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Idiosyncratic Volatility, Firm Fundamentals and the Credit Crisis

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Aggregate idiosyncratic volatility spiked to unprecedented levels during the December 2007 to June 2009 credit crisis. We present evidence that this rise in idiosyncratic risk persists when controlling for a sample of firm fundamentals that have previously been linked to idiosyncratic volatility. Despite bearing explanatory power on idiosyncratic volatility in prior periods, these fundamentals are unable to explain the observed disparity in the cross-section or in the time series.

1. Introduction

Average firm-specific returns volatility has displayed distinctly different behavior than market-level returns volatility over the past fifty years. Although market-level volatility increases during certain isolated episodes (i.e. October 1987), it otherwise remains stable. Firm-level volatility, however, exhibits significant fluctuations over this time period. Campbell, Lettau, Malkiel, and Xu (2001) (henceforth CLMX) document that idiosyncratic volatility trends gradually upwards from 1962 to 1997. Following their methodology, we find that idiosyncratic volatility maintains this trend until 2000, declines moderately from 2001 to 2007, sharply rises during the credit crisis of December 2007 to June 2009, and falls thereafter.[1]

The increase of idiosyncratic volatility that occurs during the credit crisis is the largest in our sample. It is natural to inquire if this episode can be explained by theories developed in response to CLMX's initial discovery. In this study, we examine the relationship between idiosyncratic volatility during the credit crisis and several firm fundamental variables that have been shown to be drivers of volatility during CLMX sample. In particular, we examine the effects of return-on-equity and return-on-equity volatility, as studied by Wei and Zhang (2006), and several proxies for growth options as in Cao, Simin, and Zhao (2008). Additionally, we investigate idiosyncratic volatility at the industry level.

[1] We define the credit crisis time-period to be the NBER-dated recession from December 2007 to June 2009.

We find that return-on-equity, return-on-equity volatility, and several other firm fundamental variables exhibit statistically different cross-sectional relationships with idiosyncratic volatility during the credit crisis than in the 1976 to 2005 period. In our time series analysis, we find that return-on-equity, return-on-equity volatility, and growth option proxies are unable to reduce the significance of the increase of idiosyncratic volatility during the credit crisis. Upon examining idiosyncratic risk at the industry level, we find that although the Banking, Trading, Insurance, Automobile, and Real Estate industries experienced the largest increases of idiosyncratic volatility during the credit crisis, firm fundamentals remain unable to explain the credit crisis episode when these industries are excluded from our dataset.

We proceed as follows. Section II presents the decomposition of firm volatility as described by CLMX and determines the significance of idiosyncratic volatility during the NBER-dated recession associated with the credit crisis of December 2007 to June 2009. Section III tests the cross-sectional explanatory power of return-on-equity, return-on-equity volatility, and several firm-fundamental factors on idiosyncratic volatility during the credit crisis. Section IV examines time series relationships between return-on-equity, return-on-equity volatility, and several proxies for firm growth option and idiosyncratic volatility. Section V explores idiosyncratic volatility within individual industries. We conclude in Section VI.

2. Volatility Decomposition

We follow the methodology established by CLMX to create time series estimates of idiosyncratic volatility. First, we obtain all domestic daily returns data in the CRSP database from July 1962 to December 2010.[2] Next, we partition our sample into the forty-eight industries defined by Fama and French (1997). We create an additional industry containing all firms that do not fall into one of Fama and French's categories. Daily firm returns are decomposed into three portions: market return, industry-specific return, and firm-specific return. Daily market return is defined as the average daily return of firms in excess of the appropriate risk-free rate, weighted by their market capitalization.[3] The daily industry-specific return of an industry *i* is the value-weighted average daily return of firms within industry *i* in excess of the daily market return. Firm-specific return is defined as a firm's return in excess of its industry's return. We calculate monthly idiosyncratic volatility for each firm by summing the squares of its daily firm-specific returns. Lastly, we compute the value-weighted average of these volatility estimates each month to obtain a time series that represents the idiosyncratic volatility of a randomly selected stock. The annualized, value-weighted time series of idiosyncratic volatility is presented in Figure 1.

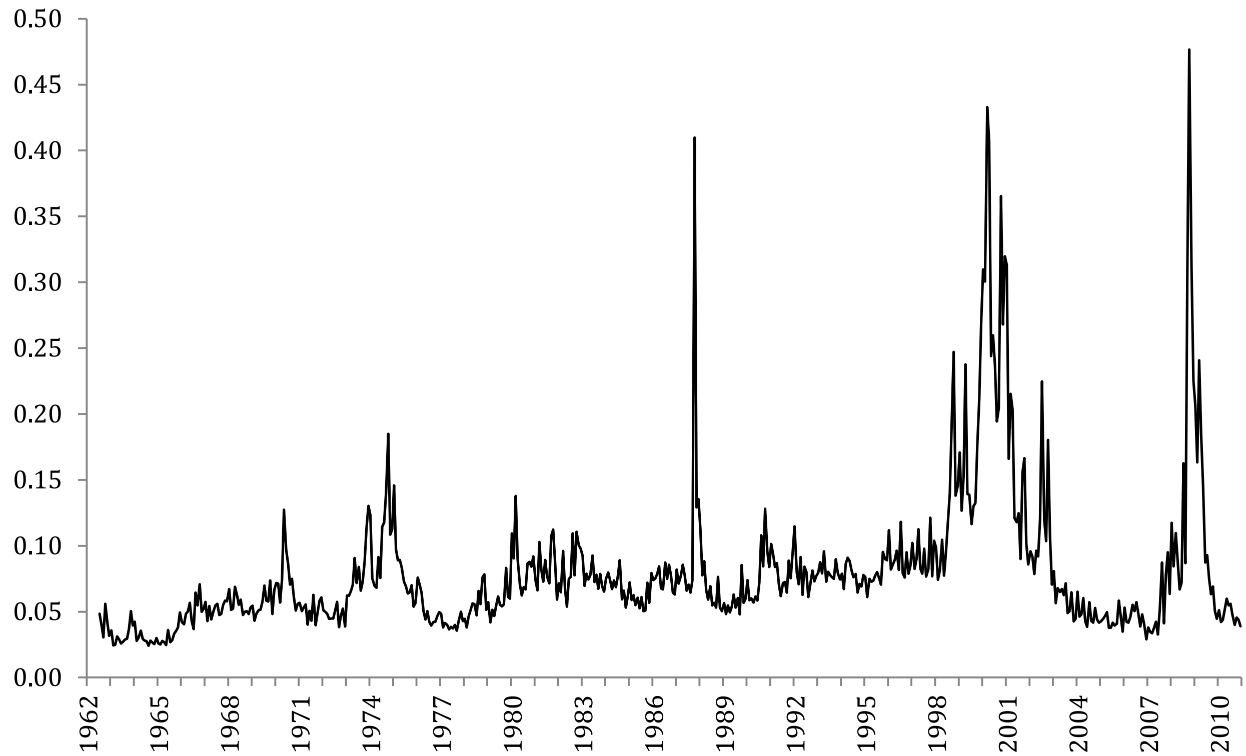
The idiosyncratic volatility time series is consistent with CLMX in that it displays a gradual upward trend from 1962 to 1997.[4] This trend continues into the Internet boom, peaks in the year 2000, and declines until 2007. During 2008, idiosyncratic volatility spikes to record levels and then subsequently declines. As the 2008 episode is the largest in our sample, it is of particular interest. To verify the impact of the credit crisis time-period on idiosyncratic volatility, we estimate the coefficients of the following regression,

$$IDIO_t = \Phi_0 + \Phi_{IDIO}\, IDIO_{t-1} + \Phi_{CREDIT}\, CREDIT + \varepsilon_t, \tag{1}$$

[2] As in CLMX, our dataset begins in July 1962.
[3] We define the risk free rate as the going 30-day Treasury rate divided by the average number of trading days in a month.
[4] CLMX's dataset begins in July 1962 and ends in December 1997.

where $IDIO_t$ and $IDIO_{t-1}$ are the value-weighted idiosyncratic volatility in periods t and *(t-1)* respectively, and CREDIT is a binary variable equal to one if the observation occurs during the NBER-dated recession period of December 2007 to June 2009 and zero otherwise. Parameter estimates and t-statistics from equation (1) are reported in Table 1.

Figure 1. Value-Weighted Idiosyncratic Volatility



Note: Updated monthly from July 1962 to December 2010. Monthly values are annualized by multiplying by twelve.

Table 1. Time Series Regression Estimates of Equation (1)

Eq. (1) $IDIO_t = \Phi_0 + \Phi_{IDIO}\, IDIO_{t-1} + \Phi_{CREDIT}\, CREDIT + \varepsilon_t$

	Value-Weighted Idiosyncratic Volatility			
	Φ_0	Φ_{IDIO}	Φ_{CREDIT}	*Adj.* R^2
Eq. (1)	.00159	.77247	.00234	63.93%
t-stat	(2.99)*	(9.12)*	(2.11)†	

*: Statistically significant at the 1% level. †: Statistically significant at the 5% level. ‡: Statistically significant at the 10% level.
Note: Estimation is done with monthly data from 1962 through 2010.
Note: Regression is estimated using generalized method of moments. We follow Cao et al. (2008) and calculate t-statistics using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with twelve lags.

All coefficients are positive and statistically significant. This test determines that, controlling for its own first-order lag, idiosyncratic volatility experienced a significantly large, positive shock during the credit crisis. Next, we seek to determine if this shock can be explained by a sample of firm-fundamental variables that previous researchers have shown to be linked to idiosyncratic volatility during the CLMX sample period.

3. Cross-sectional Analysis

In this section, we explore the cross-sectional explanatory power of several firm-fundamental variables on idiosyncratic volatility. We model our cross-sectional analysis after Wei and Zhang (2006). Wei and Zhang (2006) show that return-on-equity, return-on-equity volatility, firm age, firm size, leverage, and book-to-market equity explain idiosyncratic volatility in the cross-section. We augment Wei and Zhang's study with firm age as defined by Fink, Fink, Grullon, and Weston (2010). Fink et al. (2010) define firm age as the time elapsed since a firm's founding, and find that firm age is inversely related to idiosyncratic volatility.[5]

Quarterly financial data is obtained from the CRSP-Compustat merged database with founding dates from the Jay Ritter IPO database. All data from the first quarter of 1976 to the fourth quarter of 2010 are included in this study.[6] Return-on-equity (ROE) is defined as quarterly earnings divided by the book value of equity. The variance of return-on-equity (VROE) is calculated as the sample variance of quarterly ROEs over the last three years. Observations without twelve prior quarters of sequential ROE data are excluded from our sample. Firm size (SZ) is defined as the natural logarithm of firm equity. Leverage (LV) is long-term debt scaled by total assets. Book-to-market equity (BM) is the natural logarithm of the ratio of book value of equity to market value of equity. Firm age (AGE) is the natural logarithm of the sample year less the firm's founding year.

As a firm's ROE declines or becomes more volatile, investors become less certain of the firm's future profitability. Thus, it is logical to expect that if a relationship between idiosyncratic volatility and ROE exists, it is negative. Similarly, it can be expected that the relationship between idiosyncratic volatility and VROE is positive. As a firm ages and matures, investors gain information regarding its sustainability. Therefore, older and larger firms are expected to experience lower levels of idiosyncratic volatility than younger and smaller firms. Since riskier firms incur greater expenses when issuing debt, it follows that leverage and idiosyncratic volatility may be inversely related. We now seek to formally determine these relationships. We estimate the parameters of the following cross-sectional regression,

$$\begin{aligned} \mathrm{IDIO}_{j,t} = \; & \Phi_0 + \Phi_{\mathrm{ROE}}\,\mathrm{ROE}_{j,t-1} + \Phi_{\mathrm{VROE}}\,\mathrm{VROE}_{j,t-1} + \Phi_{\mathrm{IDIO}}\,\mathrm{IDIO}_{j,t-1} + \Phi_{\mathrm{R}}\,\mathrm{R}_{j,t} \\ & + \Phi_{\mathrm{AGE}}\,\mathrm{AGE}_{j,t} + \Phi_{\mathrm{SZ}}\,\mathrm{SZ}_{j,t} + \Phi_{\mathrm{LV}}\,\mathrm{LV}_{j,t-1} + \Phi_{\mathrm{BM}}\,\mathrm{BM}_{j,t-1} + \varepsilon_{j,t} \end{aligned} \qquad (2)$$

for each five-year period from 1976 to 2010 and for the credit crisis period of December 2007 to June 2009. $R_{j,t}$ is firm *j*'s firm-specific return in month *t*.[7] Since returns volatility is known to be serially correlated, we include $\mathrm{IDIO}_{j,t-1}$ as an independent variable in our regression. We present the results for each five-year period and for the credit crisis period in Table 2.

[5] Fink et al. (2010) note that since firms may be privately held or trade in OTC markets for many years before being listed in the CRSP database, founding dates are more appropriate than first observation dates for determining age.
[6] We follow Wei and Zhang (2006) and Cao et al. (2008) and begin our sample in Q1 1976.
[7] Wei and Zhang (2006) note that since expected return and expected risk are positively related, their realizations have a common component. Thus, contemporaneous firm-level return and idiosyncratic volatility may be related.

Table 2. Cross-Sectional Regression Estimates of Equation (2)

Eq. (2) $IDIO_{j,t} = \Phi_0 + \Phi_{ROE}\, ROE_{j,t-1} + \Phi_{VROE}\, VROE_{j,t-1} + \Phi_{IDIO}\, IDIO_{j,t-1} + \Phi_R\, R_{j,t} + \Phi_{AGE}\, AGE_{j,t} + \Phi_{SZ}\, SZ_{j,t} + \Phi_{LV}\, LV_{j,t-1} + \Phi_{BM}\, BM_{j,t-1} + \varepsilon_{j,t}$

Period	Φ_0	Φ_{ROE}	Φ_{VROE}	Φ_{IDIO}	Φ_R	Φ_{AGE}**	Φ_{SZ}**	Φ_{LV}**	Φ_{BM}**
1976 - 1980	0.0233	-0.0156	0.1343	0.3114	0.0410	-0.1440	-0.2240	-0.0220	-0.0270
t-stat	(21.39)*	(-8.19)*	(10.87)*	(12.93)*	(10.62)*	(-6.06)*	(-21.24)*	(-3.20)*	(-0.79)
1981 - 1985	0.0260	-0.0189	0.1115	0.4006	0.0415	-0.3150	-0.1250	0.0018	0.0150
t-stat	(13.99)*	(-13.16)*	(9.96)*	(9.46)*	(9.28)*	(-10.87)*	(-13.41)*	(0.28)	(0.63)
1986 - 1990	0.0530	-0.0326	0.1387	0.3909	0.0348	-0.4450	-0.3950	0.0253	0.6673
t-stat	(7.66)*	(-7.81)*	(6.54)*	(4.32)*	(3.28)*	(-6.65)*	(-7.28)*	(0.61)	(7.69)*
1991 - 1995	0.0769	-0.0364	0.0867	0.4868	0.1483	-0.4360	-0.8090	0.0520	1.1142
t-stat	(3.07)*	(-4.29)*	(2.48)†	(3.00)*	(6.15)*	(-2.77)*	(-3.09)*	(1.67)‡	(3.23)*
1996 - 2000	0.1330	-0.0758	0.1806	0.1015	0.2681	-0.7900	-1.2300	-0.2020	0.8351
t-stat	(17.63)*	(-15.55)*	(6.29)*	(2.20)†	(3.80)*	(-7.68)*	(-15.85)*	(-8.16)*	(6.52)*
2001 - 2005	0.0829	-0.0485	0.1957	0.1718	0.1256	-0.4870	-0.7050	-0.0930	0.8354
t-stat	(19.93)*	(-17.76)*	(13.21)*	(4.58)*	(11.19)*	(-12.95)*	(-19.43)*	(-6.74)*	(13.86)*
2006 - 2010	0.1019	-0.0424	0.5116	0.0066	0.3608	-0.0700	-1.1500	0.0234	1.1348
t-stat	(9.54)*	(-2.16)†	(1.33)	(1.42)	(2.42)†	(-0.06)	(-3.82)*	(1.66)‡	(2.71)*
Dec 07 - Jun 09	0.1768	-0.0451	1.1995	0.0051	0.4416	-0.0050	-2.2060	0.2128	0.7716
t-stat	(5.96)*	(-0.93)	(1.17)	(1.40)	(1.99)†	(-0.02)	(-2.78)*	(3.86)*	(0.64)

*: Statistically significant at the 1% level. †: Statistically significant at the 5% level. ‡: Statistically significant at the 10% level.
**: Parameter estimate multiplied by 100.
Note: Regression is estimated using generalized method of moments. Following Wei and Zhang (2006), we calculate t-statistics using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with three month lags.

Our results indicate that idiosyncratic volatility exhibits different relationships with firm fundamentals during the credit crisis than in previous periods. In each five-year sample period from 1976 to 2005, the coefficient on ROE is negative and statistically significant, and the coefficient on VROE is positive and statistically significant. This confirms our conjecture that ROE (VROE) is inversely (directly) related to idiosyncratic volatility. These findings are consistent with Wei and Zhang's results. However, during the credit crisis sample period, the coefficients on ROE and VROE are not statistically different from zero. Thus, while ROE and VROE have previously maintained their theoretical relationships with idiosyncratic volatility, these relationships were not present during the credit crisis. Furthermore, we note that in each sample period prior to 2005, idiosyncratic volatility is highly dependent on its own first-order lag, and that this relationship is not present during the credit crisis period.

In each period from 1976 to 2005, idiosyncratic volatility is inversely related to firm size and firm age. Although firm size maintains its relationship with idiosyncratic volatility during the credit crisis period, firm age does not.[8] Additionally, the coefficient on firm size is more pronounced during the credit crisis than in prior periods. While the relationship between idiosyncratic volatility and the book-to-market ratio is statistically positive in the periods from 1986 to 2005, the coefficient on book-to-market is insignificant during the credit crisis. Although leverage does not display a consistent relationship with idiosyncratic volatility from 1976 to 2005, its coefficient is statistically negative in the periods surrounding the Internet boom, and statistically positive in the credit crisis sample period. This implies that while idiosyncratic volatility was driven by firms with low amounts of leverage during the Internet boom, idiosyncratic volatility was driven by firms with higher amounts of leverage during the credit crisis. Additionally, our results from each sample confirm that idiosyncratic volatility is positively related to contemporaneous returns, suggesting that investors may be compensated for bearing diversifiable risk.

4. Time Series Analysis

From the estimation of equation (1) in Section II, it was demonstrated that idiosyncratic volatility increased by a statistically significant amount during the credit crisis. In this section, we seek to determine if ROE, VROE, and several proxies for firm's growth options have time series explanatory power on idiosyncratic volatility, and if they are able to explain the increase of idiosyncratic volatility during the credit crisis.

Wei and Zhang (2006) present evidence that the gradual upwards trend over the CLMX sample period is explained by trends in ROE and VROE. Cao, Simin, and Zhao (2008) perform an analysis similar to Wei and Zhang (2006) using proxies for growth options and their respective volatilities. They demonstrate that the trend in idiosyncratic volatility present in the CLMX sample period is eliminated or reversed when controlling for firms' growth options.

We examine four proxies for firm growth options presented by Cao et al. (2008). These four proxies are an estimate of Tobin's Q, the ratio of market value to book value of assets (MABA), the debt-to-equity ratio (DTE), and the ratio of capital expenditures to fixed assets (CAPFIX).

As there is much debate associated with growth option proxies, it is important to note why these measurements were chosen. MABA proxies for growth, since market-value-of-assets captures investors' perceived future value of growth opportunities and book-value-of-assets does not. Similarly, Tobin's Q represents the market value of assets scaled by their replacement costs. Cao et al. state that MABA and Q primarily capture price-based growth options, and thus they include DTE and CAPX to provide alternative approaches. Cao et al. claim that DTE is representative of growth options since firms with high growth opportunities may theoretically have lower financial leverage. CAPX proxies growth since increased capital expenditures naturally leads to additional business opportunities. While there are certain criticisms associated with each growth option proxy, the diversity of these proxies provides robustness. Furthermore, these proxies provide us with fundamental measures that are indicative of idiosyncratic volatility.

We use quarterly accounting data from the CRSP-Compustat Merged database to construct estimates of Cao et al.'s growth option proxies. Following Cao et al., we define MABA, Q, DTE, and CAPEX as

- $\text{MABA} = \frac{(\text{Total Assets})-(\text{Total Common Equity})+\text{Price}*(\text{Shares Outstanding})}{\text{Total Assets}}$,

[8] For robustness, we re-estimate the coefficients in equation (2) defining firm age as the difference between the observation date and the firm's first appearance in the CRSP database. Our results are consistent. It is interesting to note that the relationship between idiosyncratic volatility and firm age in each sample from 1976 to 2005 is less pronounced when age is computed using the first appearance in CRSP date.

- $Q = \frac{\text{Price}*(\text{Shares Outstanding})+(\text{Preffered Stock})+(\text{Current Liabilities})-(\text{Current Assets })+(\text{Long Term Debt})}{\text{Total Assets}}$,
- $DTE = \frac{(\text{Debt in Current Liabilities})+(\text{Long Term Debt})+(\text{Preffered Stock})}{\text{Price}*(\text{Shares Outstanding})}$, and
- $CAPEX = \frac{\text{Capital Expenditures}}{\text{Property, Plant, and Equipment}}$.

Subsequent to calculating quarterly values for our growth proxies, we produce a time series of volatility estimates for each growth option by computing the sample variance of each proxy's quarterly observations over the past three years. Observations without twelve prior quarters of sequential proxy data are excluded from our sample.

We proceed to formally establish time series relationships between ROE, VROE, our growth option proxies, and idiosyncratic volatility. To do so, we estimate regressions of the following types,

$$IDIO_t = \Phi_0 + \Phi_{ROE}\, ROE_{t-1} + \Phi_{VROE}\, VROE_{t-1} + \Phi_{IDIO}\, IDIO_{t-1} + \Phi_{CREDIT}\, CREDIT + \varepsilon_t \quad (3)$$

$$IDIO_t = \Phi_0 + \Phi_{GO}\, GO_{t-1} + \Phi_{VGO}\, VGO_{t-1} + \Phi_{IDIO}\, IDIO_{t-1} + \Phi_{CREDIT}\, CREDIT + \varepsilon_t \quad (4)$$

$$IDIO_t = \Phi_0 + \Phi_{GO}\, GO_{t-1} + \Phi_{VGO}\, VGO_{t-1} + \Phi_{ROE}\, ROE_{t-1} + \Phi_{VROE}\, VROE_{t-1} + \Phi_{IDIO}\, IDIO_{t-1} + \Phi_{CREDIT}\, CREDIT + \varepsilon_t \quad (5)$$

where GO and VGO are the value-weighted averages of a particular growth option and its volatility. We include the first order lag of value-weighted idiosyncratic volatility to determine if return-on-equity, return-on-equity volatility, growth options, and growth options volatility contain predictive power that is not already inherent to the volatility series. In equations (3), (4), and (5), we lag ROE, VROE, GO, and VGO by one quarter, and we lag IDIO by one month.

The relationship between idiosyncratic volatility, return-on-equity, and return-on-equity volatility is examined in equation (3). We examine the relationship between idiosyncratic volatility, growth options, and growth options volatility in equation (4). In equation (5), we include both return-on-equity and growth options to determine their combined explanatory power on idiosyncratic volatility. Equation (4) and equation (5) are estimated separately for each growth option. Since the four growth options proxy for the same factor, we do not include multiple growth options in a single equation to avoid collinearity.

Since the primary objective of this study is to examine idiosyncratic volatility during the credit crisis, the coefficient on CREDIT is of particular interest. In Section II, we found the coefficient on CREDIT to be positive and statistically significant in our estimation of equation (1). If the coefficient on CREDIT resulting from an estimation of equation (3), (4), or (5) is negative or statistically insignificant, then it can be concluded that the abnormal idiosyncratic volatility that occurred during the credit crisis is explained by firm-fundamental factors. Regression results are reported in Table 3.

Table 3. Time Series Regression Estimates of Equations (1), (3), (4), and (5)

Eq. (1)	$IDIO_t = \Phi_0 + \Phi_{IDIO} IDIO_{t-1} + \Phi_{CREDIT}\ CREDIT + \varepsilon_t$
Eq. (3)	$IDIO_t = \Phi_0 + \Phi_{ROE}\ ROE_{t-1} + \Phi_{VROE}\ VROE_{t-1} + \Phi_{IDIO}\ IDIO_{t-1} + \Phi_{CREDIT}\ CREDIT + \varepsilon_t$
Eq. (4)	$IDIO_t = \Phi_0 + \Phi_{GO}\ GO_{t-1} + \Phi_{VGO}\ VGO_{t-1} + \Phi_{IDIO}\ IDIO_{t-1} + \Phi_{CREDIT}\ CREDIT + \varepsilon_t$
Eq. (5)	$IDIO_t = \Phi_0 + \Phi_{GO}\ GO_{t-1} + \Phi_{VGO}\ VGO_{t-1} + \Phi_{ROE}\ ROE_{t-1} + \Phi_{VROE}\ VROE_{t-1} + \Phi_{IDIO}\ IDIO_{t-1} + \Phi_{CREDIT}\ CREDIT + \varepsilon_t$

Return-on-equity								
	Φ_0	–	–	Φ_{ROE}	Φ_{VROE}	Φ_{IDIO}	Φ_{CREDIT}	*Adj. R^2*
Eq. (1)	0.00153					0.77078	0.00236	63.98%
t-stat	(3.01)*					(9.07)*	(2.11)†	
Eq. (3)	-0.00104			0.01288	0.07791	0.73088	0.00259	64.85%
t-stat	(-0.77)			(1.87)‡	(2.18)†	(9.26)*	(2.31)†	
Tobin's Q								
	Φ_0	Φ_Q	Φ_{VQ}	Φ_{ROE}	Φ_{VROE}	Φ_{IDIO}	Φ_{CREDIT}	*Adj. R^2*
Eq. (4)	0.00897	0.00133	0.00018			0.58378	0.00381	67.89%
t-stat	(2.19)†	(3.22)*	(1.56)			(7.98)*	(2.57)†	
Eq. (5)	0.00139	0.00167	0.00019	-0.00057	-0.08386	0.57305	0.00399	68.06%
t-stat	(1.37)	(3.32)*	(1.91)‡	(-0.08)	(-2.33)†	(7.73)*	(2.72)*	
Debt-to-equity								
	Φ_0	Φ_{DTE}	Φ_{VDTE}	Φ_{ROE}	Φ_{VROE}	Φ_{IDIO}	Φ_{CREDIT}	*Adj. R^2*
Eq. (4)	0.00447	-0.00693	-0.02574			0.73394	0.00268	64.73%
t-stat	(2.93)*	(-1.91)‡	(-1.44)			(9.21)*	(2.31)†	
Eq. (5)	0.00091	-0.00157	-0.04484	0.00793	0.07692	0.72320	0.00262	64.87%
t-stat	(0.41)	(-0.42)	(-1.78)‡	(1.17)	(2.23)†	(8.97)*	(2.25)†	
Market Assets to Book Assets								
	Φ_0	Φ_{MABA}	Φ_{VMABA}	Φ_{ROE}	Φ_{VROE}	Φ_{IDIO}	Φ_{CREDIT}	*Adj. R^2*
Eq. (4)	0.00039	0.00104	0.00020			0.60646	0.00355	67.33%
t-stat	(0.63)	(2.53)†	(1.57)			(8.24)*	(2.71)*	
Eq. (5)	0.00037	0.00133	0.00024	0.00220	-0.09093	0.59563	0.00373	67.52%
t-stat	(0.38)	(2.41)†	(1.98)†	(0.29)	(-2.32)†	(8.00)*	(2.67)*	
Capital Expenditures								
	Φ_0	Φ_{CAPEX}	Φ_{VCAPEX}	Φ_{ROE}	Φ_{VROE}	Φ_{IDIO}	Φ_{CREDIT}	*Adj. R^2*
Eq. (4)	-0.00239	0.02326	0.00000			0.68553	0.00260	65.04%
t-stat	(-1.72)‡	(3.16)*	(-3.12)*			(10.04)*	(2.20)†	
Eq. (5)	-0.00494	0.02157	-0.00001	0.00718	0.16828	0.64557	0.00325	65.78%
t-stat	(-2.38)†	(3.54)*	(-2.69)*	(1.20)	(3.15)*	(10.25)*	(2.66)*	

*: Statistically significant at the 1% level. †: Statistically significant at the 5% level. ‡: Statistically significant at the 10% level.
Note: Equations (1) and (3) are estimated from 1962 to 2010. Equations (4) and (5) are estimated from 1976 to 2010 for DTE, MABA, and Q, and from 1984 to 2010 for CAPEX. Sufficient data is not available for growth option volatility before these dates.
Note: Regressions are estimated using generalized method of moments. We follow Cao et al. (2008) and calculate t-statistics using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with twelve lags.

From the estimation of equation (3), we find that ROE and VROE have statistically positive effects on idiosyncratic volatility. From the estimations of equation (4), we find that all four growth options exhibit statistically significant relationships with idiosyncratic volatility. Idiosyncratic volatility is positively related to Q, MABA, and CAPEX, and inversely related to DTE. From equation (4), we also find that the coefficients on VQ, VDTE, and VMABA are statistically insignificant, and the coefficient on VCAPEX is statistically negative. The estimations of equation (5) show that the coefficients on Q, MABA, and CAPEX are statistically positive, and the coefficients on ROE and DTE are not statistically different from zero. From equation (5), we observe that the volatility of ROE exhibits varied behavior when interacted with the volatilities of the growth options. The coefficient on the volatility of ROE is statistically positive when the coefficient on growth option volatility is statistically negative or insignificant, and statistically negative when the coefficient on growth option volatility is statistically positive. In all of our estimations, idiosyncratic volatility exhibits a statistically positive relationship with its first order lag.

The resulting coefficients on CREDIT from our estimations of equations (3), (4), and (5) with each growth option proxy are positive and statistically significant. This significance indicates that return-on-equity and growth option proxies based on firm fundamentals are unable to explain the increase of value-weighted idiosyncratic volatility during the credit crisis.

5. Industry Analysis

In this section, we explore the impact of individual industries on aggregate idiosyncratic volatility during December 2007 to June 2009. We seek to determine if the observed increase of aggregate idiosyncratic volatility was localized within any particular industries. For each industry, we calculate its average level of idiosyncratic volatility during the credit crisis. We also calculate the percentage change from each industry's average monthly level of idiosyncratic volatility for the period 1990 to 2010 to its average monthly level of idiosyncratic volatility during the credit crisis. The five industries that experienced the largest increases and highest levels are presented in Table 5.

Table 5. Percentage Increase of Idiosyncratic Volatility During Credit Crisis by Industry

Industry	Percent Increase from 1990 to 2010 Monthly Average	Average Monthly Idiosyncratic Volatilitiy Dec 2007 – Jun 2009	Average Monthly Weight Dec 2007 - Jun 2009
Banking	269%	0.364	7.53%
Trading	235%	0.332	3.00%
Insurance	227%	0.302	5.11%
Automobiles	150%	0.299	0.59%
Real Estate	141%	0.401	0.11%
Aggregate	**68%**	**0.169**	**100.00%**

Note: Sixteen industries experienced increases of more than 68%, twenty-seven industries experienced increases of less than 68%, and six industries experienced decreases. Fourteen of forty-nine industries exhibit average levels of idiosyncratic risk higher than the value-weighted aggregate level during the credit crisis.

The Banking, Trading, Insurance, Automobile, and Real Estate industries experienced the largest increases in their average monthly levels of idiosyncratic volatility during the credit crisis. These five industries also exhibited the highest average levels of idiosyncratic volatility during this period. The levels of idiosyncratic risk within the Banking, Trading, and Insurance industries display little variation from 1962 to 2007 and rise dramatically during the credit crisis. Idiosyncratic volatility within the Automobile industry trends gradually upwards from 1962 to 2000, slowly declines from 2000 to 2007, and spikes during the credit crisis. Real Estate exhibits high amounts of variation in its level of idiosyncratic volatility throughout the sample period, rising noticeably during the mid-1970s, the early-1990s, the early-2000s, and during the 2008.

We seek to determine if abnormal levels of idiosyncratic volatility persist during the credit crisis when the industries that exhibit the largest deviations in this period are excluded from our dataset. Banking, Trading, Insurance, Automobile, and Real Estate companies are removed from our dataset by subtracting their value-weighted idiosyncratic volatility values from the series developed in Section II. Equations (1), (3), (4), and (5) are estimated while excluding these five industries from our dataset. Results from these estimations are reported results in Table 6.

Our results confirm that idiosyncratic volatility continues to exhibit abnormal levels during the credit crisis without these industries' presence. When the five industries that experienced the largest positive shocks are excluded from our dataset, the coefficient on CREDIT estimated from equation (1) remains positive and statistically significant. However, while the coefficient is significant at the ten-percent level, it is not significant at the five-percent level. (In Section II, the coefficient on CREDIT from equation (1) is statistically significant at the five-percent level.) This indicates that although the observed increase of aggregate idiosyncratic volatility persists in the absence of these industries, it is less pronounced.

From equation (3), we find that ROE and VROE maintain statistically positive relationships with idiosyncratic volatility. Our estimations of equation (4) reveal that Q, MABA, and CAPEX bear positive, statistically significant explanatory power on idiosyncratic volatility, while the relationship between DTE and idiosyncratic volatility is statistically negative. When we interact growth options with return-on-equity in equation (5), we find that Q, MABA, and CAPEX maintain significant relationships with idiosyncratic volatility, while the coefficient on DTE is no longer significant. In all of our estimations, the coefficient on VCAPEX is statistically negative. The coefficients on VQ, VDTE, and VMABA are insignificant in equation (4) and statistically significant in equation (5). All estimations verify that value-weighted, aggregate idiosyncratic volatility is highly dependent on its own first-order lag.

Although the resulting coefficient on CREDIT from equation (4) with CAPEX is statistically insignificant, the coefficient on CREDIT is statistically positive at the ten-percent level in all other estimations. This demonstrates that even in the absence of the most varying industries, firm fundamentals that have previously been linked to idiosyncratic volatility are largely unable to explain its episodic rise during the credit crisis.

Table 6. Time Series Regression Estimates of Equations (1), (3), (4), and (5)

Excluding Banks, Trading, Insurance, Automobiles, and Real Estate

Eq. (1) $IDIO_t = \Phi_0 + \Phi_{IDIO} IDIO_{t-1} + \Phi_{CREDIT}\ CREDIT + \varepsilon_t$

Eq. (3) $IDIO_t = \Phi_0 + \Phi_{ROE}\ ROE_{t-1} + \Phi_{VROE}\ VROE_{t-1} + \Phi_{IDIO}\ IDIO_{t-1} + \Phi_{CREDIT}\ CREDIT + \varepsilon_t$

Eq. (4) $IDIO_t = \Phi_0 + \Phi_{GO}\ GO_{t-1} + \Phi_{VGO}\ VGO_{t-1} + \Phi_{IDIO}\ IDIO_{t-1} + \Phi_{CREDIT}\ CREDIT + \varepsilon_t$

Eq. (5) $IDIO_t = \Phi_0 + \Phi_{GO}\ GO_{t-1} + \Phi_{VGO}\ VGO_{t-1} + \Phi_{ROE}\ ROE_{t-1} + \Phi_{VROE}\ VROE_{t-1} + \Phi_{IDIO}\ IDIO_{t-1} + \Phi_{CREDIT}\ CREDIT + \varepsilon_t$

				Return-on-equity				
	Φ_0	–	–	Φ_{ROE}	Φ_{VROE}	Φ_{IDIO}	Φ_{CREDIT}	*Adj. R^2*
Eq. (1)	0.00106					0.81097	0.00092	66.67%
t-stat	(2.67)*					(10.10)*	(1.76)‡	
Eq. (3)	-0.00097			0.01041	0.05735	0.77293	0.00099	67.70%
t-stat	(-0.90)			(1.93)‡	(2.06)†	(10.11)*	(1.88)‡	
				Tobin's Q				
	Φ_0	Φ_Q	Φ_{VQ}	Φ_{ROE}	Φ_{VROE}	Φ_{IDIO}	Φ_{CREDIT}	*Adj. R^2*
Eq. (4)	0.00058	0.00119	0.00017			0.59155	0.00163	70.68%
t-stat	(1.59)	(3.15)*	(1.58)			(7.41)*	(2.25)†	
Eq. (5)	0.00117	0.00160	0.00019	-0.00089	-0.09044	0.56745	0.00181	71.07%
t-stat	(1.44)	(3.53)*	(2.11)†	(-0.16)	(-2.72)*	(7.19)*	(2.23)†	
				Debt-to-equity				
	Φ_0	Φ_{DTE}	Φ_{VDTE}	Φ_{ROE}	Φ_{VROE}	Φ_{IDIO}	Φ_{CREDIT}	*Adj. R^2*
Eq. (4)	0.00335	-0.00528	-0.02173			0.77290	0.00107	67.28%
t-stat	(2.72)*	(-1.84)‡	(-1.56)			(9.70)*	(1.93)‡	
Eq. (5)	0.00047	-0.00108	-0.03584	0.00671	0.05844	0.76385	0.00099	67.41%
t-stat	(0.25)	(-0.37)	(-1.78)‡	(1.20)	(2.18)†	(9.51)*	(1.78)‡	
				Market Assets to Book Assets				
	Φ_0	Φ_{MABA}	Φ_{VMABA}	Φ_{ROE}	Φ_{VROE}	Φ_{IDIO}	Φ_{CREDIT}	*Adj. R^2*
Eq. (4)	0.00012	0.00092	0.00018			0.62385	0.00145	70.01%
t-stat	(0.22)	(2.50)†	(1.55)			(7.66)*	(2.21)†	
Eq. (5)	0.00022	0.00126	0.00022	0.00138	-0.09548	0.59999	0.00162	70.41%
t-stat	(0.27)	(2.54)†	(2.11)†	(0.22)	(-2.59)*	(7.31)*	(2.16)†	
				Capital Expenditures				
	Φ_0	Φ_{CAPEX}	Φ_{VCAPEX}	Φ_{ROE}	Φ_{VROE}	Φ_{IDIO}	Φ_{CREDIT}	*Adj. R^2*
Eq. (4)	-0.00212	0.01896	-0.00000			0.72168	0.00089	68.16%
t-stat	(-1.77)‡	(2.92)*	(-4.11)*			(10.22)*	(1.48)	
Eq. (5)	-0.00442	0.01820	-0.00000	0.00604	0.14793	0.67349	0.00136	68.99%
t-stat	(-2.41)†	(3.31)*	(-3.35)*	(1.31)	(3.22)*	(10.05)*	(2.20)†	

*: Statistically significant at the 1% level. †: Statistically significant at the 5% level. ‡: Statistically significant at the 10% level.
Note: Equations (1) and (3) are estimated from 1962 to 2010. Equations (4) and (5) are estimated from 1976 to 2010 for DTE, MABA, and Q, and from 1984 to 2010 for CAPEX. Sufficient data is not available for growth option volatility before these dates.
Note: Regressions are estimated using generalized method of moments. We follow Cao et al. (2008) and calculate t-statistics using Newey and West (1987) heteroscedasticity and autocorrelation-consistent standard errors with twelve lags.

6. Concluding Remarks

Following CLMX's decomposition of firm returns and construction of idiosyncratic volatility, we find that aggregate, value-weighted idiosyncratic volatility experiences a significant, positive shock during the NBER-dated recession from December 2007 to June 2009. Since CLMX's discovery, many explanations have been provided for the trend present in their sample period. In this study, we focus on explanations that relate firm fundamentals to idiosyncratic volatility.

First, we examine the cross-sectional relationship between return-on-equity, return-on-equity volatility, firm age, size, leverage, book-to-market equity, and idiosyncratic volatility. We find that although significant cross-sectional relationships exist between these firm fundamentals and idiosyncratic volatility from 1976 to 2005, these relationships exhibit statistically different behavior during the credit crisis.

Second, we study the time series effects of return-on-equity, growth options, and their respective volatilities on idiosyncratic volatility. While Tobin's Q, debt-to-equity, market-to-book assets, and capital expenditures scaled by property, plant and equipment exhibit significant effects on idiosyncratic volatility, none of these factors are able to explain the abnormal idiosyncratic volatility during the credit crises.

Lastly, we inspect idiosyncratic volatility within individual industries. The Banking, Trading, Insurance, Automobile, and Real Estate industries experienced the largest increases of idiosyncratic volatility during the credit crisis. When these industries are excluded from our dataset, firm fundamentals remain unable to reconcile the observed disparity.

We conclude that during the December 2007 to June 2009 financial crisis, the market experienced an erratic increase of idiosyncratic volatility that cannot be fully explained by a sample of firm fundamentals which have previously been linked to idiosyncratic risk.

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