Revisiting Idiosyncratic Volatility and Stock Returns

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Abstract

This paper's aim is to revisit the relation between idiosyncratic volatility and future stock returns. There are three key findings: First, we confirm earlier studies which show a negative relation. Further we show that it is the month to month changes in idiosyncratic volatility that produce this observed relation. More specifically, a portfolio of stocks that move from a lower (higher) idiosyncratic volatility quintile to higher (lower) one earns positive (negative) abnormal returns. Eliminating all firm-month observations with idiosyncratic volatility quintile changes, we find a positive relation. Second, we link our findings with corporate related events. Third, we find that after 2000, the idiosyncratic volatility effect disappears.

Keywords: Idiosyncratic volatility; stock abnormal returns; change in idiosyncratic volatility.
JEL Classification: G12, G13.

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1 - Introduction

A recent study by Ang, Hodrick, Xing, and Zhang (2006) [Ang et al.] finds a strongly significant negative relation between idiosyncratic volatility and stock returns. In a follow-up paper Ang et al. (2009) show that this pattern is also visible internationally. After controlling for almost all related firm characteristics, they call their result a "puzzle": why do low idiosyncratic volatility firms earn higher future returns than ones with higher idiosyncratic volatility?

The pricing of idiosyncratic volatility in the cross-section of stock returns has been the subject of research for almost 40 years. In early work, Douglas (1969) and Lintner (1965) found that the variance of the residuals from the market model was highly significant in explaining the cross-section of stock returns. More recently the debate on the relevance of idiosyncratic volatility has been revived with conflicting results. Lehmann (1990), Goyal and Santa-Clara (2003), and Fu (2009) present evidence of a positive relationship between idiosyncratic volatility and future returns. Bali, Cakici, Yan and Zhang (2005) and Bali and Cakici (2008) find that there is no significant relation between idiosyncratic volatility and future returns. A recent paper by Huang et al. (2010) also shows that there is no relation between idiosyncratic volatility and future returns once we control for short-term reversal. Moreover, they show that estimation procedures also accounts for these conflicting results in the literature. On the other hand, the theory on pricing idiosyncratic volatility is very clear: there is a positive relation (if any) between idiosyncratic volatility and future stock returns.[2]

We contribute to this literature with three key results. First, we show that it is the month to month change in idiosyncratic volatility that produces the negative relation between the lagged idiosyncratic volatility and future stock returns. More specifically, a portfolio of stocks that moves from a lower (higher) to a higher (lower) idiosyncratic volatility quintile earns positive (negative) abnormal returns. If we eliminate all firm-month observations with idiosyncratic volatility quintile changes, we find a positive relation between idiosyncratic volatility and future stock returns. In addition to the portfolio approach, we also use the Fama-MacBeth (1973) cross-sectional regression methodology to show that lagged idiosyncratic volatility has a positive coefficient once we control for the changes in idiosyncratic volatility.

[2] Merton (1987) shows that in the presence of market frictions where investors have limited access to information, stocks with high idiosyncratic volatility have high expected returns. Levy (1978) also investigates idiosyncratic volatility and shows it is priced.

Second, we argue that many of the extreme changes in idiosyncratic volatility are related to business events. In general, the pattern usually observed is that an announcement or an event increases uncertainty about a stock and hence, its idiosyncratic volatility increases. After the event, uncertainty is resolved and the stock returns to a lower idiosyncratic volatility quintile.

Third, we find that after the year 2000, the idiosyncratic volatility effect disappears. This can partly be explained by the better explanatory power of the Fama-French three-factor model during this period on the idiosyncratic volatility portfolios. Prior to 2000, the idiosyncratic volatility quintile portfolios include a wide range of stocks that have different sensitivities to the three Fama-French risk factors. Therefore, the loadings on SMB and HML are not always significant. Whereas post 2000, the idiosyncratic volatility sorted portfolios are more homogenous in terms of stock characteristics and we observe significant estimates on SMB and HML factors.

The paper is organized as follows. In Section 2, we discuss the data and provide an explanation for the negative relation between lagged idiosyncratic volatility and future stock returns. Section 3 interprets the results. Section 4 shows disappearing effect of idiosyncratic volatility. Section 5 shows robustness tests. Section 6 concludes.

2 - Rethinking idiosyncratic volatility puzzle

2.1 - Data description

All stock related data are gathered from the Center for Research in Security Prices (CRSP) database for U.S. listed stocks from 1963-2008. We follow the procedures used in the existing literature. For each stock, idiosyncratic volatility is computed as the standard deviation of the residuals from the Fama-French three-factor (excess of the risk-free rate) (FF 3-Factor) model of daily returns within the month. In particular, the residuals are estimated from the following regression of daily returns for each firm, each month:

$$r_t^i - r_f = \alpha^i + \beta_{MKT}^i MKT + \beta_{SMB}^i SMB + \beta_{HML}^i HML + \varepsilon_t^i \text{.....................(1)}$$

Idiosyncratic volatility is defined as $\sqrt{Var(\epsilon_t^i)}$ in Equation 1.[3] This study only uses idiosyncratic volatility estimated from stocks that have more than 17 daily observations due to possible biases because of infrequent trading.

2.2 - Empirical results

2.2.1 - Portfolio approach

It is shown that there is a negative relation between lagged idiosyncratic volatility and future stock returns by relating returns earned in month *t* with the stock's idiosyncratic volatility in month *t*–1. That is, high idiosyncratic volatility stocks in the current month earn low returns in the next month. However, we relate the returns earned in month *t* with the stock's idiosyncratic volatility in month *t*–1 and month *t*. We consider three cases: idiosyncratic volatility is similar in both months, idiosyncratic volatility in month *t*–1 is significantly less than that in month *t*, and idiosyncratic volatility in month *t*–1 is significantly greater than that in month *t*. The behavior of these three groups is markedly different. For those stocks that experience a significant change in idiosyncratic volatility, the return earned in month *t* is consistent with the contemporaneous idiosyncratic volatility and is inconsistent with idiosyncratic volatility in month *t*−1.

First, we confirm that a trading rule long the high and short the low idiosyncratic volatility quintile earns −0.96% per month based on the raw unadjusted returns for the period 1963-2008[4]. These findings are both statistically and economically significant. However, for the equally-weighted portfolio we don't see any significant difference between the high and low idiosyncratic volatility quintile portfolios.[5] The reason for this is the substantially different average return for the high idiosyncratic volatility quintile portfolios. It is 0.96% based on equal weights and -0.06% based on value weights.

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[3] Other asset pricing models generate similar estimates of idiosyncratic volatility.
[4] Ang et al's sample period is 1963-2000.
[5] Bali et al. (2005 and 2008) show that there is no relation between lagged idiosyncratic volatility and future stock returns when we use equally-weighted portfolio returns.

Table 1 also shows portfolio alphas for each idiosyncratic volatility quintile. The high minus low portfolio earns −1.19% per month relative to the FF 3-Factor model and −1.24% per month relative to the CAPM.[6] Clearly, there is a negative relation between the lagged idiosyncratic volatility and future stock returns using value weighted portfolio returns. Table 1 also reports that High (Low) idiosyncratic volatility stocks are the smallest (biggest) in size.

Table 1: Negative Relation between Idiosyncratic Volatility and Stock Returns

IVOL Quintile	CAPM Alpha	FF-3 Alpha	VWRET	EWRET	Size
Low	0.14	0.09	0.90	1.02	5.34
	[2.65]	[2.08]			
2	0.08	0.05	0.93	1.26	5.20
	[1.85]	[1.31]			
3	0.06	0.06	0.98	1.30	4.60
	[0.81]	[0.95]			
4	-0.35	-0.32	0.65	1.12	3.94
	[-2.58]	[-3.23]			
High	-1.10	-1.10	-0.06	0.96	2.93
	[-5.12]	[-7.01]			
High–Low	-1.24	-1.19	-0.96	-0.07	
	[-4.86]	[-6.54]	[-2.42]	[-0.16]	

This table shows: VWRET and EWRET refer to value-weighted and equally-weighted portfolio simple unadjusted monthly percentage returns, respectively. Quintile 1 contains stocks with the lowest idiosyncratic volatility and Quintile 5 consists of the highest idiosyncratic volatility stocks. The row

[6] These results are consistent with Ang et al.'s (2006) findings which are −1.31% and −1.38% per month with respect to the FF 3-Factor model and the CAPM, respectively. Unreported Fama-French three factor model estimates are as follows: market betas increase monotonically with the ranking by idiosyncratic volatility quintile: the higher the idiosyncratic volatility the higher the systematic risk. Similarly the SMB betas increase monotonically with idiosyncratic volatility while the HML betas decrease. The SMB rankings are consistent with the size variable reported in Table 1. The HML results suggest that low idiosyncratic volatility stocks have high book to market values and are value stocks, while high idiosyncratic volatility stocks have low book to market values and are growth stocks. Results can be provided upon request.

"High-Low" refers to the difference in monthly returns between Quintile 5 and Quintile 1. IVOL is idiosyncratic volatility. Size is the average log market capitalization of stocks within the portfolio. The Alpha columns show Jensen's alpha with respect to the CAPM or to the FF 3-Factor Model. Robust Newey-West (1987) *t*-statistics are reported in brackets. Value-weighted quintile portfolios are formed every month *t* based on the stock's idiosyncratic volatility in month t–1 relative to FF 3-Factor Model computed using daily data in month *t*–1. The sample period is July 1963 to December 2008. All reported variables are calculated in month *t*.

Second, we use the fact that idiosyncratic volatility is time-varying. Table 2 shows that for the whole sample period the mean and standard deviation of the individual stock's monthly idiosyncratic volatility averages 3.41% and 2.04%, respectively. The standard deviation is almost 60% of the mean.[7] Therefore, we relate the returns earned in month *t* with the stock's idiosyncratic volatility in month *t*–1 and month *t* rather than relating returns earned in month *t* with the stock's idiosyncratic volatility in month *t*–1. That is we explore the relation between changing idiosyncratic volatility and portfolio return.[8]

We form twenty-five value-weighted portfolios based on the idiosyncratic volatility quintiles in month *t*–1 and month *t* and use the change in idiosyncratic volatility rankings over the two months. For each firm we create a variable called MIGRATE, which indicates the movement from one quintile to another. For a stock that was in quintile *X* at *t*–1 and is in quintile *Y* at *t* the MIGRATE is *Y*–*X*. For example a stock in idiosyncratic volatility quintile 1 (Low) at *t*–1 and in idiosyncratic volatility quintile 5 (High) at *t* the MIGRATE value is +4. In contrast, a firm that is in quintile 5 in month *t*–1 which moves to quintile 1 in month *t* has a MIGRATE value of −4. A firm may experience nine possible migration values from −4 to +4 and stocks with a MIGRATE value of 0 are considered to have highly persistent idiosyncratic volatility.

[7] Fu (2009) finds for an average individual stock, the standard deviation of its monthly idiosyncratic volatilities is 55 percent of the mean. The sample period is from July 1963 to December 2006.

[8] Fu (2009) uses an EGARCH model to capture the time varying property of idiosyncratic volatility when he looks at the relationship between idiosyncratic volatility and future returns. Fu's EGARCH estimates fail to pick up extreme volatility movers and they largely captures the small changes in volatility level. We will discuss this in detail in Section 3.1.

Table 2: Time-varying Idiosyncratic Volatility

IVOL Quintile	Std.	Mean
Low	1.24%	1.83%
2	1.61%	2.59%
3	1.97%	3.26%
4	2.33%	3.95%
High	2.75%	4.79%
All	2.04%	3.41%

For each stock, idiosyncratic volatility are formed every month *t* based on residuals from FF 3-Factor Model computed using daily data in month *t*–1. Mean is the average idiosyncratic volatility and Std. is the standard deviation of idiosyncratic volatility. IVOL is idiosyncratic volatility. The sample period is July 1963 to December 2008.

For each portfolio the return in month *t* is calculated and the FF 3-Factor model estimated using the time series of monthly portfolio returns. Table 3 reports the portfolio alphas relative to the FF 3-Factor model for the 25 portfolios formed from the five possible idiosyncratic volatility quintiles in time period t for each of the five idiosyncratic volatility quintiles at t-1. The upper panel of Table 3 reports the estimated alphas and the lower panel the Newey-West *t*-statistics. Alpha estimates statistically significant at the 5% level are bolded.

In general, the portfolios in which stocks have migrated from lower to higher quintiles (the upper right hand triangle of the table) have positive alphas. Similarly, the portfolios in which stocks have migrated from higher to lower quintiles (the lower left hand triangle of the table) have negative alphas. If we consider only the significant results, all cases that involve a migration from a lower to a higher quintile have positive alphas; all cases that involve a migration from a higher to a lower quintile have negative alphas.

Since we use value-weighted portfolio returns, it is important to have significant market capitalizations of stocks that move from lower to higher idiosyncratic volatility quintiles or vice versa. Panel B of Table 3 shows that the average size of the migration portfolios is big enough to influence the entire idiosyncratic volatility quintile. Note that stocks that move from a lower to a higher idiosyncratic volatility quintile tend to be smaller than ones that stay in the same quintile for the next month. On the other hand, it tends to be bigger stocks that move from higher to lower idiosyncratic volatility quintiles. The influence of migration stocks on the entire idiosyncratic volatility quintile is significant enough to create the negative relation.

In Table 3 we noted that among statistically significant results, stocks that migrate from low to high idiosyncratic volatility quintiles have positive alphas. Those that migrate from high to low idiosyncratic volatility quintiles have negative alphas. To explore this further, the twenty-five portfolios based on the idiosyncratic volatility quintiles in month t–1 and month t are pooled into the nine possible value-weighted portfolios based on MIGRATE: the difference between the idiosyncratic volatility quintile in months t and t–1. For each of these portfolios the return in month t is calculated and the FF 3-Factor model is fitted to the time series of monthly portfolio returns. The results are shown in Table 4.

Table 3: Estimates of Alpha for Fama-French Three Factor Model by MIGRATE

Panel A. Portfolio alpha with respect to FF 3-factor model						
		IVOL Quintile at *t*				
		1	2	3	4	5
IVOL Quintile at *t*–1	1	0.07	**0.24**	0.19	0.13	**4.95**
	2	-0.13	**0.14**	**0.35**	0.12	**1.41**
	3	**-0.61**	**-0.18**	**0.36**	**0.69**	**1.12**
	4	**-1.11**	**-0.74**	**-0.53**	0.08	**0.70**
	5	**-0.73**	**-1.98**	**-2.15**	**-1.78**	0.08

t-statistics for the alphas

		IVOL Quintile at *t*				
		1	2	3	4	5
IVOL Quintile at *t*–1	1	1.28	3.17	1.18	0.33	5.96
	2	-1.74	2.39	3.59	0.48	2.32
	3	-6.56	-2.16	4.45	4.51	2.79
	4	-8.31	-5.71	-4.85	0.58	2.33
	5	-4.57	-10.26	-12.73	-11.27	0.29

Panel B. Mean Size of Stocks						
		IVOL Quintile at *t*				
		1	2	3	4	5
IVOL Quintile at *t*–1	1	5.49	5.46	4.74	3.94	3.19
	2	5.45	5.51	5.03	4.40	3.65
	3	4.69	5.03	4.76	4.29	3.63

	4	3.88	4.38	4.29	3.95	3.36
	5	3.63	3.54	3.61	3.38	2.58

Twenty-five value-weighted quintile portfolios are formed every month *t* based on idiosyncratic volatility relative to FF 3-Factor Model computed using daily data in month *t*–1 and daily data in month *t*. IVOL is idiosyncratic volatility. The sample period is July 1963 to December 2008. Panel A reports the alpha from time series estimates of the FF 3-Factor Model using monthly data for each portfolio. Panel B shows Size, the average log market capitalization of stocks within the portfolio. Alphas that are statistically significant at the 5% level are bolded. The lower panel shows robust Newey-West (1987) *t*-statistics for the alphas in the upper panel.

Table 4: The Impact of MIGRATE on Excess Returns

MIGRATE	Market beta	SMB beta	HML beta	Alpha
-4	0.51	0.17	0.25	-0.73
	[10.59]	[3.69]	[4.27]	[-4.57]
-3	0.81	0.20	0.17	-1.34
	[24.29]	[4.35]	[2.97]	[-10.27]
-2	0.96	0.11	0.08	-0.76
	[39.64]	[3.03]	[1.97]	[-8.84]
-1	0.97	0.04	0.01	-0.25
	[61.62]	[1.77]	[0.32]	[-4.57]
0	0.92	-0.07	0.02	0.12
	[135.97]	[-5.13]	[1.19]	[4.60]
1	1.13	0.10	-0.03	0.23
	[60.11]	[3.29]	[-0.68]	[3.95]
2	1.31	0.44	-0.05	0.05
	[22.49]	[4.29]	[-0.51]	[0.29]
3	1.42	1.00	0.29	0.33
	[13.67]	[5.50]	[1.33]	[0.76]
4	1.40	1.74	0.90	4.95
	[7.37]	[6.37]	[2.61]	[5.96]

MIGRATE is the idiosyncratic volatility quintile number computed using daily data in month *t* less the idiosyncratic volatility quintile number computed daily data in month *t*–1. Value-weighted portfolios are then formed every month based on the MIGRATE value. MIGRATE 0 refers to stocks that stay in the same quintile. MIGRATE +4 refers to a firm that moves from Quintile 1 to Quintile 5 and MIGRATE −4 refers to a firm that moves from Quintile 5 to Quintile 1. The sample period is July 1963 to December 2008. Robust Newey-West (1987) *t*-statistics are reported in brackets.

The change in a firm's idiosyncratic volatility ranking has an asymmetric impact on its future return. Consistent with the results in Table 3, portfolios of stocks that have migrated from lower to higher idiosyncratic volatility quintiles have more positive alphas than those of stocks that have migrated from higher to lower idiosyncratic volatility quintiles. In particular, stocks that migrate from the highest to the lowest idiosyncratic volatility quintile earns 4.95% per month whereas it is only -0.73% per month for stocks migrating from the lowest to highest. It is also clear that while the loadings on the HML and SMB factors vary, there is a fairly consistent increase in market betas as MIGRATE gets larger, that is, as idiosyncratic volatility tends to increase.

The remaining case is for the portfolio of stocks that had the same quintile in month *t*–1 and month t. The results for this group, sorted by their quintile in month *t*–1, are shown in Table 3 where we have the results for constant idiosyncratic volatility for all five quintiles. In Table 4 we have the result for the entire group of constant idiosyncratic volatility stocks for all five quintiles. When the group is sorted by the original quintile all of the alphas are positive, but not all are statistically significant. When we consider the entire group, the alpha is small and positive, and is statistically significant. In this case the statistical significance is largely a result of the larger size of the portfolio since it represents about half of all the observations. However, it is clear that for persistent idiosyncratic volatility there is a positive relation with the subsequent return.

2.2.2 - Cross-sectional results

In this section, we use the Fama-MacBeth (1973) cross-sectional regression model rather than a portfolio approach to investigate the negative relation between future stock returns and lagged idiosyncratic volatility.

Table 5 shows the results. We use the estimates of Equation (1) for the month *t* values[9] for the market, SML, and HML betas used in equations 2a and 2b. For the whole sample, the average coefficient on lagged idiosyncratic volatility is -0.12 indicating that there is a negative relation between lagged idiosyncratic volatility and future stock returns. If we only use stocks that stay in the same idiosyncratic volatility ranking for two consecutive months, Migrate 0 stocks, the coefficient is positive which indicates that there is a positive relation between lagged idiosyncratic volatility and future stock returns for firms with persistent idiosyncratic volatility.

When we add the change in idiosyncratic volatility from month *t-1* to *t* into the regression analysis as in Equation (2b), we see that the coefficient on lagged idiosyncratic volatility is positive for the whole sample. Moreover, the change in idiosyncratic volatility has a positive impact on future stock returns. A positive (negative) change in idiosyncratic volatility increases (decreases) future stock returns indicating a positive contemporaneous relation between stock returns and idiosyncratic volatility.

Table 5: Fama-MacBeth (1973) Cross-Sectional Regressions

	Whole data	Migrate "0"	Whole data
γ_4	-0.12	0.17	0.64
t-stat	[-2.96]	[3.36]	[9.30]
γ_5			1.90
t-stat			[22.34]

For each month, we run the following regressions. i=1,..., N where N is the number of stocks that is used to estimate the regressions and t=1,..., T where T is the total number of months. The sample period is 1963-2008.

$$r_t^i = \alpha^i + \beta_{MKT}^i \gamma_1 + \beta_{SMB}^i \gamma_2 + \beta_{HML}^i \gamma_3 + IVOL_{t-1}\gamma_4 + \varepsilon_t^i$$

$$r_t^i = \alpha^i + \beta_{MKT}^i \gamma_1 + \beta_{SMB}^i \gamma_2 + \beta_{HML}^i \gamma_3 + IVOL_{t-1}\gamma_4 + \Delta IVOL_t \gamma_5 + \varepsilon_t^i$$

[9] The results are the same if we use the previous month's values.

3 - Interpretation of the results: corporate related events

So far we have shown that the negative relation between lagged idiosyncratic volatility and future stock returns is a result of the change in idiosyncratic volatility from one month to another. The obvious question is what is driving these results?

We show that business related events cause this positive relation by looking at delisted stocks. [10] The reason for is that delisting from a stock exchange occurs for a variety of reasons, such as mergers and acquisition activity, bankruptcy, and negative performance. These corporate events all cause significant stock price movements around their announcement dates, which translate into higher monthly idiosyncratic volatility. For example, a target firm may experience a significant stock price increase in the month of an acquisition announcement. In the same spirit, firms going bankrupt experience downward price movements during the last one or two years of their listing history, which again translates into higher levels of idiosyncratic volatility. However, in order to have a positive contemporaneous relation between stock returns and idiosyncratic volatility, we should have more stock price increase related high idiosyncratic volatility in our sample. In fact, in our sample we observe more M&A related migrations than bankruptcy related ones.

Therefore, a negative relation between idiosyncratic volatility and future stock returns is contaminated by delisting stocks to the extent that these events do not reflect the relation between persistent idiosyncratic volatility and returns. Table 6 bears out this intuition and shows that a trading strategy high minus low idiosyncratic volatility for delisted stocks earns -1.44% per month, whereas the same strategy for firms that have never been delisted, termed survivor stocks, earns -0.73% per month, that is, the negative relation is twice as strong for delisted firms than it is for survivors. [11]

These results show that although the difference between delisted

[10] Positive contemporaneous relation between stock returns and idiosyncratic volatility is more significant for delisted stocks than non-delisted one. The coefficient on the current return is 0.21 and 0.15, respectively when the current idiosyncratic volatility is the dependent variable in the regression.

[11] There is a more pronounced negative relation between current return and the change in future idiosyncratic volatility for delisted stocks than non-delisted stocks. The coefficient on the current return is -0.56 and -0.07, respectively when the change in future idiosyncratic volatility is the dependent variable in the regression. This shows that risk based and event based explanations are not mutually exclusive.

versus non-delisted stocks is significant, there is still a negative relation between idiosyncratic volatility and future stock returns even for survivor stocks.

Table 6: Idiosyncratic Volatility Effect on Delisting versus Non-delisted Stock

	FF 3-Factor Model Alpha		Size	
IVOL Quintile	Delisted	Non-delisted	Delisted	Non-delisted
Low	0.10 [1.23]	0.16 [2.95]	4.78	6.05
2	0.09 [1.19]	0.13 [2.34]	4.64	6.06
3	0.09 [0.68]	0.29 [3.50]	4.13	5.51
4	-0.30 [-2.13]	-0.10 [-0.71]	3.55	4.87
High	-1.34 [-7.76]	-0.60 [-2.93]	2.36	3.93
High–Low	-1.44 [-4.55]	-0.76 [-5.23]		

Quintile 1 contains stocks with the lowest idiosyncratic volatility and Quintile 5 consists of the highest idiosyncratic volatility stocks.The row “High-Low” refers to the difference in monthly returns between Quintile 5 and Quintile 1. Size is the average log market capitalization of stocks within the portfolio. The Alpha columns show Jensen’s alpha with respect to the FF 3-Factor Model. Robust Newey-West (1987) *t*-statistics are reported in brackets.

Table 6 also shows the average size of the stocks in each idiosyncratic volatility quintile separately for delisted and non-delisted stocks. The difference in size between high and low idiosyncratic volatility stocks is larger for delisted stocks than for non-delisted stocks. But nonetheless high idiosyncratic volatility stocks are larger compared to low idiosyncratic volatility stocks in both sub-samples.

In summary, business related events may cause increases in idiosyncratic volatility which affect stock returns during the event period. These event effects are captured by the negative relation between idiosyncratic volatility and future stock returns.

4 - Disappearing effect of idiosyncratic volatility

We repeat the analysis on the negative relation between lagged idiosyncratic volatility and future stock returns for the sub-samples: 1963-1971, 1981-1990, 1991-2000, and 2001-2008.[12] Panel A of Table 7 confirms that a trading strategy that is high minus low idiosyncratic volatility earns around -1% to -2% per month. The more pronounced idiosyncratic volatility effect is seen in the period of 1981-1990. However, this strategy earns -0.14% per month during the period of 2001-2008 and it is statistically insignificant. It seems that the idiosyncratic volatility puzzle has almost disappeared after 2000. This is because during this period high idiosyncratic volatility stocks perform better compared to previous years and the spread between high and low idiosyncratic volatility stocks has shrunk.

We investigate whether the disappearing effect of idiosyncratic volatility is related to the level of aggregate idiosyncratic volatility in the market. The financial crisis has an impact on the aggregate level of idiosyncratic volatility from 2007 and onwards. Hence, we divide the post 2000 sample into two sub-periods: 2001-2005 and 2006-2008. The average monthly aggregate idiosyncratic volatility is 1.43% per month for the former and 1.41% per month for the latter period. The slightly higher idiosyncratic volatility in the period of 2001-2005 comes from the high idiosyncratic volatility levels in years 2001 and 2002 associated with the bursting of the Internet bubble. However, idiosyncratic volatility has a different effect on future stock returns in both periods: there is no effect in the period 2001-2005 and a significant negative effect in the period 2006-2008. Hence, we conclude that the level of aggregate idiosyncratic volatility is not an explanation for the disappearing effect of idiosyncratic volatility in the period of 2001-2005.

There is more short-term reversal during 2001-2005 compared to 2006-2008. This also confirms that short-term reversal alone cannot explain why a high minus low idiosyncratic volatility trading portfolio earns negative future abnormal returns This is because during the former period we don’t

[12] We follow Ang et al. (2006) for the cut points for the periods. Moreover, our results are in line with their findings.

observe any impact of idiosyncratic volatility on future stock returns despite the prevalence of short term return reversal.

We also investigate stock characteristics such as size, idiosyncratic volatility, turnover, and market risk, value-weighted future and previous month's portfolio returns for the periods 2001-2008 and 1981-1990. Panel A of Table 8 shows the results for the former period and Panel B shows for the latter period. The reason for making such a comparison is that during the former period we have no idiosyncratic volatility effect, while for the latter period we have the most pronounced effect.

For 1981 to 1990 only the highest idiosyncratic volatility quintile earns negative abnormal future returns and there is a significant short-term return reversal for stocks in that particular quintile. During 2001-2008, however, except for the lowest quintile portfolio, all other idiosyncratic volatility portfolios earn negative future returns. During this period, short-term return reversal is lower compared to the period 1981-1990. In both periods, higher idiosyncratic volatility quintile portfolios are smaller than lower idiosyncratic volatility stocks. The biggest difference between the two periods is the turnover between low and high idiosyncratic volatility quintile portfolios. Turnover is high for higher idiosyncratic volatility quintiles during 1981-1990 and it is the reverse for 2001-2008. Moreover, turnover for the whole sample is significantly higher during the same period.

Table 7: Disappearing Effect of Idiosyncratic Volatility

	Panel A. Fama-French Three Factor Alpha					
	IVOL Quintile					
	Low	2	3	4	High	High-Low
1963-1970	0.07	0.04	0.12	-0.35	-0.86	-0.92
	[1.49]	[0.56]	[1.15]	[-1.93]	[-3.97]	[-4.98]
1971-1980	-0.12	0.28	0.28	0.02	-0.89	-0.78
	[-1.36]	[3.63]	[2.55]	[0.12]	[-4.53]	[-3.12]
1981-1990	0.17	0.00	-0.05	-0.65	-2.08	-2.25
	[2.68]	[0.00]	[-0.46]	[-4.31]	[-9.01]	[-9.03]
1991-2000	0.19	0.06	0.03	-0.57	-1.37	-1.57
	[1.65]	[0.51]	[0.18]	[-2.47]	[-3.62]	[-3.10]
2001-2008	0.04	-0.05	-0.01	0.02	-0.10	-0.14
	[0.41]	[-0.62]	[-0.04]	[0.07]	[-0.25]	[-0.50]

Panel B. Sub-periods of 2001-2008						
	2001-2005					
IVOL quintile	Market beta	SMB beta	HML beta	Alpha	VWRET	Past VWRET
Low	0.71	-0.13	0.29	-0.06	0.29	0.95
	[18.67]	[-2.21]	[4.81]	[-0.44]		
2	0.98	-0.05	0.18	-0.11	0.23	1.16
	[38.96]	[-1.47]	[4.31]	[-1.04]		
3	1.26	0.30	-0.20	0.02	0.36	1.30
	[25.00]	[4.04]	[-2.64]	[0.11]		
4	1.60	0.43	-0.65	-0.07	0.01	1.34
	[16.17]	[3.70]	[-5.24]	[-0.19]		
High	2.08	0.65	-0.85	-0.04	0.07	4.50
	[17.12]	[3.49]	[-4.32]	[-0.07]		
High-Low				0.02		
				[0.10]		
IVOL quintile	2006-2008					
Low	0.78	-0.10	0.10	0.22	-0.19	-0.09
	[16.98]	[-1.18]	[0.98]	[1.30]		
2	0.98	-0.06	0.08	0.02	-0.57	-0.18
	[18.23]	[-1.17]	[0.80]	[0.21]		
3	1.21	0.17	-0.16	-0.13	-0.95	0.03
	[20.95]	[1.61]	[-1.28]	[-0.74]		
4	1.39	0.28	-0.33	-0.01	-1.01	-0.05
	[12.84]	[1.27]	[-1.16]	[-0.02]		
High	1.43	0.54	-0.53	-0.73	-1.77	1.87
	[11.36]	[2.59]	[-1.84]	[-2.01]		
High-Low				-0.95		
				[-3.25]		

Quintile 1 contains stocks with the lowest idiosyncratic volatility and Quintile 5 consists of the highest idiosyncratic volatility stocks. The row “High-Low” refers to the difference in monthly returns between Quintile 5 and Quintile 1. VWRET and Past VWRET refer to month *t* and month *t-1* value-weighted portfolio simple unadjusted monthly percentage returns, respectively. Robust Newey-West (1987) *t*-statistics are reported in brackets. Panel A. The Alpha columns show Jensen’s alpha with respect to the FF 3-Factor Model. Panel B. Fama-French three factor model estimates for the sub-periods of 2001-2008: 2001-2005 and 2006-2008.

Table 8: Stock Characteristics of Idiosyncratic Volatility Quintiles in 2001-2008 and in 1981-1990

Stock Characteristics: Size, Turnover, Idiosyncratic Volatility, Market Beta					
	Panel A. Disappearing Idiosyncratic Volatility Effect: 2001-2008				
IVOL Quintile	VWRET	Past VWRET	Size	IVOL	Turnover
Low	0.14	0.57	6.04	0.94%	1.98%
2	-0.03	0.68	6.38	1.62%	1.56%
3	-0.07	0.86	5.89	2.25%	1.72%
4	-0.27	0.89	5.23	3.10%	1.74%
High	-0.49	3.63	4.09	5.08%	1.94%
	Panel B. More Pronounced Idiosyncratic Volatility Effect: 1981-1990				
IVOL Quintile	VWRET	Past VWRET	Size	IVOL	Turnover
Low	1.32	1.25	4.83	1.25%	0.38%
2	1.08	1.52	4.65	1.79%	0.51%
3	0.96	2.05	4.04	2.36%	0.59%
4	0.34	2.81	3.37	3.10%	0.59%
High	-1.07	8.19	2.45	5.06%	0.54%

Table shows: VWRET and Past VWRET refer to month *t* and month *t-1* value-weighted portfolio simple unadjusted monthly percentage returns, respectively. Quintile 1 contains stocks with the lowest idiosyncratic volatility and Quintile 5 consists of the highest idiosyncratic volatility stocks. Size is the average log market capitalization of stocks within the portfolio. IVOL is idiosyncratic volatility. Turnover is average monthly trading volume divided by the number of shares outstanding

Another way of examining stock characteristics is by investigating the loadings on the Fama-French risk factors. Table 9 shows the estimated coefficients on the market, SMB and HML factors for each sub-sample. Loadings on the market portfolio are about 1 to 1.5 except 1.80 for the period of 2001-2008. This means that stocks in the highest idiosyncratic volatility quintile are getting riskier through time. In contrast, SMB factor loadings are getting smaller over time and reach their lowest values during the most recent period. This means that stocks in the highest idiosyncratic volatility quintile are getting bigger. Moreover, loadings on HML are getting more negative indicating that in the highest idiosyncratic volatility quintile, we are seeing more growth stocks during this later period.

During this period the FF 3–Factor Model explains the returns on our idiosyncratic risk portfolios better than in earlier periods, that is, prior to 2000 idiosyncratic volatility quintile portfolios include a wide range of stocks that have different sensitivities to the Fama-French risk factors. In particular, the loadings on SMB and HML are not always significant. Whereas post 2000, the idiosyncratic volatility sorted portfolios are more homogenous in terms of stock characteristics, therefore we observe significant estimates on SMB and HML factors. This might explain the disappearing idiosyncratic volatility effect since 2000.

Table 9: Sub-sample Analysis: Fama-French Three Factor Model Estimates

1963-1970				
IVOL Quintile	Market beta	SMB beta	HML beta	Alpha
Low	**0.92**	**-0.20**	0.04	0.07
2	**1.05**	0.01	-0.01	0.04
3	**1.19**	**0.28**	-0.05	0.12
4	**1.18**	**0.76**	-0.04	-0.35
High	**1.02**	**1.39**	-0.13	**-0.86**
1971-1980				
Low	**0.84**	**-0.14**	0.00	-0.12
2	**1.05**	**-0.02**	0.03	**0.28**
3	**1.12**	**0.29**	0.04	**0.28**
4	**1.14**	**0.71**	0.12	0.02
High	**1.13**	**1.16**	**0.25**	**-0.89**

1981-1990				
Low	**0.91**	**-0.19**	**0.12**	**0.17**
2	**1.06**	**0.14**	-0.02	0.00
3	**1.10**	**0.45**	-0.08	-0.05
4	**1.14**	**0.70**	-0.06	**-0.65**
High	**1.02**	**0.78**	0.07	**-2.08**
1991-2000				
Low	**0.84**	-0.09	**0.19**	0.19
2	**0.99**	0.07	0.09	0.06
3	**1.19**	0.16	-0.04	0.03
4	**1.41**	0.39	-0.21	**-0.57**
High	**1.57**	0.74	-0.19	**-1.37**
2001-2008				
Low	**0.73**	**-0.14**	**0.26**	0.04
2	**0.97**	**-0.06**	**0.15**	-0.05
3	**1.24**	**0.27**	**-0.21**	-0.01
4	**1.51**	**0.42**	**-0.65**	0.02
High	**1.80**	**0.67**	**-0.94**	-0.10

Value-weighted quintile portfolios are formed every month *t* based on idiosyncratic volatility relative to FF 3-Factor Model computed using daily data in month *t*–1. IVOL is idiosyncratic volatility. Bold ones are significant at 5% level using robust Newey-West (1987) statistics.

If the migration stocks are the reason for a negative relation between lagged idiosyncratic volatility and future stock returns then one might wonder whether during the period of 2001-2008 the migration effect has disappeared. Table 10 shows that it is indeed the case. There is no pattern associated with stocks moving from lower to higher idiosyncratic volatility quintiles or vice versa. For example, stocks that move from lower to higher idiosyncratic volatility quintiles don't earn higher future returns as was the case for the Ang et al period 1963-2000. These results confirm our claim that it is the change in idiosyncratic volatility that explains the negative relation between lagged idiosyncratic volatility and future stock returns during the Ang et al sample period.

Table 10: Migration Stocks: Portfolio Alpha with respect to Fama-French Three Factor Model

Sample period. 2001-2008

		IVOL Quintile at month *t*				
		1	2	3	4	5
IVOL Quintile at month *t*–1	1	0.21	0.12	-0.64	**-3.04**	1.91
	2	**0.36**	**0.22**	**-0.51**	**-1.55**	**-5.41**
	3	0.04	0.16	**0.58**	-0.34	**-3.52**
	4	0.45	**0.58**	0.45	0.11	**-1.37**
	5	0.07	-0.46	0.12	-0.09	-0.01

Twenty-five value-weighted quintile portfolios are formed every month *t* based on idiosyncratic volatility relative to FF 3-Factor Model computed using daily data in month *t*–1 and daily data in month *t*. IVOL is idiosyncratic volatility. The sample period is January 2001 to December 2008. Table reports the alpha from time series estimates of the FF 3-Factor Model using monthly data for each portfolio. Alphas that are statistically significant at the 5% level are bolded.

5 - Robustness tests

In this section, we discuss some related issues. The first section discusses the “true” relation (if any) between idiosyncratic volatility and future stock returns, the second section investigates short-term return reversal explanation and the final section looks at the subsample analysis with particular attention to the post 2000.

5.1 - “True relation”

Theoretical models are based on expected return and expected idiosyncratic volatility so a negative relation between lagged idiosyncratic volatility and future stock returns does not invalidate a theoretical model that justifies idiosyncratic volatility being priced. This is because lagged idiosyncratic volatility might not be a good estimate of expected idiosyncratic volatility due to time-varying property of idiosyncratic volatility. Recall Table 2 which shows that the standard deviation is almost 60% of the mean of the individual stock's monthly idiosyncratic volatility. Clearly, idiosyncratic volatility is time-varying and therefore lagged idiosyncratic volatility may not be an appropriate proxy for next month's expected idiosyncratic volatility.

To adjust for this Fu (2009) used an Exponential Generalized AutoRegressive Conditional Heteroskedasticity (EGARCH) model to estimate expected idiosyncratic volatility. He found a positive relation between future stock returns and expected idiosyncratic volatility. Instead we use a sample which excludes firm-month observations where idiosyncratic volatility changes and find a positive relation between idiosyncratic volatility and future stock returns. Recall from Table 4 that these stocks earn 0.12% in the next month. This sub-sample includes stocks that have stable idiosyncratic volatility in two consecutive months such that lagged idiosyncratic volatility can be used as a proxy for expected idiosyncratic volatility. Consequently, the "true" relation between idiosyncratic volatility and expected return is positive to the extent that the current estimate of idiosyncratic volatility can be used as an estimate for future idiosyncratic volatility. This also implies that Fu's results are driven by the fact that his EGARCH model fails to pick up extreme volatility movers and his forecasts largely captures the existing volatility level as well as small volatility changes.

In conclusion the previous negative relation may not imply that the true relation between idiosyncratic volatility and the expected return is negative.

5.2 - Short-Term Reversal

Fu (2009) and Huang et al. (2010) show that the negative relation between lagged idiosyncratic volatility and future stock returns can be largely explained by the return reversal of stocks. In particular, high idiosyncratic volatility stocks are shown to have high contemporaneous returns. The positive abnormal returns tend to reverse, resulting in negative abnormal returns in the following month. These results are largely attributed to negative serial correlation in monthly returns and the positive contemporaneous relation between realized idiosyncratic volatility and stock returns. However, they did not give any explanation as to why there is a return reversal.

Panel A of Table 11 shows that stocks that are in the highest idiosyncratic volatility quintile earn abnormally high positive returns in the current month and then earn abnormally low returns in the next month. However, this is not the case for lower idiosyncratic volatility quintile stocks. If there is a short-term reversal, it can only explain why high idiosyncratic volatility stocks earn negative returns. Also equally-weighted portfolio returns don't show any significant return reversal indicating that it is larger stocks that experience most of the reversal. This is line with the results in Panel B of Table 3 that larger stocks migrate from higher to lower idiosyncratic volatility quintiles.

Panel B of Table 11 shows that migration stocks do experience significant return reversal as opposed to those that stay in the same idiosyncratic volatility quintile. The pattern usually observed is that an announcement or an event increases uncertainty about a stock and hence its idiosyncratic volatility increases. After the event, uncertainty is resolved and the security returns to a lower idiosyncratic volatility quintile. This indicates that return reversal is related to business events which cause a positive skewness in stock returns, which is why we see a positive contemporaneous relation between stock returns and idiosyncratic volatility.

We also use Fama-MacBeth (1973) cross-sectional regressions to investigate the negative relation between future stock returns and lagged idiosyncratic volatility while controlling for the lagged return. In Table 12 column 1 repeats Ang et al's results; column 2 shows our result that changes in idiosyncratic volatility drive Ang et al's results while column 3 confirms Huang et al.'s results that the level of idiosyncratic volatility does not matter once we account for short-term return reversal. However, the results in column 4 indicate that the change in idiosyncratic volatility still matters even if we account for short-term reversal and it is far more significant. As a result our key result is intact. In column 5 we show that there is still a negative relation between idiosyncratic volatility and future stock returns even after controlling for the previous six month's returns, which captures both short-term reversal and the momentum effect. The implication is that changes in idiosyncratic volatility dominate the other explanations for a negative relation between idiosyncratic volatility and future stock returns suggested in the existing literature.

Table 11: Short-term Return Reversal

Panel A. All Stocks				
IVOL Quintile	VWRET	Past VWRET	EWRET	Past WRET
Low	0.90	1.00	1.02	0.29
2	0.93	1.46	1.26	0.37
3	0.98	2.03	1.30	0.44
4	0.65	2.85	1.12	0.68
High	-0.06	7.21	0.96	4.07
High-Low	-0.96	6.21	-0.07	3.78
t-stats	[-2.42]	[3.21]	[-0.16]	[2.58]

Panel B. High Idiosyncratic Volatility Stocks (Quintile 5)				
Migration	VWRET	Past VWRET	EWRET	Past EWRET
-4	0.05	24.13	-0.58	21.88
-3	-1.08	7.97	-2.07	8.76
-2	-1.21	6.47	-2.50	6.92
-1	-0.77	6.42	-1.88	5.73
0	1.31	5.61	2.97	2.43

Value-weighted quintile portfolios are formed every month t based on idiosyncratic volatility relative to FF 3-Factor Model computed using daily data in month t–1. The sample period is July 1963 to December 2008. VWRET and EWRET refer to month t value-weighted and equally-weighted portfolio simple unadjusted monthly percentage returns, respectively. Past VWRET and Past EWRET refer to month *t-1* value-weighted and equally-weighted portfolio simple unadjusted monthly percentage returns, respectively. "High-Low" refers to the difference in monthly returns between Quintile 5 and Quintile 1.

In the time-series analysis, we also show that the negative relation between idiosyncratic volatility and future stock returns is still valid even after controlling for short-term return reversal. To do so, we run time-series regressions of the value-weighted excess return of a portfolio, that is, high minus low idiosyncratic volatility stocks on Market, the market excess returns, SMB, the size, HML, the value, UMD, the momentum factor and SHREV, the short-term reversal factor.

All the factors as well as the construction of SHREV and UMD are taken from Kenneth French's web page.[13] Regression 1 shows that the FF 3-Factor Model alpha for the high minus low idiosyncratic volatility portfolio is -1.19% per month. With the addition of UMD, the momentum factor, this portfolio earns -1.10% per month implying that only a small proportion of the FF 3-Factor alpha is explained by the momentum factor. Moreover, the coefficient on UMD is insignificant. The asset pricing model which includes the Fama-French factors plus short-term reversal, SHREV, gives -1.18% per month on the same high minus low idiosyncratic volatility portfolio. Again the coefficient on the SHREV factor is insignificant. The result is that the inclusion of both UMD and SHREV increases the FF 3-Factor alpha to -1.05% per month for the same trading portfolio. However, none of these factors could explain the negative alpha that is earned by the high minus low idiosyncratic volatility portfolio.[14]

[13] Portfolios that are the intersections of 2 portfolios formed on size (market equity, ME) and 3 portfolios formed on prior (1-1) return are used to construct SHREV. It is the average return on the two low prior return portfolios minus the average return on the two high prior return portfolios. UMD is constructed by the portfolios that are the intersections of 2 portfolios formed on size and 3 portfolios formed on prior (2-12) return. It is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios.

[14] Huang et al. (2009) used WML to capture the short-term reversal. It is the equally-weighted average return difference between the past winner portfolio and the past loser portfolio during the formation period. They find that inclusion of WML explains the negative alpha earned by the high minus low idiosyncratic volatility portfolio. However, they find the similar results to ours when they use Short Term Reversal Factor constructed by Kenneth French.

Table 12: Short-term Reversal and Idiosyncratic Volatility

Panel B. Time-Series Regressions							
Regression models	Market	SMB	HML	UMD	SHREV	Constant	R^2
1	0.46	1.09	-0.26			-1.19	0.51
	(4.30)	(4.57)	(-1.52)			(-6.54)	
2	0.45	1.08	-0.28	-0.09		-1.10	0.51
	(3.87)	(4.66)	(-1.44)	(-0.64)		(-5.16)	
3	0.47	1.10	-0.26		-0.02	-1.18	0.51
	(3.76)	(5.04)	(-1.48)		(-0.12)	(-5.74)	
4	0.46	1.09	-0.28	-0.11	-0.07	-1.05	0.51
	(3.67)	(4.98)	(-1.45)	(-0.82)	(-0.45)	(-4.57)	

Panel A. For each month, we run the Fama-MacBeth regressions. Dependent variable is the simple unadjusted monthly stock returns. Past IVOL is the month *t-1* idiosyncratic volatility, Change in IVOL is the difference between month *t* and month *t-1* idiosyncratic volatility, Lagged Return is the month *t-1* simple unadjusted monthly stock returns and 6month's Return is the past six month's cumulative return. The sample period is 1963-2008. Panel B shows the time-series regression where the dependent variable is the value-weighted excess return of a portfolio that high minus low idiosyncratic volatility stocks. Market is the market excess returns, SMB is the size premium, HML is the value premium, UMD is the momentum factor and SHREV is the short-term reversal factor. All factors as well as the construction of SHREV and UMD are taken from the Kenneth French web page. Portfolios that are the intersections of 2 portfolios formed on size (market equity, ME) and 3 portfolios formed on prior (1-1) return are used to construct SHREV. It is the average return on the two low prior return portfolios minus the average return on the two high prior return portfolios. UMD is constructed by the portfolios that are the intersections of 2 portfolios formed on size and 3 portfolios formed on prior (2-12) return. It is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. Robust Newey-West (1987) *t*-statistics are reported in brackets. Sample period is 1963-2008.

6 - Conclusion

This paper's main focus is to understand the observed negative relation between returns in month *t* and idiosyncratic volatility in month t–1. This anomalous relation appears to be the result of changes in idiosyncratic volatility between the time at which the portfolio is formed and the time at which the return is observed. Eliminating all firm months in which idiosyncratic volatility changes, we find that low idiosyncratic volatility stocks earn consistently lower returns than high idiosyncratic volatility stocks. The impact is asymmetric: changes from the low to high quintiles have a larger impact than changes from high to low.

Many of the extreme changes in idiosyncratic volatility are related to business events. The pattern usually observed is that an announcement or an event increases uncertainty about a stock and hence, its idiosyncratic volatility increases. After the event, uncertainty is resolved and the security returns to a lower idiosyncratic volatility. Therefore, as an example the impact of delisted firms is investigated. Although the negative relation between idiosyncratic volatility and future stock returns is more pronounced for those particular stocks, we still observe the same negative relation for survivor stocks. This indicates there are events other than delisted related may also provide a similar effect.

However, the negative relation between idiosyncratic volatility and future stock returns seems to disappear between 2000 and 2008. There is no gain (loss) from a trading strategy high minus low idiosyncratic volatility stocks. Moreover, post 2000 the factor loadings of Fama-French risk factors are all significant, whereas pre-2000 they are not, in particularly for the HML factor. This is also a surprising result. It means that post 2000, idiosyncratic volatility sorted portfolios contain similar stocks in terms of their size and book to market which lead to significant estimates for the loadings on the Fama-French risk factors. On the other hand, the pre-2000 idiosyncratic volatility quintile portfolios include a wide range of stocks with different sensitivities which leads to insignificant coefficient estimates especially on the HML factor.

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