Further, unlike before, labor income shocks do not affect the correlation directly but enter the mean equation for returns via the *RISK* term. Nevertheless, we have verified that the conditional covariance and correlation estimates from (13) show countercyclical variation.

Panel A of Table 4 shows results from estimating (13) for USQ data. We find that γ_1 is positive and significant, implying that the mean return is negatively related to the return variance, consistent with recent evidence from US data.¹⁸ Further, the ARCH coefficients for the covariance (b_{12}) are mostly significant. The CCAPM model (obtained when $\gamma_3 = \gamma_4 = 0$) performs poorly, as the estimated risk-aversion is negative although not significant. Indeed, the Wald test rejects the restriction for all specifications. However, the coefficient of $CCOV_t * RISK_{t-1}$ (i.e. γ_4) is always significant and has the predicted sign. In addition, in the conditional models, γ_2 is positive and significant, indicating a positive relation between the equity premium and the conditional covariance. Hence, all risk factors are priced in US data, in contrast to the two-stage results.

Fig. 4 plots the estimated price of risk $PRISK_t = \hat{\gamma}_2 + \hat{\gamma}_4 RISK_{t-1}$ for USQ data from the GARCH-IN-MEAN model. The average price of risk is positive with values ranging between 6 (when *UG* is the risk factor) and 71 (when *SCON* is the risk factor). Further, the conditional price of risk is positive in all quarters for all risk factors except *CAY* (for which $PRISK_t < 0$ for 16% of quarters) and *UG* (for which $PRISK_t < 0$ for 3.45% of quarters).

Panel B of Table 4 reports results for Canada, France, UK, Japan and Germany for the CCAPM and — *UG* specifications. As with the US data, the CCAPM specification is rejected for all countries except the UK. We find that $\gamma_4 < 0$ for all countries, as predicted by asset pricing, and it is significant for Canada, Germany and Japan. In addition, for the specification with time-varying risk (column — *UG*), we observe that $\gamma_2 > 0$ for all countries except France, indicating a positive relation between the equity premium and *CCOV*.

Fig. 5 plots *PRISK* for all countries except France. The results show that the average price of risk is positive for all four countries although, for the UK, there are many quarters when $PRISK_t < 0$ (about 43% of quarters).

We conclude that the relation between *CCOV* and *EP* is positive on average for the US and for the four G7 countries with significant countercyclical covariance. Moreover, the conditional price of risk is related to proxies for time-varying consumption risk as predicted by theory.

7. Conclusion

We examine implications of time-varying correlation and covariance between equity returns and consumption growth for the G7 countries. We find that the correlation and covariance are higher when there is a negative shock to labor income and a positive shock to stock returns. We show that the correlation and covariance are countercyclical when labor income and stock return shocks are combined, and imply countercyclical variations in the equity premium. These results hold for different recession proxies, after controlling for lower consumption volatility in the post-1990 period, and after allowing for non-seasonally adjusted consumption.

The low unconditional correlation between returns and consumption growth observed in the data has prompted some authors to find alternatives to aggregate consumption risk for explaining risk and returns. However, our results show that time-varying consumption risk retains an important role for understanding the dynamics of the equity premium. Since we estimate a relatively high average price of risk, we do not resolve the equity premium puzzle. Incorporating realistic features of consumer behavior, like costs of adjusting consumption decisions, may be necessary to explain both the level and variation in the conditional covariance and the equity premium.

Appendix A. Data appendix

U.S.

1. Sample dates: January 1959 Q1 to June 2003.
2. Monthly and quarterly consumption expenditures (seasonally adjusted) on nondurables and services, and population figures, from USECON.

¹⁸ See, for example, Campbell (1987), Whitelaw (2000), Lettau and Ludvigson (2003), and Brandt and Kang (2004).

3. CPI, unemployment rates, GDP and Treasury bill/bond yields from the FRED II database of the Federal Reserve Bank of St. Louis.
4. The S&P 500 index returns, from Bloomberg.
5. The S&P 500 dividend yield and Moody's BAA corporate bond yields from DFDATA.
6. Moody's AA corporate bond yields from DRI.
7. The consumption–wealth ratio CAY, from Martin Lettau's web site <http://pages.stern.nyu.edu/~mlettau/research.htm>.
8. The price–earnings ratio, from Robert Shiller's web site <http://aida.econ.yale.edu/~shiller/>.
9. MEC, the ratio of stock market wealth to consumption, and surplus consumption from Gregory R. Duffee's web site <http://faculty.haas.berkeley.edu/duffee/>The sample ends 2002 Q2.
10. LIC, the ratio of labor income to consumption, is the ratio of employees' compensation to total consumption (nondurables plus services). Employee compensation data is from NIPA Table 1.12 Line 2 (see <http://www.bea.doc.gov/bea/dn/home/gdp.htm>).

U.K.

1. Sample dates: 1963 Q1 to 2003 Q1 except unemployment data, which starts from 1965 Q1.
2. Quarterly nondurable and services (seasonally adjusted) and GDP, at current prices, from the U.K. Office of National Statistics.
3. Midyear population statistics, from www.census.gov/ipc/www/idbprint.html. The mid-year statistics were used to interpolate quarterly population figures.
4. The dividend yield and price–earnings ratio from Global Financial Data.
5. Monthly FT-Actuaries All-share total return stock index, corporate and Treasury bond rates, the dividend yield and price–earnings ratio from Global Financial Data.
6. Unemployment rates from DRI International.

Canada

1. Sample dates: 1961 Q1 to 2003 Q2 except unemployment data, which starts from 1966 Q1.
2. Quarterly private final consumption expenditure (seasonally adjusted), at current prices, from OECD Quarterly National Accounts.
3. Midyear population, from the U.S. Census Bureau www.census.gov/ipc/www/idbprint.html. The mid-year statistics were used to interpolate quarterly population figures.
4. Consumer Price Index, from quarterly OECD economic indicators.
5. Monthly S&P/Toronto Stock Exchange Composite Index, corporate and Treasury bond rates, from Statistics Canada Online.
6. The dividend yield and price–earnings ratio from Global Financial Data.
7. Unemployment rates from DRI International.

Japan

1. Sample dates: 1970 Q1 to 2003 Q1.
2. Quarterly Household Consumption Expenditure (seasonally adjusted), at current prices, from IMF's International Financial Statistics.
3. Midyear population, from the U.S. Census Bureau www.census.gov/ipc/www/idbprint.html. The mid-year statistics were used to interpolate quarterly population figures.
4. Consumer Price Index, from quarterly OECD economic indicators.
5. Monthly MSCI stock index, from Morgan Stanley Capital International.
6. Corporate and Treasury bond rates, the dividend yield and price–earnings ratio from Global Financial Data.
7. Unemployment rates from DRI International.

France

1. Sample dates: 1970 Q1 to 2003 Q2 except unemployment data, which starts from 1970 Q4.
2. Quarterly Private Final Consumption Expenditure (seasonally adjusted), at current prices, from OECD Quarterly National Accounts.
3. Midyear population, from the U.S. Census Bureau www.census.gov/ipc/www/idbprint.html. The mid-year statistics were used to interpolate quarterly population figures.
4. Consumer Price Index, from quarterly OECD economic indicators.
5. Monthly MSCI stock index, from Morgan Stanley Capital International.
6. Corporate and Treasury bond rates, the dividend yield and price–earnings ratio from Global Financial Data.
7. Unemployment rates from DRI International.

Germany

1. Sample dates: 1970 Q1 to 2003 Q2.
2. Western Germany Private Final Consumption Expenditure until 1990, and United Germany Private Final Consumption Expenditure from 1991. Both series are quarterly, at current prices, seasonally adjusted, and from the OECD Quarterly National Accounts.

3. Midyear population, from the U.S. Census Bureau www.census.gov/ipc/www/idbprint.html. The mid-year statistics were used to interpolate quarterly population figures. We use West Germany's population before 1991 Q1 and use Unified Germany's population after that. This is consistent with standard practice of the main data agencies.
4. Consumer Price Index, from quarterly OECD economic indicators.
5. Monthly MSCI stock index, from Morgan Stanley Capital International.
6. Corporate and Treasury bond rates, the dividend yield and price–earnings ratio from Global Financial Data.
7. Unemployment rates from DRI International.

Italy

1. Sample dates: 1970 Q1 to 2003 Q1 except unemployment data, which starts from 1980 Q1.
2. Quarterly Private Final Consumption Expenditure (seasonally adjusted), at current prices, from OECD Quarterly National Accounts.
3. Midyear population, from the U.S. Census Bureau www.census.gov/ipc/www/idbprint.html. The mid-year statistics were used to interpolate quarterly population figures.
4. Consumer Price Index, from quarterly OECD economic indicators.
5. Monthly MSCI stock index, from Morgan Stanley Capital International.
6. Corporate and Treasury bond rates, the dividend yield and price–earnings ratio from Global Financial Data.
7. Unemployment rates from DRI International.

Appendix B. Models that imply time-varying correlation or covariance

We discuss several asset pricing models to motivate the idea that time-variation in the correlation and the covariance is economically meaningful and intuitive. While some models do not address the covariance or correlation directly, nevertheless their results imply that the correlation or covariance is countercyclical (section A) or pro-cyclical (section B). In our own analysis, we treat the cyclical property of the correlation or covariance as an empirical issue.

Models that imply countercyclical correlation

Labor income shocks. In Santos and Veronesi (2006), investors have both dividend and labor income. When the share of labor income in consumption decreases, the covariance between consumption growth and dividend growth is higher, and this implies a higher covariance between returns and consumption growth. Polkovnichenko (2004) shows that, with fixed stock market participation costs, the consumption correlation of shareholders endowed with labor income is lower compared to a model where they have no labor income. An implication is that the correlation increases after a negative labor income shock.

Inattentive consumer. Gabaix and Laibson (2001) argue that slow updating of consumption (e.g. due to decision or attention allocation costs) leads to a downward bias in the measured covariance between consumption growth and returns. They show that the covariance increases with the frequency of updating. In addition, if households adjust consumption quicker after large stock return shocks, then the covariance is increasing in the size of return shocks. Reis (2003) models the costs of information acquisition by consumers and finds that they adjust quicker in response to large and predictable shocks. If unemployment is predictable, then an implication is higher consumption correlation during times of high unemployment.

Absent-minded consumer. Ameriks et al. (2004) find that many consumers are highly uncertain of their spending behavior. Their model of the absent-minded consumer implies that, in a cyclical downturn, those with fewer resources and more time (such as the unemployed) may decide to monitor their spending more closely. This may exacerbate the decline in consumption during recessions, and cause its correlation with returns to increase.

Less consumption smoothing during recessions. Borrowing constraints imply that consumption smoothing is weaker during recessions than expansions. Zeldes (1989) finds that an inability to borrow against future labor income affects most consumption. Other methods of consumption smoothing may also be less effective during recessions. For example, Stephens (2001) reports that, following the head's unemployment, the reduction in family income is less than the reduction in the head's earnings, possibly due to increased spousal earnings and transfers from relatives. In recessions, we expect that spouses may find it harder to increase their labor supply.

Models that imply procyclical correlation

Composition effect. When the share of stock market wealth (SMW) in total wealth is high, consumption will be low relative to SMW and more sensitive to changes in SMW. Thus, Duffee (2005) argues, the correlation is higher when the share of SMW in total wealth is above average.

Time-varying stock market participation. Shareholders' consumption is more closely correlated with stock returns than non-shareholder consumption (Mankiw and Zeldes, 1991). Further, there is large turnover in the set of stock market participants and, among participants, large changes in the portfolio shares of equity over time (Vissing-Jorgensen, 2002). Thus, if high stock returns attract increased participation, the correlation may increase with returns.¹⁹

¹⁹ Hong et al. (2004) show that multiple participation equilibria can occur if market entry costs decrease with the number of participants. Antunovich and Sarkar (2006) provide empirical evidence on participation externality.

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