Appendix to Modeling Financial Return Dynamics via Decomposition

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1 Empirical Results with Quarterly Data

The quarterly data cover the period 1952Q1–2002Q4. The excess returns, dividend-price ratio (dp) and interest rate variables are obtained from Campbell and Yogo's (2006) data set. We used data on consumption, asset wealth and labor income from Martin Lettau's web site (`http://pages.stern.nyu.edu/~mlettau/data/cay_q_06Q4.txt`) to construct the consumption-wealth ratio cay as in Ludvigson and Lettau (2001). In particular, cay is computed as a cointegrating residual between log consumption, log asset wealth and log labor income estimated by DOLS with 8 leads and lags. We also used Campbell and Yogo's (2006) interest rate data to construct the variable "relative T-bill rate" ($rrel$) as the difference between the one-month rate and its 4-quarter moving average as in Guo (2006) and Ludvigson and Ng (2007). Finally, the realized measure of stock return volatility (RV) is constructed from daily data on NYSE/AMEX value-weighted index from CRSP. Results with other realized measures are not reported because they do not appear as important as they are in the models for higher frequency (monthly) data.

The results from the linear predictive regression of er_t on a constant, cay_{t-1} and RV_{t-1} are presented in Table A.1. As reported in Lettau and Ludvigson (2001, 2008), Ludvigson and Ng (2007) and Guo (2006), the variables cay and RV prove to be very good predictors of next period excess returns. The variables $rrel$ and dp also possess some incremental predictive power but their contribution is only marginal and we drop them from the subsequent analysis.

Tables A.2, A.3 and A.4 report the results from the decomposition model. Both *cay* and RV are statistically significant for predicting the sign of excess returns. The percentage of correct predictions of the sign of next period excess returns is the impressive 68.6% (compared to 62.6% for the linear model). Forecasting the direction of stock market moves has important implications for portfolio allocation. We use the predicted returns from the decomposition and linear models to construct trading strategies as described in the paper. The benchmark is the buy-and-hold strategy. The transaction costs from changing positions from stocks to bonds and vice versa are 0.25% of the portfolio value. The dynamics in the values of the different portfolios (the initial investment is $100) is plotted in Figure A.1. After accounting for transactions costs, the value of the portfolios at the end of sample is $20,351 for the buy-and-hold strategy, $31,969 for the predictive regression and $58,026 for the decomposition model.

The predicted returns from the linear and decomposition models are plotted in Figure A.2. While the predicted returns from both models exhibit pretty similar dynamics prior to 1990s, there are some differences in the period of 1990s although the differences are not as pronounced as those for monthly data. The pseudo-R^2 of 8.5% for the linear model increases to 11.04% for the decomposition model which is possibly due to the richer structure of the decomposition model that accounts for implicit nonlinearities.

These and additional experiments for quarterly and annual data for the period 1927–2002 show that the improvements in in-sample predictions from the decomposition model appear to be robust to different data frequencies and model specifications.

References

[1] Campbell, J.Y., and Yogo, M. (2006), "Efficient tests of stock return predictability," *Journal of Financial Economics*, 81, 27–60.

[2] Guo, H. (2006), "On the out-of-sample predictability of stock market returns," *Journal of Business*, 79, 645–670.

[3] Lettau, M., and Ludvigson, S. (2001), "Consumption, aggregate wealth and expected stock returns," *Journal of Finance*, 56, 815–849.

[4] Lettau, M., and Ludvigson, S. (2008), "Measuring and modeling variation in the risk-return tradeoff," in: Y. Ait-Sahalia and L.P. Hansen (eds.) *Handbook of Financial Econometrics*, forthcoming.

[5] Ludvigson, S., and Ng, S. (2007), "The empirical risk-return relation: A factor analysis approach," *Journal of Financial Economics* 83, 171–222.

Table A.1. Estimation results from the predictive regression.

$t(cay)$	$t(RV)$	LR	R^2
4.68	2.04	14.95	8.54%

Notes: See notes to tables in the paper for detailed description.

Table A.2. Estimation results from the direction model.

	ω_d	ϕ_d	$\delta_d(cay)$	$\delta_d(RV)$
coeff	−0.274	0.629	43.50	121.22
s.e.	0.341	0.335	12.12	47.85
t-stat	−0.80	1.88	3.59	2.53
% correct predictions = 68.6%				
pseudo-R^2 = 9.06%				

Notes: See notes to tables in the paper for detailed description.

Table A.3. Estimation results from the volatility model.

	ω_v	β_v	γ_v	ρ_v	$\delta_v(cay)$	ς
coeff	−0.326	0.824	0.0188	−0.168	−1.960	1.328
s.e.	0.154	0.082	0.0411	0.072	1.117	0.079
t-stat	−2.11	9.99	0.46	−2.32	−1.75	4.15
excess dispersion (ED) test statistic = 0.19						
pseudo-R^2 = 7.03%						

Notes: See notes to tables in the paper for detailed description.

Table A.4. Estimates and summary statistics from the Clayton copula specification of the decomposition model.

unconditional correlation	dependence parameter α			conditional correlation	$LogL$	pseudo-R^2
	coeff	s.e.	t-stat			
0.774	−0.031	0.095	−0.327	−0.104	1.2455	11.04%

Notes: See notes to tables in the paper for detailed description.

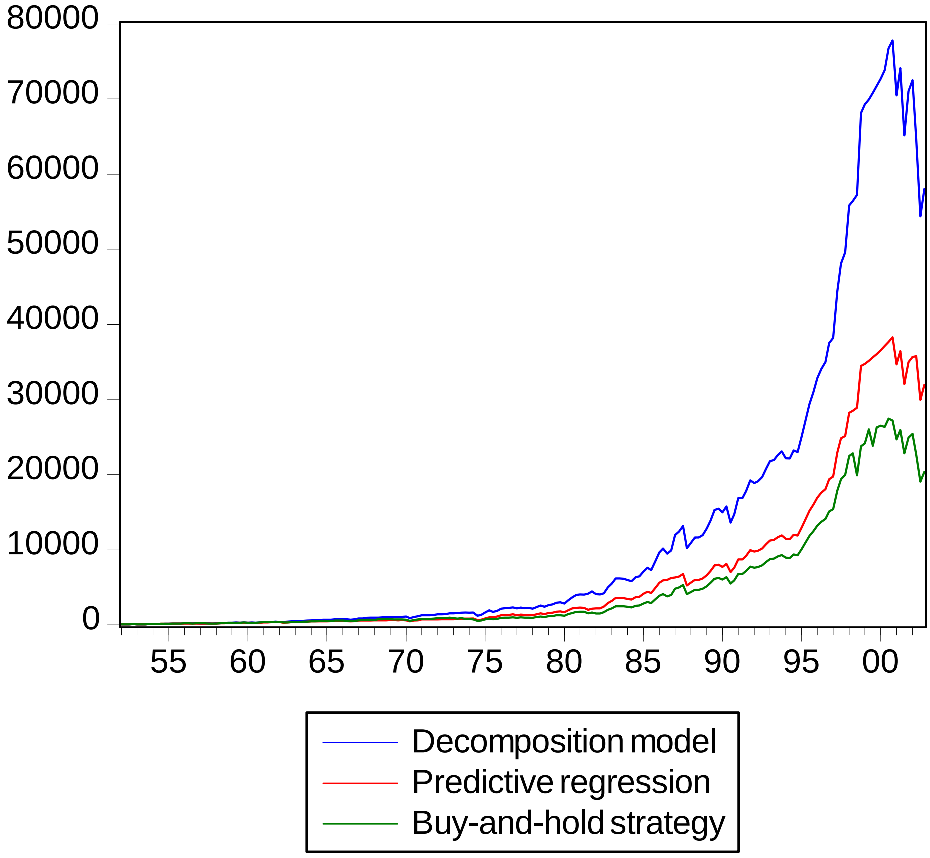

Figure A.1. Performance of portfolios constructed from different models.

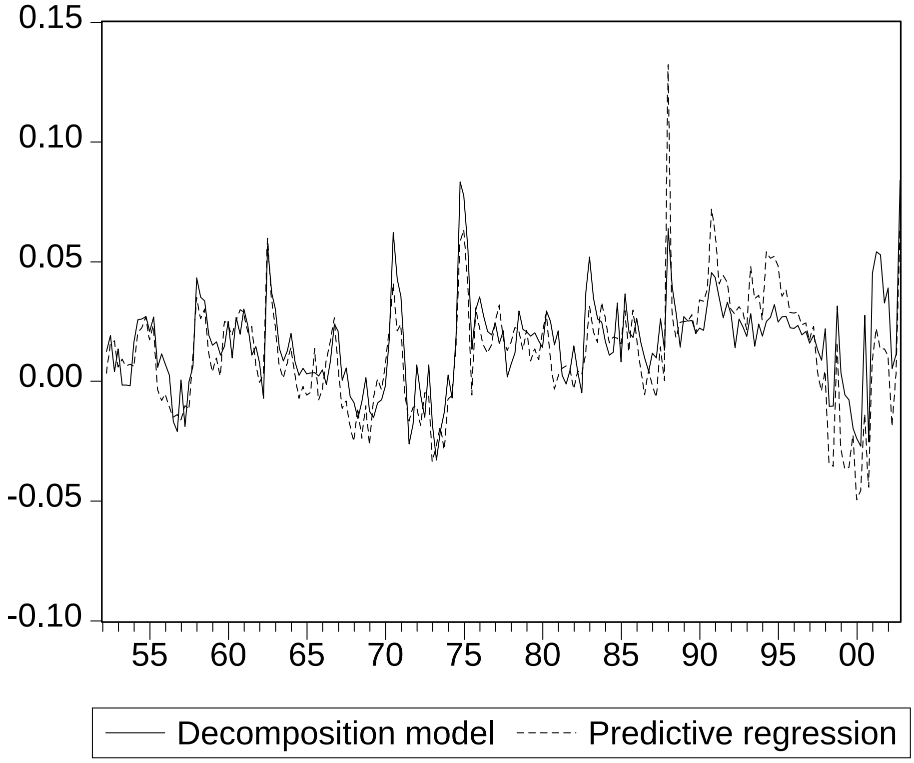

Figure A.2. Predicted (in-sample) returns from decomposition model and predictive regression.