Is There a Trend in Idiosyncratic Volatility?

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Abstract

We examine idiosyncratic volatility in 23 developed equity markets, measured using various alternative methodologies, and find no evidence that it is trending upward. Instead, idiosyncratic volatility appears to be well described by a stationary autoregressive process that occasionally switches into a higher-variance regime that has relatively short duration. We find evidence of a component in idiosyncratic volatility that is highly correlated across countries. Our results have important implications for studies of portfolio diversification and return volatilities.

JEL Classification: C52, G11, G12.

Keywords: idiosyncratic volatility, trend test, regime switching model, diversification, volatility dynamics.

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1. Introduction

Much recent research in finance has focused on idiosyncratic volatility. A rapidly growing literature considers the pricing of idiosyncratic risk[2]. The level of idiosyncratic volatility is also an important input in the study of diversification benefits. Here, a growing literature attempts to explain the increase in idiosyncratic volatility first documented by Campbell, Lettau, Malkiel and Xu (2001), CLMX henceforth. Aktas, de Bodt and Cousin (2007) and Kothari and Warner (2004) study how this increase affects the use of one of the most powerful empirical techniques in finance, the event study. Comin and Mulani (2006) examine how and why trends in the macro-economy seem to diverge from the "micro-trend". However, in this article, we show that there is no trend in idiosyncratic volatility, not in the U.S. and not in other developed countries.

CLMX's results appear quite robust to alternative methodologies to compute idiosyncratic volatility and to the use of some alternative trend tests. Nevertheless, we show that the implications of the tests are quite sensitive to the sample period used: ending the sample somewhere around 1997 is key to finding a trend! Of course, when a time series exhibits time trends over part of its sample path, it is likely characterized by near non-stationary-behavior. We examine two types of time series models that potentially may capture such behavior: a simple autoregressive model with breaks in the drift and a regime-switching model. We show that average idiosyncratic volatility is better described by a relatively stable autoregressive process that occasionally switches into a higher-variance regime that has relatively low duration. We also show that idiosyncratic volatility has relatively high correlation across countries.

The rest of the article is organized as follows. Section 2 describes the data. Section 3 contains the main results for trend tests. Section 4 considers structural break tests, and section 5 considers regime-switching models. Section 6 summarizes some robustness checks, and section 7 further examines the commonality in idiosyncratic volatility. In the conclusions, we also discuss the implication of our findings for the various studies attempting to explain the CLMX findings. There we discuss the implications of our findings for the explanation offered by Brand, Brav, Graham and Kumar (2008), which reports a similar finding that the apparent trend in U.S. idiosyncratic volatility is not robust to additional data.

[2] See Ang, Hodrick, Xing and Zhang (2006, 2008) and the references therein. We do not address expected return issues here.

2. Data

2.1 The U.S. Sample

In order to replicate and extend the CLMX study, we first collect daily U.S. stock returns between 1964 and 2005 from CRSP. We calculate excess returns by subtracting the U.S. T-bill rate, which is obtained from the CRSP riskfree 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 for day t is:

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

Here, $IND_{J,t}$ is the return on a corresponding industry portfolio J to which firm j belongs[3]. The firm's idiosyncratic variance is then the variance of the residual $u_{j,t}^{CLMX}$, computed with one month of daily return data. Value-weighting the firm-level idiosyncratic variances produces the CLMX idiosyncratic variance. That is,

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

where day t belongs to month m. Here the weight $w_{j,m}$ is computed using firm j's last month market capitalization, and N is the number of firms. Implicitly, CLMX assume that systematic risks are captured by the industry return and that firms have unit betas with respect to the industry to which they belong[4].

Bekaert, Hodrick and Zhang (2008), BHZ henceforth, show that the unit beta restrictions in the CLMX approach severely limit the factor model's ability to match stock return comovements. We therefore also consider the Fama-French (1996) model, which fits stock return comovements better:

$$R_{j,t} = b_{0,j,m} + b_{1,j,m}MKT_t + b_{2,j,m}SMB_t + b_{3,j,m}HML_t + u_{j,t}^{FF}, \tag{3}$$

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 Fama-French factors are obtained from Kenneth French's website. To allow the betas to vary through time, we re-estimate

[3] In this article, we always require the industry portfolios to have a minimum of 5 firms.

[4] CLMX also assume that the industry returns have unit betas with respect to the market portfolio, which then leads to a decomposition of total risk into market, industry and idiosyncratic risk, which requires no beta estimation.

the model every month with daily data. The idiosyncratic variance for asset j is the variance of the residual of the regression, that is, $\sigma^2(u_{j,t}^{FF})$. We again compute the idiosyncratic variance at the country level using value weighting:

$$\sigma_{FF,m}^2 = \sum_{j=1}^{N} w_{j,m}\sigma^2(u_{j,t}^{FF}), \qquad (4)$$

where day t belongs to month m.

2.2 The Developed Countries Sample

We study daily excess returns for individual firms from 23 developed markets, including the U.S. The sample runs from 1980 to 2005. All returns are U.S. dollar denominated. Our selection of developed countries matches the countries currently in the Morgan Stanley Developed Country Index. Data for the U.S. are from Compustat and CRSP; data for the other countries are from DataStream. We estimate domestic models, such as the CLMX model in equation (1) and the FF model in equation (3), for each developed country, where the industry, size and value factors are constructed in the corresponding national market.

The advantage of using the domestic models is that we do not need to construct global risk factors across different markets, which would imply non-synchronous trading issues for daily data. However, there is a concern whether the domestic models can adequately capture the global risk exposure of firm returns. We therefore conduct a robustness check in Section 6 using models which explicitly allow both global and local factors. To reduce the magnitude of the non-synchronous trading problem, we use weekly data in Section 6.

2.3 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 504 monthly observations. The mean of the annualized CLMX idiosyncratic variance is 7.91% with a standard deviation of 5.56%, and the mean of the annualized Fama-French idiosyncratic variance is 6.91% with a standard deviation of 4.65%. Hence, the Fama-French risk adjustments lower both the mean of the idiosyncratic variance relative to the CLMX-idiosyncratic variance and the volatility of the time-series of idiosyncratic variances. The correlation between the two idiosyncratic variances is nonetheless 98%.

Panel B of Table 1 reports idiosyncratic variance statistics computed for 23 countries, using the CLMX model on the left and the FF model on the right. Interestingly, the U.S. always has the highest idiosyncratic variance, independent of the risk model. Unlike the U.S., the idiosyncratic variances generated by the CLMX model are sometimes lower than those produced by the FF model.

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 various periods of temporarily higher volatility in the U.S., including 1971, 1974, 1987 and a longer-lasting increase in 1995, which seems to reverse after 2001. In other countries, the most obvious pattern is that the variances increase after 1995, but they decrease after 2001. 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.

3. Trend Tests

The main result in CLMX is that the average idiosyncratic variance in the U.S. exhibits a positive time trend. To formally test for trends, we use Vogelsang's (1998) simple linear time trend test as do CLMX. The benchmark model is

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

where y_t is the variable of interest, and t is a linear time trend. We use the PS1 test in Vogelsang (1998) to test $b_1 = 0$. The test statistic is robust to I(0) and I(1) error terms. In all of the ensuing tables, we report the trend coefficient, the t-statistic and the 5% critical value derived in Vogelsang (1998) (for a two-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" subscript, as the test uses a "Daniell kernel" to non-parametrically estimate the error variance needed in the test. In fact, tests based on this kernel maximize power among a wide range of kernels. Vogelsang generously provided us with the code for both the t-ps1 and t-dan tests.

Table 2 reports the trend test results for the U.S.[5] Panel A presents results using the same sample as in CLMX, which is 1964-1997. Panel B presents results using the full sample, 1964-2005. In each panel, we consider pre-whitened time-series using an AR(1)-model for the t-dan test because Bunzel and Vogelsang (2005) show that pre-whitening improves the finite sample properties of the test. For the sample period 1964-1997, we find a significant trend in the idiosyncratic variance, no matter whether we use the FF or CLMX model. In Panel B, we include 8 more years of data, and the idiosyncratic variance does not display a significant trend for whatever case we consider. Clearly, the trend documented in CLMX is time-period dependent. Since the pre-whitened and non-pre-whitened results are very similar, we only report the pre-whitened results for the t-dan test in later sections.

Panel A of Table 3 reports trend test results for the 23 developed countries, country by country. We fail to detect a significant positive time trend for all countries, except Denmark, either using the t-dan test or the t-ps1 test, and whatever risk model is used to compute the idiosyncratic variances. Denmark exhibits a significant positive test result only for the t-ps1 test and the CLMX model. Italy, Finland, Greece, and Portugal have negative trend coefficients which are significantly different from zero only for Portugal. The last few lines aggregate the idiosyncratic variances over various important country groups: the G7, the three large regions (North America, Europe and Asia) and the core European Union countries, comprising the original European Community countries, that is, France, Italy, Belgium, the Netherlands and Germany. Not surprisingly, we do not detect trends for any of these aggregated series.

It is important to understand that the lack of significance is not due to a lack of power. Apart from using a quite powerful test, we also note that many of the trend coefficients are actually negative rather than positive. This by itself makes it of little use to apply a joint test across countries to increase power. Nevertheless, we use the tests developed in Vogelsang and Franses (2005) to test for equality of the trends and the null of them jointly being zero for various country groups (G7, North America, Far East and Core Europe). Panel B of Table 3 presents the results. There is one case in which we reject a zero trend for both the CLMX and FF models: the case where

[5] We examined the unit root hypothesis using the Dickey and Fuller (1979) and Phillips and Perron (1988) tests, and invariably rejected the null of a unit root. This is consistent with the evidence in Guo and Savakis (2007).

idiosyncratic variances are obtained from daily data for the Core Europe group. Unfortunately, for this set of countries, we also reject that the trends are equal across countries, so that a joint test is not super-meaningful.

4. A Model with Structural Breaks

We have now rejected the presence of a gradual and permanent increase in idiosyncratic variances, as captured by a time trend. There are a variety of models that may give the illusion of a time trend over short or even relatively long time series samples. A prime candidate is a model with structural breaks. In fact, Figure 1 suggests that the time-series of idiosyncratic variances is highly volatile with a peak around 1997-2000, which could represent a (temporary) structural break.

To test for breaks, we adopt the methodology in Bai and Perron (1998). We simply test for breaks in the mean, given that the methodology allows for quite general dynamics of the residuals. Bai and Perron's methodology identifies the number of breaks and their dates. The program is obtained from Perron's website. We use the BIC (Bayesian Information Criterion) to choose the number of breaks, and we set the maximum number of breaks to 5, the maximum for which critical values are provided in Bai and Perron (1998). Finding many breaks would strongly suggest that a parameter-break model is not an adequate representation of the data. We present the results in Table 4, in which we report the number of breaks and the break dates.

Panel A reports structural breaks estimated for U.S. daily data over 1964-2005 using both the CLMX model and the FF model. The results for both cases show that there exist at least 5 significant breaks. The first break occurs during 1966 for both models; but the second break is quite different across the two models. However, the last three structural breaks are identical for both the FF and CLMX models. The third break occurs in 1999, when the variance level becomes very high. The fourth break occurs in 2001, when the variance level declines and becomes more similar to the level before 1999. The fifth break occurs in 2003, when the variance level drops further.

Panel B reports structural breaks for the G7 countries over 1980-2005, using both the CLMX and FF models[6]. Across these countries, we observe strikingly similar results. First, most of the

[6] The results for the other countries are very similar to those for the G7 countries, and are available on request.

country time-series display at least 4 or 5 break dates, which indicates that models with breaks in the parameters might not adequately capture the data dynamics. Using either risk model, the tests reveal almost the same two break dates for most of the countries: end of 1997/1998 and 2001/2002[7]. Consequently, the structural break tests pick up a temporary period of higher idiosyncratic volatility associated with what many economists have called the Internet or Tech Bubble. For Canada (using both CLMX and FF), Germany (using CLMX) and Italy (using both CLMX and FF), the tests also detect a break during the 1980s. Generally, we find that the "break tests" identify periods of temporary higher volatility that may occur more than once during the sample period. A better model to capture such behavior is a regime-switching model.

5. A Regime Switching Model

5.1 U.S. Data

We formulate a parsimonious regime switching model, following Hamilton (1994). A discrete regime variable, s_t, takes on two possible values (1 and 2) and follows a Markov Chain with constant transition probabilities. Let the current regime be indexed by i and the past regime by j. Let y_t represent the original idiosyncratic variance; y_t follows an AR(1) model where all parameters can take on one of two values:

$$y_t - \mu_i = b_i(y_{t-1} - \mu_j) + \sigma_i e_t, \ \ i, j \in \{1, 2\}. \tag{6}$$

In estimation, we force regime 1 to be the lower idiosyncratic variance regime and regime 2 to be the higher idiosyncratic variance regime, and the mean levels of idiosyncratic variances in both regimes to be non-negative, $\mu_2 > \mu_1 > 0$.

Even though there are only two transition probabilities to be estimated, the residual at time t depends on the regime realizations at t and $t-1$, through the mean parameters μ_1 and μ_2. We therefore define a regime variable s_t^* that can take on 4 values, indexing (s_t, s_{t-1}) to be (1,1), (2,1), (1,2), (2,2). Consequently, the transition probability matrix, Φ, is 4x4, where each probability represents $P[s_t^* = m | s_{t-1}^* = n] = P[s_t = i, s_{t-1} = j | s_{t-1} = l, s_{t-2} = k]$, with $m, n \in \{1, 2, 3, 4\}$ and

[7] In the case of Italy, there is no break date around 1997 when using the CLMX model, possibly because the time-series are pretty volatile in the early part of the sample.

$i, j, k, l \in \{1, 2\}$:

$$\Phi = P[s_t^* = m | s_{t-1}^* = n] = \begin{pmatrix} p11 & 1-p11 & 0 & 0 \\ 0 & 0 & 1-p22 & p22 \\ p11 & 1-p11 & 0 & 0 \\ 0 & 0 & 1-p22 & p22 \end{pmatrix}, \tag{7}$$

where n (m) is associated with the rows (columns) in Φ and $p11$ ($p22$) represents $P[s_t = 1|s_{t-1} = 1]$ ($P[s_t = 2|s_{t-1} = 2]$). The model features only 8 parameters, $\{\mu_1, \mu_2, b_1, b_2, \sigma_1, \sigma_2, p11, p22\}$.

The estimation results for both σ^2_{CLMX} and σ^2_{FF} are reported in Table 5. The standard errors are computed using the robust White (1980) covariance matrix. The annualized idiosyncratic variance level for regime 1, μ_1, is 0.064 for σ^2_{CLMX}, and 0.056 for σ^2_{FF}, but the level increases dramatically for regime 2, with μ_2 equal to 0.106 for σ^2_{CLMX} and 0.100 for σ^2_{FF}. Using a Wald test, these differences in level between the two regimes are highly statistically significant. Consistent with general intuition, regime 2 has much higher volatility than regime 1. For instance, σ_1 is 0.011 and σ_2 becomes 0.085 for σ^2_{CLMX}, with similar results when we use σ^2_{FF}. While in other applications it is typical for a high-variance regime to show more mean-reverting behavior, this is only the case for the CLMX-model's idiosyncratic variances. Even there, the difference between the two autocorrelation coefficients is not statistically significant. All parameters are highly significant.

Figure 2 presents smoothed probabilities of being in regime 2 over the time series. The smoothed probability of being in regime 2 at time t is computed using information from the whole time-series up to time T, that is, $P[s_t = 2|y_T, ..., y_1]$. As can be expected from the parameter estimates, the high-variance regime is a short-lived regime. However, it does occur several times over the sample period with some consistency over the two risk models. High variance episodes that occur in both cases include 1970, 1974, 1980, 1987, 1996 and 1998-2002. 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 10 regime switches over the 40 year sample, and y_t is in regime 2 10% of the time. On average, regime 2 lasts about 5 months.

It is not difficult to give some economic content to the regimes. The shaded areas in Figure 2 are NBER recessions. Clearly, the high-level idiosyncratic variance regimes mostly coincide with periods of recessions, although recessions are neither necessary not sufficient to have a high volatility regime. It is well-known (see Schwert 1989) that in recession periods market volatility tends to be high as well. We also find that our high idiosyncratic variance regimes also coincide with market volatility being about twice as high as in normal regimes.

These results help us interpret CLMX's trend findings. Essentially, the idiosyncratic variance process very clearly does not show a trend but has covariance stationary behavior with regime switching. Of course, trend tests, despite having good finite sample properties, may perform much worse in an environment where we start the sample in a low level regime and end the sample in a high level regime. That is exactly what happened in the case of CLMX's analysis.

The CLMX sample started during a "normal" idiosyncratic variance regime in the 1960's and ended in 1997. While 1997 itself 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 October 1987[8], 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.

To see the effect more concretely, Figure 3 shows the values of the t-dan test recursively, starting the sample in 1964:01, but varying the end point between 1970:04 and the end of the sample (2005:12). The date 1970:04 is not chosen arbitrarily, it is in the first 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 October 1987, and an upward trend would have been found all the way until 2000:4. Using the less powerful t-ps1 test, actually employed by CLMX, this period of "false rejections" would have lasted about two years less long. The "fake trend" experiment has two important implications: first, the level of idiosyncratic volatility has been high over the 1990s; second, 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.

5.2 G7 Countries

In this section, we estimate regime switching models for each of the G7 countries, analogous to the one for the U.S. The results are reported in Table 6.

The levels of idiosyncratic variances differ across countries, but not by much. In the low variance

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

regime, the means vary between 6.3% (Germany) and 12.1% (Japan); but the five other countries all have means in the 8.1% - 10.3% range. For the high variance regime, the mean is very close to 17.5% for four of the seven countries. The mean reverting parameters are mostly between 0.4-0.7, except for Japan, where the persistence parameter in the high variance regime drops below 0.3. The corresponding time-series of smoothed probabilities in regime 2 (high volatility regime) using the CLMX model are presented in Figure 4. The results using the FF model are very similar, and we do not report them to save space. The idiosyncratic variances of all 6 countries are mostly in regime 2 around 1997 to 2002, and are also likely to be in regime 2 around the 1987 crash. Most countries experience additional transitions into the higher variance regime, especially France and Italy.

6. Robustness

6.1 Equal Weighting

In this subsection, we examine the time-series behavior of equally weighted idiosyncratic variances. Because small firms dominate in the equally weighted idiosyncratic variances, it is conceivable that the results change. This is particularly relevant as one of the reasons suggested for the trend in idiosyncratic variances is that small firms may have sought public funding at an earlier stage in their life cycle than before (see Fink, Fink, Grullon and Weston 2007).

The results are presented in Table 7, where we focus on the U.S. daily idiosyncratic variance sample over 1964 - 2005. Since the results for the other developed countries are very similar, we do not report those to save space. In Panel A, the time-series mean of the equal-weighted CLMX (FF) idiosyncratic variance is 0.4291 (0.3533), which is much larger than the value-weighted counterpart of 0.0791 (0.0691). Obviously, smaller firm returns are much more volatile.

In Panel B, we report the Vogelsang trend test results. Interestingly, the equally weighted idiosyncratic variance time series shows a larger trend coefficient, but the value is now insignificantly different from zero for all cases, even for the 1964-1997 period. This, in fact, confirms the results in CLMX.

Panel C presents the parameter estimates for a regime switching model as in section 5.1. For the equally weighted variances, the regime identification is mostly similar to the value-weighted case, but there is much stronger persistence in the low-variance regime. In Figure 5, the equally weighted idiosyncratic variances move into regime 2 from 1998 to 2001, similar to what happens in Figure 2, where we use value-weighting. However, the equally weighted idiosyncratic variances stay in regime 2 much longer than the value-weighted counterparts, because they only return to regime 1 during the second half of 2003. Other shifts into regime 2 occur in 1970, 1974, 1980, 1987 and the early 1990s.

6.2 Weekly International Data and Alternative Risk Specification

So far, we focused on daily data across different countries, using domestic risk models (CLMX and FF) to arrive at idiosyncratic shocks. One potential drawback of the two models is that they may not adequately capture global risks. In this subsection, we consider two alternative models using both global and local factors explicitly. Since the global factors are constructed over different countries, and due to the non-synchronous trading problem, we only estimate the models using weekly data.

First, 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 (2008). 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 ($LHML$):

$$\begin{aligned} R_{j,t} &= b_{0,j,s} + b_{1,j,s}WMKT_t + b_{2,j,s}WSMB_t + b_{3,j,s}WHML_t \\ &\quad + b_{4,j,s}LMKT_t + b_{5,j,s}LSMB_t + b_{6,j,s}LHML_t + u_{j,t}^{WLFF}. \end{aligned} \tag{8}$$

where week t belongs to a six-month period s. To allow the betas to be time-varying, 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 be imperfect and 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 assets. 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 way 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 (2008) 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 asset 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:

$$\sigma^2_{WLFF,s} = \sum_{j=1}^{N} w_{j,s}\sigma^2(u_{j,t}^{WLFF}), \tag{9}$$

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.

Alternatively, we compute the idiosyncratic variance following CLMX's model:

$$R_{j,t} = WIND_{J,t} + u_{j,t}^{WCLMX}. \tag{10}$$

We now use the global industry portfolio returns $(WIND)$ to adjust the firm returns. If we value-weight the firm level idiosyncratic variances, we obtain the WCLMX-style idiosyncratic variance. That is,

$$\sigma^2_{WCLMX,s} = \sum_{j=1}^{N} w_{j,s}\sigma^2(u_{j,t}^{WCLMX}), \tag{11}$$

where week t belongs to the six-month period s.

We first report the summary statistics of weekly idiosyncratic variances in Panel A of Table 8. Similar to the summary statistics in Panel A of Table 1, using the WLFF model decreases the idiosyncratic variances, often by several percentage points, relative to the variances computed from the WCLMX model. We report trend test results for the 23 developed countries in Panel B. We fail to detect a significant time trend for any country, using either the t-dan test or the t-ps1 test, and whatever risk model is used to compute the idiosyncratic variances. Panel C reports structural breaks for the G7 countries using weekly data over 1980-2005, using both the WCLMX model and the WLFF model. Across these countries, we observe strikingly similar results. Using either risk model, the tests reveal almost the same two break dates for 5 countries: the end of 1997/beginning of 1998 and the end of 2001. In the case of France, these break dates only appear when the WLFF model is used. For France (using WLFF), Italy (using both WCLMX and WLFF), and the UK (using WCLMX), the tests also detect a break during the mid to late 1980's. Overall, the break tests results are similar to what we find for the monthly volatility time-series using domestic risk models.

We choose not to estimate a regime switching model for the G7 countries using weekly data. The two international models, WCLMX and WLFF, yield only 51 semi-annual observations. This small number of observations makes a country-by-country estimation of a regime-switching model infeasible.

6.3 TMT Industries

Brooks and Del Negro (2004) and Ferreira and Gama (2007) argue that the TMT industries (Telecom, Media and Info Tech industries) drove up stock market volatility over the 1990s. While our analysis so far includes the TMT industries, we also conduct tests excluding them. Other than a slight reduction in the level of idiosyncratic variances, all our results remain largely unchanged.

7. Commonality in Idiosyncratic Volatilities

One new empirical fact that we uncovered deserves further scrutiny. Idiosyncratic volatility has a large common component across countries. This is definitely somewhat surprising and may have implications for the analysis of issues such as international diversification and contagion. It should also be explored in theoretical and empirical work that examines why we have different idiosyncratic regimes.

Table 9 provides more information about this phenomenon. We report the correlations of the idiosyncratic volatilities in the G7 countries with respect to the U.S. idiosyncratic variance, and we record how much of the total variance of the G7 idiosyncratic variances is explained by the first principal component. We do so for all four different methodologies to obtain idiosyncratic variances, used in this article.

Across the panels, the correlations with the U.S. vary between 0.20 (Italy) and 0.84 (UK) for the monthly time-series, and between 0.14 (Italy) and 0.91 (Canada) for the half-year time-series. The variance explained by the first principal component varies between 10% (Italy) and 90% (U.S.) for the monthly time-series. It is considerably higher for the half-year models, varying between 36%

for Italy and 77% for UK. While a missing common component is a potential explanation of this phenomenon, it is striking that the phenomenon is robust to the method with which we compute the idiosyncratic volatility. Moreover, the actual idiosyncratic residuals between countries are relatively uncorrelated. Bekaert, Hodrick and Zhang (2008) show that the idiosyncratic correlations of country portfolios, computed using the WLFF model, are essentially zero. It is not inconceivable that globalization has brought about a global component in uncertainty (e.g. the intensity of competitive forces, technological shocks) that only affects second moments of diversified portfolios.

To demonstrate that the common component seems to have gained in importance over time, Table 9 also shows the correlations and importance of the principle component in the first and second parts of the sample. The increase in the importance of the common component is remarkable. The only case for which there is a decrease in importance of the common component is Italy, where using half-year data, the explained variance drops by about 50%.

As a simpler summary statistic, we also compute the equally weighted correlation between the idiosyncratic variances of the G7 countries. Using the weekly WLFF model to compute idiosyncratic variances, it is 57% over the whole sample; 24% over the 1980-1992 period but 75% over the 1993-2005 period. The magnitudes are qualitatively robust to the use of other methods to obtain idiosyncratic volatilities, or to the use of daily data, instead of weekly data. Hence, while our article explained away an existing puzzle in the literature about idiosyncratic volatility, we may have well introduced another one.

To capture the common component in a parsimonious stochastic model, we estimate a regime-switching model for the G7 countries jointly, where the probability of being in regime 1 or 2 for each country depends on a common driving force, the U.S. volatility level. To make estimation less complicated, we remove the dependence of the conditional mean on the regime variable at $t-1$, so that the model effectively only has a $2*2$ (instead of $4*4$) transition probability matrix for country k,

$$y_t^k = \mu_i + b_i y_{t-1}^k + \sigma_i e_t^k,\ i \in \{1,2\}. \tag{12}$$

We attempt to capture the correlation structure through the modelling of the transition probability matrices. For the U.S., we have the usual structure:

$$\Phi^{US} = \begin{pmatrix} p11 & 1-p11 \\ 1-p22 & p22 \end{pmatrix}. \tag{13}$$

For country k of the remaining G7 countries, the transition probability matrix depends on the contemporaneous U.S. regime, that is, $P[s_t^k = i | s_{t-1}^k = j, s_t^{US} = l]$, $i, j, l \in \{1, 2\}$. So when $s_t^{US} = 1$, we have

$$\Phi(s_t^{US} = 1) = \begin{pmatrix} q11 & 1 - q11 \\ 1 - q22 & q22 \end{pmatrix}, \tag{14}$$

and when $s_t^{US} = 2$, we have

$$\Phi(s_t^{US} = 2) = \begin{pmatrix} r11 & 1 - r11 \\ 1 - r22 & r22 \end{pmatrix}. \tag{15}$$

Consequently, the regimes will be correlated across countries, potentially capturing the correlations in idiosyncratic volatilities. The above model has 12 parameters, $\{\mu_1, \mu_2, b_1, b_2, \sigma_1, \sigma_2, p11, p22, q11, q22, r11, r22\}$. We estimate those parameters using monthly data σ^2_{CLMX} and σ^2_{FF} over the period 1980-2005.

The parameter estimates are presented in Table 10. All coefficients are significantly different from zero. Because the results are very similar using both models, we focus the discussion on the CLMX model in the left side panel. The drift level in regime 1, μ_1, is 0.009, and the drift level in regime 2, μ_2, increases to 0.059. Taking into account the AR structure of the model, the mean level in regime 1 becomes $\frac{\mu_1}{1-b_1} = 0.047$, and the mean level in regime 2 becomes $\frac{\mu_2}{1-b_2} = 0.126$. Both mean magnitudes are somewhat smaller than those in Table 6, when we estimate regime-switching models, country by country. We find the auto-regressive coefficient in regime 1, b_1, at 0.809, to be higher than the auto-regressive coefficient in regime 2, b_2, at 0.534. This is comparable to the pattern we observe in Table 6. The volatility coefficients, σ_1 and σ_2, are both smaller than their counterparts in Table 6. The effect of the U.S. regime on the other countries manifests itself primarily through a very different value of $q11$ than $r11$. When the U.S. is in regime 2, the probability of moving to or staying in regime 1 is much reduced for all countries. We choose not to present the smoothed probabilities over time, because they are really similar to those in Figure 4. All 7 countries have a relatively high probability of a high volatility regime starting in 1998, and ending in 2003. Several countries also have a non-trivial probability of being in the high volatility regime around 1987.

8. Conclusions

This article 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 mean-reverting process with occasional shifts to a higher-mean, higher-variance regime. Given the claim to the contrary for the U.S. in the influential CLMX article, a substantial literature has attempted to explain trending behavior in idiosyncratic volatilities.

It is important to trace out the implications of our findings for this literature. Xu and Malkiel (2003) and Bennett, Sias, and Starks (2003) ascribe the rise in idiosyncratic volatility to an increase in institutional ownership; but Fink, Fink, Grullon and Weston (2005) and Brown and Kapadia (2007) ascribe it to the increasing propensity of firms to issue public equity at an earlier stage in their life cycle. If the increase in institutional ownership exhibits a trend, it cannot explain the evidence. However, it is possible that the propensity to issue public equity is not trending upward but also shows mean-reverting behavior, so our work does not necessarily exclude this explanation. Irvine and Pontiff (2008) point to increasingly competitive product markets as an explanation. Guo and Savakis (2007) link changes in idiosyncratic volatilities to changes in the investment opportunity set; while Cao, Simin and Zhao (2007) also find growth options to be a critical determinant of the increase in idiosyncratic volatility, and Comin and Philippon (2005) link firm volatility to research and development spending as well as access to external financing. Wei and Zhang (2008) ascribe the trend to more volatile fundamentals, which is somewhat surprising given that macro-fundamentals are generally believed to have become less volatile since 1985. Our findings suggest that these explanatory factors must show regime-switching behavior (other than a trend). In fact, the regime-switching results and their link with business cycles suggest that all those factors may have explanatory power for idiosyncratic volatilities, because of their cyclical, not their permanent components.

The article most in line with our findings is Brandt, Brav, Graham and Kumar (2008). They show that by 2007 idiosyncratic volatility fell to pre-1990s levels, reversing the time trend observed through the 1990s, and that the period between 1926 and 1933 exhibited a temporary increase in idiosyncratic volatility closely resembling the recent episode. They ascribe the episode to "speculative behavior" as evidenced by retail traders in the Internet Bubble. While the common evidence across countries is potentially consistent with this interpretation, the recurring nature of high-variance regimes likely is not, as previous regimes did not seem to be characterized by speculative excess. The idea that the small and low priced stocks, favored by retail investors, are the cause of the apparent trend seems difficult to reconcile with the finding that the spurious trend is actually more apparent in value-weighted, rather than equally-weighted data. Nevertheless, both Brandt et al (2008) and our article convincingly show that idiosyncratic volatility displays episodic shifts in higher volatility regimes. Our article demonstrates that any explanatory factor is likely to have an important international component.

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Table 1. Idiosyncratic variance summary statistics

Panel A provides summary statistics for the U.S. sample of January 1964 to December 2005. Panel B reports summary statistics for the developed countries sample of January 1980 to December 2005. Panel C presents correlations between G7 idiosyncratic variances. We use bold font if the correlation is significantly different from zero 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 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, 1963 – 2005

	σ^2_{CLMX}		σ^2_{FF}	
N	Mean	Std	Mean	Std
504	0.0791	0.0556	0.0691	0.0465

Panel B. Developed countries sample, 1980 – 2005

		σ^2_{CLMX}		σ^2_{FF}	
	N	Mean	Std	Mean	Std
CANADA	306	0.0643	0.0342	0.0662	0.0319
FRANCE	306	0.0616	0.0340	0.0637	0.0359
GERMANY	306	0.0465	0.0371	0.0447	0.0360
ITALY	306	0.0646	0.0399	0.0623	0.0350
JAPAN	306	0.0872	0.0464	0.0785	0.0402
U.K.	306	0.0478	0.0334	0.0497	0.0337
U.S.	306	0.0949	0.0640	0.0825	0.0526
AUSTRALIA	306	0.0490	0.0293	0.0496	0.0249
AUSTRIA	306	0.0306	0.0237	0.0437	0.0262
BELGIUM	306	0.0338	0.0261	0.0368	0.0227
DENMARK	306	0.0421	0.0348	0.0512	0.0334
FINLAND	227	0.0585	0.0545	0.0709	0.0544
GREECE	215	0.0806	0.0608	0.0685	0.0384
HK	306	0.0587	0.0445	0.0528	0.0350
IRELAND	306	0.0292	0.0226	0.0517	0.0377
NETHERLANDS	306	0.0257	0.0234	0.0329	0.0278
NEW ZEALAND	239	0.0247	0.0200	0.0368	0.0148
NORWAY	306	0.0635	0.0453	0.0762	0.0423
PORTUGAL	215	0.0496	0.0384	0.0502	0.0326
SINGAPORE	306	0.0660	0.0574	0.0584	0.0414
SPAIN	239	0.0353	0.0272	0.0407	0.0290
SWEDEN	287	0.0492	0.0355	0.0585	0.0352
SWITZERLAND	306	0.0273	0.0264	0.0303	0.0243

Panel C. Correlations between G7 countries idiosyncratic variances, 1980 – 2005

	σ^2_{CLMX}					
	Canada	France	Germany	Italy	Japan	U.K.
France	**59%**					
Germany	**73%**	**72%**				
Italy	**21%**	**41%**	**14%**			
Japan	**59%**	**54%**	**63%**	**23%**		
U.K.	**78%**	**75%**	**84%**	**32%**	**72%**	
U.S.	**80%**	**66%**	**77%**	**20%**	**66%**	**81%**

	σ^2_{FF}					
	Canada	France	Germany	Italy	Japan	U.K.
France	**71%**					
Germany	**80%**	**76%**				
Italy	**39%**	**51%**	**29%**			
Japan	**66%**	**63%**	**68%**	**32%**		
U.K.	**82%**	**80%**	**86%**	**45%**	**75%**	
U.S.	**82%**	**73%**	**82%**	**34%**	**69%**	**84%**

Table 2. Trend test for U.S.

This table reports trend test results for the U.S. idiosyncratic variance time-series, using Vogelsang's (1998) t-PS1 test and Bunzel and Vogelsang's (2005) t-dan test. The 5% critical value (two sided) for t-dan is 2.052, and for t-ps1 is 2.152. We report both pre-whitened results using AR (1) and non-pre-whitened results for the t-dan test. 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. Idiosyncratic variance over 1964-1997, daily data

	Pre-whitened		Not pre-whitened			
	b-dan	t-dan	b-dan	t-dan	b-ps1	t-ps1
σ^2_{CLMX}	0.0001	4.842	0.0001	4.966	0.0001	3.893
σ^2_{FF}	0.0001	4.356	0.0001	4.727	0.0001	3.364

Panel B. Idiosyncratic variance over 1964-2005, daily data

	Pre-whitened		Not pre-whitened			
	b-dan	t-dan	b-dan	t-dan	b-ps1	t-ps1
σ^2_{CLMX}	0.0002	1.110	0.0002	1.194	0.0002	1.350
σ^2_{FF}	0.0001	0.794	0.0001	0.914	0.0002	1.060

Table 3. Trend test for developed countries

Panel A reports trend test results for all developed countries idiosyncratic variance time-series, using the Vogelsang (1998) t-PS1 test and the Bunzel and Vogelsang (2005) t-dan test. The 5% critical value (two sided) for t-dan is 2.052, and for t-ps1 it is 2.152. The t-dan test applies pre-whitening using an AR (1) model. Panel B reports a joint trend test for a subset of developed countries, using the F1 statistic. The number 0 indicates that a joint test fails to reject the null of either a zero trend or the trends being equal across countries at the 5% level, and the number 1 indicates a 5% significant rejection. 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. Country by country test

	σ^2_{CLMX}				σ^2_{FF}			
	b-dan	t-dan	b-ps1	t-ps1	b-dan	t-dan	b-ps1	t-ps1
CANADA	0.0001	0.880	0.0002	0.797	0.0001	0.526	0.0002	0.578
FRANCE	0.0001	0.469	0.0001	1.083	0.0001	0.337	0.0001	0.643
GERMANY	0.0002	0.435	0.0002	0.704	0.0002	0.215	0.0003	0.486
ITALY	-0.0001	-2.300	-0.0001	-1.062	-0.0001	-1.142	0.0000	-0.367
JAPAN	0.0001	0.478	0.0002	0.761	0.0001	0.345	0.0001	0.506
U.K.	0.0001	0.464	0.0002	0.874	0.0001	0.313	0.0001	0.603
U.S.	0.0002	0.361	0.0003	0.671	0.0002	0.233	0.0003	0.552
AUSTRALIA	0.0000	0.551	0.0000	0.458	0.0000	0.256	0.0000	0.170
AUSTRIA	0.0001	1.567	0.0002	1.534	0.0001	0.661	0.0002	0.835
BELGIUM	0.0001	0.828	0.0001	0.830	0.0000	0.126	0.0001	0.244
DENMARK	0.0001	2.006	0.0002	2.714	0.0002	0.297	0.0002	0.561
FINLAND	-0.0003	-0.617	-0.0003	-0.599	-0.0005	-0.950	-0.0005	-1.175
GREECE	-0.0003	-1.997	-0.0003	-1.242	-0.0001	-0.572	-0.0001	-0.291
HK	0.0001	0.669	0.0001	0.702	0.0001	0.608	0.0001	0.677
IRELAND	0.0001	1.733	0.0001	1.465	0.0001	0.759	0.0001	0.647
NETHERLANDS	0.0001	1.161	0.0001	0.998	0.0001	0.698	0.0001	0.748
NEW ZEALAND	0.0000	0.330	0.0000	0.048	0.0000	0.072	0.0000	0.104
NORWAY	0.0002	0.692	0.0003	1.310	0.0001	0.217	0.0002	0.577
PORTUGAL	-0.0003	-5.249	-0.0003	-4.223	-0.0002	-3.724	-0.0002	-2.277
SINGAPORE	0.0000	0.406	0.0001	0.347	0.0003	0.655	0.0004	1.061
SPAIN	0.0000	-0.480	0.0000	-0.041	-0.0001	-0.186	0.0000	0.008
SWEDEN	0.0001	0.654	0.0002	1.298	0.0001	0.513	0.0002	1.271
SWITZERLAND	0.0001	1.600	0.0001	1.471	0.0001	1.429	0.0001	1.483
G7	0.0001	0.290	0.0001	0.658	0.0001	0.179	0.0001	0.458
N. America	0.0002	0.414	0.0002	0.653	0.0002	0.222	0.0002	0.472
Far East	0.0000	0.319	0.0000	0.346	0.0000	0.270	0.0001	0.361
Core EU	0.0001	0.501	0.0001	0.969	0.0001	0.295	0.0001	0.549
Europe	0.0001	0.652	0.0001	1.296	0.0001	0.326	0.0001	0.558

Panel B. Joint test

	σ^2_{CLMX}				σ^2_{FF}			
	G7	N. America	Far East	Core EU	G7	N. America	Far East	Core EU
all zero	0	0	0	1	1	0	0	1
all equal	0	0	0	1	1	0	0	1

Table 4. Structural Breaks

This table reports structural break test results for the U.S. and all developed countries idiosyncratic variance time-series, using the methodology of Bai and Perron (1998). The maximum number of breaks is 5. We choose the optimal number of breaks based on the BIC. 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 – 2005

Breaks	σ^2_{CLMX}	σ^2_{FF}
BIC break #	5	5
	1966:03	1966:07
	1979:12	1990:06
	1999:06	1999:06
	2001:04	2001:04
	2003:05	2003:05

Panel B. G7 countries sample, 1980 – 2005

Breaks	CA	FR	GE	IT	JP	U.K.	U.S.
σ^2_{CLMX}							
BIC break #	5	2	5	5	5	4	4
	1982:11	1997:09	1985:05	1981:10	1992:10	1997:09	1998:07
	1997:02	2003:04	1997:06	1984:09	1997:08	1999:10	1999:12
	1999:10		1999:10	1986:06	1999:07	2001:01	2001:04
	2001:03		2001:03	2000:05	2000:10	2003:03	2002:11
	2002:12		2003:06	2003:03	2003:11		
σ^2_{FF}							
BIC break #	5	4	5	5	5	4	5
	1983:02	1998:02	1997:02	1981:10	1992:10	1997:12	1995:09
	1997:09	1999:10	1998:06	1985:01	1997:07	1999:10	1998:07
	1999:10	2001:01	1999:10	1998:08	1999:07	2001:01	1999:11
	2001:03	2003:06	2001:03	2000:05	2000:10	2003:03	2001:03
	2002:12		2003:06	2003:03	2003:11		2002:11

Table 5. Regime switching model for the U.S.

This table reports the regime switching model results for the U.S. idiosyncratic variance time-series computed using daily data, where the model is described as follows:

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

$$\text{Transition probability } \Phi = \begin{bmatrix} p11 & 1-p11 & 0 & 0 \\ 0 & 0 & 1-p22 & p22 \\ p11 & 1-p11 & 0 & 0 \\ 0 & 0 & 1-p22 & p22 \end{bmatrix}.$$

The above model is estimated over the sample period 1964 – 2005. 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. The parameters p11 and p22 are constrained to be in (0,1) during estimation; we also re-parameterize to ensure $0 < \mu_1 < \mu_2$.

	σ^2_{CLMX}		σ^2_{FF}	
	coef.	std.	coef.	std.
μ_1	0.064	0.003	0.056	0.003
μ_2	0.106	0.008	0.100	0.009
b_1	0.834	0.027	0.818	0.026
b_2	0.744	0.090	0.823	0.085
σ_1	0.011	0.001	0.010	0.000
σ_2	0.085	0.009	0.061	0.006
p_{11}	0.981	0.007	0.988	0.007
p_{22}	0.856	0.052	0.893	0.055

Table 6. Regime switching models for the G7 countries

This table reports the regime switching model results for the aggregate idiosyncratic variance time-series of the G7 countries, computed using daily data. The risk model is CLMX, as defined in equation (2). The model is described as follows:

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

$$\text{Transition probability } \Phi = \begin{bmatrix} p11 & 1-p11 & 0 & 0 \\ 0 & 0 & 1-p22 & p22 \\ p11 & 1-p11 & 0 & 0 \\ 0 & 0 & 1-p22 & p22 \end{bmatrix}.$$

The above model is estimated over the sample period 1980 – 2005. Variance time-series statistics are annualized. The parameters p11 and p22 are constrained to be in (0,1) during estimation; we also re-parameterize to ensure $0 < \mu_1 < \mu_2$.

	CA		FR		GE		IT		JP		U.K.		U.S.	
	coef.	std	coef.	std	coef.	std	coef.	std	coef.	std	coef.	std	coef.	std
μ_1	0.081	0.003	0.088	0.003	0.063	0.003	0.103	0.007	0.121	0.007	0.075	0.004	0.096	0.004
μ_2	0.170	0.014	0.172	0.018	0.138	0.013	0.177	0.017	0.260	0.019	0.126	0.012	0.173	0.015
b_1	0.565	0.032	0.549	0.039	0.603	0.036	0.654	0.048	0.631	0.045	0.704	0.037	0.638	0.077
b_2	0.447	0.130	0.601	0.158	0.613	0.126	0.451	0.124	0.294	0.169	0.545	0.168	0.508	0.125
σ_1	0.018	0.001	0.022	0.001	0.017	0.001	0.030	0.002	0.034	0.002	0.019	0.001	0.020	0.001
σ_2	0.129	0.012	0.120	0.012	0.098	0.009	0.140	0.014	0.125	0.013	0.142	0.019	0.200	0.020
p_{11}	0.954	0.015	0.917	0.020	0.946	0.016	0.851	0.036	0.925	0.020	0.938	0.018	0.963	0.013
p_{22}	0.856	0.055	0.651	0.086	0.815	0.057	0.539	0.102	0.643	0.107	0.495	0.111	0.817	0.059

Table 7. Robustness check: Equal weighting

In Panel A, we report summary statistics for the U.S. sample, and the sample period is January 1964 to December 2005. In Panel B, we report trend test results for U.S. idiosyncratic variance time-series, using the Vogelsang (1998) t-PS1 test and the Bunzel and Vogelsang (2005) t-dan test. The 5% critical value (two sided) for t-dan is 2.052, and for t-ps1 is 2.152. In Panel B, we use a pre-whitened model for the t-dan test. In Panel C, we report the parameter estimates for a regime switching model estimated over 1964 – 2005. The variables σ^2_{CLMX} and σ^2_{FF} are the aggregate firm level idiosyncratic variances, as defined in equations (2) and (4), respectively, except they are now equally weighted. All variance time-series statistics are annualized.

Panel A. summary statistics for the U.S.

	σ^2_{CLMX}		σ^2_{FF}	
N	Mean	Std	Mean	Std
504	0.4291	0.2882	0.3533	0.2355

Panel B. Trend test for the U.S.

	1964-1997				1964-2005			
	b-dan	t-dan	b-ps1	t-ps1	b-dan	t-dan	b-ps1	t-ps1
σ^2_{CLMX}	0.0015	1.200	0.0013	0.869	0.0013	0.932	0.0016	1.412
σ^2_{FF}	0.0013	0.522	0.0012	0.584	0.0011	0.719	0.0013	1.243

Panel C. Regime switching model for the U.S.

	σ^2_{CLMX}		σ^2_{FF}	
	coef.	std.	coef.	std.
μ_1	0.699	0.065	0.569	0.050
μ_2	0.824	0.064	0.646	0.050
b_1	0.996	0.005	0.997	0.005
b_2	0.620	0.087	0.689	0.073
σ_1	0.041	0.002	0.030	0.002
σ_2	0.221	0.017	0.157	0.011
p_{11}	0.971	0.011	0.967	0.012
p_{22}	0.880	0.048	0.895	0.038

Table 8. Alternative model specifications for weekly international data

Panel A reports summary statistics for the developed countries sample of January 1980 to December 2005. Panel B reports trend test results for idiosyncratic variance time-series, using Vogelsang (1998) t-ps1 test and Bunzel and Vogelsang (2005) t-dan test. The 5% critical value (two sided) for t-dan is 2.052, and for t-ps1 is 2.152. Panel C reports break test results as in Bai and Perron (1998). The variables σ^2_{WCLMX} and σ^2_{WLFF} are the aggregate firm level idiosyncratic variances, as defined in equations (11) and (9), respectively. All variance time-series statistics are annualized.

Panel A. Summary statistics

		σ^2_{WCLMX}		σ^2_{WLFF}	
	N	Mean	Std	Mean	Std
CANADA	51	0.1010	0.0460	0.0706	0.0325
FRANCE	51	0.1087	0.0551	0.0709	0.0342
GERMANY	51	0.0858	0.0483	0.0510	0.0303
ITALY	51	0.1247	0.0785	0.0832	0.0598
JAPAN	51	0.1180	0.0619	0.0627	0.0301
U.K.	51	0.0894	0.0381	0.0554	0.0278
U.S.	51	0.0953	0.0485	0.0675	0.0343
AUSTRALIA	51	0.0956	0.0423	0.0654	0.0253
AUSTRIA	51	0.0970	0.0554	0.0600	0.0370
BELGIUM	51	0.0749	0.0383	0.0472	0.0274
DENMARK	51	0.1077	0.0506	0.0709	0.0356
FINLAND	38	0.1519	0.1030	0.1089	0.0735
GREECE	36	0.2190	0.1519	0.1436	0.1091
HK	51	0.1361	0.0829	0.0959	0.0572
IRELAND	51	0.1012	0.0450	0.0672	0.0306
NETHERLANDS	51	0.0632	0.0322	0.0403	0.0224
NEW ZEALAND	40	0.1080	0.0496	0.0701	0.0344
NORWAY	51	0.1403	0.0670	0.0980	0.0457
PORTUGAL	36	0.1193	0.0664	0.0721	0.0395
SINGAPORE	51	0.1269	0.0850	0.0847	0.0528
SPAIN	40	0.1058	0.0854	0.0725	0.0719
SWEDEN	48	0.1220	0.0609	0.0791	0.0409
SWITZERLAND	51	0.0587	0.0257	0.0354	0.0161

Panel B. Trend test

	σ^2_{WCLMX}				σ^2_{WLFF}			
	b-dan	t-dan	b-ps1	t-ps1	b-dan	t-dan	b-ps1	t-ps1
CANADA	0.0008	0.139	0.0012	0.398	0.0008	0.135	0.0010	0.401
FRANCE	-0.0011	-0.428	-0.0008	-0.411	-0.0005	-0.240	-0.0003	-0.219
GERMANY	0.0012	0.022	0.0015	0.155	0.0009	0.006	0.0011	0.087
ITALY	-0.0024	-1.279	-0.0019	-1.019	-0.0017	-0.878	-0.0014	-0.744
JAPAN	0.0013	0.066	0.0017	0.319	0.0004	0.055	0.0006	0.245
U.K.	-0.0004	-0.089	-0.0001	-0.043	0.0003	0.033	0.0006	0.241
U.S.	0.0008	0.012	0.0014	0.158	0.0007	0.003	0.0010	0.082
AUSTRALIA	-0.0007	-0.434	-0.0007	-0.544	-0.0004	-0.226	-0.0003	-0.309
AUSTRIA	0.0006	0.195	0.0008	0.430	0.0004	0.297	0.0005	0.537
BELGIUM	-0.0005	-0.077	-0.0005	-0.159	-0.0004	-0.106	-0.0004	-0.207
DENMARK	-0.0002	-0.008	-0.0001	-0.013	-0.0003	-0.058	-0.0004	-0.111
FINLAND	-0.0023	-0.255	-0.0015	-0.291	-0.0008	-0.091	0.0000	-0.007
GREECE	-0.0027	-0.078	-0.0005	-0.034	-0.0017	-0.101	-0.0002	-0.029
HK	-0.0009	-0.387	-0.0006	-0.228	-0.0004	-0.197	-0.0001	-0.025
IRELAND	0.0003	0.105	0.0001	0.056	0.0006	0.209	0.0004	0.263
NETHERLANDS	0.0003	0.088	0.0005	0.212	0.0003	0.071	0.0005	0.234
NEW ZEALAND	-0.0014	-0.295	-0.0010	-0.265	-0.0010	-0.378	-0.0009	-0.388
NORWAY	-0.0007	-0.240	-0.0002	-0.124	-0.0005	-0.249	-0.0002	-0.159
PORTUGAL	-0.0038	-0.459	-0.0035	-0.576	-0.0023	-0.804	-0.0021	-0.801
SINGAPORE	0.0006	0.027	0.0013	0.170	0.0002	0.005	0.0006	0.063
SPAIN	-0.0038	-0.020	-0.0036	-0.082	-0.0032	-0.037	-0.0032	-0.125
SWEDEN	-0.0001	-0.026	0.0006	0.321	0.0000	0.011	0.0005	0.380
SWITZERLAND	0.0004	0.156	0.0007	0.521	0.0004	0.344	0.0005	1.001

Panel C. Break test

Breaks	CA	FR	GE	IT	JP	U.K.	U.S.
σ^2_{WCLMX}							
BIC break #	2	0	2	1	2	3	2
	1998:06		1998:06	1986:12	1997:12	1987:12	1998:06
	2001:12		2001:12		2001:12	1998:06	2001:12
						2001:12	
σ^2_{WLFF}							
BIC break #	2	3	2	1	2	2	2
	1998:06	1988:06	1997:12	1983:12	1998:06	1998:06	1998:06
	2001:12	1998:06	2001:12		2001:12	2001:12	2001:12
		2001:12					

Table 9. The common component in idiosyncratic variances across countries

For each panel, the left half reports correlations of G7 countries' idiosyncratic variance with the U.S. idiosyncratic variance, and the right half reports the percentage of the variance of the idiosyncratic variances explained by the first principal component of the G7 idiosyncratic variances. The different panels use different models to compute idiosyncratic variances.

Panel A. Daily CLMX model

σ^2_{CLMX}	Correlation with U.S.			Variance explained by first PC		
	1980-2005	1980-1992	1993-2005	1980-2005	1980-1992	1993-2005
Canada	80%	63%	86%	72%	39%	88%
France	66%	45%	74%	61%	42%	74%
Germany	77%	49%	79%	76%	43%	80%
Italy	20%	14%	47%	10%	14%	32%
Japan	66%	23%	76%	64%	27%	76%
U.K.	81%	73%	81%	84%	67%	87%
U.S.	100%	100%	100%	90%	77%	90%

Panel B. Daily FF model

σ^2_{FF}	Correlation with U.S.			Variance explained by first PC		
	1980-2005	1980-1992	1993-2005	1980-2005	1980-1992	1993-2005
Canada	82%	64%	84%	78%	39%	87%
France	73%	34%	83%	74%	45%	87%
Germany	82%	40%	82%	81%	37%	86%
Italy	34%	26%	57%	23%	28%	47%
Japan	69%	18%	77%	66%	23%	78%
U.K.	84%	65%	86%	88%	57%	93%
U.S.	100%	100%	100%	88%	62%	89%

Panel C. Weekly WCLMX model

σ^2_{WCLMX}	Correlation with U.S.			Variance explained by first PC		
	1980-2005	1980-1992	1993-2005	1980-2005	1980-1992	1993-2005
Canada	91%	80%	96%	72%	33%	92%
France	51%	23%	86%	65%	64%	90%
Germany	87%	36%	89%	72%	34%	88%
Italy	19%	16%	52%	36%	75%	45%
Japan	81%	27%	86%	67%	17%	85%
U.K.	81%	71%	94%	77%	31%	97%
U.S.	100%	100%	100%	72%	24%	89%

Panel D. Weekly WLFF model

σ^2_{WLFF}	Correlation with U.S.			Variance explained by first PC		
	1980-2005	1980-1992	1993-2005	1980-2005	1980-1992	1993-2005
Canada	90%	70%	95%	57%	23%	84%
France	55%	26%	88%	73%	62%	93%
Germany	83%	1%	86%	53%	10%	80%
Italy	14%	34%	41%	44%	88%	41%
Japan	73%	-17%	86%	45%	1%	75%
U.K.	87%	38%	92%	66%	7%	95%
U.S.	100%	100%	100%	62%	23%	88%

Table 10. Joint regime switching model for the G7 countries

This table reports the joint regime switching model results for the aggregate idiosyncratic variance time-series of the G7 countries. The model is described as follows:

$$y_t^k = \mu_i + b_i y_{t-1}^k + \sigma_i e_t, i = 1,2, k = \text{individual G7 countries.}$$

$$\text{Transition probability matrix for US, } \Phi^{US} = \begin{bmatrix} p11 & 1-p11 \\ 1-p22 & p22 \end{bmatrix}.$$

$$\text{Transition probability matrix for G7 countries other than US when } s_t^{US} = 1,$$

$$\Phi(s_t^{US} = 1) = \begin{bmatrix} q11 & 1-q11 \\ 1-q22 & q22 \end{bmatrix},$$

$$\text{Transition probability matrix for G7 countries other than US when } s_t^{US} = 2,$$

$$\Phi(s_t^{US} = 2) = \begin{bmatrix} r11 & 1-r11 \\ 1-r22 & r22 \end{bmatrix}.$$

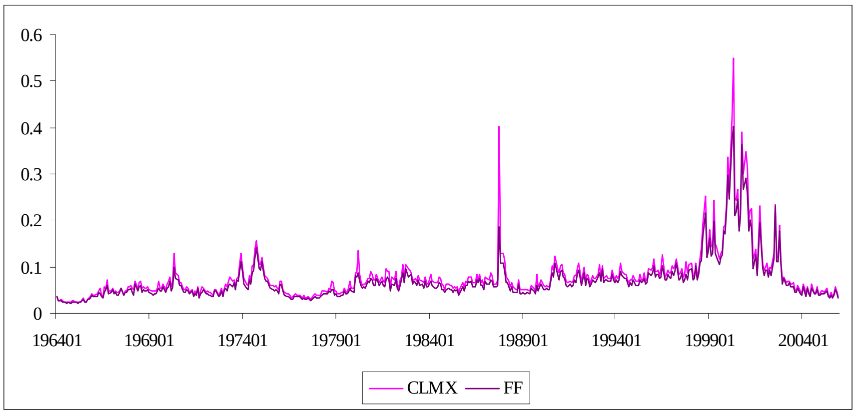
The above model is estimated over the sample period 1980 – 2005 using monthly data of σ_{CLMX}^2 and σ_{FF}^2, which are the aggregate firm level idiosyncratic variances, as defined in equations (2) and (4), respectively.

	σ_{CLMX}^2		σ_{FF}^2	
	coef.	std.	coef.	std.
μ_1	0.009	0.001	0.009	0.001
μ_2	0.059	0.006	0.042	0.004
b_1	0.809	0.014	0.794	0.015
b_2	0.534	0.041	0.628	0.036
σ_1	0.012	0.000	0.010	0.000
σ_2	0.055	0.002	0.041	0.002
p_{11}	0.992	0.008	0.997	0.002
p_{22}	0.914	0.044	0.918	0.034
q_{11}	0.961	0.008	0.963	0.008
q_{22}	0.705	0.048	0.744	0.049
r_{11}	0.648	0.095	0.354	0.161
r_{22}	0.732	0.087	0.718	0.084

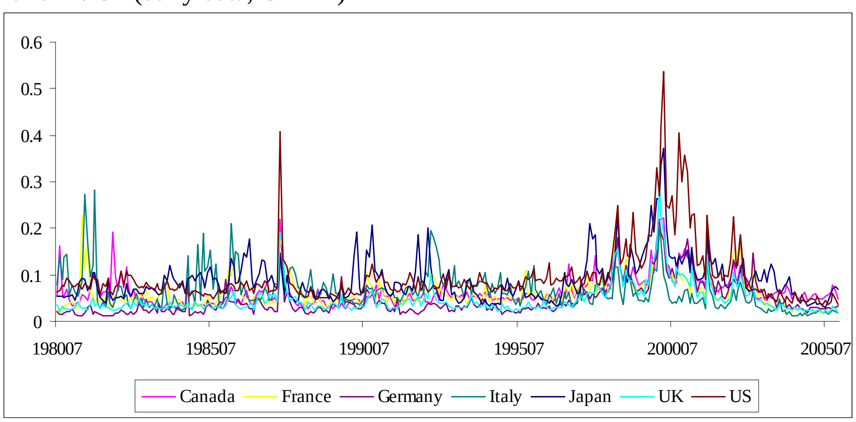
Figure 1. Idiosyncratic variance time-series plot

In Panel A, we plot the time-series idiosyncratic variance for the U.S. sample. The sample period is January 1964 to December 2005. In Panels B and C, we plot the time-series idiosyncratic variances for G7 countries. The aggregate idiosyncratic variance measures using CLMX and FF 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 the returns are denominated in U.S. dollars. All variance time-series statistics are annualized.

Panel A. U.S. (daily data)



Panel B. G7 (daily data, CLMX)



Panel C. G7 (daily data, FF)

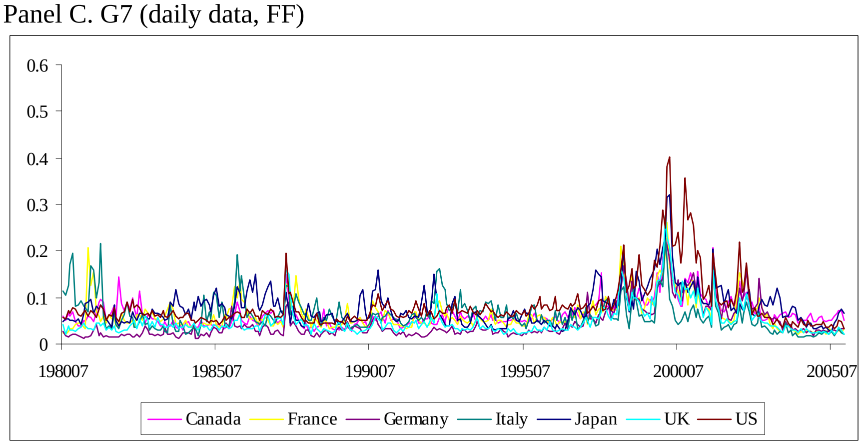
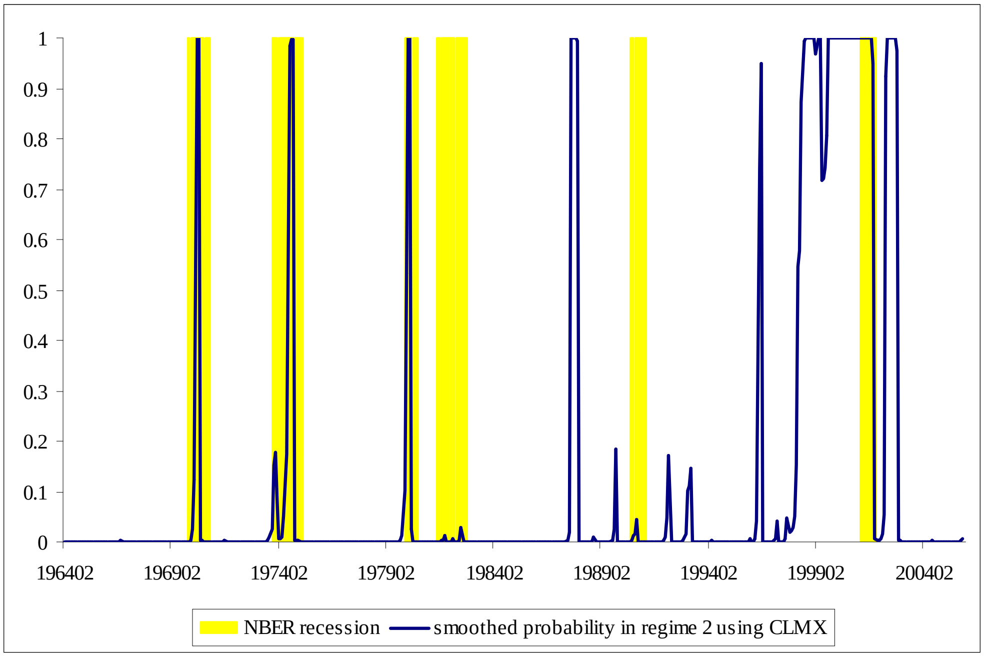


Figure 2. Regime probabilities for U.S. idiosyncratic variances

This figure reports the smoothed probability of being in regime 2 for U.S., using a regime switching model defined in equations (6) and (7). The model is estimated over sample period 1964 – 2005. Variables σ^2_{CLMX} and σ^2_{FF} are the aggregate firm level idiosyncratic variances, as defined in equations (2) and (4), respectively.

Panel A. σ^2_{CLMX}



Panel B. σ^2_{FF}

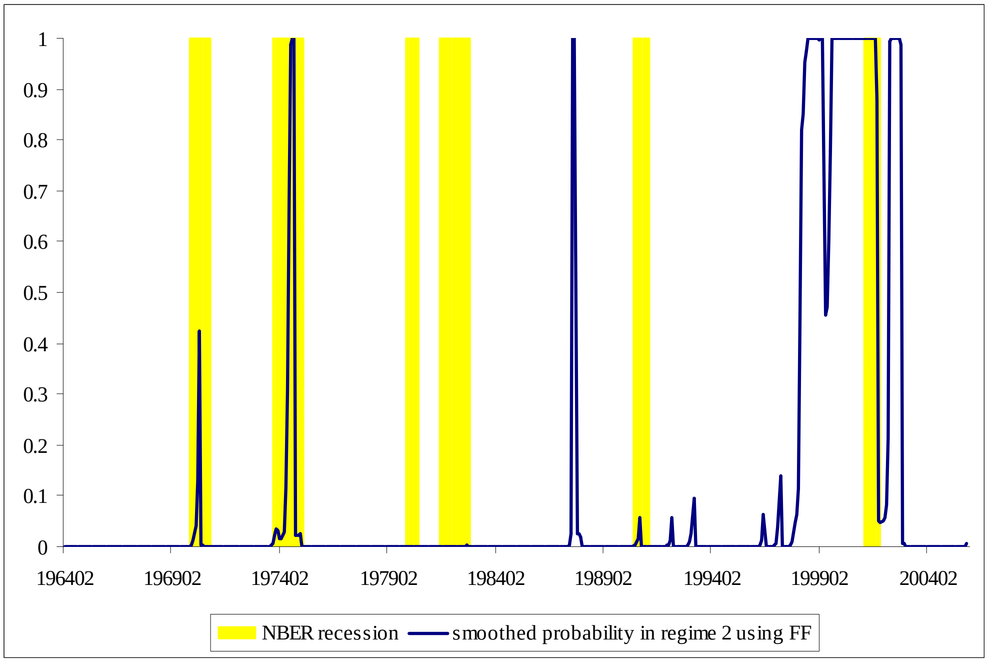


Figure 3. When can we find a significant trend in the U.S.?

This figure reports the t-dan test statistics for the U.S., which is estimated over 1964:01 to an end date between 1970:04 (the first high variance regime) and 2005:12. 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%.

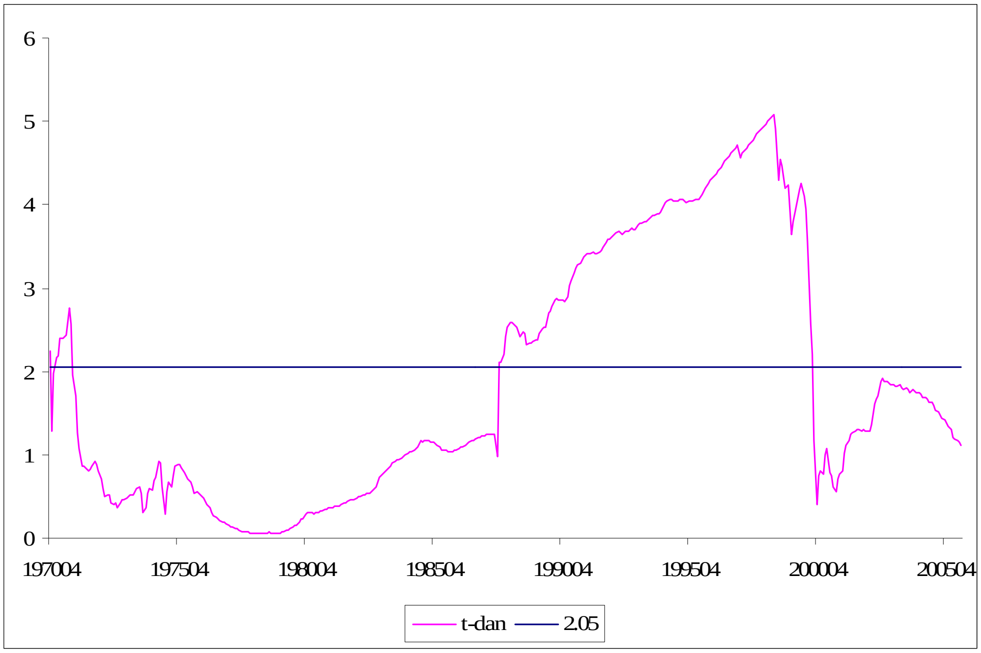


Figure 4. Regime probabilities for G7 countries

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 (6) and (7). The model is estimated over sample period 1980 – 2005, country by country. The variable σ^2_{CLMX} is the aggregate firm level idiosyncratic variance, as defined in equation (2), estimated using daily data.

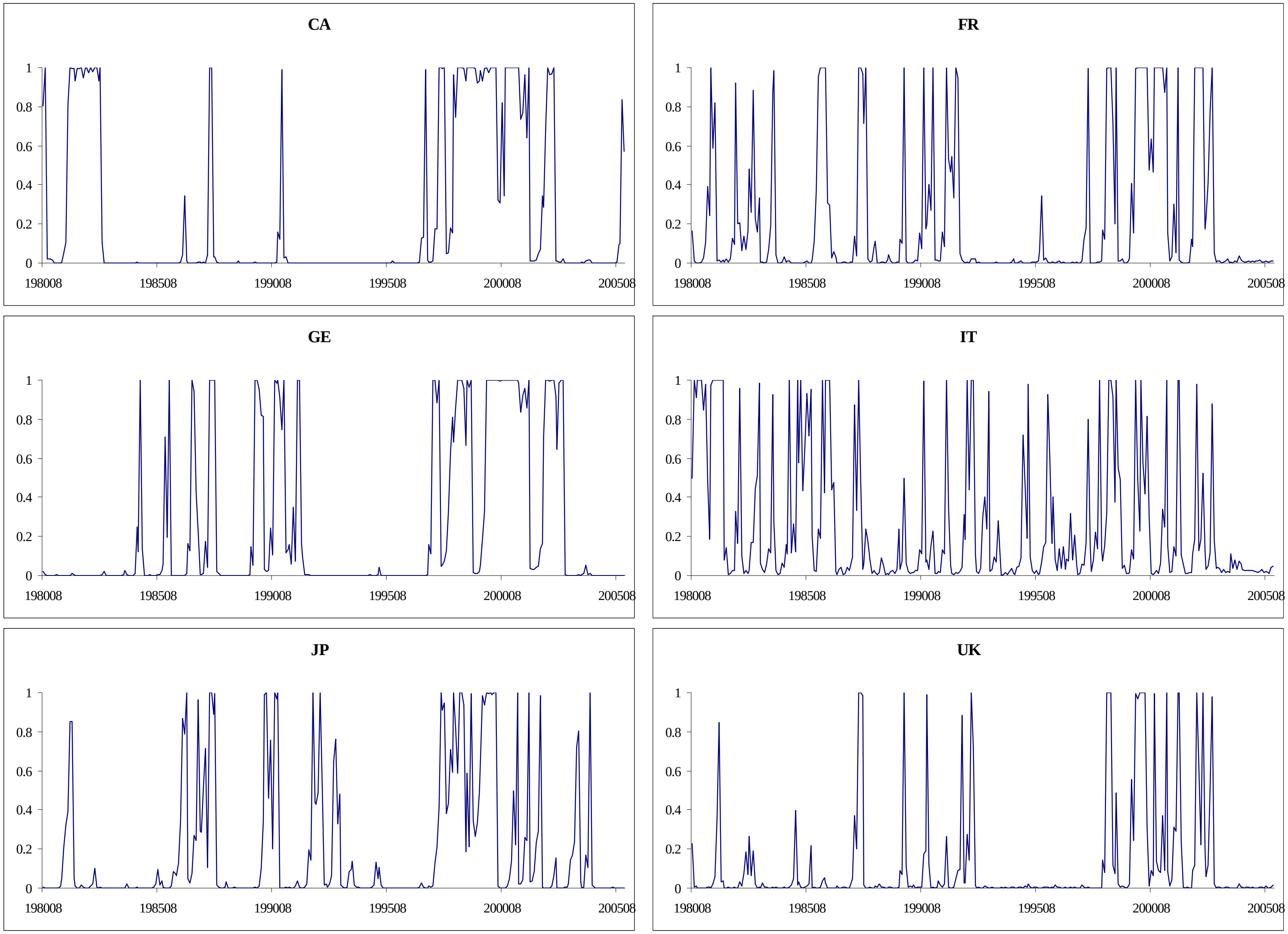
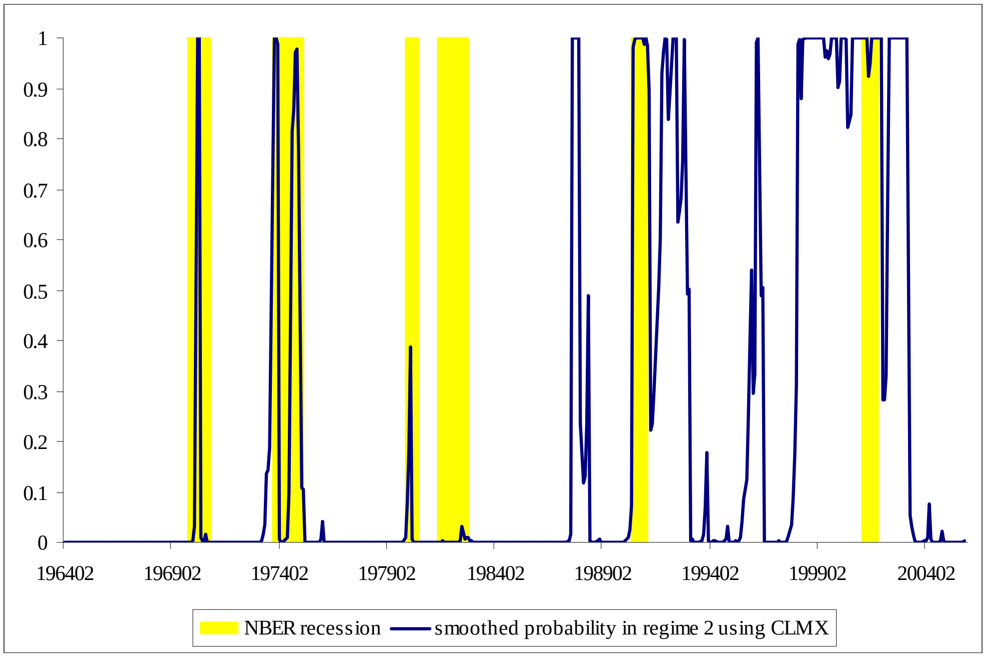


Figure 5. Regime probabilities for U.S. idiosyncratic variances, equally weighted

This figure reports the smoothed probability of being in regime 2 for U.S., using a regime switching model defined in equations (6) and (7). The model is estimated over sample period 1964 – 2005. Variables σ^2_{CLMX} and σ^2_{FF} are the aggregate firm level idiosyncratic variances, as defined in equations (2) and (4), respectively, except they are now equally weighted.

Panel A. σ^2_{CLMX}



Panel B. σ^2_{FF}