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Aggregate Idiosyncratic Volatility

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Abstract

We examine aggregate idiosyncratic volatility in 23 developed equity markets, measured using various methodologies. We find no evidence of upward trends after extending the sample to 2008. Instead, idiosyncratic volatility is well described by a stationary autoregressive process that occasionally switches into a higher-variance regime that has relatively short duration. We also document that idiosyncratic volatility is highly correlated across countries. Most of the time variation in idiosyncratic volatility can be attributed to variation in a growth opportunity proxy, total (U.S.) market volatility, and in most specifications, the variance premium, a business cycle sensitive risk indicator.

I. Introduction

Much recent research in finance has focused on idiosyncratic volatility.[1] Morck, Yeung, and Yu (2000) suggest that the relative importance of idiosyncratic variance in total variance is a measure of market efficiency. The level of idiosyncratic volatility clearly is also an important input in the study of diversification benefits. Here, a growing literature attempts to explain the trend in idiosyncratic volatility first documented by Campbell, Lettau, Malkiel, and Xu (CLMX) (2001). Aktas, De Bodt, and Cousin (2007) and Kothari and Warner (2004) study how this permanent increase affects the use of one of the most powerful empirical

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[1]We use the terms volatility and variance interchangeably.

techniques in finance, the event study. Comin and Mulani (2006) examine how and why trends in the macroeconomy seem to diverge from the "microtrend."[2]

Our 1st contribution is to expand the study of the time-series behavior of aggregate idiosyncratic volatility to international data. This is not only important for purely statistical reasons, but it also helps to inform the debate about the determinants of the time variation in idiosyncratic volatility. Our results are in fact startling: There are no significant trends in idiosyncratic volatility for non-U.S. developed countries. For the 1980–2008 sample, we estimate negative trend coefficients for 9 countries. For the full sample of U.S. data, we also find no support for the hypothesis of a trend in idiosyncratic volatility. This finding is consistent with the results in Brandt, Brav, Graham, and Kumar (2010), who argue that the increase in idiosyncratic volatility in the 1990s was temporary.[3]

The results in CLMX (2001) appear quite robust to alternative methodologies to compute idiosyncratic volatility and to the use of alternative trend tests within their sample. Nevertheless, we show that the test results are sensitive to the sample period: Ending the sample in the 1988–1998 decade is key to finding a trend. Of course, when a time series exhibits apparent time trends over part of its sample, it is likely characterized by near-nonstationary behavior. We show that average idiosyncratic volatility is well described by a relatively stable autoregressive (AR) process that occasionally switches into a higher-variance regime that has relatively low duration. Hence, our evidence does not support *permanent* changes in idiosyncratic volatility. We also document a new empirical fact: Idiosyncratic volatility is highly correlated across countries, and these correlations have increased over time.

Our findings provide a challenge for some of the explanations for the "trend" in aggregate idiosyncratic variance proposed in the literature. Successful theories should capture the low frequency changes in the idiosyncratic volatility time-series data and the correlation across countries. The literature has identified roughly 3 types of determinants. A 1st set focuses on the changing composition of stock market indices. Fink, Fink, Grullon, and Weston (2010) ascribe the trend to the increasing propensity of firms to issue public equity at an earlier stage in their life cycle, while Brown and Kapadia (2007) argue that the trending behavior is due to the listings of more riskier firms over the years. The 2nd and largest set of explanations focuses on what we call "corporate variables": firm-specific characteristics that ultimately determine idiosyncratic cash flow variability. These articles include Guo and Savickas (2008) (changes in the investment opportunity set), Cao, Simin, and Zhao (2008) (growth options), Comin and Philippon (2006) (research and development (R&D) spending and access to external financing), and Wei and Zhang (2006) (earnings quality). Gaspar and Massa (2006) and Irvine and Pontiff (2009) point to increasingly competitive product markets as a potential "deeper" explanation of increased idiosyncratic cash flow variability. Financial

[2]A rapidly growing literature considers the pricing of idiosyncratic risk. See Ang, Hodrick, Xing, and Zhang (2006), (2009) and the references therein. We do not address expected return issues here.

[3]In a study focusing on the predictive relation between idiosyncratic volatilities and aggregate returns, Guo and Savickas (2008) point out there is no significant trend in idiosyncratic volatility for the G7 countries, and that these volatilities are highly correlated with U.S. idiosyncratic volatility.

development has made stock markets more informative and increased idiosyncratic variability, relative to total market variability (see Chun, Kim, Morck, and Yeung (2008)). The 3rd set of articles is more "behavioral" in nature and relies on changes in the degree of market inefficiency to generate changes in idiosyncratic variability. Xu and Malkiel (2003) and Bennett, Sias, and Starks (2003) ascribe the rise in idiosyncratic volatility to an increase in institutional ownership, and especially the increased preferences of institutions for small stocks. Brandt et al. (2010) attribute the temporary increase to "speculative behavior," as evidenced by retail traders in the Internet bubble. They find that the period between 1926 and 1933 exhibited a similar temporary increase in idiosyncratic volatility, which they also ascribe to speculative behavior.

Our time-series characterization of idiosyncratic volatility immediately excludes certain variables as important determinants. For example, because institutional ownership exhibits a clear trend, it cannot fully explain the evidence. However, it is possible that the propensity to issue public equity is not trending upward but also shows regime-switching behavior. The final part of our article runs horse races between the various determinants, in addition to exploring the links between idiosyncratic volatility and market volatility and the business cycle, which have not been studied before. This turns out to be an important omission: Together with growth opportunities, market volatility and a cyclical risk aversion indicator appear to drive most of the variation in idiosyncratic volatility, both in the United States and internationally.

The remainder of the article is organized as follows: Section II describes the data. Section III contains the main results for trend tests. Section IV characterizes the time-series properties of aggregate idiosyncratic volatility. Section V examines the explanatory power of a large number of potential determinants. In Section VI, we summarize our findings.

II. Data

A. The U.S. Sample

In order to replicate and extend the CLMX (2001) study, we first collect daily U.S. stock return data between 1964 and 2008 from the Center for Research in Security Prices (CRSP). We calculate excess returns by subtracting the U.S. T-bill rate, which is obtained from the CRSP risk-free file. We calculate the idiosyncratic volatility of a firm's return using two methods. First, we compute the idiosyncratic variance as in CLMX. The model for individual firm j on day t is

$$R_{j,t} = \mathrm{IND}_{J,t} + u_{j,t}^{\mathrm{CLMX}}. \tag{1}$$

Here, $\mathrm{IND}_{J,t}$ is the return on a corresponding industry portfolio J to which firm j belongs.[4] The firm's idiosyncratic variance is then the variance of the residual

[4]We use 26 industries by merging Standard Industrial Classification (SIC) codes for U.S. firms and FTSE industry codes for foreign firms, as in Bekaert, Hodrick, and Zhang (2009).

$u_{j,t}^{\text{CLMX}}$, computed with 1 month of daily return data. Value weighting the firm-level idiosyncratic variances produces the CLMX aggregate idiosyncratic variance. That is,

$$\sigma^2_{\text{CLMX},m} = \sum_{j=1}^{N} w_{j,m}\, \sigma^2\left(u_{j,t}^{\text{CLMX}}\right), \tag{2}$$

where day t belongs to month m. Here, the weight $w_{j,m}$ is computed using firm j's previous month market capitalization, and N is the number of firms. Implicitly, CLMX assumes that systematic risks are captured by the industry return and that firms have unit betas with respect to the industry to which they belong.

Bekaert, Hodrick, and Zhang (BHZ) (2009) show that the unit beta restrictions in the CLMX (2001) approach severely limit the factor model's ability to match stock return comovements. We therefore also consider the Fama-French (FF) (1996) model, which fits stock return comovements better:

$$R_{j,t} = b_{0,j,m} + b_{1,j,m}\text{MKT}_t + b_{2,j,m}\text{SMB}_t + b_{3,j,m}\text{HML}_t + u_{j,t}^{\text{FF}}, \tag{3}$$

where day t belongs to month m. Here, the variable MKT represents the excess return on the market portfolio, SMB is the size factor, and HML is the value factor. This model is more in line with standard methods to correct for systematic risk. Data on the FF factors are obtained from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). To allow the betas to vary through time, we reestimate the model every month with daily data. The idiosyncratic variance for firm j is the variance of the residual of the regression, that is, $\sigma^2(u_{j,t}^{\text{FF}})$. We again compute the idiosyncratic variance at the country level using value weighting:

$$\sigma^2_{\text{FF},m} = \sum_{j=1}^{N} w_{j,m}\, \sigma^2\left(u_{j,t}^{\text{FF}}\right), \tag{4}$$

where day t belongs to month m.

B. The Developed Countries Sample

We study daily excess returns for individual firms from 23 developed markets, including the United States. The sample runs from 1980 to 2008. All returns are U.S. dollar denominated. Our selection of developed countries matches the countries currently in the Morgan Stanley Capital International Developed Markets Index. Data for the United States are from Compustat and CRSP; data for the other countries are from DataStream. In the DataStream data, it is likely that new and small firms are increasingly represented in the sample. This could bias our tests toward finding a trend. We estimate domestic models, such as the CLMX (2001) model in equation (1) and the FF (1996) model in equation (3), for each developed country, where the industry, size, and value factors are constructed in the corresponding national market. In Section III.B, we conduct a robustness check using a model that explicitly allows for both global and local factors.

C. Summary Statistics

Table 1 presents summary statistics for the time series of annualized idiosyncratic variances. Panel A focuses on the long U.S. sample, where we have 540 monthly observations. The mean of the annualized CLMX (2001) idiosyncratic variance is 0.0800 with a time-series standard deviation of 0.0592, and the mean of the annualized FF (1996) idiosyncratic variance is 0.0697 with

TABLE 1

Idiosyncratic Variance Summary Statistics

Panel A of Table 1 provides summary statistics for the U.S. sample of Jan. 1964–Dec. 2008. Panel B reports summary statistics for the developed countries sample of Jan. 1980–Dec. 2008. Panel C presents correlations between G7 idiosyncratic variances. We use bold font if the correlation is significantly different from 0 at the 5% level. The U.S. return data are obtained from CRSP, and the return data for other countries are obtained from DataStream. All of the returns are denominated in U.S. dollars. The variables σ^2_{CLMX} and σ^2_{FF} are the aggregate firm-level idiosyncratic variances, as defined in equations (2) and (4), respectively. All variance time-series statistics are annualized.

Panel A. U.S. Sample (1964–2008)

	σ^2_{CLMX}		σ^2_{FF}	
N	Mean	Std.	Mean	Std.
540	0.0800	0.0592	0.0697	0.0484

Panel B. Developed Countries Sample (1980–2008)

		σ^2_{CLMX}		σ^2_{FF}	
	N	Mean	Std.	Mean	Std.
Canada	342	0.0880	0.0476	0.0844	0.0433
France	342	0.0692	0.0377	0.0696	0.0386
Germany	342	0.0537	0.0655	0.0492	0.0426
Italy	342	0.0758	0.0536	0.0727	0.0485
Japan	342	0.0912	0.0487	0.0815	0.0426
United Kingdom	342	0.0529	0.0429	0.0550	0.0459
United States	342	0.0931	0.0661	0.0814	0.0544
Australia	342	0.0745	0.0482	0.0712	0.0455
Austria	342	0.0413	0.0503	0.0433	0.0422
Belgium	342	0.0487	0.0584	0.0459	0.0367
Denmark	342	0.0473	0.0297	0.0523	0.0365
Finland	288	0.0547	0.0527	0.0711	0.0529
Greece	251	0.0901	0.0701	0.0798	0.0480
Hong Kong	342	0.0792	0.0564	0.0710	0.0454
Ireland	342	0.0474	0.0598	0.0683	0.0683
Netherlands	342	0.0292	0.0303	0.0369	0.0322
New Zealand	275	0.0404	0.0311	0.0518	0.0252
Norway	342	0.0800	0.0526	0.0859	0.0537
Portugal	251	0.0677	0.0958	0.0597	0.0385
Singapore	342	0.0656	0.0556	0.0591	0.0388
Spain	275	0.0435	0.0406	0.0457	0.0361
Sweden	342	0.0568	0.0425	0.0664	0.0403
Switzerland	342	0.0312	0.0292	0.0326	0.0262

Panel C. Correlations between the Idiosyncratic Variances of the G7 Countries (1980–2008)

	Canada	France	Germany	Italy	Japan	United Kingdom
σ^2_{CLMX}						
France	**56%**					
Germany	**62%**	**57%**				
Italy	**31%**	**51%**	**20%**			
Japan	**56%**	**54%**	**57%**	**23%**		
United Kingdom	**74%**	**68%**	**81%**	**31%**	**72%**	
United States	**75%**	**65%**	**68%**	**20%**	**70%**	**80%**
σ^2_{FF}						
France	**63%**					
Germany	**77%**	**67%**				
Italy	**32%**	**53%**	**19%**			
Japan	**65%**	**62%**	**71%**	**31%**		
United Kingdom	**68%**	**62%**	**74%**	**33%**	**70%**	
United States	**76%**	**71%**	**81%**	**27%**	**72%**	**71%**

a time-series standard deviation of 0.0484. Hence, the FF risk adjustments lower both the mean and the volatility of the idiosyncratic variance series relative to the CLMX-idiosyncratic variance. The correlation between the 2 idiosyncratic variance series is nonetheless 98%.

Panel B of Table 1 reports idiosyncratic variance statistics computed for 23 countries, using the CLMX (2001) model on the left-hand side and the FF (1996) model on the right-hand side. Among the G7 countries, the United States, Japan, and Canada have the highest idiosyncratic variances, and Germany and the United Kingdom have the lowest idiosyncratic variances. Among the other countries, the idiosyncratic volatility is the highest for Greece at 0.0901 when using the CLMX model, and it is 0.0798 when using the FF model. The idiosyncratic variance is the lowest for Switzerland at around 0.03.[5]

Panel C of Table 1 presents correlations among the idiosyncratic variances of the G7 countries. No matter which model we use, the idiosyncratic variances are highly correlated across countries. Using Pearson's test, we find that all correlation coefficients are significant at the 5% level. This is an important new fact, as it suggests that there might be a common driving force for idiosyncratic variances across countries.

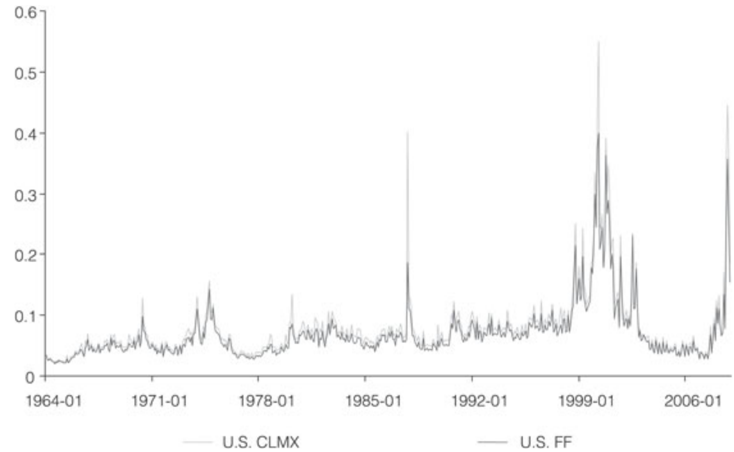
Figure 1 presents the time series of the various idiosyncratic variance measures. There are periods of temporarily higher volatility in the United States,

FIGURE 1

Idiosyncratic Variances over Time

In Graph A of Figure 1, we plot the time-series idiosyncratic variance for the U.S. sample. The sample period is Jan. 1964–Dec. 2008. In Graph B, we plot the time-series idiosyncratic variances for G7 countries. The aggregate idiosyncratic variance measures using CLMX (2001) and FF (1996) are defined in equations (2) and (4), respectively. The U.S. return data are obtained from CRSP, and the return data for other countries are obtained from DataStream. All of the returns are denominated in U.S. dollars. All variance time-series statistics are annualized.

Graph A. U.S. (daily data)



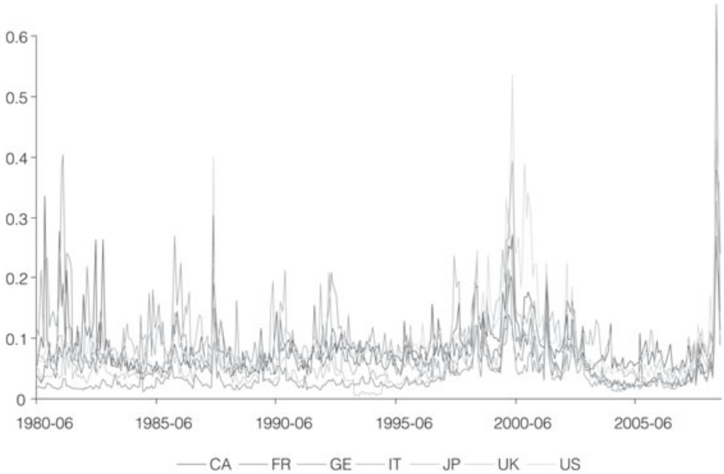
(continued on next page)

[5]Bartram, Brown, and Stulz (2012) find that a typical U.S. firm has higher idiosyncratic risk than a comparable foreign firm and explore the cross-sectional determinants of this difference.

FIGURE 1 (continued)

Idiosyncratic Variances over Time

Graph B. G7 (daily data, CLMX)



including 1970, 1974, 1987, a longer-lasting increase in 1998, which seems to reverse after 2003, and the recent crisis period. In other countries, the most obvious high-variance periods are again 1998–2001 and the recent crisis period. However, periods of higher volatility are apparent earlier in the sample as well; for instance, around 1987 for a number of countries and in the early 1980s for France and Italy.

III. Trend Tests

A. Main Results

One of the main results in CLMX (2001) is that the average idiosyncratic variance in the United States exhibits a positive time trend. To formally test for trends, we follow CLMX and use Vogelsang's (1998) linear time trend test. The benchmark model is

$$y_t \quad = \quad b_0 + b_1 t + u_t, \tag{5}$$

where y_t is the variable of interest, and t is a linear time trend. We use the PS1 test in Vogelsang to test $b_1 = 0$. The conditions on the error terms under which the distributions for the test statistics are derived are quite weak and accommodate most covariance stationary processes (e.g., regime-switching models) and even I(1) processes. In all of the ensuing tables, we report the trend coefficient, the t-statistic, and the 5% critical value derived in Vogelsang (for a 2-sided test). In addition, Bunzel and Vogelsang (2005) develop a test that retains the good size properties of the PS1 test, but it has better power (both asymptotically and in finite samples). We denote this test with a "DAN" suffix, as the test uses a "Daniell kernel" to nonparametrically estimate the error variance needed in the test. In fact, tests based on this kernel maximize power among a wide range of kernels. We use an AR(1) model to prewhiten the data because Bunzel and Vogelsang show that prewhitening improves the finite sample properties of the test. Vogelsang generously provided us with the code for both the *t*-PS1 and *t*-DAN tests.

Table 2 reports the trend test results. Panel A considers the same U.S. sample as in CLMX (2001), which is 1964–1997, and we find a significant trend in the idiosyncratic variance whether we use the FF (1996) or CLMX model. Panel B includes 11 more years of data, and the idiosyncratic variance does not display a significant trend in any of the cases. Clearly, the trend documented in CLMX

TABLE 2

Trend Tests

Panels A and B of Table 2 report trend test results for the U.S. idiosyncratic variance time series, and Panel C reports trend test results for the idiosyncratic variance time series of all developed countries. All panels use Vogelsang's (1998) *t*-PS1 test and Bunzel and Vogelsang's (2005) *t*-DAN test. The 5% critical value (2-sided) for *t*-DAN is 2.052, and for *t*-PS1 it is 2.152. We report both prewhitened results using AR(1) and nonprewhitened results for the *t*-DAN test in Panels A and B, and for Panel C, we only use the prewhitened results. Variables σ^2_{CLMX}, σ^2_{FF}, and σ^2_{BCL} are the aggregate firm-level idiosyncratic variances, as defined in equations (2), (4), and (6), respectively. All variance time-series statistics are annualized. All coefficients are multiplied by 100.

	Prewhitened		Not Prewhitened			
	b-DAN	*t*-DAN	*b*-DAN	*t*-DAN	*b*-PS1	*t*-PS1
Panel A. Idiosyncratic Variances over 1964–1997 (daily data)						
σ^2_{CLMX}	0.011	4.84	0.011	4.97	0.011	3.89
σ^2_{FF}	0.009	4.35	0.009	4.72	0.009	3.36
σ^2_{BCL}	0.007	3.27	0.007	3.37	0.007	2.51
Panel B. Idiosyncratic Variances over 1964–2008 (daily data)						
σ^2_{CLMX}	0.015	0.95	0.015	1.04	0.016	1.35
σ^2_{FF}	0.013	0.76	0.013	0.87	0.014	1.15
σ^2_{BCL}	0.012	0.93	0.012	1.00	0.014	1.18

Panel C. Idiosyncratic Variances over 1980–2008 (daily data)

	σ^2_{CLMX}				σ^2_{BCL}			
	b-DAN	*t*-DAN	*b*-PS1	*t*-PS1	*b*-DAN	*t*-DAN	*b*-PS1	*t*-PS1
Canada	0.059	0.35	0.097	0.48	0.014	0.31	0.014	0.46
France	−0.090	−0.28	−0.004	−0.01	0.001	0.06	0.005	0.23
Germany	0.290	0.48	0.346	0.73	0.020	0.66	0.021	0.84
Italy	−0.414	−2.62	−0.375	−1.86	−0.014	−1.21	−0.014	−0.95
Japan	0.016	0.07	0.050	0.23	0.006	0.29	0.009	0.40
United Kingdom	0.070	0.06	0.053	0.08	0.012	0.27	0.012	0.38
United States	0.053	0.03	0.141	0.15	0.013	0.32	0.020	0.51
Australia	−0.055	−0.27	−0.125	−0.81	−0.001	−0.03	−0.010	−0.57
Austria	0.496	0.93	0.543	0.82	0.017	0.45	0.012	0.79
Belgium	−0.052	−0.06	−0.058	−0.13	0.006	0.21	−0.001	−0.04
Denmark	0.065	0.37	0.126	0.50	0.011	0.46	0.011	0.52
Finland	−0.514	−0.21	−0.584	−0.41	−0.023	−1.01	−0.024	−0.97
Greece	−0.323	−1.57	−0.377	−1.77	−0.017	−0.83	−0.021	−1.02
Hong Kong	0.030	0.14	0.001	0.00	0.000	−0.02	−0.003	−0.14
Ireland	0.077	0.08	−0.008	−0.02	0.017	0.14	0.004	0.11
Netherlands	0.198	0.31	0.253	0.45	0.012	0.52	0.013	0.56
New Zealand	−0.019	−0.04	−0.089	−0.20	−0.010	−1.15	−0.014	−1.33
Norway	0.017	0.06	0.060	0.18	0.003	0.21	0.002	0.11
Portugal	−0.651	−4.33	−0.773	−4.93	−0.015	−1.94	−0.022	−2.76
Singapore	0.049	0.42	0.002	0.01	0.008	0.79	0.008	0.58
Spain	−0.298	−1.38	−0.350	−1.61	−0.011	−0.75	−0.010	−0.60
Sweden	−0.013	0.03	0.028	0.07	0.008	0.44	0.013	0.65
Switzerland	0.120	0.41	0.159	0.51	0.008	1.21	0.008	1.15

is time-period dependent. Since the prewhitened and nonprewhitened results are very similar, we only report the prewhitened results for the *t*-DAN test in later sections.

Panel C of Table 2 reports trend test results for the 23 developed countries, country by country. Using σ^2_{CLMX}, we fail to detect a significant positive time trend for all countries, either using the *t*-DAN test or the *t*-PS1 test. France, Italy, Australia, Belgium, Finland, Greece, New Zealand, Portugal, and Spain have negative trend coefficients, which are significantly different from 0 for Italy and Portugal. Because the results for σ^2_{FF} are entirely similar, we do not report them to save space. In summary, positive trending behavior is simply not visible in idiosyncratic volatility across the developed world.

B. Robustness and Further Tests

Whereas the 2 models deliver highly correlated idiosyncratic variance series, the dependence of the idiosyncratic variance on a risk model remains an issue of concern. Here we consider several robustness checks. First, we compute the model-free measure proposed by Bali, Cakici, and Levy (BCL) (2008), σ^2_{BCL} henceforth:

$$\text{(6)} \qquad \sigma^2_{\text{BCL},m} \quad = \quad \left(\sum_{j=1}^{N} w_{j,m}\, \sigma(R_{j,t}) \right)^2 - \sigma^2(R_{\text{MKT},t}).$$

Here, the various σs are simply the monthly volatilities of individual stocks, and therefore the measure does not require the computation of any risk exposures. Intuitively, the measure subtracts systematic risk, measured by the market variance, from the square of the average volatility. When all risk is systematic (i.e., when stocks are perfectly or very highly correlated), the measure goes to 0. With equal standard deviations across stocks, the measure equals the σ^2_{CLMX} measure, but the BCL (2008) measure will generally be smaller than the CLMX (2001) measure, with the difference increasing in the cross-sectional dispersion of individual volatilities (see BCL).

Table 2 also contains trend estimates using the BCL (2008) measure. The BCL measure delivers exactly the same inference as our other measures do. There is a trend in U.S. idiosyncratic variance over the CLMX (2001) sample, but not over the full sample, and there are no trends in international data, except for a negative trend in Portugal.

Another drawback of the models used so far is that they may not adequately capture global risks. In the online Appendix at the JFQA Web site (www.jfqa.org), we produce results using the risk model advocated by BHZ (2009). The model has global and local FF (1996) factors and is estimated using weekly data every 6 months. Nevertheless, the results remain similar, and we again fail to detect a significant time trend for any country.

A final concern is that the trend results are due to a small subset of stocks. For example, one of the reasons suggested for the trend in aggregate idiosyncratic variance is that small firms may have sought public funding at an earlier stage in their life cycle than before (see Fink et al. (2010)). This would imply that small firms would have a large effect on the results, which is less likely with the value-weighted measures we consider than it is with equal-weighted measures. In the online Appendix at the JFQA Web site, we consider trend tests for equal-weighted idiosyncratic variances for the United States. We do not find a significant trend, even for the 1964–1997 period (consistent with CLMX (2001), in fact).

Various authors propose looking at subclasses of stocks, and we come back to such explanations for trend behavior in Section V. Here, we follow BCL (2008) in considering tests for NYSE and NASDAQ stocks, large and small stocks, old and young stocks, and high-priced and low-priced stocks. BCL find weaker trends for NYSE stocks and for older stocks. The online Appendix at the JFQA Web site shows that for our expanded sample, there are no meaningful differences in trend results for any of these subgroups.

IV. Characterizing the Dynamics of Idiosyncratic Volatility

The results in Section III fail to support the presence of a gradual permanent increase in idiosyncratic variances, as captured by a deterministic time trend. Other forms of nonstationary behavior remain a possibility, however. We first examine the presence of stochastic trends. Using the Dickey and Fuller (1979) and Phillips and Perron (1988) tests, we invariably reject the null hypothesis of a unit root, consistent with the evidence in Guo and Savickas (2008).

We also examine models with structural breaks, adopting the methodology in Bai and Perron (1998). For all countries, we identify a relatively large number of breaks, with the break dates highly correlated across countries. In particular, the tests consistently reveal the ends of 1997/1998 and 2001/2002 as break dates, thus selecting a temporary period of higher idiosyncratic volatility associated with what many economists have called the Internet or tech bubble. For the U.S. long sample, the Bayesian information selection criterion is minimized at 5 (3) breaks, when the minimum subsample size is 5% (15%) of the total sample. Generally, the "break tests" identify periods of temporarily higher volatility that may occur more than once during the sample period. We consequently estimate a regime-switching model to capture such behavior.

A. Country-Specific Regime-Switching Model

1. The Model

Let y_t represent the original aggregate idiosyncratic variance. Following Hamilton (1994), we allow y_t to follow an AR(1) model where all parameters can take on 1 of 2 values, depending on the realization of a discrete regime variable, s_t. The regime variable follows a Markov chain with constant transition probabilities. Let the current regime be indexed by i:

$$y_t = (1 - b_i)\mu_i + b_i y_{t-1} + \sigma_i e_t, \qquad i \in \{1, 2\}, \tag{7}$$

with $e_t \sim N(0, 1)$. In estimation, we force regime 1 (regime 2) to be the lower (higher) idiosyncratic variance regime, and the mean levels of idiosyncratic variances in both regimes to be nonnegative (i.e., we constrain $\mu_2 > \mu_1 > 0$).

The transition probability matrix, Φ, is 2×2, where each probability represents $P[s_t = i | s_{t-1} = j]$, with $i, j \in \{1, 2\}$:

$$\Phi = \begin{pmatrix} p11 & 1 - p11 \\ 1 - p22 & p22 \end{pmatrix}. \tag{8}$$

The model is parsimonious, featuring only 8 parameters, $\{\mu_1, \mu_2, b_1, b_2, \sigma_1, \sigma_2, p11, p22\}$.

2. Estimation Results

In Panel A of Table 3, we report the estimation results for both σ^2_{CLMX} and σ^2_{FF} for the long U.S. sample. The standard errors are computed using the robust White (1980) covariance matrix. The annualized idiosyncratic variance level for regime 1, μ_1, is 0.062 for σ^2_{CLMX}, and 0.055 for σ^2_{FF}, but the level increases dramatically for regime 2, with μ_2 equal to 0.181 for σ^2_{CLMX} and 0.155 for σ^2_{FF}. Using a Wald test, the level differences between the 2 regimes are highly statistically significant. It seems likely that a regime with high mean volatility also has high innovation volatility, and that is indeed what we find. Regime 2 has much higher volatility than regime 1, as σ_1 is 0.011 but σ_2 is 0.082 for σ^2_{CLMX}, with similar results when we use σ^2_{FF}. It is also typical for a high-variance regime to show more mean-reverting behavior, and we also find this to be the case for the point estimates for both σ^2_{CLMX} and σ^2_{FF}. The difference between the 2 autocorrelation coefficients is statistically significant.

TABLE 3

Regime-Switching Model Estimation Results

Table 3 reports the regime-switching model results for the idiosyncratic variance time series computed using daily data, where the model is described as

$$y_t = (1 - b_i)\mu_i + b_i y_{t-1} + \sigma_i e_t, \quad i = 1, 2.$$

The transition probability matrix is

$$\Phi = \begin{bmatrix} p11 & 1 - p11 \\ 1 - p22 & p22 \end{bmatrix}.$$

The transition probability parameters, $p11$ and $p22$, are constrained to be in (0,1) during estimation. We also reparameterize to ensure $0 < \mu_1 < \mu_2$. Panel A reports results for the United States. The sample period is 1964–2008. The variables σ^2_{CLMX} and σ^2_{FF} are the aggregate firm-level idiosyncratic variances, as defined in equations (2) and (4), respectively. Panel B reports results for the aggregate idiosyncratic variance time series of the G7 countries. The sample period becomes 1980–2008. All variance time-series statistics are annualized.

	Panel A. Long Sample (1964–2008)				*Panel B. Short Sample (1980–2008)*						
	US				CA	FR	GE	IT	JP	UK	US
	σ^2_{CLMX}		σ^2_{FF}		σ^2_{CLMX}	σ^2_{CLMX}	σ^2_{CLMX}	σ^2_{CLMX}	σ^2_{CLMX}	σ^2_{CLMX}	σ^2_{CLMX}
	Coef.	Std.	Coef.	Std.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
μ_1	0.062	0.003	0.055	0.003	0.071	0.051	0.033	0.049	0.072	0.036	0.070
μ_2	0.181	0.023	0.155	0.020	0.160	0.125	0.121	0.139	0.156	0.122	0.198
b_1	0.823	0.028	0.813	0.027	0.604	0.628	0.761	0.681	0.639	0.735	0.686
b_2	0.585	0.090	0.677	0.080	0.226	0.273	0.316	0.431	0.564	0.584	0.512
σ_1	0.011	0.001	0.010	0.001	0.013	0.012	0.008	0.016	0.018	0.009	0.013
σ_2	0.082	0.007	0.057	0.005	0.073	0.048	0.113	0.061	0.055	0.058	0.086
p_{11}	0.981	0.008	0.987	0.007	0.934	0.904	0.933	0.927	0.952	0.940	0.984
p_{22}	0.900	0.061	0.935	0.044	0.672	0.593	0.750	0.804	0.830	0.716	0.934

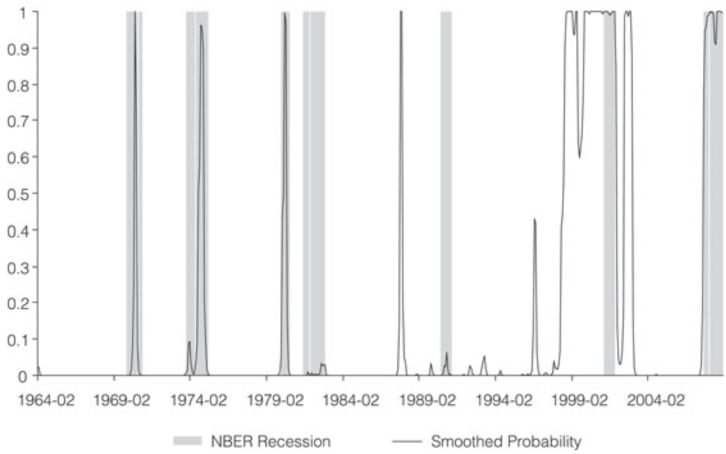
Figure 2 presents the time series of the smoothed probabilities of being in regime 2, which are computed using information from the whole time series. The high-variance regime is a short-lived regime, but it occurs several times during the sample period with some consistency across the 2 risk models. High-variance episodes that occur in both cases include 1970, 1974, 1987, 1996, 1998–2002, and 2007–2008. If we define y_t to be in regime 2 if the probability of being in regime 2 is higher than 0.5, and vice versa for regime 1, then there are 13 (11) regime switches over the 45-year sample for σ^2_{CLMX} (σ^2_{FF}), and 14% of the time, y_t is in regime 2. On average, regime 2 lasts about 10–11 months.

FIGURE 2

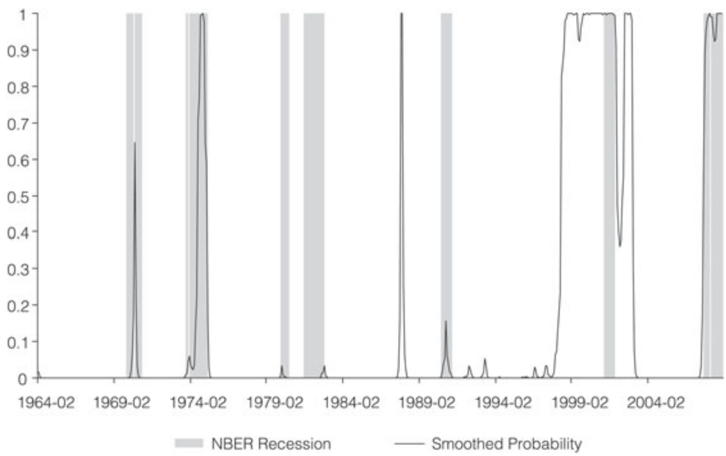
Regime Probabilities for U.S. Idiosyncratic Variances

Figure 2 reports the smoothed probability of being in regime 2 for the United States, using a regime-switching model defined in equations (6) and (7). The model is estimated over sample period 1964–2008. The variables σ^2_{CLMX} and σ^2_{FF} are the aggregate firm-level idiosyncratic variances, as defined in equations (2) and (4), respectively.

Graph A. σ^2_{CLMX}



Graph B. σ^2_{FF}



It is not difficult to give some economic content to the regimes. The shaded areas in Figure 2 are National Bureau of Economic Research (NBER) recessions. Clearly, the high-level idiosyncratic variance regimes mostly coincide with periods of recessions, although recessions are neither necessary nor sufficient to have a high-volatility regime. It is well known that market volatility tends to be high in recessions (see Schwert (1989)). We also find that our high-idiosyncratic-variance regimes coincide with market volatility being about twice as high as in normal regimes. We come back to this finding in a later section. The link between high-idiosyncratic-variance regimes and recessions appears stronger for σ^2_{CLMX} than for σ^2_{FF}.

The results for the shorter sample period of G7 countries are in Panel B of Table 3. The levels of idiosyncratic variances differ across countries, but not dramatically. In the low-variance regime, the means vary between 0.033 (Germany) and 0.072 (Japan). For the high-variance regime, the means vary between 0.121 (Germany) and 0.198 (United States). The persistence parameters are mostly lower in regime 2, but not significantly in Japan, the United Kingdom, and the United States. The results using the FF (1996) model are very similar, and we do not report them to save space. In Figure A1 of the online Appendix at the JFQA Web site, the smoothed probabilities in regime 2 (high-volatility regime) using the CLMX (2001) model are presented. Essentially, the idiosyncratic variances of all 6 countries are mostly in regime 2 around 1997–2002 and back again in the recent crisis period. They are also likely to be in regime 2 around the 1987 crash. Most countries experience additional transitions into the higher-variance regime.

We also consider an extensive set of specification tests for the regime-switching model for all countries, comparing it to a number of simpler models and also to models applied to the logarithm of the variance. The regime-switching models discussed here outperform the alternative models, and most specification tests fail to reject, with the model performing least well for Canada, Germany, and the United Kingdom. The online Appendix at the JFQA Web site describes the specification tests and contains detailed results.

3. Regime Switches and the CLMX Results

These results help us interpret the CLMX (2001) finding of a trend. Essentially, the idiosyncratic variance process does not exhibit a trend, but it exhibits covariance stationary behavior with regime switching. Of course, trend tests, despite having good finite sample properties, may perform much worse in an environment that starts the sample in a low-level regime and ends in a high-level regime.

The CLMX (2001) sample starts during a "normal" idiosyncratic variance regime in the 1960s and ends in 1997. While 1997 is not classified as a high-variance regime, it is in the middle of a period with frequent shifts into the high-variance regime. As Figure 2 shows, the probability that σ^2_{CLMX} is in the high-level, high-variance regime increased briefly around Oct. 1987,[6] and

[6]Schwert (1990) shows how stock market volatility, during and after the crash, was very unusual but returned to normal levels relatively quickly.

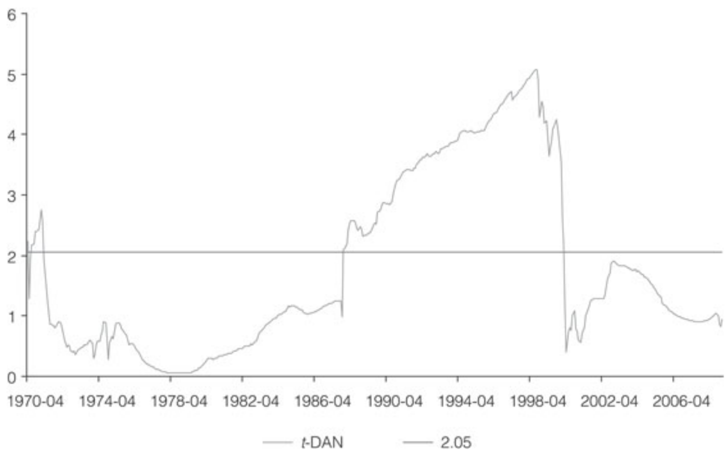
it increases slightly several times in the following years, before increasing substantially but briefly in June and July of 1996. In April 1998, a longer-lasting high-variance regime starts. Conditioning on such a sample selection, a trend test may be more likely to reject than the asymptotic size of the test indicates.

To see the effect more concretely, Figure 3 shows the recursively computed values of the *t*-DAN test, starting the sample in Jan. 1964 but varying the end point between April 1970 and the end of the sample (Dec. 2008). The date April 1970 is not chosen arbitrarily; it is in the 1st high-variance regime selected by the regime-switching model, and it is striking that the trend test would have rejected when dates around that time were chosen as sample end points. The trigger date for finding an upward trend was the crash of Oct. 1987, and an upward trend would have been found all the way until April 2000. Using the less powerful *t*-PS1 test, actually employed by CLMX (2001), this period of "false rejections" would have lasted about 2 years less. This analysis has 2 important implications: i) The level of idiosyncratic volatility has been high over the 1990s; and ii) if the time series starts in a low-volatility period and ends in a high-volatility period, the trend test tends to be significant, even though the time series follows an overall stationary process. The recent data reinforce the regime-switching nature of the idiosyncratic variance process. By 2004, the level of idiosyncratic variance had dropped back to pre-1970 levels, only to rise starkly (and most likely temporarily) in the financial crisis that started in 2008.

FIGURE 3

Recursive Trend Tests for the United States

Figure 3 reports the *t*-DAN test statistics for the United States, which is estimated for a sample period starting in Jan. 1964 and ending between April 1970 (the 1st high-variance regime) and Dec. 2008. The variable σ^2_{CLMX} is the annualized aggregate firm-level idiosyncratic variance computed using daily data, as defined in equation (2). The horizontal line at 2.05 represents the critical value for the trend test (*t*-DAN test) to be significant at 5%.



B. Commonality in Idiosyncratic Volatilities

The fact that idiosyncratic volatility has a large common component across countries deserves further scrutiny. This fact may have implications for the analysis of issues such as international diversification and contagion. Table 4 reports the correlations of the aggregate idiosyncratic variances in the G7 countries with respect to the aggregate U.S. idiosyncratic variance. Across the panels, the correlations with the United States vary between 0.20 (Italy) and 0.81 (United Kingdom). Table 4 also gives these correlations over the 1st and 2nd halves of the sample. The increase in the correlation with the United States over time is remarkable.

TABLE 4

The Common Component in Idiosyncratic Variances across Countries

For each panel, Table 4 reports the correlations of G7 countries' idiosyncratic variance with the U.S. idiosyncratic variance. The different panels use different models to compute idiosyncratic variances. We also report the average correlations in the 2 regimes identified for the United States, using smoothed regime probabilities in Regime 2.

	Correlation with the United States				
	1980–2008	1980–1994	1995–2008	Regime 1	Regime 2
Panel A. Daily CLMX Model (σ^2_{CLMX})					
Canada	80%	63%	86%	53%	82%
France	66%	45%	74%	51%	68%
Germany	77%	49%	79%	37%	57%
Italy	20%	14%	47%	25%	60%
Japan	66%	23%	76%	28%	79%
United Kingdom	81%	73%	81%	57%	70%
United States	100%	100%	100%	100%	100%
Panel B. Daily FF Model (σ^2_{FF})					
Canada	82%	64%	84%	56%	68%
France	73%	34%	83%	41%	76%
Germany	82%	40%	82%	27%	73%
Italy	34%	26%	57%	28%	58%
Japan	69%	18%	77%	24%	77%
United Kingdom	84%	65%	86%	17%	73%
United States	100%	100%	100%	100%	100%

It is possible that the phenomenon is also related to the regime-switching behavior of idiosyncratic variances. In the last 2 columns of Table 4, we report the bivariate correlations with the United States, conditioning on the idiosyncratic variance in the United States being either in the low-level/low-variance or high-level/high-variance regime. Perhaps not surprisingly, we find that the correlations are generally higher in the high-level/high-variance regime.[7]

Because a missing common risk factor is a potential explanation of the commonality in idiosyncratic variances, we verified that our results are robust to using the international factor model with local and global factors mentioned in Section III.B. BHZ (2009) show that the idiosyncratic return correlations of country portfolios, computed using this risk model, are essentially 0. Using the BHZ risk model to compute idiosyncratic variances, the equal-weighted correlation between the idiosyncratic variances of the G7 countries is 57% over the

[7]In a previous version of the article, we estimate a joint regime-switching model over the G7 countries, where the U.S. regime variable functions as the standard regime variable and the regime variables in other countries depend on the U.S. variable. Results are available from the authors. The joint model shows that when the United States is in the high-level/high-variance regime, the other G7 countries are more likely to be in this regime as well.

whole sample; it is 24% over the 1980–1994 period, but 75% over the 1995–2008 period.

V. Determinants of Idiosyncratic Volatility Dynamics

Section IV documents that idiosyncratic variances follow a stationary regime-switching process, characterized by relatively low frequency changes in regime, in which they become temporarily higher, more variable, and more mean reverting. These patterns are apparent in all countries. Moreover, there is a strong common component in idiosyncratic variances across countries that has increased in importance over time. These facts have significant implications for the rapidly growing literature trying to explain the time variation in idiosyncratic volatility.

In this section, we attempt to determine which prevailing explanation best fits the time-series movements of idiosyncratic variances in the United States and other countries. Because we have more data available in the United States, we start there in Section V.A. Table 5 lists all of the independent variables we use in the analysis and the acronyms we assign to them.

We distinguish 3 types of variables: variables affecting changes in the index composition, "corporate" variables correlated with cash flow volatility, and finally, business cycle variables and market-wide volatility, a category new to this literature. The first 3 subsections in Section V.A discuss these 3 groups of variables in more detail. Section V.A.4 runs a statistical horse race to determine which variables best capture the time-series variation in U.S. aggregate idiosyncratic volatility. Section V.A.5 then examines whether the determinants can account for the time-series behavior discovered in Section IV. Specifically, we assess whether accounting for these determinants leads to residuals that are well behaved and no longer exhibit regime-switching behavior. In Panel B of Table 5, we list the variables that are available internationally, which is a subset of the variables available for the United States. Section V.B then conducts an analysis of the determinants of aggregate idiosyncratic volatility in the G7 countries. Given the more limited nature of our data, this analysis should be viewed as a preliminary first look at the data.

A. Analysis of U.S. Data

Most of the literature has focused on U.S. data. Our general approach is to regress the idiosyncratic variance time series on a set of explanatory variables, mostly constructed exactly as in the extant literature. The reported standard errors are heteroskedasticity consistent and always allow for 12 Newey-West (1987) lags.

1. Index Composition and Behavioral Variables

One possible explanation offered for a potential increase in idiosyncratic variances over time is that the composition of the index has changed toward younger, more volatile firms. Fink et al. (2010) show that the age of the typical firm at its initial public offering (IPO) date has fallen dramatically from nearly 40 years old in the early 1960s to less than 5 years old by the late 1990s. Since

TABLE 5
Explanatory Variables

Table 5 lists explanatory variables and their notations for idiosyncratic volatilities. Panel A discusses the variables used in the U.S. study, and Panel B discusses the variables used in the international study.

Variable	Description
Panel A. For the U.S. Analysis	
1. Index Composition/Behavioral Variables	
PYOUNG	The % of market capitalization of firms less than 10 years old since foundation.
PSMALL	The % of market capitalization of firms smaller than 25% of all firms listed.
PLOW	The % of market capitalization of firms with share price lower than $5.
LOWTO	The average volume turnover for firms with share price lower than $5.
DTO	Aggregate dollar volume over aggregate market capitalization.
2. Corporate Variables	
VWROE	The value-weighted average of firm-level return on equity.
VWVROE	The value-weighted average of 12-quarter time-series variance of firm-level return on equity.
CVROE	The cross-sectional variance of firm-level return on equity.
VEPS	The cross-sectional variance of shocks to earnings per share.
INDTO	The average industry turnover.
MABA	The value-weighted average of firm-level market assets over book assets.
VMABA	The value-weighted average of 12-quarter time-series variance of firm-level market assets over book assets.
CVMABA	The cross-sectional variance of firm-level market assets over book assets.
RD	The value-weighted average of firm-level R&D expenditure scaled by sales.
CVRD	The cross-sectional variance of firm-level R&D expenditure scaled by sales.
3. Business Cycle Variables	
DIP	The 1st-order difference in industrial production.
CONFI	The Conference Board's index of consumer confidence.
DEF	The yield spread between BAA and AAA corporate bonds.
TERM	The yield spread between 10- and 1-year government bonds.
MVP	The market variance premium.
MKTTV	The market index realized variance.
DISP	The dispersion of survey forecasts of aggregate corporate profit growth.
Panel B. For the International Analysis	
1. Corporate Variables	
VWROE	The value-weighted average of firm-level return on equity.
VWVROE	The value-weighted average of 12-quarter time-series variance of firm-level return on equity.
CVROE	The cross-sectional variance of firm-level return on equity.
VEPS	The cross-sectional variance of shocks to earnings per share.
INDTO	The average industry turnover.
MABA	The value-weighted average of firm-level market assets over book assets.
VMABA	The value-weighted average of 12-quarter time-series variance of firm-level market assets over book assets.
CVMABA	The cross-sectional variance of firm-level market assets over book assets.
2. Business Cycle Variables	
MKTTV	The market index realized variance.
USMVP	The U.S. market variance premium.
DGDP	The 1st-order difference in each country's annual gross domestic product.
DEF	The yield spread between each country's corporate debt and government bonds.
TERM	The yield spread between each country's long- and short-term government bonds.

younger firms tend to be more volatile, this systematic decline in the average age of IPOs, combined with the increasing number of firms going public over the last 30 years, may have caused a significant increase in idiosyncratic risk. Brown and Kapadia (2007) also ascribe increases in firm-specific risk to new listings by riskier companies (although not necessarily solely related to age), whereas Xu and Malkiel (2003) argue that the increase can be partly attributed to the increasing prominence of the NASDAQ market. We proxy for the age effect using the percentage of market capitalization of firms that are less than 10 years old since foundation (PYOUNG).

A related possibility is that small-capitalization stocks, which tend to have higher idiosyncratic volatilities, have become relatively more important (see Bennett et al. (2003)). It is possible that such a trend is a fundamental response to markets becoming more efficient over time, making it possible for smaller firms to list and be priced efficiently. Bennett et al. explicitly ascribe the trend to institutional investors becoming more actively interested in small-capitalization stocks over time, which could increase trading in these stocks and make these markets more liquid and consequently more efficient, thereby providing higher valuations. Xu and Malkiel (2003) also argue that an increase in institutional ownership is associated with higher idiosyncratic volatility. To measure the effect of the relative importance of small-capitalization firms on idiosyncratic variability, we use the proportion of market capitalization represented by the smallest 25% of all listed firms (PSMALL).

Such an explanation is hard to distinguish from certain "behavioral explanations." Brandt et al. (2010) ascribe episodic shifts in idiosyncratic volatility to speculative behavior. While difficult to measure, they argue that the 1990s episode of high and increasing idiosyncratic volatility is concentrated primarily in firms with low stock prices and limited institutional ownership. Their explanation is hence quite different from and almost contradictory to the arguments made by Bennett et al. (2003) and Xu and Malkiel (2003), but it nonetheless also gives a primary role to small stocks. We use 2 variables to imperfectly measure the "speculative trading" channel: the percentage of market capitalization of firms with a stock price lower than $5 (PLOW), and the average turnover of firms with a stock price lower than $5 (LOWTO).

More generally, retail investors can potentially act as noise traders and increase trading volume and volatility (see also Foucault, Sraer, and Thesmar (2011)). We also use a general measure of turnover, computed as total dollar volume over total market capitalization. A positive effect of turnover on volatility could also reflect increased turnover, indicating a more developed, more efficient stock market, which in turn may be associated with higher idiosyncratic variability; see Jin and Myers (2006).[8]

The 1st column of Table 6 runs a regression of our CLMX (2001) measure of idiosyncratic variances onto the 5 variables described previously. While the fraction of young firms is positively associated with aggregate idiosyncratic variability, the effect is not statistically significant. The proportions of both small stocks and low-priced stocks are negatively associated with aggregate idiosyncratic risk, with the effects significant at the 10% level. The turnover in low-priced stocks is negatively associated with idiosyncratic risk, yet overall turnover is positively associated with idiosyncratic risk. Neither effect is significant. In summary,

[8]Ferreira and Laux (2007) suggest corporate governance policy as a concrete channel promoting informational efficiency and higher idiosyncratic volatility.

the variables that provide some marginal explanatory power have the wrong sign. The R^2 of the regression is 35%.

TABLE 6

What Drives U.S. Idiosyncratic Volatility?

Table 6 presents ordinary least squares (OLS) regressions of aggregate idiosyncratic variances in the United States over 1964–2008, computed using the CLMX (2001) model, on various determinants, labeled on the left. We show 4 regressions, one for each group of variables, and a final one based on a paring-down technique picking significant variables from the previous regressions, discussed in the text. All *p*-values are based on a standard error, using 12 Newey-West (1987) lags. The last column reports the covariance decomposition described in the text.

	I. Behavioral and Compositional		II. Corporate Variables		III. Business Cycle Variables		IV. Significant Variables from I–III		
	Coef.	*p*-Value	Coef.	*p*-Value	Coef.	*p*-Value	Coef.	*p*-Value	Cov Decomp
PYOUNG	0.783	0.154							
PSMALL	−12.380	0.084							
PLOW	−3.903	0.072							
LOWTO	−0.007	0.750							
DTO	0.043	0.216							
VWROE			1.342	0.020					
VWVROE			−5.053	0.380					
CVROE			−0.564	0.311					
VEPS			0.014	0.028					
INDTO			0.006	0.010			0.006	0.003	2%
MABA			0.083	0.013			0.091	0.000	42%
VMABA			−0.006	0.559					
CVMABA			0.001	0.071					
RD			0.251	0.029			0.140	0.034	26%
CVRD			−0.008	0.002			−0.006	0.000	−10%
MVP					1.405	0.001			
MKTTV					0.697	0.000	0.726	0.000	40%
DIP					−0.664	0.053	−0.842	0.008	1%
DEF					−0.025	0.021	0.019	0.001	−2%
TERM					−0.004	0.176			
CONFI					0.0002	0.446			
DISP					−0.604	0.473			
Adj. R^2	35%		56%		57%		80%		

Introducing institutional ownership would help to distinguish the Bennett et al. (2003) explanation from that of Brandt et al. (2010). Unfortunately, the fraction of shares owned by institutional investors is only available from 1981 onward, eliminating 17 years from the sample period. Over this shorter sample period, institutional ownership is univariately positively related with idiosyncratic variability, but the coefficient is insignificantly different from 0. When we run a regression including our 5 other variables, the coefficient on institutional ownership becomes significantly negative, which is not consistent with the Bennett et al. hypothesis. The results are somewhat hard to interpret, because institutional ownership is quite highly correlated with the 5 variables included in our analysis. In fact, these 5 variables explain 77% of the variation in institutional ownership. The fact that institutional ownership shows a clear upward trend also implies that it cannot really be a major factor driving the time-series variation in idiosyncratic variability.

2. Corporate Variables

Another part of the literature argues that the movements in idiosyncratic variances reflect fundamental (idiosyncratic) cash flow variability. The various articles differ in what aspects of fundamental variability they focus on and how they interpret their results. Details about how to construct those variables can be found in the online Appendix at the JFQA Web site.

Building on theoretical work by Pastor and Veronesi (2003), Wei and Zhang (2006) argue that the upward trend in average stock return volatility is fully accounted for by a downward trend in the return on equity, indicating poorer earnings quality, and an upward trend in the volatility of the return on equity. To mimic their results, we create 3 empirical measures: the value-weighted average of the firm-level return on equity (VWROE); the value-weighted firm-level time-series variance of the return on equity computed using the past 12 quarters of data (VWVROE); and the cross-sectional variance of the return on equity at each point in time (CVROE).

Irvine and Pontiff (2009) attribute the increases in idiosyncratic return volatility to an increase in the idiosyncratic volatility of fundamental cash flows. We mimic their procedure to construct idiosyncratic cash flow volatility by first using a pooled AR(3) model for firms' earnings per share to create earnings innovations. Then, we define the cross-sectional variance of these innovations (VEPS). Both Irvine and Pontiff (2009) and Gaspar and Massa (2006) ascribe increases in fundamental idiosyncratic variability to more intense economy-wide product competition. To proxy for "competition," we use a measure of industry turnover computed by first taking the percentage of market capitalization of firms entering and exiting the same industry at the industry level each month and then assigning this percentage to individual firms in the various industries. We use the value-weighted average of firm-level industry turnover (INDTO).

Cao et al. (2008) show that both the level and variance of corporate growth options are significantly related to idiosyncratic volatility. A bigger menu of projects presumably makes it easier for managers to increase idiosyncratic risk, which in turn increases equity value. We therefore use 2 variables: the value-weighted firm-level market value of assets over the book value of assets (MABA), as a proxy for growth options; and the value-weighted variance of the firm level's MABA, VMABA, computed using data over the past 3 years. Finally, following the spirit of CVROE, we also compute the cross-sectional variance of MABA at each point in time (CVMABA).

Finally, Chun et al. (2008) argue that a more intensive use of information technology and faster production growth created a wave of creative destruction, leading to higher idiosyncratic volatility. Chun et al. and Comin and Philippon (2006) therefore link idiosyncratic volatility to research intensity and spending. Following Comin and Mulani (2006), for each firm, we first compute its fiscal year R&D expenditure divided by the quarter's total revenue. We then construct 2 R&D-related variables: the value-weighted average of the scaled R&D expenditure (RD), and the cross-sectional variance of firm-level scaled R&D expenditure (CVRD).

The 2nd column of Table 6 reports results for a regression of CLMX (2001) idiosyncratic variance onto the 10 corporate variables described previously. The total adjusted R^2 is 56%, so these variables explain more of the time-series variation in aggregate idiosyncratic variances than the index variables did. We expect positive coefficients for all of these variables. Of course, many of them are highly correlated, causing some multicollinearity. Of the return-on-equity variables, only the level is significant. Both earnings per share variability and industry turnover are significant. In addition, the growth option variable, MABA, and both research spending variables are significant, but the volatility of R&D has a surprisingly negative effect on idiosyncratic volatility.

3. Business Cycles and Market-Wide Volatility

This section examines a number of potential determinants that the extant literature has not yet considered, namely business cycle variables and aggregate market volatility. Business cycle variables could affect aggregate idiosyncratic variability through a variety of channels. A 1st channel is simply that recessions are associated with increases in macroeconomic uncertainty, which in turn drives up both systematic and idiosyncratic risk. In principle, the corporate variables we have used so far should pick up this effect, but it is possible that they do not, or do so imperfectly.

Another possibility is that there is discount rate volatility that somehow was missed in the systematic factor measurement and that causes idiosyncratic volatility fluctuations that may even be correlated across countries. This could be a missing risk factor, or the functional form of systematic risk measurement could be incorrect (e.g., the true factor model is really nonlinear). For example, if aggregate stock return predictability reflects variation in discount rates, the evidence in Henkel, Martin, and Nardari (2011) suggests that it is concentrated in certain periods, particularly recessions.

We use 7 variables to analyze business cycle effects. The 1st variable is the variance premium, MVP, which is the difference between the square of the VIX index, an option-based measure of the expected volatility in the stock market, and the actual physical expected variance of stock returns (see also Carr and Wu (2009)). We take this measure from Baele, Bekaert, and Inghelbrecht (2010), who show that it is an important determinant of stock market volatility. Bollerslev, Tauchen, and Zhou (2009) show that MVP is an important predictor of stock returns, and hence constitutes an aggregate discount rate factor. Bali and Hovakimian (2009) find a significant link between variance risk premiums and the cross section of expected stock returns. Theoretically, a variance premium can arise through stochastic risk aversion and nonlinearities in fundamentals (see Bekaert and Engstrom (2010), Drechsler and Yaron (2011)) or through Knightian uncertainty (see Drechsler (2009)). Next, the regime-switching model indicated an important link between market volatility (MKTTV) and idiosyncratic volatility. We use this variable as the 2nd business cycle variable in the regression. Note that idiosyncratic and aggregate volatility need not be automatically correlated, as long as the index is sufficiently well diversified.[9] We also include the growth rate in the industrial production variable,

[9]We check the source of correlations between aggregate total and aggregate idiosyncratic variance for the G7 countries, by splitting the aggregate total variance into 2 components, a variance component (which should converge to 0 in well-diversified indices as the number of firms gets large) and a systematic component (which only depends on covariances). We find that the bulk of the correlation

DIP, computed as industrial production minus its own 2-year moving average. We include 2 market-driven indicators of business cycle conditions, the term spread (TERM) and the default spread (DEF). Default spreads have long been used to predict economic activity (e.g., Harvey (1988)); and more recently, the links between default spreads and future economic activity have been explored, by Mueller (2009) and Gilchrist, Yankov, and Zakrajsek (2009). We also use a survey measure of consumer confidence (CONFI), from the Conference Board.

The last business cycle variable, DISP, is a measure of uncertainty about corporate profits. The Survey of Professional Forecasters provides forecasts of nominal corporate profits for the previous quarter, the current quarter, and the next 4 quarters. We calculate the forecasted growth rate for each forecaster by dividing the 4th quarter forecast by the current quarter forecast. We then compute the standard deviation across the different growth forecasts, obtaining a quarterly time series of the dispersion of the survey forecasts.[10] This time series may be correlated with true macroeconomic uncertainty and the variability of cash flows, or it may reflect different beliefs of different forecasters. In Anderson et al. (2009) these forecasts are used to construct a measure of Knightian uncertainty that should be a key factor driving the aggregate market risk premium.

The 7 business cycle variables explain 57% of the total variation in aggregate idiosyncratic volatility. Thus, business cycle variables are slightly more important than the corporate variables, and much more important than compositional variables. The significant variables include the variance premium, the market variance, industrial production growth (albeit marginally), and the default spread. However, the sign of the default spread is surprisingly negative.

4. What Drives Idiosyncratic Variability?

We now run a horse race between the various determinants. Unfortunately, a regression model using all variables together would be plagued by extreme multicollinearity and would include many useless and insignificant variables. Our 1st methodology to pare down the regression model simply uses all of the variables that are significant at the 10% level from the previous subgroup regressions. This regression has 13 regressors. We then eliminate regression variables yielding coefficients that are not significant at the 10% level and rerun the regression. The result is reported in part IV of Table 6. We find that 7 independent variables explain 80% of the variation in the aggregate idiosyncratic variance. No compositional variables survive this procedure, but 4 corporate variables and 3 business cycle variables survive. The cash flow variables are industry turnover and the growth option variable, the variables stressed by, respectively, Irvine and Pontiff (2009) and Cao et al. (2008); and the R&D spending variables stressed by

is accounted for by the systematic component, with the lowest proportions being 88% for Germany and Italy.

[10]There are a minimum of 9 forecasters and a maximum of 76 forecasters. We also experiment with the methodology in Anderson, Ghysels, and Juergens (2009) to downweight the extreme forecasts, which generated highly analogous results. To make the time series monthly, we take the weighted average of the previous and current quarter observations (e.g., for January, ⅔ the December observation and ⅓ the March observation; for February, ⅓ the December observation and ⅔ the March observation). Using the past quarterly observation yields analogous results.

Chun et al. (2008) and Comin and Philippon (2006). The business cycle variables are the total market variance, the growth in industrial production, and the default spread, with the default spread now having the correct sign, indicating higher idiosyncratic variability when credit conditions are bad.

To gauge the relative importance of the various variables in explaining the time variation in idiosyncratic variances, the last column reports a simple covariance decomposition of the fitted value of the regression. Let independent variable x_{it} have a regression coefficient of $\hat{b_i}$, and denote the fitted value of the regression by $\hat{y_t}$. Then, for each variable, we report the sample analogue of the ratio, $\mathrm{cov}(\hat{b_i} x_{it}, \hat{y_t})/\mathrm{var}(\hat{y_t})$. These ratios add up to 1 by construction. Clearly, the most important variables are the growth option variable, MABA, and market-wide volatility. R&D expenditure also explains a nonnegligible part of the variation of aggregate idiosyncratic variability.

When applied to the idiosyncratic variances computed using the FF (1996) model, the final "subgroup" model is similar, but it includes 4 more variables: VWROE, VEPS, CVMABA, and MVP. Qualitatively, the results for the FF model are largely similar, with MABA, MKTTV, and RD accounting for most of the variation in idiosyncratic volatility. We do not report these results to save space.

Research on model reduction techniques by Hendry and Krolzig (2001), among many others, suggests that starting from the most general model yields better-specified parsimonious models. We therefore also apply a model reduction technique close in spirit to the PcGets ("general-to-specific") system, proposed and commercialized by Hendry and his associates. We refer to this approach as the Hendry approach or Hendry model. The model starts from a regression using all regressors, eliminating insignificant variables, while making sure that the eliminated variables are not jointly significant. We refer to the online Appendix at the JFQA Web site for more details.

The alternative model selects a less parsimonious model than the model resulting from the subgroup regressions, but the qualitative results are largely the same. The few additional variables retained increase the R^2 to 86%, yet, the key variables of before, the growth option variable and market volatility, now also are the most important variables. Of the additional variables, very few are both statistically and economically significant. The main exception is the variance premium, which is highly statistically significant and contributes 10% to the predicted variance.

Our results shed new light on the debate regarding the determinants of the time variation in U.S. aggregate idiosyncratic volatility. We find that compositional and behavioral variables are relatively unimportant, failing to survive in our 1st multivariate model, and barely accounting for 10% of the total in the 2nd (unreported) model. Corporate variables account for 55%–60% of the explained variation, leaving a significant part of the variation to business cycle variables. The addition of these latter variables, not examined before, helps increase the explained variation to over 80%.

The Role of Business Cycle Variables. Why are these business cycle variables so important? There are 2 main possibilities. First, the business cycle variables may reflect cash flow variability not accounted for by our corporate variables. Second, they may reflect discount rate variation not accounted for in our factor model. Let's start with the cash flow channel. When regressing the aggregate idiosyncratic variance time series onto an NBER recession indicator, we obtain a highly significant positive coefficient. It is possible that true cash flow variability is countercyclical, but that measurement error in our variables implies that business cycle variables capture this countercyclicality better. The evidence seems largely inconsistent with this interpretation, as most of our cash flow variables either show no significant relation with the NBER recession dummy variable or a significantly negative relation (e.g., all return-on-equity variables).

In a more direct analysis, we orthogonalize the corporate variables with respect to all of our business cycle variables and repeat the regression of Table 6, regressing idiosyncratic variability on "pure" cash flow variables. The R^2 drops from 56% to 25%, but the coefficients on some of the most important variables, including MABA, hardly change. The coefficients on the return-on-equity variables and VEPS do become significantly smaller in absolute magnitude. When we reverse the exercise, the R^2 of the business cycle variables is also cut in half, but importantly, the coefficient on the total market variance hardly changes. These results (available from the authors) suggest that some of the explanatory power of the business cycle variables may run through cash flow variability and that it is related to the corporate variables we use, but a significant part is totally independent of it.

One obvious candidate for the independent explanatory power of business cycle variables is the presence of discount rate variation not accounted for in our factor model. To assess the validity of this interpretation, we replace our business cycle variables with a risk premium proxy extracted from these variables. Specifically, we run a regression of market excess returns at time $t+1$ onto the 7 variables at time t. The fitted value of this regression is an estimate of the risk premium on the market, which naturally varies through time. We then repeat our explanatory analysis of aggregate idiosyncratic variance, but we replace the business cycle variables by this risk premium proxy. Consequently, in this regression the business cycle variables only enter to the extent that they can predict market excess returns. Despite using only one business cycle variable, the explanatory power of the regression, pared down using the Hendry approach, only drops from 86% to 69%. The risk premium variable is highly significant, and it accounts for 26% of the explained variation. This suggests that more than half of the explanatory power of the business cycle variables is related to these variables capturing discount rate variation not accounted for by standard risk models. The current literature on return predictability suggests that most of the predictable variation is concentrated in recession periods (e.g., Henkel et al. (2011)), and it is this time variation in discount rates that standard models of risk may not quite capture, leading to common risk factors contaminating estimates of idiosyncratic variance.

Our analysis is related to but more comprehensive than the recent work by Zhang (2010), who also runs a horse race between explanatory variables for aggregate U.S. idiosyncratic variability, but with a more limited set of variables. He uses the return on equity and MABA, but he uses one variable that we do not use: institutional ownership (see our discussion above and note that this variable is highly correlated with our "DTO" variable). Zhang finds the "fundamentals" variables to be the more robust determinants of idiosyncratic variability. He also notes that there is a trend upward in idiosyncratic volatility from 1980 until 2000, and a trend downward after 2000. In his empirical analysis, he allows for different coefficients in the 2 periods and finds some evidence in favor of coefficient changes. We examine the possibility of shifts in the relationship between idiosyncratic variance and its determinants in more detail in the next subsection.

5. Explaining Regime Switches and Regression Fit

Specification tests, applied to the residuals of the regression models, reveal that they do not fully fit the time-series dynamics of the aggregate idiosyncratic variances. To conserve space, all results referred to in this section are reported in a detailed table in the online Appendix at the JFQA Web site.

To explore this further, we estimate a regime-switching model for the regression residuals, using exactly the same specification as in Section III. However, because the residuals ought to have mean 0, we identify the 2 regimes by their variability rather than their mean. The mean level of residuals is not significantly different across regimes, but the regression residuals exhibit significant autocorrelation. There is, of course, still some regime-switching behavior left in the variance, and the variances in the 2 regimes are significantly different.

Finally, we investigate whether the coefficients in the regression models vary with the regime. We therefore let each coefficient (including the intercept) in the 2 final models depend on a regime 2 dummy variable, which takes the value of 1 if the smoothed probability of being in regime 2 is higher than 0.5, and 0 otherwise. Across the 2 regressions, roughly half of the dummy coefficients are significantly different from 0. When significant, the coefficients mostly become larger in magnitude in regime 2. This is true for the 2 most important determinants, namely MABA and aggregate market volatility. Overall, allowing for this nonlinearity improves the R^2 in both models by about 10%, making it nearly perfect. It is conceivable that this nonlinear dependence reflects a "crisis" effect, where in turbulent times all volatility measures increase dramatically. We further reflect on this in the conclusions.

B. International Analysis

As Panel B of Table 5 shows, our international data are much more limited than the U.S. data. First, we do not construct compositional variables. DataStream gradually increased its coverage of international firms over time, which makes the time series of compositional variables difficult to interpret. Fortunately, the U.S. analysis suggests that these variables are far less important than corporate and business cycle variables. Moreover, many of our variables are only available at the annual frequency. With such limited data, the best we can do is run a panel analysis. We create country-specific variables for the fundamentals and the business cycle variables, except for the variance premium, where we simply use the U.S. values as an indicator of global risk appetite. We consider 2 models for the international analysis.

In a 1st model, we simply take the same model as we applied to the United States, using country-specific explanatory variables, but pooling the coefficients across the G7 countries. The panel model uses country dummy variables and clusters the standard errors on year, so that correlations between countries are taken into account. The assumption of pooled coefficients is restrictive, but because the sample only starts in 1983, we have only 26 time-series observations. Thus, imposing such restrictions is necessary. Table 7 reports the results from the subgroup regressions; an online Appendix at the JFQA Web site contains the Hendry model results. For the subgroup analysis, we end up with 7 significant variables, INDTO, and the 3 MABA variables, among the fundamentals; and market volatility, the term spread, and the U.S. variance premium, among the business cycle variables. Market-wide variability is now the most important determinant, accounting for 31% of the predictable variation. The business cycle variables jointly account for about 55% of the predictable variation, the corporate variables for about 45%, with MABA still being the most important cash flow variable. This decomposition reverses the relative importance of the corporate versus business cycle variables relative to the U.S. results, but it is at the same time rather similar. A surprising result is the importance of the U.S. market variance premium as a determinant of time-series movements in international idiosyncratic variances. Note that this decomposition excludes the effect of the country dummy variables. The country dummy variables by themselves account for about 14% of the 69% R^2 of the model.

TABLE 7

Idiosyncratic Volatility across G7 Countries

Table 7 presents OLS regressions of aggregate idiosyncratic variances in the G7 countries over 1983–2008, computed using the CLMX (2001) model, on various determinants, labeled on the left. The annual data time series for idiosyncratic variances are averaged over monthly observations in the year. More details about the data are in the Appendix. We show 3 regressions, one for each group of variables, and a final one based on a paring-down technique picking significant variables from the previous regressions, discussed in the text. All regressions include country dummy variables. All p-values are based on a standard error using 12 Newey-West (1987) lags, and they are adjusted by clustering on years. All regressions include country dummy variables. The last column reports the covariance decomposition described in the text.

	I. Corporate Variables		II. Business Cycle Variables		III. Significant Variables		
	Coef.	p-Value	Coef.	p-Value	Coef.	p-Value	Cov Decomp
VWROE	−0.129	0.299					
VWVROE	0.129	0.918					
CVROE	0.232	0.234					
VEPS	0.042	0.153					
INDTO	0.133	0.007			0.062	0.033	0.3%
MABA	0.024	0.000			0.022	0.000	25.2%
VMABA	0.004	0.000			0.002	0.036	7.2%
CVMABA	0.003	0.088			0.003	0.001	11.3%
MKTTV			0.455	0.000	0.459	0.000	31.1%
DGDP			−0.035	0.225			
DEF			−0.001	0.702			
TERM			−0.004	0.094	−0.002	0.061	0.4%
USMVP			1.180	0.001	0.916	0.002	24.4%
Adj. R^2	41%		56%		69%		
Adj. R^2 (w/o country dummies)	27%		41%		55%		

When we consider the Hendry approach, the results are largely similar. In the decomposition, it is again MABA, the growth option proxy, consistent with the U.S. results, that is by far the most important corporate variable. Among the business cycle variables, the decomposition again reveals that about 30% of the total explained variation is accounted for by the total market variance, and about 20% by the variance premium. The split between corporate variables and business cycle variables is now about 50–50.

One interesting question to be addressed is how much of the strong international commonality in idiosyncratic variances these models can explain. Table 8 provides the answer. We first report the correlation for the original raw data and then for the residuals of the 2 regression models we just discussed. With few exceptions, the correlations drop rather substantially, often becoming negative. While the correlations do not seem negligible in many cases, they are statistically much closer to 0 than the original, raw correlations. Of the 21 correlations, 16 were originally statistically and significantly different from 0. Using regression residuals, only 9 (6) significant correlations remain when we use the subgroup (Hendry) model.[11]

TABLE 8

Correlations for the Annual Idiosyncratic Volatility Data

Table 8 reports correlations for annual data of aggregate idiosyncratic variance time series. Panel A reports correlation coefficients for the original annual idiosyncratic variance data. Panels B and C report correlation coefficients for the residuals from the final regression in the subgroup model and Hendry model, respectively. The bold font indicates that the correlation is significant at the 5% level using a Pearson test.

	Canada	France	Germany	Italy	Japan	United Kingdom
Panel A. Correlation for Original Annual Idiosyncratic Variances						
France	**77%**					
Germany	**85%**	**67%**				
Italy	14%	**55%**	2%			
Japan	**75%**	**78%**	**74%**	29%		
United Kingdom	**87%**	**74%**	**90%**	19%	**86%**	
United States	**92%**	**81%**	**82%**	21%	**84%**	**89%**
Panel B. Correlation for Regression Residuals from the Subgroup Model						
France	**65%**					
Germany	35%	−26%				
Italy	20%	**71%**	−**52%**			
Japan	**49%**	**42%**	**44%**	16%		
United Kingdom	**67%**	32%	**53%**	−8%	**76%**	
United States	34%	28%	27%	26%	16%	15%
Panel C. Correlation for Regression Residuals from the Hendry Model						
France	38%					
Germany	**52%**	−22%				
Italy	3%	**66%**	−37%			
Japan	34%	37%	**47%**	22%		
United Kingdom	**71%**	33%	**54%**	2%	**63%**	
United States	30%	27%	37%	20%	13%	12%

The 2nd model we consider recognizes the strong correlation between idiosyncratic volatilities across countries, and it investigates whether country-

[11]It is difficult to dismiss the possibility of a missing common factor. In that scenario, country residuals should still show significant correlations. In the CLMX (2001) model, these residuals are by construction 0. When we use the FF (1996) model, the average correlation among the residuals is 23%, but when we employ the international BHZ (2009) model, the average correlation becomes 12%. This indicates that the domestic risk models do omit important systematic variation.

specific determinants of idiosyncratic variability are still important once we control for a "U.S. factor" in idiosyncratic variances. The model is

$$\sigma^2_{i,t} \quad = \quad \beta_i \sigma^2_{\mathrm{US},t} + \gamma' (z_{i,t} - z_{\mathrm{US},t}) + e_{i,t}.$$

That is, we allot each country a beta relative to the United States and then see if differences in the usual explanatory variables, $z_{i,t} - z_{\mathrm{US},t}$, further explain time variation in the idiosyncratic variance. The results are reported in the online Appendix at the JFQA Web site. We find that all betas with respect to the United States' variance are highly statistically significant, and economically they account for most of the explained variance. While most of the explanatory variables surviving remain similar to what we found in the 1st model,[12] their explanatory power has become very limited, compared to the 1st model. The contribution to the explained variance only remains economically significant for the variance premium. In other words, the joint comovement with the United States captures most of the explained variance, and the economic importance of market volatility in explaining idiosyncratic volatility seems to be primarily U.S. driven. Of course, such a conclusion might change if we had better international data, but it again confirms the importance of the common component in idiosyncratic variances.

VI. Conclusions

This article first documents a simple fact: There is no upward trend in idiosyncratic volatility anywhere in the developed world. Instead, we find that idiosyncratic volatility is well described by a stationary regime-switching, mean-reverting process with occasional shifts to a higher-mean, higher-variance regime. While a substantial literature has attempted to explain trending behavior in idiosyncratic volatilities, because of the findings of a trend in CLMX (2001), such explanations should be redirected to explain regime-switching behavior.

Such explanations include the increasing propensity of firms to issue public equity at an earlier stage in their life cycle, and more volatile cash flows/fundamentals. We conduct a comprehensive horse race using the variables proposed in the literature regarding index composition and cash flow variability, but we add business cycle variables and market-wide variability to the mix. We find that the cash flow variables (especially a growth option proxy, market-to-book value of assets), various business cycle variables, and market-wide volatility are the most important determinants of the time variation in U.S. aggregate idiosyncratic variability. However, a linear regression model does not eliminate the regime-switching characteristics of the idiosyncratic variability, and we find a significant regime dependence of the regression coefficients.

One potential explanation is that in times of crisis, all risk variables increase disproportionately in ways that are hard to capture by simple linear models. It may be that a correlated and therefore undiversifiable tail risk exposure of firms that is present in deep crises such as the recent financial crisis may be driving the common movement in aggregate idiosyncratic volatility across countries.

[12]This would not be surprising if the betas were all close to 1, as then the 2nd model is implied by the 1st model we estimated.

To provide some initial exploration, we define a crisis or bear market to be a market return 2 standard deviations below the mean for the U.S. sample series over 1980–2008 (to be consistent with our international sample). Aggregate idiosyncratic volatility is 22.2% in crises, much higher than the sample average of 9.3%, just as aggregate market volatility is also considerably higher in bear markets. Using the U.S.-based definition of a crisis to investigate idiosyncratic variance in other countries, we find that idiosyncratic variance is uniformly higher in these crisis periods than in normal periods, typically by a large margin. On average, the idiosyncratic variance over the G7 countries is 16.4% in crises, much higher than the sample average of 7.5%. Note that these U.S. crises also represent local crises, as the mean return is -12.1% over the G7 countries. In a nice analogy with findings regarding international return correlations (see Longin and Solnik (2001), Ang and Bekaert (2002)), idiosyncratic variances are also much more highly correlated across countries during crises. In fact, the difference between normal and bear market correlations is much larger for idiosyncratic volatilities than it is for actual returns. For actual returns, the G7 correlation is on average 52%, and the bear market correlation is 60.9%; for idiosyncratic volatilities, the average correlation across G7 countries is 56%, but the bear market correlation is 80.3%. While extreme movements in discount rates may be part of the story here, a full explanation of this phenomenon is beyond the scope of the article.[13]

Consequently, the crisis interpretation may also partially explain another new finding in this article: Idiosyncratic variability is highly correlated across countries, and this correlation has increased over time. Preliminary work with a linear model for annual data also detected some significant explanatory power for corporate variables, the business cycle, and market-wide volatility, and the model did succeed in significantly reducing the correlation across countries, suggesting that part of the comovement may have a fundamental explanation.

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