Risk components in UK cross-sectional equities: evidence of regimes and overstated parametric estimates

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Modelling systematic and non-systematic risk in U.K. cross-sectional equities: evidence of regimes and overstated parametric estimates

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Abstract

We study the behavior and interaction of systematic and idiosyncratic components of risk in a cross-section of U.K. stocks. We find no clear evidence of a trend in any component of total risk, but we document different "regimes" in the behavior of each component of total risk, in their correlation patterns and thus in their contribution to aggregate risk. Comparing parametric and non-parametric estimates of residual risk, we find the former to significantly overstate diversifiable risk, opposite to some previous findings for the U.S. market, with the difference being very large especially when we include an industry component.

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1. Introduction

1.1 Modelling the behaviour and role of idiosyncratic risk

Traditional asset pricing frameworks distinguish the determinants of the risk of assets between systematic components, i.e. those driven by common, explicit risk factors, and "residual", "non-systematic" or "idiosyncratic" components. The idiosyncratic component can be thought of as the component of returns that is specific of each single security – but also as the residual component from a model that is by nature incomplete.

Within a broader stream of literature that looks to identify empirical pricing "anomalies", several researchers have studied the behaviour and role of the idiosyncratic component of stock returns volatility, often documenting aggregate or cross-sectional effects partly incompatible with the assumptions of traditional models. For instance, the CAPM assumption that idiosyncratic risk should not be priced has been challenged both theoretically and empirically, although with mixed results. But from a modelling standpoint, the behaviour of idiosyncratic risk and its interaction with other risk sources is important for a number of reasons. Firm-level volatility accounts for a large share - over sixty-percent according to some estimates - of total volatility and volatility variation; in addition, asset holders and portfolio managers are exposed to idiosyncratic risk because of portfolio or wealth constraints, transaction costs, regulation, informational differences and explicit choice. As a result, improving the knowledge of the determinants of such risk will bear consequence on asset allocation decisions and from a risk-management standpoint improve the assessment of portfolio risk exposures, in terms of breaking down the overall risk into factor exposures and evaluating scenarios for the movement and correlation between them.

Idiosyncratic risk is defined as the risk that is unique to a specific firm, and it unobservable, thus it must be estimated with some cross-sectional asset pricing model or aggregate decomposition techniques to isolate it from systematic components of risk. Our analysis starts from the results of papers such as Malkiel and Xu (1997), Campbell et al. (2001), Xu and Malkiel (2003), that have measured and modelled idiosyncratic risk as part of an effort to model the behaviour of total volatility, seen as the sum of market, sector and stock components, revealing important features of the size, variation and trends of each component that have important implication in a pricing framework. These papers using U.S. samples have documented a strong correlation between the components, a particularly high variability of the idiosyncratic one and its apparent upward trend - not accompanied by a rise in market volatility. Although the finding of rising idiosyncratic risk has been questioned by more recent papers (Bekaert, Hodrick, and Zhang (2008); Brandt, Brav, Graham, and Kumar (2010); Bartram et al. (2009), Guo and Savickas (2008)) that have shown it is a product of a particular sample, ending with the nineties, Campbell et al. (2001) also present evidence on the characteristics and movement of the components of average volatility: firm-level volatility accounts for the largest share of total volatility and volatility variation over time; the three components of volatility move together and are countercyclical; market volatility tends to lead the other volatility series. Moving away from U.S. samples, the results for international markets are mixed. Bekaert et al. (2008) show that idiosyncratic risk has a large common component across countries, which has gained importance over time. But the findings of Hamao et al. (2003) for the post-crash Japanese market - a reduction in firm-level volatility in the context of rising market volatility and equity co-movement – show clearly that the different micro and macro characteristics of each markets could lead to different results.

1.2 Contribution

In our analysis of a U.K. sample, we apply the aggregate volatility decompositions of Malkiel and Xu (1997) and Campbell et al. (2001), but we find no clear evidence of a trend in any component of total risk; instead we find the idea of "regimes" emerging in Bekaert et al. (2008) applicable and useful not only in modelling the pattern of each of the sub-components of total risk, but also in modelling correlation patterns between each of them, and thus their contribution to aggregate risk. This implies that the relative importance, variability and co-variation of the components of total risk change significantly over time.

Comparing direct and indirect estimates of residual risk, we find the former to significantly overstate diversifiable risk; this is the opposite of the findings of Xu and Malkiel (2003), although they operate on a U.S. sample, use conditional estimates of both measures, and obtain a moderate difference, while our difference is very large especially when we include the industry component.

2. Methodology and results

We estimate aggregate measures of volatility using both non-parametric and parametric techniques.

2.1 Dataset

Our starting universe includes all stocks listed on the London stock exchange from January 1990 until December 2009, for which we collect monthly data from Datastream (prices, returns, volume, outstanding shares and classification tags). A key issue emerging from the literature on residual risk is the importance of controlling for the cross-sectional impact of outliers, in the form of small and illiquid stocks. Bali et al. (2005) and Wei and Zhang (2005) recommend to this end the use of median and value-weighted average measures of risk, less influenced by outliers. We deal with this issue, and with data-related problems in general, using a combination of rigorous data-quality and investability filters, detailed fully in Rossi (2011), including an in-depth cross-check and correction of the Datastream sample using a second data source, Bloomberg. As a result, we are confident that our results are not influenced to any significant degree by data errors or liquidity issues.

2.2 Non-parametric volatility measures

First, we compute the volatility of the market, as the standard deviation of the value-weighted average of all single stock returns in our filtered sample[1], over a twelve-month rolling window. Second, we calculate the value-weighted sum of the volatilities of all stocks over time; this corresponds to the "aggregate" volatility measure of Malkiel and Xu (2003), is of course higher than the market volatility due to the correlation effect, and can be viewed as the overall volatility of a typical stock. Then we take the difference between the two measures to obtain the portion of idiosyncratic volatility of the stocks in the index, which is diversified away in the value-weighted portfolio. This idiosyncratic risk component is found to be trending up in Xu and Malkiel (1997), Malkiel and Xu (2003) and Campbell et al. (2001) for a sample of U.S. stocks; Campbell et al. (2001), for instance, report that while market volatility has no significant trend, firm-level variance displays a large and significant positive trend, more than doubling between 1962 and 1997, with a corresponding decrease in correlations and in the explanatory power of the single factor model. But later studies, such as Bekaert et al. (2008), have questioned the existence of such trend, showing it is highly dependent on the specific sample cut-off; Frazzini and Marsh (2003) find no trend on the idiosyncratic volatility component for the U.K. market. In our sample, the existence of a trend is anything but evident, with the idiosyncratic component oscillating around a level of 10%; graphical analysis points to

[1] All results and aggregations are based on a sample filtered and cleaned as described in Rossi (2011)

different "regimes" or periods of increased firm-specific risk, followed by phases of normalization, implying that a trend could be detected if the end-point of a specific sample falls during such episodes, but not otherwise. Two phases of marked increases in firm-level variance can be observed in coincidence with the tech bubble and with the financial crisis at the end of the sample. In contrast to the firm-specific component, the market component is much more volatile around its mean, with multiple sharp increases corresponding to periods of turbulence or recessions; the two components are comparable in average size, and one can graphically spot that how they seem to move pretty independently of one another, often exhibiting a negative correlation, except during the 2008 financial crisis. For example, it is evident that while the volatility spikes of 1999 and 2002 are driven by only one component while the other remains fairly stable, the 2008 spike is driven by increases in both components.

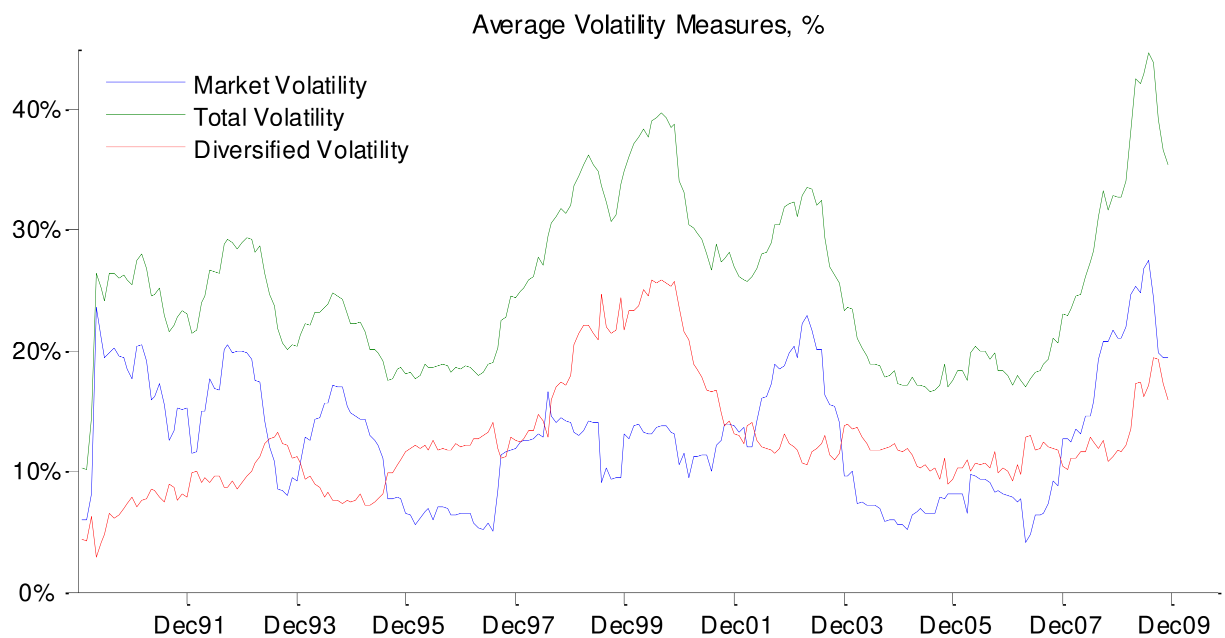

Figure 1 - Aggregate volatility measures, % - The figure shows Total, Market and Diversified aggregate volatility, computed as in Malkiel and Xu (2003). The values are annualized, estimated with a rolling window of twelve monthly returns

We then perform a second non-parametric variance decomposition using the methodology of Campbell et al. (2001), decomposing aggregate variance into market, industry, and idiosyncratic components. The average variance of a randomly drawn stock is split into market volatility[2] σ_{mt}^2 (called MKT), average industry volatility $\sigma_{\varepsilon t}^2$ (IND) and average firm-level volatility $\sigma_{\eta t}^2$ (FIRM), without requiring any beta-estimation[3].

$$\sum_i \omega_{it} \sum_{j \in i} \omega_{jt} Var(R_{jit}) = \sigma_{mt}^2 + \sigma_{\varepsilon t}^2 + \sigma_{\eta t}^2 \qquad [1]$$

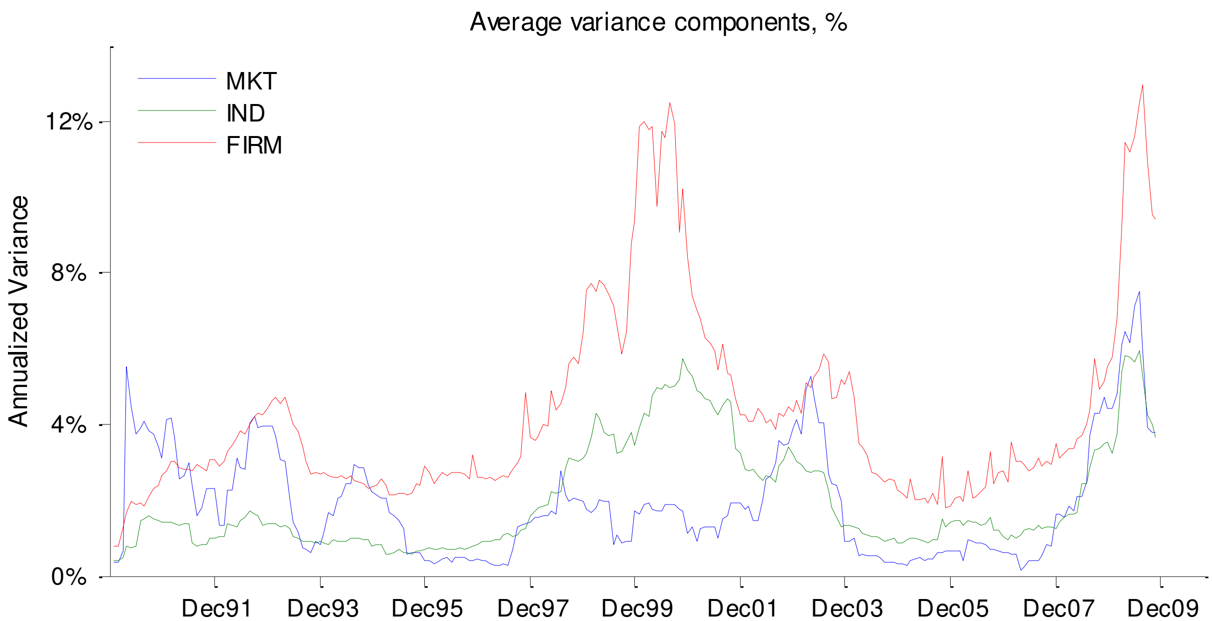

Figure 2 - Average variance components, % - The figure shows the components of the average variance of a random stock: the market component (MKT), the industry-level (IND) and the firm-level component (FIRM). Data are annualized and estimated with a rolling window of twelve monthly returns

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[2] Campbell et al. (2001) use the terms variance and volatility interchangeably, and so we will do in this section
[3] The only required information is industry classification for each single stock

The industry and firm components show a high degree of co-variation throughout the entire sample. The market component, on the other hand, is fairly de-correlated with the other two at least until the start of the last decade. Compared to the previous decomposition, which separated systematic from the diversified component of volatility, this more granular disaggregation into three components allows a better characterization of the volatility spike corresponding to the 2008 financial crisis. Not only has the size of the increase in aggregate total volatility been exceptional, but remarkably all three components moved up at the same time, which had not been the case in the 1999 episode. Table I shows the correlation between the three components of variance for the whole sample and for the sub-periods 1990-2002 and 2003-2009. While the correlation between the IND and the FIRM components remains always very high, the correlation between the MKT component and the other two drops to zero to slightly negative for the period up and including 2002, but becomes as high as 0.95 for the second part of the sample from 2003 to 2009. To our knowledge, these distinctly different correlation "regimes" have not been previously documented.

Table I - Correlation of variance components

1990-2009

MKT	**IND**	**FIRM**
1.00	0.43	0.40
	1.00	0.89
		1.00

1990-2002

MKT	**IND**	**FIRM**
1.00	0.02	-0.02
	1.00	0.87
		1.00

2003-2009

MKT	**IND**	**FIRM**
1.00	0.95	0.86
	1.00	0.93
		1.00

The Table shows the correlation between the three components of variance for the whole sample (1990-2009) and for the sub-periods 1990-2002 and 2003-2009

We now turn to examine how important the three volatility components are relative to the total volatility of an average firm, in terms of mean and variation. Campbell et al. (2001) had found firm-level volatility to be on average the largest portion of total volatility, accounting for over 70%, followed by marked volatility at 16% and firm-level volatility at 12%. Or results, shown in Table II, are broadly consistent with Campbell et al. (2001), although they paint a somewhat more balanced picture: the largest component is indeed FIRM, which accounts on average for over 50% of total variance, with the rest evenly split between MKT and IND. The importance of the industry-specific component is higher in our sample. However, the most striking result is that, if we split again the sample in two around 2002, the relative contributions to the average total variance vary very little over the two selected sub-periods.

Table II - Decomposition of Mean of total variance, % values

	MKT	**IND**	**FIRM**
1990-2009	0.23	0.25	0.52
1990-2002	0.23	0.25	0.53
2003-2009	0.24	0.24	0.52

Campbell et al. (2001) had shown, through a variance decomposition, that most of the time-series variation in total volatility was due to variation in MKT and FIRM, with FIRM variance and the covariation of MKT and FIRM being the two largest components; together they accounted for about 60 percent of the total time-series variation in volatility, while the market component alone contributed just by 15 percent. Relative to its mean, however, MKT showed the greatest time-series variation, while the volatility of IND was more stable over time. To perform a decomposition[4] of the variance of variance (VOV), we split our sample in three periods of roughly equal length: 1990-1996, 1997-2002 and 2003-2009. Table III shows the

[4] In this paragraph we are discussing the “variance of variance” (VOV), thus terminology becomes slightly cumbersome to avoid misinterpretation

contribution to total VOV by the three components and their covariance terms. Similar to the results of Campbell et al. (2001), the variance of FIRM is often a key driver of total VOV, but in fact we can identify distinctively different “regimes” corresponding to our sub-sample periods. In the 1990-1996 period, MKT is the primary driver, accounting alone for 43% of total VOV, and totalling 75% with the added impact of its covariation with IND and FIRM; this was a period of fairly low aggregate volatility, the variability of which was thus driven by market-wide movements, with no industry-specific shocks. During the following period, 1997-2002, total VOV is instead driven almost entirely by FIRM (44%) and by its covariation with IND (35%), while the importance of MKT is negligible. This period, leading to and including the tech bubble and its eventual burst, captures a regime dominated by stock-specific and industry-specific volatility. The final period, 2003-2009, shows a more balanced contribution, in line with the high correlations between the three components documented in Table I: the co-variation terms make up the bulk of total VOV.

Table III - Contribution to total variance of variance (VOV)

1990-2009

	MKT	**IND**	**FIRM**
MKT	10%	8%	**14%**
IND		9%	**29%**
FIRM			**30%**

1990-1996

	MKT	**IND**	**FIRM**
MKT	**43%**	**16%**	**15%**
IND		3%	8%
FIRM			16%

1997-2002

	MKT	**IND**	**FIRM**
MKT	3%	3%	4%
IND		11%	**35%**
FIRM			**44%**

2003-2009

	MKT	**IND**	**FIRM**
MKT	12%	**15%**	**27%**
IND		5%	**20%**
FIRM			21%

The Table shows a decomposition of the variance of total variance (VOV) for the average stock, after having decomposed total variance in market, industry and firm-specific components using the methodology of Campbell et al. (2001). We show results for the overall sample and for three distinct sub-periods. Bold values highlight the key contributors to total VOV for each period.

To describe the time-series variation of the variance components, we show in Table IV that FIRM has the largest variance and mean, which explains its significant contribution to total volatility; MKT and IND have lower values, similar to each other. Campbell et al. (2001) had found MKT to have the highest variance relative to its mean; this is not true for our sample, although both MKT and IND show a greater volatility relative to their means than FIRM[5]. Overall, we can say that the contribution of FIRM to total VOV is expected to be always high, given its high mean and variance. The contribution of MKT and IND is more variable with time, but we can state that the contribution of MKT is the least predictable, as it shows the weaker correlation with the other two components and a high volatility around its mean; IND shows instead a more slow-moving nature, and often mirrors FIRM, as can be seen easily in Figure 2.

Table IV - Time-series variation of variance components

	MKT	**IND**	**FIRM**
Variance	0.02%	0.02%	0.07%
Mean	1.91%	2.01%	4.29%
Variance/Mean	1.1%	1.0%	1.6%
Volatility/Mean	77.0%	70.3%	60.5%

The Table shows the means, variance and volatility for the three components of total variance

Summarizing, we have the following results:

i. The correlation between the three components of total variance varies substantially over time, although they tend to move together and experience periods of strongly positive co-variation. The exception is the relationship between FIRM and IND, which is always very strong: this implies that the joint contribution of the FIRM and IND (the stock-specific and industry-specific components) to total variance is substantial, and very frequently a large portion of that comes through the covariance terms. In contrast, the MKT

[5] The inconsistency is only apparent here, as we are in fact showing that the results vary significantly with the selected time-period, and Campbell results cover not only a different time span but also a different market

component shows periods of high correlation with the other two components, but also periods of very weak or near zero correlation

ii. In terms of relative contribution to total variance, FIRM explains on average (including the impact of half of its covariance terms) 52% of the total, followed by IND and MKT with 28% and 21% respectively, roughly a quarter each. However, although those contributions to the level of overall variance appear quite stable, looking at the drivers of changes in volatility we find the contributions of each component to the variance of variance to vary greatly in different sub-periods, identifying distinctly different regimes

iii. In terms of time-series variation, FIRM has the largest absolute variance and mean; yet MKT and then IND show the greatest volatility relative to their means. The contribution of FIRM to total variation is expected to be always high, while the share of MKT and IND changes more over time. Correlation analysis tells us that the contribution of MKT in particular is more uncertain and difficult to predict, as it is more weakly correlated with the other two components

2.3 Comparison of parametric and non-parametric measures

2.3.1 Parametric estimation of risk factor loadings and residual risk

We obtain parametric estimates of systematic and idiosyncratic risk exposures running two alternative regressions

$$r_{i,t}= \alpha_{i,t} + \beta_{i,t}\, r_{M,t} + \varepsilon_{i,t} \qquad [2]$$

$$r_{i,t}= \alpha_{i,t} + \beta_{i,t}\, r_{M,t} + h_{i,t}\, HML_t + s_{i,t}\, SMB_t + \varepsilon_{i,t} \qquad [3]$$

The first one is the market model, while the second one controls for the two additional systematic risk factors of Fama and French (1992). We use a rolling window of 24 monthly data points, expanding from a minimum of 12 observations[6]. The monthly returns for the *HML* factor is obtained from Kenneth R. French's website[7], while we compute the *SMB* factor by sorting our filtered sample into ten size deciles.

We collect the series of *β, s, h,* estimated from the above regressions as our (contemporaneous) estimates of systematic risk exposures. We also collect the series of the residuals ε_t to generate estimates of the idiosyncratic risk σ^2. We then build σ^2 using the two alternative approaches most common in the literature:

i. as the rolling standard deviation of the (rolling) series of ε_t over the 24 months window[8]

ii. fitting a GARCH(1,1) model to the series of the variance of ε_t over the 24 months window, and generating on each period a forecast for the conditional volatility of ε_t . The model is

$$\sigma_t^2 = k + g\ \sigma_{t-1}^2 + a\ \varepsilon_{t-1} \qquad [4]$$

The results of the two estimation procedures are shown in Figure 3, where we display aggregate, value-weighted measures of σ_t^2 across the entire sample.

[6] Empirical methods to obtain estimates of risk premia vary, and should be considered carefully for their econometric implications. For insance, OLS estimation over a rolling window assumes there is sufficient structure on the temporal variation in the parameters that OLS estimates may reasonably be interpreted as estimates of their mean values

[7] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#International

[8] The most commonly used procedure to estimate idiosyncratic volatility is to use the standard deviation of residuals from the market model regression. The chosen sampling frequency and the length of the interval for calculating such standard deviation vary. We are not comfortable with the frequently used practice that involves estimating this standard deviation using daily returns over the previous month, and then uses this estimate in subsequent analysis with monthly return data. We stick to a homogenous sampling frequency – monthly - for both risk premia estimation and tests of the pricing model

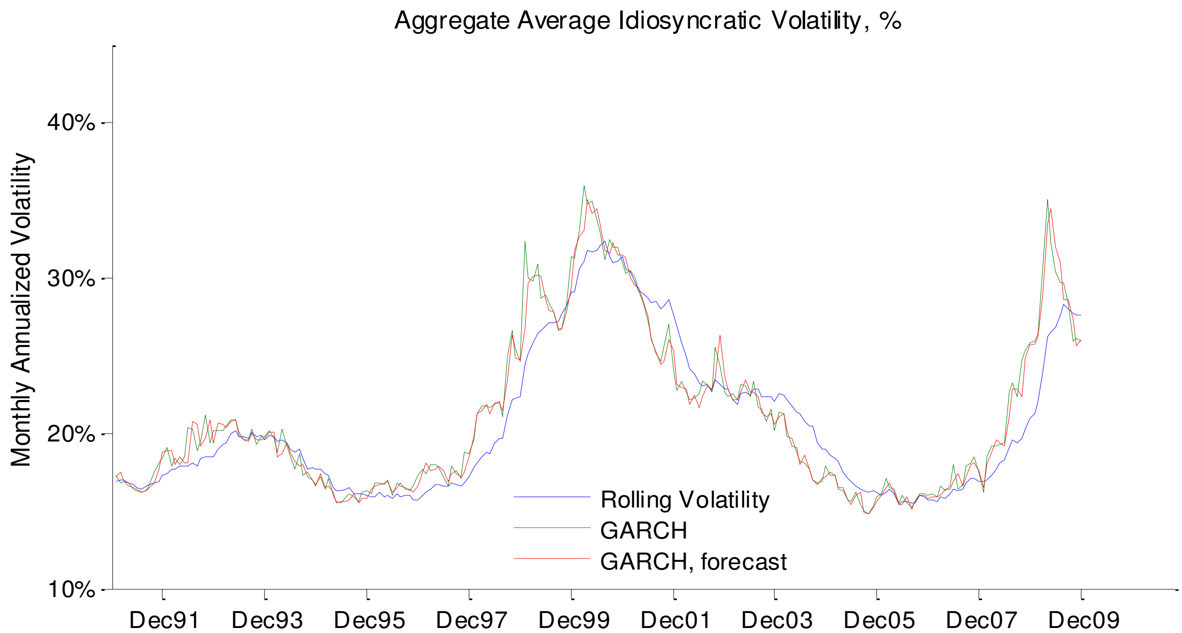

Figure 3 - Average idiosyncratic volatility, % - The figure shows average (value-weighted) idiosyncratic volatility measures, in annualized % terms, built from the residuals series from the cross-sectional single factor model regression. For each month t, we show three alternative volatility estimates: the simple standard deviation of the residual series, the conditional GARCH(1,1) volatility, and the conditional GARCH(1,1) volatility forecast for month t+1

Having obtained estimates of risk-factor exposures, Table V presents the variable descriptive statistics of the pooled sample.

Table V - Variable descriptive statistics for the pooled sample

Variables	Mean	Median	Std.Dev.
Return	1.26%	1.07%	11.17%
Β	1.098	1.038	0.828
β t-stat	2.461	2.297	1.660
IVOL - mkt model	7.15%	6.34%	3.72%
IVOL - mkt model – Garch	7.61%	6.54%	4.71%
E(IVOL) - mkt model – Garch	7.70%	6.58%	4.88%
IVOL - FF model	6.47%	5.82%	3.22%
Turnover	10.86%	7.71%	12.92%

Descriptive statistics for the pooled sample - monthly data from January 1990 to December 2009. The "Mean" values are not market-value weighted but equally weighted. The first 12 months (January-December 1990) have been excluded to allow for estimation of betas and volatility terms. *"IVOL"* is the cross-sectional idiosyncratic volatility, obtained regressing stock returns on a constant and the market return; "*IVOL - mkt model*", "*IVOL - mkt model – Garch*" and "*E(IVOL) - mkt model - Garch*" are obtained from the residuals of a single factor model regression, and are respectively a rolling 24-month average, a GARCH(1,1) term and its 1-period-ahead forecast. "*IVOL - FF model*" is instead obtained from a 24-month average of residuals from a Fama-French regression.

2.3.2 Comparing parametric and non-parametric residual risk measures

Comparing the average measure of residual risk built from the factor model regression residuals to the non-parametric estimates of residual risk of Section 2.2, as we do in Figure 4 and Table VI, it is evident how either the single factor model or the Fama-French model do a pretty poor job in capturing all sources of systematic risk. The single factor model parametric measure is on average 1.6 and up to 2.5 times higher that the "diversified" non-parametric measure (5.4 and up to 9 times higher than the "firm-level" measure built using the methodology of Campbell et al. (2001), which obtains as the component of average total risk not driven by market or industry risk). The comparison does not improve much using the parametric measure obtained from the Fama-French regression, as shown in Table VI . In annualized volatility terms, this translates into a gap of 7.6% (16%) on average - and up to 15% (23%) - between the single factor model measure and the two non parametric measures; this implies that idiosyncratic risk measures built from standard regressions reflect a substantial amount of risk that, in reality, is systematic. It is worth noting that this result is the opposite of the findings of Xu and Malkiel (2003), although they employ conditional estimates of both measures, their sample is U.S.-based and their difference between the two measures is smaller (the non-parametric measure is 0.1 times larger on average).

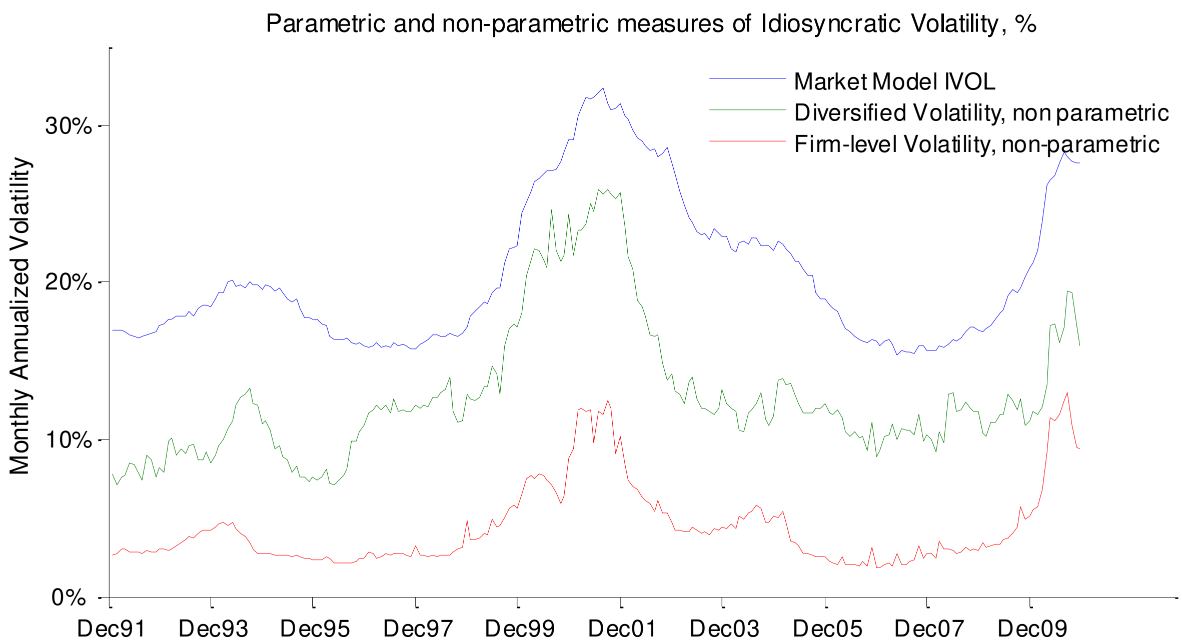

Figure 4 - Parametric and non-parametric measures of Idiosyncratic Volatility, % - The figure shows in blue the average (value-weighted) idiosyncratic volatility from the single factor model cross-sectional regression, together with the two non-parametric measures described in section **Error! Reference source not found.**: the "diversified" component of market-wide aggregate volatility (in green) and the "firm-level" component from the MKT-IND-FIRM decomposition (in red). The values shown are in annualized % terms

Table VI - Ratio of parametric estimates of average idiosyncratic volatility to non-parametric estimates of diversified or stock-specific risk

	Parametric Estimates			
	Single Factor Model		Fama-French Model	
Non-parametric measures	Max	Average	Max	Average
Malkiel's "diversified" volatility	2.43	1.67	2.19	1.51
Campbell's firm-specific volatility	9.05	5.43	8.46	4.94

The table shows the ratio of parametric estimates of average idiosyncratic volatility (obtained with a single factor model regression or with a Fama-French regression) to non-parametric estimates of diversified or stock-specific risk (the average "diversified" volatility built as in Xu and Malkiel (2003) or the firm-specific average volatility as in Campbell et al. (2001))

The extent of this over-estimation of the idiosyncratic component, of extremely large proportions in comparison to the measure of Campbell et al. (2001), suggests considerable caution towards results claiming to find a significant cross-sectional price for residual risk; they likely point to structural issues with the pricing model or with the systematic factor exposures estimation procedure.

3. Conclusions

We have reviewed and expanded some results on the behaviour of idiosyncratic risk and its interaction with systematic components of total risk. Our analysis of a U.K. sample has confirmed the idea that the components of total risk, including the idiosyncratic one, exhibit no time trend, but we show that they are subject to regimes affecting substantially the pattern of their movement and correlation and thus their contribution to aggregate risk. This implies that the relative importance, variability and co-variation of the components of total risk change significantly over time. We would stress two results. First, the Industry component and the firm-specific (or idiosyncratic) component are always highly correlated, while the market component's correlation with the other two is much more variable. Secondly, while the contribution of the three components to total risk is quite stable (with the firm-specific component accounting for over half of the total), the drivers of changes in total risk are not. We obtain another important result comparing parametric and non-parametric estimates of residual risk, and finding that parametric measures greatly overstate diversifiable risk; this implies that a large portion of parametric estimates of residual risk are likely to be in fact driven by systematic factor, for instance an industry component.

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