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Aggregate Idiosyncratic Volatility

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Appendix

1. Robustness

1.1 Weekly International Data and Alternative Risk Specification

We consider an alternative risk model using both global and local factors. Since the global factors are constructed with data from different countries, and due to the well-known non-synchronous trading problem, we estimate this model using weekly data.

We calculate firm idiosyncratic volatilities according to a modified Fama-French type model that we call WLFF (for Fama-French model with world and local factors), as in BHZ (2009). The model has six factors, a global market factor ($WMKT$), a global size factor ($WSMB$), a global value factor ($WHML$), a local market factor ($LMKT$), a local size factor ($LSMB$) and a local value factor ($LHML$):

$$\begin{aligned} R_{j,t} &= b_{0,j,s} + b_{1,j,s}WMKT_t + b_{2,j,s}WSMB_t + b_{3,j,s}WHML_t \\ &\quad + b_{4,j,s}LMKT_t + b_{5,j,s}LSMB_t + b_{6,j,s}LHML_t + u_{j,t}^{WLFF}. \end{aligned} \tag{1}$$

where week t belongs to a six-month period s. To allow for time-varying betas, the above model is re-estimated every six months with weekly data. The combination of local and global factors with time-varying betas makes the model flexible enough to fit stock market comovements in an environment where the degree of global market integration may change over time. The local factors are in fact regional factors, where we consider three regions: North America, Europe and the Far East. The global market factor, $WMKT$, is calculated as the demeaned value-weighted sum of returns on all stocks. To calculate $WSMB$, we first compute $SMB(k)$ for each country k, which is the difference between the value-weighted returns of the smallest 30% of firms and the largest 30% of firms within country k. Factor $WSMB$ is the demeaned value weighted sum of individual country $SMB(k)$s. Factor $WHML$ is calculated in a similar manner as the demeaned value weighted sum of individual country $HML(k)$s using high versus low book-to-market values. The local factors ($LMKT, LSMB, LHML$) are all orthogonalized relative to the global factors ($WMKT, WSMB, WHML$). BHZ (2009) show that this model fits the comovements between country-industry portfolios and country-style portfolios very well, and it also captures firm level comovements well.

We calculate the idiosyncratic variance for stock j as the variance of the residual of the regression, that is, $\sigma^2(u_{j,t}^{WLFF})$, and we then aggregate to the country level:

$$\sigma^2_{WLFF,s} = \sum_{j=1}^{N} w_{j,s}\ \sigma^2(u_{j,t}^{WLFF}), \tag{2}$$

where week t belongs to the six-month period s. The weight $w_{j,s}$ is computed from firm j's relative market capitalization at the end of the last six-month period, and N represents the number of firms within one country.

Table A1 Panel A reports trend test results for the 23 developed countries. We fail to detect a significant time trend for any country, using either the t-dan test or the t-ps1 test.

1.2 Equal Weighting

In Panels B and C of Table A1, we examine the time-series behavior of equally weighted idiosyncratic variances. We focus on the U.S. idiosyncratic variance over 1964 - 2008, computed from daily data. Since the results for the other developed countries are very similar, we do not report those to save space. In Panel B, the time-series mean of the equal-weighted CLMX (FF) idiosyncratic variance is 0.4308 (0.3530), which is much larger than its value-weighted counterpart of 0.0800 (0.0697). Obviously, the returns of smaller firms are much more volatile. In Panel C, we report the Vogelsang trend test results. Interestingly, the equally weighted idiosyncratic variance time series shows a larger trend coefficient than the value-weighted time series, but the coefficient is now insignificantly different from zero for all cases, even for the 1964-1997 period. This, in fact, confirms the results in CLMX. Equally weighted idiosyncratic variances are too noisy to allow strong statistical inference.

1.3 Subsamples

In Panel D, we report trend test results for different groups of stocks. We first separate firms based on the listing exchange: NYSE/AMEX vs. Nasdaq. Next, we separate large/small firms using the median NYSE market cap; we separate old/young firms using the median firm age; and we separate high price/low price stocks using \$10 as a benchmark.

For the 1964-1997 samples, we mostly confirm the results in BCL, finding trends for most sub-groups but not for the NYSE stocks. For the longer sample, we fail to reject the null of "no trend" for all subgroups.

2. Residual specification tests

2.1 The tests

We apply the specification test to three models:

$$
\begin{aligned}
AR(1) &: \quad y_t = b_0 + b_1 y_{t-1} + e_t^{AR}, &(3)\\
GARCH(1,1) &: \quad y_t = b_0 + b_1 y_{t-1} + e_t^{GARCH}, &(4)\\
h_t &= \sigma^2_{t|t-1}(e_t^{GARCH}) = w + c_0 h_{t-1} + c_1 (e_{t-1}^{GARCH})^2, &(5)\\
RS &: \quad y_t = (1-b_i)\mu_i + b_i y_{t-1} + \sigma_i e_t^{RS}, i = 1, 2, &(6)
\end{aligned}
$$

where y_t is the variable of interest. In the estimation, all error terms are assumed to be normally distributed. We examine specification tests for the residuals, e_t, which should have the following first order moment conditions:

$$
\begin{aligned}
E(e_t) &= 0, &(7)\\
E(e_t e_{t-1}) &= 0. &(8)
\end{aligned}
$$

Because e_t is forced to have mean zero in the autoregressive specification, but may not have zero mean in other specifications, we work with demeaned residuals. For second order moments, we have

$$E(e_t^2) - \sigma^2_{t|t-1}(e_t) = 0,$$

where $\sigma^2_{t|t-1} = var(e_t)$ for the AR(1) model, and $\sigma^2_{t|t-1} = h_t$ for the GARCH(1,1) model. Moreover, the serial correlation of the squared residuals also ought to be zero, for which we use

$$E[(e_t^2 - \sigma^2_{t|t-1})(e_{t-1}^2 - \sigma^2_{t-1|t-2})] = 0, \tag{9}$$

Finally, we test the correct specification of the higher order moments for the residuals. For skewness, we have

$$E[e_t^3 - (\sigma^2_{t|t-1})^{3/2}] = 0; \tag{10}$$

for kurtosis, we have

$$E[e_t^4 - [\sigma^2_{t|t-1}]^2] = 0. \tag{11}$$

The calculations are more complicated for the RS model. We start by computing the residuals conditioning on the $t-1$ information in an obvious manner:

$$e_t^{RS} = y_t - E(y_t|t-1) = y_t - p_1[(1-b_1)\mu_1 + b_1 y_{t-1}] - p_2[(1-b_2)\mu_2 + b_2 y_{t-1}], \qquad (12)$$

where p_1 denotes the probability of being in regime 1, and p_2 the probability of being in regime 2. We compute residuals using ex-post (smoothed) probabilities.

To shorten future formulas, we define

$$\begin{aligned} y_{t|t-1} &= E(y_t|t-1) \\ &= p_1[(1-b_1)\mu_1 + b_1 y_{t-1}] + p_2[(1-b_2)\mu_2 + b_2 y_{t-1}], \\ k_1 &= (1-b_1)\mu_1 + b_1 y_{t-1} - y_{t|t-1}, \\ k_2 &= (1-b_2)\mu_2 + b_2 y_{t-1} - y_{t|t-1}, \end{aligned}$$

The conditional variance is as follows,

$$\sigma^2_{t|t-1} = p_1\sigma_1^2 + p_2\sigma_2^2 + p_1 k_1^2 + p_2 k_2^2. \qquad (13)$$

Now we can compute the moment conditions (7) through (9) as before.

The formulas for the unscaled skewness and kurtosis are in Timmermann (2000) and become, for our model:

$$\begin{aligned} skew_{t|t-1} &= [p_1(3\sigma_1^2 k_1 + k_1^3) + p_2(3\sigma_2^2 k_2 + k_2^3)], \qquad (14) \\ kurt_{t|t-1} &= [p_1(3\sigma_1^4 + k_1^4 + 6\sigma_1^2 k_1^2) + p_2(3\sigma_2^4 + k_2^4 + 6\sigma_2^2 k_2^2)] - 3(\sigma^2_{t|t-1})^2. \qquad (15) \end{aligned}$$

Consequently, the last two moment conditions are,

$$\begin{aligned} E[(e_t^{RS})^3 - skew_{t|t-1}] &= 0, \qquad (16) \\ E[(e_t^{RS})^4 - kurt_{t|t-1}] &= 0. \qquad (17) \end{aligned}$$

To test all moment conditions jointly, we always use a Newey-West (1987) covariance matrix with 12 lags.

2.2 Empirical Results

It is important to verify that a RS model indeed fits the data well, and that it fits the data better than simpler alternative models. We conduct a number of specification tests on the residuals of various RS models, and we report tests for two alternative benchmark models: an AR(1) model in levels with Gaussian shocks, and an AR(1) model with a GARCH(1,1) volatility process. Our tests examine 6 moment conditions: the mean and one auto-correlation of the residuals; the variance and one auto-correlation of the squared residuals; and the third and fourth order moments. Section 2.1 of this appendix details the tests. While we use asymptotic critical values, it is quite likely that our tests over-reject in small samples. This is particularly true if the data are actually generated from a non-linear RS model (see e.g. Baele, Bekaert and Inghelbrecht (2010)).

Table A.2 reports the results. The three panels investigate, respectively, the mean and variance specification; the higher moments conditions; and finally in Panel C, a joint test. For the RS models, we use smoothed ex-post probabilities to infer residuals and model moments. We present both the long sample for U.S. for the two risk models and the short sample for all countries. Focusing on the joint test first, the regime switching model clearly outperforms the two other models. Over the 9 tests, there is not a single 1% rejection, and only three 5% rejections (for Canada, Germany and the UK). The AR model on the other hand is always rejected at the 1% level, whereas the GARCH model features only two cases for which it is not rejected at the 5% level (short sample U.S., and long sample U.S. when the FF model is used). The sources of the rejections differ across countries, and in some cases the joint test simply adds power to the two sub-tests.

In unreported work, we also apply the three models to the logarithm of the variance. Such a model keeps the variance everywhere positive and the non-linear transformation may sufficiently reduce the outliers in the data to make the idiosyncratic variance process more amenable to linear modeling. However, none of the models performs better in logarithmic form, so that we restrict further analysis to the untransformed variances.

3. Accounting Data Details

In this appendix, we describe how we construct the accounting data variables as in Table 5.

All return on equity (ROE) related variables are computed as in Wei and Zhang (2006), where the variable “vwroe” is the value weighted average of firm level return on equity; the variable “vwvroe” is the value weighted average of the 12-quarter time-series variance of firm level return on equity, and the variable “cvroe” is the cross-sectional variance of the firm level return on equity.

Irvine and Pontiff (2008) focus on competition measures. We follow their procedure and compute “veps” as the cross-sectional variance of shocks to earnings per share (EPS). The shocks to EPS are computed using a pooled auto-regressive regression of year-to-year changes in quarterly EPS. To be more specific, the dependent variable is the annual difference in earnings per share, $EPS(t) - EPS(t-4)$, at the firm level, where t is current quarter, and the independent variables are $EPS(t-1) - EPS(t-5)$, $EPS(t-2) - EPS(t-6)$, and $EPS(t-3) - EPS(t-7)$. This regression attempts to adjust for seasonality in the EPS data. By computing the cross-sectional variance, this approach implicitly adjusts for the market average level of shocks to EPS, in the same spirit of "cvroe". We also compute industry turnover as the cross-sectional average at firm level for industry entries and exits each month.

Cao, Simin and Zhao (2007) consider growth options as an explanation. The most successful variable in their paper is "maba", the value weighted average of firm level market assets over book assets. We also compute "vmaba" as the value weighted average of the 12-quarter time-series variance of firm level market assets over book assets. Following the same reasoning as for "cvroe" and "veps", we also compute "cvmaba" as the cross-sectional variance of firm level market assets over book assets.

For the R&D expenditure variables, quarterly data on R&D is not reported by the majority of firms in U.S. So we rely on annual data on R&D. Following Comin and Mulani (2006), for each quarter, we take the corresponding fiscal year R&D, and then divide by the quarter's total revenues (sales). We also compute the cross-sectional dispersion in R&D (denoted cvrd) across firms each quarter, and it has a correlation of 80% with R&D expenditures.

Notice that all U.S. accounting data are from Compustat, and thus they are quarterly data on a firm-by-firm basis. However, because firms have different fiscal year end's, the data are spread out over the year. To ensure that each month represents the full sample of firms, we follow the procedure in Irvine and Pontiff (2008) and for each month average the accounting measures of that month and the previous two months. We apply the same methodology to all quarterly accounting data.

For the international data, we compute ROE, maba, and competition related variables as we do for U.S. firms. The variable "vwroe" is the value weighted average of the annual firm level return on equity; the variable "vwvroe" is the value weighted average of the 3-year time-series variance of the annual firm level return on equity, and one variable "cvroe" is the cross-sectional variance of the firm level return on equity each year. We compute "veps" as the cross-sectional variance of shocks to annual earnings per share, where the shocks are estimated using a pooled regression within each country. To be more specific for the pooled regression, the dependent variable becomes $EPS(t) - EPS(t-1)$, where t is current year, and the independent variable is $EPS(t-1) - EPS(t-2)$. The variable "maba" is the value weighted average of the annual firm level market assets over book assets. We also compute "vmaba" as the value weighted average of the 3-year time-series variance of annual firm level market assets over book assets, and "cvmaba" as the cross-sectional variance of annual firm level market assets over book assets.

4. Hendry Regressions

We also use a model reduction techniques inspired by Hendry and Krolzig's (2001) PCGets ("general-to-specific") system. We first run a regression using all possible regressors (21 in total). We then verify the joint significance of all the variables that are not significant at the 10% level. The joint test also uses a 10% significance level. If the joint test fails to reject that a set of variables is insignificant, we eliminate these variables from the regression and then run one final regression with the remaining variables. However, if the set of variables is jointly significant, we increase the significance level by 5% for both the individual and joint tests. The results are reported in Table A3. We end up using a 10% significance level.

The model is less parsimonious than the subgroup model reported in the paper, as it retains 14 variables, all significant at the 1% level except for industry turnover, which is significant at 5% level. After eliminating the useless variables, the adjusted R^2 remains unchanged at 86%, and the coefficients of the retained variables remain similar to what they were in the full model. Interestingly, the signs for the compositional variables "psmall" (the relative importance of small firms) and "pyoung" (the relative importance of young firms) are now as expected. However, psmall contributes a negative 13% to the explained variation, whereas psmall's contribution is about 12%. Together, they explain nothing. General turnover does enter significantly and explains about 10% of the total explained variation. The four corporate variables retained in the subgroup model survive here too with about the same economic and statistical significance. Two additional corporate variables are retained as well (earnings variability, veps, and the cross-sectional variance of the return on equity, cvroe). While veps explains 7% of the variation in idiosyncratic variances, cvroe's contribution is a negative 11%. Maba (growth options) remains very important with a 44% contribution to the overall variance of the fitted value. As for the business cycle variables, the variance premium, the term spread and the confidence index are the additional business variables in the final model. The term spread and confidence index are not economically important, but the variance premium accounts for 10% of the explained variation. Its coefficient is in line with expectations. The default spread is no longer significant, but industrial production and the total market variance still are. They have similar coefficients as they do in the subgroup model, and similar economic significance as well, with the market variance now contributing 32% of the total explained variation.

5. Other Tables

The Tables A4 to A6 and Figure A1 depict results and analysis that is adequately summarized in the main text.

Table A1. Robustness checks: global model idiosyncratic volatilities and equal weighted idiosyncratic variances

Panel A reports trend test results for 23 countries idiosyncratic volatilities time series, using the Vogelsang (1998) t-PS1 test and the Bunzel and Vogelsang (2008) t-dan test. The 5% critical value (two sided) for t-dan is 2.052, and for t-ps1 is 2.152. The variable σ^2_{WLFF} is the aggregate firm level idiosyncratic variances, as defined in equation (1) in the appendix. In Panel B, we report summary statistics for equally weighted aggregate idiosyncratic volatilities for the U.S. sample, and the sample period is January 1964 to December 2008. In Panel C, we report trend test results for U.S. idiosyncratic variance time-series, using the trend tests described above. We report results for both σ^2_{CLMX} and σ^2_{FF}. In Panel D, we report trend test results for different groups of stocks, using σ^2_{CLMX}. We separate large/small firms using median NYSE market cap; we separate old/young firms using median firm age; and we separate high price/low price stocks using $10 as a benchmark. We compute idiosyncratic variances using the CLMX and FF model. In Panels A, C and D, we use a pre-whitened model for the t-dan test. Coefficients in Panels A, C and D are multiplied by 100. All variance time-series statistics are annualized.

Panel A. Trend test for WLFF model idiosyncratic volatilities

	σ^2_{WLFF}			
	b-dan	t-dan	b-ps1	t-ps1
CANADA	0.218	0.07	0.234	0.16
FRANCE	-1.495	-0.18	-1.294	-0.44
GERMANY	1.019	0.01	1.089	0.10
ITALY	-2.566	-0.91	-2.212	-1.08
JAPAN	0.234	0.02	0.223	0.07
U.K.	-0.154	-0.01	-0.120	-0.04
U.S.	0.003	0.00	0.255	0.03
AUSTRALIA	-0.732	-0.03	-1.089	-0.36
AUSTRIA	1.533	0.47	1.756	0.66
BELGIUM	-0.705	0.00	-0.866	-0.06
DENMARK	-0.693	-0.04	-0.682	-0.16
FINLAND	-1.951	-0.01	-1.909	-0.07
GREECE	-1.877	-0.05	-1.673	-0.19
HK	-0.669	-0.36	-0.778	-0.55
IRELAND	0.180	0.01	-0.337	-0.06
NETHERLANDS	0.261	0.01	0.295	0.06
NEW ZEALAND	-1.683	-0.33	-1.798	-0.82
NORWAY	-0.805	-0.59	-0.975	-1.33
PORTUGAL	-3.383	-0.12	-4.344	-0.77
SINGAPORE	0.049	0.01	-0.001	0.00
SPAIN	-2.733	-0.16	-3.007	-0.71
SWEDEN	-0.748	-0.40	-0.514	-0.35
SWITZERLAND	0.526	0.04	0.759	0.19

Panel B. Summary statistics for the U.S. equally weighted idiosyncratic variances

	σ^2_{CLMX}		σ^2_{FF}	
N	Mean	Std	Mean	Std
540	0.4308	0.3036	0.3530	0.2436

Panel C. Trend test for the U.S. equally weighted idiosyncratic variances

	1964-1997				1964-2008			
	b-dan	t-dan	b-ps1	t-ps1	b-dan	t-dan	b-ps1	t-ps1
σ^2_{CLMX}	0.154	1.20	0.135	0.87	0.109	0.23	0.142	0.71
σ^2_{FF}	0.132	0.52	0.116	0.59	0.088	0.17	0.118	0.60

Panel D. Trend test for the U.S. subsamples using σ^2_{CLMX}

	1964-1997				1964-2008			
	b-dan	t-dan	b-ps1	t-ps1	b-dan	t-dan	b-ps1	t-ps1
Nasdaq	0.051	4.32	0.053	2.93	0.025	0.54	0.047	0.96
NYSE/AMEX	0.002	0.79	0.003	0.67	0.007	0.52	0.006	0.71
Large	0.006	2.68	0.006	1.77	0.012	0.82	0.012	1.02
Small	0.039	3.54	0.031	1.51	0.047	0.71	0.054	1.01
Old	0.007	3.14	0.008	2.26	0.009	0.81	0.010	1.24
Young	0.031	5.23	0.028	3.74	0.034	0.81	0.043	1.22
High price	0.008	3.45	0.007	2.43	0.012	0.94	0.013	1.19
Low price	0.080	3.68	0.064	1.27	0.068	0.79	0.085	1.07

Table A2. Regime switching model specification tests

AR stands for a first-order autoregressive model with homoskedastic errors. GARCH is the AR model with the variance of the error term following a GARCH(1,1) process. RS stands for the regime switching model discussed in the text. The moment conditions for RS models are computed following Timmermann (2000). We use smoothed ex-post regime probabilities to compute moments. In Panel A, we use 4 moments: mean, variance, and first order autocorrelations for both. In Panel B, we consider 2 moments: skewness and kurtosis. In Panel C, we combine the 6 moments in Panels A and B. To compute the p-values of the Wald tests, we always use 12 Newey-West lags to adjust for serial correlation.

Panel A. Mean, variance and auto-correlations

	US long CLMX Wald	p	US long FF Wald	p	CA CLMX Wald	p	FR CLMX Wald	p	GE CLMX Wald	p	IT CLMX Wald	p	JP CLMX Wald	p	UK CLMX Wald	p	US CLMX Wald	p
AR	14.902	0.5%	24.566	0.0%	15.425	0.4%	6.432	16.9%	23.428	0.0%	13.834	0.8%	10.323	3.5%	7.353	11.8%	11.250	2.4%
GARCH	9.317	5.4%	5.961	20.2%	14.643	0.6%	9.738	4.5%	2.382	66.6%	14.158	0.7%	11.100	2.6%	5.319	25.6%	5.078	27.9%
RS	7.037	13.4%	7.088	13.1%	4.639	32.6%	1.251	87.0%	9.526	4.9%	5.381	25.0%	0.849	93.2%	0.456	97.8%	3.336	50.3%

Panel B. Skewness and kurtosis

	US long CLMX Wald	p	US long FF Wald	p	CA CLMX Wald	p	FR CLMX Wald	p	GE CLMX Wald	p	IT CLMX Wald	p	JP CLMX Wald	p	UK CLMX Wald	p	US CLMX Wald	p
AR	3.709	15.7%	3.898	14.2%	6.458	4.0%	10.823	0.5%	5.699	5.8%	9.280	1.0%	7.159	2.8%	6.089	4.8%	4.259	11.9%
GARCH	3.493	17.4%	3.795	15.0%	5.297	7.1%	4.706	9.5%	1.110	57.4%	6.247	4.4%	9.602	0.8%	2.914	23.3%	3.203	20.2%
RS	2.432	29.6%	4.656	9.8%	5.362	6.9%	2.763	25.1%	9.487	0.9%	5.509	6.4%	7.216	2.7%	1.610	44.7%	2.375	30.5%

Panel C. All

	US long CLMX Wald	p	US long FF Wald	p	CA CLMX Wald	p	FR CLMX Wald	p	GE CLMX Wald	p	IT CLMX Wald	p	JP CLMX Wald	p	UK CLMX Wald	p	US CLMX Wald	p
AR	25.948	0.0%	32.537	0.0%	24.609	0.0%	24.428	0.0%	26.516	0.0%	22.814	0.1%	21.562	0.2%	25.122	0.0%	21.869	0.1%
GARCH	18.937	0.4%	10.005	12.4%	24.211	0.1%	18.603	0.5%	19.906	0.3%	22.117	0.1%	17.508	0.8%	13.356	3.8%	12.501	5.2%
RS	9.543	14.5%	9.279	15.9%	12.771	4.7%	3.563	73.6%	14.650	2.3%	10.668	9.9%	11.310	7.9%	13.106	4.1%	6.530	36.7%

Table A3. What drives U.S. idiosyncratic volatility? Hendry regression

OLS regressions of aggregate idiosyncratic variances in the U.S. over 1964-2008, computed using the CLMX model, on various determinants, labeled on the left. We show the regression on all variables simultaneously and a regression reduced by the general-to-specific paring down technique, described in the appendix. In the last row, we also report a joint Wald test checking whether the variables dropped from regression I to II are jointly significantly different from zero. All p-values are based on standard errors, using 12 Newey-West lags. The last column reports the covariance decomposition described in the text.

	I. All variables		II. Significant variables from I		
	coef.	p-value	coef.	p-value	Cov decomp
pyoung	0.772	0.001	0.879	0.000	12%
psmall	11.058	0.007	13.467	0.000	-13%
plow	-0.332	0.808			
lowto	-0.001	0.807			
dto	0.023	0.003	0.024	0.009	10%
vwroe	0.086	0.836			
vwvroe	1.332	0.733			
cvroe	-0.846	0.008	-0.952	0.000	-11%
veps	0.009	0.001	0.007	0.003	7%
indto	0.003	0.005	0.004	0.013	1%
maba	0.093	0.000	0.101	0.000	44%
vmaba	-0.008	0.148			
cvmaba	0.000	0.529			
rd	0.173	0.001	0.134	0.000	23%
cvrd	-0.006	0.000	-0.006	0.000	-8%
mvp	0.534	0.000	0.542	0.000	10%
mkttv	0.642	0.000	0.633	0.000	32%
dip	-0.512	0.003	-0.510	0.005	1%
def	0.004	0.446			
term	-0.010	0.000	-0.011	0.000	2%
confi	-0.001	0.000	-0.001	0.000	-9%
disp	-0.092	0.807			
Adj. R2	86%		86%		
Wald test for eliminated variables from regression I to II					
	p-value	68.0%			

Table A4. Analyzing Model Residuals

Panel A reports specification tests of the regression model residuals and residuals for a RS model on the residuals. The residuals are computed using the subgroup model and Hendry model. We conduct specification tests on the RS model residuals using both ex ante and ex post probabilities, denoted RS ante and RS post, respectively. The moment conditions include: mean, variance, autocorrelation of first order for both mean and variance, skewness and kurtosis. To compute the p-value of the Wald tests, we always use 12 Newey-West lags to adjust for serial correlation. The parameters of the RS model are reported in Panel B. We estimate the RS model as in Table 3, except we re-parameterize to ensure $0 < \sigma_1 < \sigma_2$. The last row in Panel B reports the Wald test of $\mu_1 = \mu_2$. In Panel C, we re-estimate the subgroup and Hendry models, by allowing all coefficients to be linear functions of a dummy variable in the form of $b = b_0 + b_1 dummy$. We refer to b_0 as the "constant" coefficient, and b_1 as the "dummy" coefficient. The dummy variable takes a value of 1 if the CLMX smoothed probability in regime 2 is higher than 0.5.

Panel A. Specification test on the residuals and RS residuals of the residuals

Models	Subgroup Model		Hendry Model	
	Wald	p-value	Wald	p-value
residuals	25.71	0.0%	22.26	0.1%
RS post	9.34	15.5%	7.21	30.2%

Panel B. Regime switching model for the regression residuals

	Subgroup model		Hendry model	
	coef.	std.	coef.	std.
μ_1	-0.002	0.003	-0.001	0.002
μ_2	0.009	0.011	0.006	0.008
b_1	0.705	0.042	0.632	0.044
b_2	0.413	0.121	0.237	0.136
σ_1	0.013	0.001	0.012	0.001
σ_2	0.049	0.005	0.044	0.005
p_{11}	0.985	0.009	0.982	0.011
p_{22}	0.929	0.062	0.903	0.097
P($\mu_1 = \mu_2$)	34.9%		42.4%	

Panel C. Allowing for Regime 2 Dummy in Regression Coefficients

	Subgroup Model				Hendry Model			
	b_0		b_1		b_0		b_1	
	coef.	p-value	coef.	p-value	coef.	p-value	coef.	p-value
pyoung					0.028	10.5%	0.383	41.4%
psmall					0.200	6.3%	27.402	2.8%
plow								
lowto								
dto					-0.016	0.4%	0.057	0.0%
vwroe								
vwvroe								
cvroe					0.390	0.2%	0.754	43.1%
veps					0.000	73.4%	0.016	0.2%
indto	0.003	2.3%	0.003	48.6%	0.002	0.3%	-0.004	47.2%
maba	0.066	0.0%	0.067	0.7%	0.058	0.0%	0.087	0.2%
vmaba								
cvmaba								
rd	0.002	96.9%	0.170	1.7%	0.047	31.0%	0.116	3.8%
cvrd	-0.003	0.6%	-0.003	20.0%	-0.002	3.4%	-0.011	0.0%
mvp					0.479	0.0%	-0.295	29.9%
mkttv	0.526	0.0%	0.674	0.0%	0.514	0.0%	0.664	0.0%
dip	-0.189	20.3%	-0.642	50.4%	-0.070	55.9%	-0.780	16.4%
def	0.011	0.5%	0.039	12.7%				
term					-0.005	0.0%	-0.015	0.5%
confi					-0.001	0.0%	-0.001	4.4%
Adj. R2	89%				94%			

Table A5. Idiosyncratic volatility across G7 countries: Hendry regression

OLS regressions of aggregate idiosyncratic variances in the G7 countries over 1983-2008, computed using the CLMX model, on various determinants, labeled on the left. The annual data time series for idiosyncratic variance are averaged over monthly observations in the year. More details about the data are in the Appendix text, Section C and Table 5. We show the regression on all variables simultaneously and a regression reduced by the general-to-specific paring down technique, described in the Appendix text. In the last 4 rows, we also report joint Wald tests of whether all variables dropped step by step from regression I to II are significantly different from zero. All regressions include country dummies. All p-values are based on standard errors using 12 Newey-West lags and they are adjusted by clustering on years. All regressions include country dummies. The last column reports the covariance decomposition described in the text.

	I. all variables		II. significant variables		
	coef.	p-value	coef.	p-value	Cov decomp
vwroe	-0.142	3.8%	-0.146	2.6%	7.1%
vwvroe	-0.498	43.6%			
cvroe	0.119	24.5%			
veps	0.039	6.6%	0.050	0.5%	0.1%
indto	0.081	0.8%	0.083	0.6%	0.3%
maba	0.024	0.0%	0.024	0.0%	24.6%
vmaba	0.002	2.3%	0.002	2.1%	6.7%
cvmaba	0.003	0.1%	0.003	0.1%	10.1%
mkttv	0.457	0.0%	0.475	0.0%	29.9%
dgdp	-0.027	29.2%			
def	0.000	91.2%			
term	-0.003	2.2%	-0.002	3.5%	0.4%
usmvp	0.859	0.2%	0.832	0.5%	20.6%
Adj. R2	0.71%		71%		
R2 (w/o country dummies)	59%		59%		
Wald test for eliminating vwvroe, cvroe, dgdp, and def at 10%					
	p-value	0.678			

Table A6. Idiosyncratic volatility across G7 countries: beta model

OLS regressions of aggregate idiosyncratic variances in the G7 countries over 1983-2008, computed using the CLMX model, on various determinants, labeled on the left. The annual data time series for idiosyncratic variance are average over monthly observations in the year. More details about the data are in Appendix B. We show 5 regressions: one for each group of variables, one for all regressors, starting with the betas with respect to the U.S. variance, a final subgroup one based on a paring down technique selecting significant variables from the full regression. All p-values are based on standard errors using 12 Newey-West lags and are adjusted for clustering on years. The last column for the fifth regression reports the covariance decomposition described in the text.

		only US idio		all corp + US idio		all cycle + US idio		all variables + US idio		Hendry variables + US idio		
		coef.	p-value	coef.	p-value	coef.	p-value	coef.	p-value	coef.	p-value	cov decomp
	vwroe			-0.105	7.1%			-0.079	12.4%			
	vwvroe			0.862	23.2%			0.886	21.6%			
	cvroe			-0.046	51.4%			0.064	33.9%			
	veps			0.077	0.2%			0.064	0.6%	0.078	0.0%	1.5%
	indto			0.080	3.6%			0.059	3.0%	0.045	5.4%	1.4%
	maba			0.005	12.0%			0.001	78.0%			
	vmaba			0.001	1.4%			0.002	0.0%	0.001	0.0%	-14.1%
	cvmaba			0.000	92.6%			0.000	94.5%			
	mkttv					0.538	0.0%	0.505	0.0%	0.514	0.0%	-0.1%
	dgdp					0.018	15.6%	0.012	35.3%			
	def					0.001	32.8%	0.001	25.1%			
	term					-0.002	0.2%	-0.002	1.3%	-0.002	1.6%	0.4%
	usmvp					0.510	0.1%	0.679	0.0%	0.703	0.0%	18.6%
dca	usidio	0.549	0.0%	0.681	0.0%	0.575	0.0%	0.628	0.0%	0.612	0.0%	34.4%
dfr	usidio	0.375	0.0%	0.539	0.0%	0.399	0.0%	0.478	0.0%	0.446	0.0%	7.0%
dge	usidio	0.339	0.0%	0.472	0.0%	0.343	0.0%	0.407	0.0%	0.371	0.0%	2.7%
dit	usidio	0.318	0.0%	0.476	0.0%	0.283	0.0%	0.405	0.0%	0.331	0.0%	0.8%
djp	usidio	0.610	0.0%	0.809	0.0%	0.562	0.0%	0.728	0.0%	0.673	0.0%	47.5%
duk	usidio	0.306	0.0%	0.534	0.0%	0.310	0.0%	0.442	0.0%	0.374	0.0%	-0.1%
adj. R2		59.6%		64.9%		67.5%		71.1%		71.5%		

Figure A1. Regime probabilities for G7 countries

This figure reports the smoothed probability of being in regime 2 for the G7 countries other than the U.S., using a regime switching model defined in equations (7) and (8). The model is estimated over sample period 1980 – 2008, country by country. The variable σ^2_{CLMX} is the aggregate firm level idiosyncratic variance, as defined in equation (2), estimated using daily data.