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IDIOSYNCRATIC VOLATILITY, CONDITIONAL LIQUIDITY AND STOCK RETURNS*

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ABSTRACT: There is strong evidence showing that stocks with higher levels of idiosyncratic risk provide relatively lower returns than stocks with lower levels of it. This paper points out that this negative idiosyncratic risk - expected returns relation is not pervasive over time, and provides a plausible explanation for its time-varying nature. Our results suggest that following recessions, the conditional pricing of liquidity creates a correction in prices of the high idiosyncratic volatility stocks that persists up to 10 months. As a result, the negative relation between idiosyncratic risk and expected returns is not observed following recessions.

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1. Introduction

The nature and behavior of idiosyncratic volatility have been popular subjects of discussion in the field of asset pricing for about ten years. In essence, idiosyncratic volatility is the residual of an asset pricing model and should not be informative if this model correctly prices risk. However, in the last decade a number of papers have questioned this expectation. For instance, Campbell *et al.*, (2001) report an apparent upward trend in idiosyncratic volatility that transpires the idea that the dominant asset pricing models are somehow losing acuity. Also, Ang *et al.*, (2006 and 2009) observe a negative relation between idiosyncratic risk and returns that is difficult to explain in the mean-variance framework and puts into question the accuracy of the Fama and French (1993) model. Although opinions on whether these observations are to be translated in valuable implications for asset pricing differ, there is a renewed interest on idiosyncratic risk. In this context, the upward trend of idiosyncratic risk has been branded as just an illusion driven by the lack of controls related to returns such as available growth options (Cao *et al.*, 2008) or firms' profitability (Pastor and Varonesi, 2003, Wei and Zhang, 2006). In turn, at the firm level idiosyncratic risk has been shown to increase with expected earnings growth (Campbell *et al.*, 2001 and Malkiel and Xu, 2003), to be related with business cycles in a countercyclical way (Brown and Ferreira, 2003) and to correlate negatively with liquidity (Spiegel and Wang, 2006).

In this paper we focus on the negative relation between idiosyncratic risk and expected returns evidenced by Ang *et al.,* (2006 and 2009). In particular we show that this negative relation is not observed at all times and we provide a plausible scenario for this empirical fact. Most of the published research on the negative idiosyncratic risk – expected return relation does not treat its time-varying nature. Among available papers, the explanations focus on issues that are time-independent such as non-synchronicity of trading (Han and Lesmond, 2011), preference of investors towards stocks offering features such as positive skewness (Kapadia, 2006 and Boyer *et al.*, 2010), heterogeneity of investors time-horizons (Malagon *et al.,* 2015a) and lottery-like payoffs (Bali *et al.*, 2011) or, corporate investment and profitability (Hou *et al.,* 2015 and Malagon *et al.,* 2015b). A noticeable exception is a recent paper by Stambaugh *et al.,* (2015) that argues that this negative link does not disappear over time due to asymmetric limits to arbitrage and that the negative risk – return relation is weakened by low investor sentiment. We provide an alternative explanation for the non-pervasiveness of the negative relation between idiosyncratic risk and expected returns settled on the conditional pricing of liquidity evidenced by authors such as Vayanos (2004) and Acharya *et al.*, (2012). Our rational is as follows; the negative relation between idiosyncratic risk and expected returns lies on a ranking of stocks based on an asset pricing model that does not take into account the conditional pricing of liquidity. Moreover, the classification of stocks does not change from the period in which stocks are ranked to the period in which the expected returns are calculated. Therefore, the subsequent [5-1] returns difference, where 5 stands for the quintile with the highest level of idiosyncratic risk and 1 for the one with the lowest level of it, could be influenced by short-lived liquidity events that could affect stocks with different intensities depending on the economic regime and on their level of idiosyncratic risk at the time the ranking is made.

In particular, given that high idiosyncratic risk stocks are less liquid than low idiosyncratic risk stocks, it is to be expected that the former are more sensitive to liquidity shocks, and that this sensitivity increases during times of financial stress. These effects are likely to be reflected in contemporary and subsequent corrections in prices and they could account for the time-varying nature of the [5-1] difference. In order to test our hypothesis we estimate a Markov regime switching model allowing for different return structures for high and low idiosyncratic risk portfolios and for different loadings on the variables used to define these return structures over two distinct economic regimes. Overall, our results support the idea that liquidity shocks affect high and low idiosyncratic risk stocks with different intensities. The portfolio with highest idiosyncratic risk is significantly more affected by liquidity shocks during recessions than the one with the lowest level of risk. This implies that once the market conditions improve a large correction in prices should take place, leading the expected returns of quintile 5 up and shrinking the [5-1] difference. Our results support this hypothesis and show that the [5-1] difference turns to be not significant or positive and significant just after recessions. Moreover, our results suggest that the correction in prices can last up to 10 months after the end of the recession period. To some extend our results might also imply a flight-to-quality from the stock market to less volatile markets but that analysis is out of the scope of this paper.

The remainder of the paper is organized as follows. In Section 2 we discuss the relevance of liquidity in the context of the negative relation between idiosyncratic volatility and expected returns and link it to economic regimes. Then, in Section 3 we use several measures of economic conditions and several sample periods to demonstrate that the returns of high idiosyncratic volatility stocks are particularly low during recessions, leading to a much higher spread between high and low idiosyncratic volatility stock returns. Section 4 presents the results obtained estimating a Markov regime-switching model reflecting the conditional effect of liquidity shocks both for high and low idiosyncratic volatility stocks in alternative economic regimes. It then concludes with evidence on the duration of the correction in stock prices implied by this conditional effect taking into account different definition of recessions. The last section, Section 5, highlights the main implications and conclusions of the paper.

2. Idiosyncratic risk anomaly, liquidity and economic times

The negative relation between idiosyncratic volatility and expected returns is observed after forming quintile portfolios of stocks sorted according to the standard deviation of the residuals of a Fama and French (1993) model. Once the quintile portfolios are constructed the subsequent returns are calculated and the performance of extreme portfolios is compared. This [5-1] difference in returns is negative and significant which could imply that there is a missing factor in the asset pricing model or, alternatively, that there could be a characteristic shared by the stocks with higher idiosyncratic risk able to explain the spread in returns of the extreme idiosyncratic risk quintiles. In this context liquidity is a good candidate for both scenarios given the fact that it has been shown that both aggregate and individual liquidity levels are related to returns.

On the one hand, the relevance of liquidity as a pricing factor is shown by Pastor and Stambaugh (2003) who provide evidence that aggregate liquidity is priced in the stock market and that stocks with low liquidity betas have relatively lower returns. Also, several papers such as Amihud and Meldenson (1986), Brennan and Subrahmanyam (1996), Brennan *et al.*, (1998), Datar *et al.*, (1998) and Fiori (2000) show that, in average, illiquid stocks tend to have higher returns since investors have a preference for liquidity. On the other hand, the potentiality of liquidity in the negative relation between idiosyncratic risk and expected returns has been latent from the seminal paper by Ang *et al.,* (2006) where controls for liquidity are introduced performing double sorts based on liquidity measures and idiosyncratic risk.[1] In all cases the particular liquidity control is unable to account for the negative relation between idiosyncratic risk and expected returns and authors conclude their results are robust to liquidity. A similar conclusion is found by Spiegel and Wang (2005) who using several proxies for liquidity show that liquidity and idiosyncratic risk are negatively correlated and that, although both have effects on the cross-section of stock returns, the effect of idiosyncratic risk dominates the one of liquidity for all proxies.

However, two recent papers argue the controls for liquidity have to be included before estimating the idiosyncratic volatility and show that liquidity is in the core of the negative idiosyncratic risk – expected returns relation. Han and Lesmond (2011) argue liquidity affects the estimation of idiosyncratic volatility via the percentage of zero returns that biases the loadings on the systematic risk factors, and via the bid-ask spread that increases the variance of the returns. Therefore, authors perform double sorts first on the percentage of zero returns during a month and then on idiosyncratic risk and estimate the idiosyncratic volatility using midpoint returns to control for the bid-ask bounce. They conclude that both approaches are able to fully account for the significance of the explanatory power of idiosyncratic risk on returns and argue their results highlight the relevance of liquidity in

[1] These controls for liquidity include liquidity betas based on Pastor and Stambaugh (2003), volume, and turnover.

the discussion.[2] Their results are reinforced by Han *et al.,* (2011) who show the midpoint approach accounts for the negative relation in 45 markets, including 22 emerging ones.

This paper is innovative in that the conditional pricing of liquidity has not been considered before in the context of idiosyncratic risk and expected returns. We believe that known empirical observations in the asset pricing literature provide solid grounds to consider this conditional effect. There is evidence suggesting that the pricing of liquidity in the financial markets changes over economic regimes. For instance, Vayanos (2004) suggests that investors have a time-varying preference for liquidity lead by the fact that illiquid assets become riskier during times of high volatility. Also, Acharya *et al.,* (2012) demonstrate that liquidity shocks affect asset prices in a stronger way during recessions and that during these times there is a flight to liquidity throughout which the prices of liquid (illiquid) assets tend to raise (decline). We consider that combining the conditional pricing of liquidity with the fact that stocks with higher (lower) idiosyncratic risk are in general less (more) liquid provides an interesting framework for analysis.

Our hypothesis is that, in opposition to what would happen during normal times when liquidity shocks should be largely absorbed by the market, during recessions liquidity shocks should have a much larger impact on illiquid stocks. This effect should be reflected in a very deep decrease in their prices as investors move to more liquid assets. However, these liquidity shocks should be absorbed by the market once the economic conditions improve. Then, a correction in prices should be observed following recessions. In particular, the prices of high idiosyncratic risk stocks (less liquid) should increase as

[2] A recent paper by Chen *et al.,* (2012) argues the percentage of zero returns does not account for the anomaly. However, since it does not provide any argument related to liquidity we do not refer to it extensively here.

market´s conditions improve. In this context, the spread in returns of extreme idiosyncratic risk quintiles should decrease, becoming non-significant or even positive following recessions. Noticeably, our hypothesis has no implications on the nature of the relation between idiosyncratic risk and expected returns during normal times. Therefore, during these times we expect to observe a negative relation between these two variables and any of the potential explanations discussed in the literature to justify it could apply.

3. Preliminary evidence

We begin this section by showing that the idiosyncratic volatility is negatively and significantly related to the expected returns in our sample. We then provide evidence suggesting that the returns of high idiosyncratic volatility stocks are particularly low during recession periods, making the contemporaneous [5-1] spread in returns much larger during these times.

In order to analyze the idiosyncratic volatility – expected returns relation each month we sort stocks according to their idiosyncratic volatility estimated over the previous six months. This volatility is defined as the standard deviation of the residuals, (σ_{i,ε_t}), in the three-factor model of Fama and French (1993):

$$r_t^i = \alpha^i + \beta_{MKT}^i MKT_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \varepsilon_t^i , \quad [1]$$

where, r_t^i is the stock returns in excess of the risk free rate and $\{MKT_t, SMB_t, HML_t\}$ represent the market, size and book to market factors.[3,4] Stocks are sorted into quintiles, where the first one contains stocks with the lowest risk and the last one those with the highest risk. Then, the corresponding portfolios are value-weighted and rebalanced month by month. Our database includes daily returns of all stocks in the CRSP (*Chicago Research Stock Prices*) for NYSE, AMEX and NASDAQ markets from July 1963 to December 2009.

Table 1 reports the results we obtain using data from January 1964 to December 2009 since the first six months are lost in the initial estimation of idiosyncratic risk. The table reports monthly average returns, standard deviations, and alphas (all in percentage) for portfolios sorted on idiosyncratic volatility. Alphas CAPM correspond to Jensen's alphas calculated with respect to the CAPM and Alphas FF with respect to the three-factor model. The t-statistics are reported in brackets. The row [5-1] is the difference between portfolio 5 and portfolio 1 where Newey-West t-statistic is also reported in brackets.

[Table 1]

The average returns of quintile portfolios display an inverse U-shaped form increasing in the middle quintiles; returns rise from 0.91% in quintile 1 to 1.05% in quintile 3, then drop to 0.12% in quintile 5. The [5-1] difference is in average -0.79% per month and statistically significant. Moreover, Jensen's alphas are positive for the initial three portfolios and switch to negative from the fourth. Both [5-1] differences in CAPM alphas and in FF alphas are negative, -1.59% the former and -1.73% the latter, showing the puzzle

[3] The original methodology by Ang *et al.,* (2006) implies the estimation of the idiosyncratic risk only over one month. However, we use the estimation over six months to address the critique of error-in-variance exposed by Malkiel and Xu (2002).
[4] The factors used the model have been obtained from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

appears even after controlling for risk. These results exhibit similar patterns to the ones reported by Ang *et al.,* (2006) and provide evidence that the idiosyncratic volatility anomaly is robust as our data sample is larger, includes the latest financial crisis period and we use a longer period in the estimation of the idiosyncratic risk.

Before proceeding to the core of our analysis, we further present preliminary evidence in favor of our hypothesis. In particular, we discuss the implications of our hypothesis in the contemporary relation between idiosyncratic risk and returns. Notice that for our hypothesis to be true, the contemporary returns of stocks in the fifth quintile should be significantly lower during recessions, when they are more prone to liquidity shocks. To support our hypothesis, Table 2 reports the monthly percentage contemporaneous returns for idiosyncratic risk quintiles during recessions and expansions. The table contains evidence on three different manners to define recessions. The first one is straightforward and corresponds to the NBER business cycle data. In this case, the data sample covers the period between January 1964 and December 2009. The second definition is based on a dummy taking the value of one when the value of the Kansas index in a particular month is within the 75^{th} percentile of index values. The Kansas index is only available from December 1993. Therefore, the information using Kansas index corresponds to the data spanning the period December 1993 to December 2009. Finally, we report the results obtained when recession periods are identified using the CFNAI and includes monthly observations from May 1967, when the index was first available, to December 2009.

[Table 2]

The results in Table 2 show that the significance of the High-Low spread, the [5-1], is not pervasive over economic regimes when idiosyncratic volatility and returns are contemporary. This is, when they are calculated during the same month. Using the NBER business cycle to separate months in recessions and expansions reveals that the difference in raw returns between the fifth and the first quintile portfolio is equal to a largely significant -25.92% (t-stat = -5.72) during recessions but is insignificant (t-stat = -1.61) and equal to -4.84% during expansions. Alphas based on the Fama and French (1993) model tell a similar history; during recessions the Alphas spread is largely significant (t-stat = -5.56) and, with a value of -25.69% it is substantially lower than the -5.30% (t-stat = -1.79) observed during expansions. Kansas Index and CFNAI index suggest a similar history. Although is both cases the spread is significant during recessions and during expansions, the magnitude of the spread is much larger during recessions. The results are quite encouraging in that they highlight the fact that the economic regime at the time when the stocks are ranked may affect the empirical relation observed between idiosyncratic risk and expected (as opposed to contemporary) returns. In other words, the fact that the negative idiosyncratic risk – expected returns relation involves sorting stocks according to their idiosyncratic risk in month t and observe their returns in month t+1, implies that what happens to stocks in month t is relevant. The results displayed in Table 2 suggest that during recessions stocks with higher level of idiosyncratic risk suffer particularly acute drops in their returns. Compared to the -0.79% observed in subsequent returns, the difference between extreme idiosyncratic risk quintiles is about 32 times larger when considering contemporaneous returns during recessions.

In terms of our hypothesis, our results suggest that the large drop in returns of stocks in quintile 5 during recessions might be caused by liquidity shocks coming to the market and affecting the high idiosyncratic risk stocks in a particularly acute manner. In order to test this hypothesis in the following section we use a Markov regime switching model including a variable related to innovations in market liquidity and check the influence of liquidity shocks on high and low idiosyncratic volatility portfolios during differing business cycles.

4. Results on liquidity shocks and extreme idiosyncratic risk portfolios

In this section we test the hypothesis that the anomaly is not observed during periods following recessions because of an asymmetrical impact of liquidity shocks on the extreme idiosyncratic volatility portfolios. In particular, our estimation considers the effect of liquidity shocks on the contemporary returns of stocks. This is to say, we want to consider the effect that a liquidity shock happening during month t has on the returns of stocks also during month t. The reason why this is important is that, assuming monthly portfolio holding, the returns of an asset in month t+1 should be related to any unexpected event taking place during month t.

We use a Markov regime switching model to check the relationship between the returns of both the highest and the lowest idiosyncratic risk portfolios and liquidity shocks conditional to the economic regime.[5] The model, expressed from equation [2] to equation [5], is a good candidate to represent the asymmetric dynamic behavior of stocks with differing idiosyncratic risk levels implied in our hypothesis. It is basically formed by a

[5] For further details on a Markov regime switching model refer to Hamilton (1994)

return structure for each type of portfolios and changes conditional on an unobservable state variable identifying the regime that follows a first order Markov chain. This is to say, the model allows for all the coefficients of the returns equations to vary between both regimes and between types of portfolios.

For our purposes we follow the model proposed by Acharya *et al.,* (2012) to identify the effect of liquidity innovations on stocks returns so that the returns of the highest idiosyncratic volatility portfolio in regime k for k = {1,2} are assumed to be characterized by the model:

$$\begin{aligned} R_{HIVOL,t} = \alpha^k_{HIVOL} + \beta^k_{HIVOL,M} MKT_t + \beta^k_{HIVOL,S} SMB_t + \beta^k_{HIVOL,H} HML_t \\ + \beta^k_{HIVOL,S} Silliq_t + \varepsilon^k_{HIVOL,t}, \end{aligned} \quad [2]$$

where, R_{HIVOL} corresponds to the value-weighted returns of the quintile portfolio of stocks with highest levels of idiosyncratic risk estimated using the previous 6 months, $\{MKT_t, SMB_t, HML_t\}$ represent the market, size and book to market factors, and Silliq is the measure of aggregate liquidity shocks. The liquidity measure corresponds to the equally-weighted average of the daily Amihud (2002) illiquidity measure averaged over each month using NYSE and AMEX stocks.[6] Liquidity shocks are measured as the innovations of an AR(3) model fitted to the index.

[6] Formally, Amihud measure for stock i at the end of month t is given by

$$Amih^i_t = \frac{1}{d}\sum_{j=1}^{d} \frac{\left|ret^i_t\right|}{Vol^i_t}$$

where, d is the number of days with available data for stock i over month t, ret is the stock return and Vol its dollar volume in millions.

Similarly, the returns of the lowest idiosyncratic volatility portfolio in regime k for k = {1,2} are assumed to be characterized by the model:

$$R_{LIVOL,t} = \alpha^k_{LIVOL} + \beta^k_{LIVOL,M}MKT_t + \beta^k_{LIVOL,S}SMB_t + \beta^k_{LIVOL,H}HML_t + \beta^k_{LIVOL,S}Silliq_t + \varepsilon^k_{LIVOL,t}, \qquad [3]$$

where, R_{LIVOL} corresponds to the value-weighted returns of the quintile portfolio of stocks with lowest levels of idiosyncratic risk estimated using the previous 6 months and the rest of the variables are defined as in equation 2.

The state variable s_t changes according to the Markov switching probabilities for state transition p and q such that:

$$P(s_t = 1|s_{t-1} = 1) = p \text{ and,} \qquad [4]$$
$$P(s_t = 2|s_{t-1} = 2) = q.$$

In turn, the variance-covariance matrix is defined as:

$$\Omega_{s_t} = \begin{bmatrix} \sigma^2_{HIVOL,s_t} & \rho_{s_t}\sigma_{HIVOL,s_t}\sigma_{LIVOL,s_t} \\ \rho_{s_t}\sigma_{HIVOL,s_t}\sigma_{LIVOL,s_t} & \sigma^2_{LIVOL,s_t} \end{bmatrix}, \qquad [5]$$

and also changes with the regime, therefore capturing the idea that the variance of the returns of the extreme quintiles of idiosyncratic volatility and the correlation between them may change from one regime to the other.

All the parameters of the model are estimated by Maximum Likelihood and the nature of the model is such that, in opposition to the previous section where the classification of the economic regime was made ex-post, the underlying regime is determined endogenously. Therefore, in order to be able to interpret the results of the Markov model presented in Table 4, we first present empirical evidence supporting that Regime 2 is likely related to the high stress periods we are interested in. To characterize Regime 2 as recession, we regress the estimated probability of being in Regime 2 against (i) the NBER recession dummy, (ii) the Chicago Fed National Activity Index (CFNAI) that captures the overall economic activity in the US such that higher numbers imply higher economic activity, (iii) a negative market return dummy equal to one whenever the equity market suffers negative returns during three consecutive periods, (iv) the term structure estimated as the difference between the market yield on 10 years U.S. Treasury securities and the 3-month T-bill rate, (v) the TED spread defined as the difference between the interbank loan rate and the T-bill and that is expected to be larger when economic conditions worsen, (vi) the growth of broker-dealer assets relative to households' assets coupled with (vii) equity market volatility and (viii) the interaction between these two latter variables. These three variables together should account for involuntary intermediaries' inventory and therefore for worse economic conditions. The estimated regressions are displayed in Table 3 where, odd columns correspond to OLS regressions where the dependent variable in is the logit transform of the estimated probability of being in state 2. [7] Even columns correspond to logistic regressions where the dependent variable is a dummy equal to one if the estimated probability of being in Regime 2 is larger than 0.7.

[7] The logit transform is given by the expression log[(P2t + c)/(1- P2t + c)], where c = 0.5/419. It is used to avoid problems related to the fact that by definition the estimated probabilities range from 0 to 1 while the linear prediction Xβ might take any real value. The constant c is defined as in Acharya *et al.,* (2012) and is necessary to avoid problem with the transforms when the estimated probability is exactly equal to 0 or 1.

The results in Table 3 confirm our hypothesis; the coefficient relied to the NBER recession dummy is positive and significant at 5% confidence level for both specifications, the one relied to the CFNAI is negative and significant at 1% in the OLS regression and at 5% in the logistic regression. Also, the negative market returns dummy is positive and significant at 5% only in the OLS case. In terms of single variables, the term structure and the TED spread are the ones that offer the highest adjusted (Pseudo) R^2 for OLS (logistic) regressions. The former is negative and significant as expected during recession periods and it explains 6% (8%) of the probability to be in Regime 2. The latter is positive and significant, also as expected during recessions, and explains up to 12% of the probability of being in Regime 2. The highest R^2 is obtained when all the variables are considered together. In this case all the significant variables have the expected signs and the R^2 is 19% and 17% for the OLS and the logistic regressions respectively. We therefore conclude that the Regime 2 is likely to be related to times of high stress market conditions and Regime 1 to normal times.[8]

[Table 3]

Having identified the regimes, it is possible to highlight how the results of the regime switching model we consider support our hypothesis. Results are reported in Table 4. On the one hand, the intensity with which liquidity shocks affect the lowest and the highest idiosyncratic volatility portfolios are very different across economic regimes. During normal times liquidity shocks affect negatively the returns of the low idiosyncratic volatility stocks; the coefficient relied to Silliq is significant and equal to -0.03. At the same

[8] Using the Kansas Index instead of the CFNAI, a regression including all the variables achieves a R^2 equal to 43%. Results are available upon request.

time, there is virtually no effect of liquidity shocks on high idiosyncratic risk stock returns. This is consistent with the fact that the [5-1] difference is negative and significant after normal times. Indeed, the negative shock implies the prices of stocks in quintile 1 should increase in the following month. And, because no reaction is expected on prices of stocks in quintile 5, it is expected to observed a [5-1] spread after normal times.

[Table 4]

It is particularly interesting to observe the impact of liquidity shocks during recession periods when it should be much larger. The changes are relevant both in intensity and significance, and are fully consistent with our hypothesis in that they reflect a conditional effect of shocks on extreme idiosyncratic volatility quintile portfolios. During high stress periods, the coefficient related to liquidity shocks is a significant -0.06 for the stocks with lowest idiosyncratic risk, only slightly higher than it is during normal times. Most of the relevant effects are observed on the stocks with high idiosyncratic risk. For this type of stocks, the non-significant effect of liquidity shocks turns to a very significant value and large -0.23. This result clearly shows that the impact of liquidity on this type of stocks has to be analyzed in a conditional context if it is to be fully understood. Also, because in this scenario liquidity shocks should be a transient phenomenon, their effects should be short-lived once the financial conditions in the market improve. The immediate implication is that the prices of high idiosyncratic volatility stocks should suffer a dramatic correction after financial stress periods. In particular, our results suggest that after financial stress periods the prices of stocks in both quintiles 1 and 5 should increase. And, because the correction should be much more substantial for stocks in quintile 5, the [5-1] difference could become non-significant or even positive. Given the fact that the duration of this price correction should depend on the efficiency of the market, it also becomes interesting to consider how long it lasts.

In order to test these implications we consider two types of evidence. First, we estimate the relation between idiosyncratic volatility and expected returns following recessions, starting at one month after recession and then increasing the number of months after recessions up to moment in which a negative and significant [5-1] spread is observed again. The results of this analysis are displayed in Table 5. Panel A of the table show the analysis when recessions are defined using the NBER data. When only one month after recessions have ended is considered, the relation between idiosyncratic risk and expected returns is indeed positive, being equal to 2.06% in raw returns and to -0.38 in terms of Fama and French (1993) model's alphas. Although these differences in returns are not significant, the results are totally in line with our hypothesis and suggest that there is a correction in the prices of stocks with highest levels of idiosyncratic risk. The hypothesis is also supported by the fact that the [5-1] difference is still positive, larger and significant one period further, suggesting the correction in prices is still going on two months following recessions. In fact, it is necessary to wait up to 5 months after the end of recessions to observe the negative and significant [5-1] spread in risk adjusted returns.

[Table 5]

The identification of recessions through NBER data correspond to an ex-post analysis, so it could be interesting to understand how these results change once that an ex-ante identification of recession is considered. Therefore, in Panel B and Panel C recessions are identified using the Kansas index and the CFNAI respectively. The results in Panel B confirm the idea of a correction in prices following recessions. The [5-1] difference is positive both one and two months after recessions, but only the difference in raw returns is significant. Nevertheless, the fact that the relation between idiosyncratic risk and expected returns changes sign is interesting in itself and it highly supports our hypothesis. Panel B also shows that it takes up to 10 months after the recession ends to observe the idiosyncratic volatility anomaly in risk adjusted terms. In a similar vein, Panel C shows that when the definition of recession is based on the CFNAI the [5-1] difference in raw returns and alphas is negative but not significant one and two months following recessions. In this case, the [5-1] difference in returns becomes negative and significant 4 months after the end of recessions.

This section provides evidence in favor of a conditional liquidity effect disturbing in particular the highest idiosyncratic risk stocks. It also shows that the [5-1] differences in raw returns and alphas shrink and even become positive following recessions. A final stage in our analysis is to show that, in accordance to our hypothesis, the negative risk – return relationship is still observed in the rest of the months and moves towards negative significance over time. Therefore, we further separate our sample in three sub-periods: (i) recession periods, (ii) after recessions and (iii) not classified periods (which consider every month not classified in the initial two groups) because the question of whether the negative relation between idiosyncratic volatility and expected returns is pervasive over economic regimes has arisen in previous literature. The results of this analysis are displayed in Table 6 that displays the [5-1] differences in returns for each of the sub-periods defined above.

[Table 6]

Table 6 serves two purposes; in the one hand, it allows us to compare the evolution over time of the [5-1] differences in returns for several definitions of recession periods. On the other hand, it allows us to show that the negative and significant idiosyncratic risk – expected return relation can be observed both during recession months and during what we call "not classified" months. In terms of the evolution over time, the evidence in Table 6 is consistent with the evidence provided so far and shows that the [5-1] is significant both during recessions and during "not classified" months when recessions are defined using either the CFNAI or NBER recession dates. For the NBER case, when we consider only two months after recessions, the [5-1] difference during the "not classified" months is equal to a -0.74% in raw returns, significant at 10%, and to -1.18 in adjusted risk returns, significant at 1%. The results are virtually the same when considering 4 months after recessions. Moreover, with an alpha equal to a significant -1.50, the negative relationship between idiosyncratic risk and expected returns is also observed during recessions. For the CFNAI and the Kansas cases, results are similar although the [5-1] difference in returns is not significant during recessions in the Kansas case.

5. Conclusions

This papers intends to shed light on the effect of liquidity shocks on the [5-1] spread in expected returns observed between high and low idiosyncratic volatility stocks. To do so, we detach from the purpose of explaining why the relation between idiosyncratic volatility and expected returns observed empirically is negative. Instead, we consider the contemporary effects of liquidity shocks on high and low idiosyncratic volatility stocks over different economic regimes. The evidence provided in this paper suggests that the sensitivity of the stocks with the highest levels of idiosyncratic risk to contemporary liquidity shocks implies a large correction in prices that shadows the negative [5-1] spread in returns during several months following recessions.

Overall, our results provide a plausible view of the relevance of the conditional pricing of liquidity in the relation between idiosyncratic volatility and expected returns that has not been considered before. In the first stage of our analysis we show that the contemporaneous [5-1] difference in returns is much larger during recessions. We then turn to evidence suggesting that liquidity shocks largely decrease the returns of stocks with the highest level of idiosyncratic risk. Based on our results we then show that the correction in prices that should follow recessions is such that the [5-1] spread can become positive and significant several months after recession have finish. Our results are robust to ex-ante and ex-post definitions of recessions and also provide and interesting implications for the analysis of the idiosyncratic risk – expected returns relationship. On the one hand, the fact that liquidity shocks have explanatory power over the returns of low idiosyncratic risk but not over high idiosyncratic risk stocks during normal times might be of interest for future research. On the other hand, the fact that the anomaly is not observed during periods following recessions implies that the explanations of the [5-1] spread should consider controls for past liquidity shocks. Above all, our results highlight the fact that the relation between idiosyncratic risk and return is a complex and rich one and a potential continuous source of interesting empirical analyses.

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Table 1: Returns of portfolios sorted by idiosyncratic risk

This table reports the results we obtain by forming quintile portfolios according to idiosyncratic risk, estimated over 6 months, using data from July 1963 to December 2009. Since the six initial months are lost, effectively the table corresponds to data from January 1964. Quintile 1 corresponds to the lowest idiosyncratic risk portfolio and quintile 5 to the highest idiosyncratic risk. Returns and standard deviation (Std Dev) are reported in monthly percentage. The row [5-1] is the difference between portfolio 5 and portfolio. Alphas CAPM correspond to Jensen's alphas calculated with respect to the CAPM and Alphas FF with respect to the Fama and French (1993) model and are also reported in percentage. In this table idiosyncratic risk is calculated using data from month t-6 to month t-1 and expected returns in month t. Newey-West t-statistics are reported in brackets. * denotes significance at 10% level, ** significance at 5% level and *** significance at 1% level.

Quintile	Returns	Std Dev	Alphas CAPM	Alphas FF
1	0.91	3.88	0.12 [2.21]	0.11 [2.55]
2	0.99	5.30	0.06 [1.12]	0.02 [0.32]
3	1.05	6.88	0.02 [0.12]	0.03 [0.38]
4	0.66	8.61	-0.47 [-2.36]	-0.50 [-3.47]
5	0.12	9.83	-1.01 [-3.68]	-1.17 [-6.07]
[5-1]	-0.79** [-2.09]		-1.13*** [-3.60]	-1.28*** [-6.01]

Table 2: Contemporary returns of portfolios sorted by idiosyncratic risk in different economic regimes

This table reports the contemporary returns [5-1] difference separating the sample months into recessions and expansions. Quintile 1 corresponds to the lowest idiosyncratic risk (IVOL) portfolio and quintile 5 to the highest idiosyncratic risk. Both returns and idiosyncratic risk are calculated at t. Months are classified into these two regimes according to the NBER Business Cycle Data and covers the sample period from January 1964 to December 2009. Returns and Alphas are reported in monthly percentage. Alphas correspond to the Fama and French (1993) model. In this table idiosyncratic risk is calculated using information from month t-6 to t-1 and the returns are calculated in month t-1. Newey-West t-statistics are reported in brackets. * denotes significance at 10% level, ** significance at 5% level and *** significance at 1% level.

	Return	**Alpha**	**Return**	**Alpha**
	Recession Months		Expansion Months	
NBER				
High IVOL stocks	-28.73	-27.82	2.42	1.39
Low IVOL stocks	-2.81	-2.13	7.26	6.69
Spread High-Low	-25.92***	-25.69***	-4.84	-5.30*
	(-5.72)	(-5.66)	(-1.61)	(-1.79)
KANSAS INDEX				
High IVOL stocks	-25.12	-0.20	-4.44	-0.05
Low IVOL stocks	-0.15	0.01	7.96	0.07
Spread High-Low	-24.97**	-21.24	-12.40***	-0.12***
	(-2.01)	(-1.64)	(-2.78)	(-3.03)
CFNAI INDEX				
High IVOL stocks	-25.39	-0.27	-1.04	-0.02
Low IVOL stocks	1.13	0.35	6.51	0.06
Spread High-Low	-26.52***	-0.28***	-7.55**	-0.08**
	(-4.56)	(-5.37)	(-2.57)	(-2.70)

Table 3: Regression analysis to identify regime 2 as recession

This table reports a regression analysis intended to characterize regime 2 of the Markov regime-switching model as corresponding to recession. Odd (even) columns correspond to OLS (logistic) regressions where the dependent variable is the logit transform of the estimated probability of being in regime 2 (a dummy variable equal to 1 if the probability of being in regime 2 is larger than 0.70). The sample spans the period from May 1967 to December 2009. The independent variables are the Chicago Fed National Activity Index (CFNAI), a dummy variable equal to one for NBER recession times, a dummy variable equal to one when the S&P500 is negative during three consecutive months, the term structure estimated as the spread between the market yield on 10 years U.S. Treasury securities and the 3-month T-bill rate, the TED spread defined as the difference between the interbank loan rate and the T-bill and that is expected to be larger when economic conditions worsen, the growth of broker-dealer assets relative to households' assets (ee) coupled with the equity market volatility (eqvol) and the interaction between these two latter variables (inter). All the independent variables are lagged one month. * denotes significance at 10% level, ** significance at 5% level and *** significance at 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$CFNAI_{t-1}$	-0.72***	-0.23**									-0.21	-0.01
	(-2.75)	(-2.00)									(-0.81)	(-0.12)
$NBER_{t-1}$			2.25***	0.63**								
			(3.64)	(2.43)								
$Negm_{t-1}$					2.29***	0.57					0.84	0.00
					(2.60)	(1.58)					(0.98)	(0.01)
$Term_{t-1}$							-0.96***	-0.53***			-0.54***	-0.39***
							(-5.52)	(-6.23)			(-2.96)	(-4.23)
TED_{t-1}									1.87***	0.77***	1.46***	0.59***
									(7.78)	(6.41)	(5.32)	(4.33)
Constant	-2.29***	-0.95***	-2.62***	-1.05***	-2.42***	-0.98***	-0.66*	-0.14	-4.19***	-1.80***	-2.95***	-1.01***
	(-9.79)	(-9.05)	(-10.30)	(-8.96)	(-9.94)	(-8.96)	(-1.79)	(-0.91)	(-12.54)	(-10.08)	(-5.60)	(-4.05)
Obs.	459	459	459	459	459	459	459	459	459	459	459	459
R^2/Pseudo R^2 (%)	2%	1%	3%	1%	1%	0%	6%	8%	12%	9%	14%	12%

Table 3 – *Continued*

	(13)	(14)	(15)	(16)	(17)	(18)
$CFNAI_{t-1}$			0.02	0.07	0.18	0.21
			(0.07)	(0.37)	(0.69)	(1.50)
$NBER_{t-1}$			-0.66	-0.63		
			(-0.74)	(-1.33)		
$negm_{t-1}$			-0.15	-0.47	-0.29	-0.59
			(-0.17)	(-1.00)	(-0.34)	(-1.25)
$Term_{t-1}$			-0.54***	-0.39***	-0.55***	-0.41***
			(-2.99)	(-3.99)	(-3.10)	(-4.22)
TED_{t-1}			1.41***	0.64***	1.33***	0.56***
			(4.81)	(3.96)	(4.87)	(3.78)
$eqvol_{t-1}$	268.08***	113.90***	221.97***	123.56***	218.90***	118.99***
	(6.28)	(4.83)	(4.90)	(4.41)	(4.86)	(4.32)
ee_{t-1}	-0.00*	-0.00	-0.00**	-0.00	-0.00**	-0.00
	(-1.69)	(-0.99)	(-2.06)	(-1.29)	(-2.10)	(-1.35)
$eqvol_{t-1}$*ee_{t-1}	0.57**	0.18	0.64**	0.24	0.65**	0.24
	(2.04)	(1.26)	(2.34)	(1.49)	(2.38)	(1.53)
Constant	-4.66***	-1.99***	-4.70***	-2.05***	-4.66***	-1.98***
	(-10.53)	(-8.20)	(-7.72)	(-5.61)	(-7.68)	(-5.54)
Obs.	459	459	459	459	459	459
R^2/Pseudo R^2 (%)	9%	6%	19%	17%	19%	17%

Table 4: Estimation of the Markov regime-switching model

This table reports the results of the Markov regime-switching model. In panel A, the results on the portfolio formed by stocks with the lowest (highest) level of idiosyncratic risk are found in the column labeled "low (high) idiosyncratic volatility stocks". The dependent variable is the value weighted monthly returns of the portfolio with the lowest (highest) idiosyncratic risk stocks. The independent variables are the market, size and book-to-market factors (MKT, SMB, HML), and the liquidity shocks in the total market (Silliq). Regime 1 corresponds to normal times and Regime 2 to financial stress periods. The sample covers the period between January 1964 and December 2009. Panel B reports the Wald tests for differences in coefficients between regime 1 and regime 2 and Panel C the ones for differences in coefficients between low and high volatility stocks. In all Panels * denotes significance at 10% level, ** significance at 5% level and *** significance at 1% level.

Panel A: Estimation of the Markov regime-switching model

Regime 1

	Low IVOL		High IVOL		Parameters	
	Coefficient	p-val	Coefficient	p-val		
Constant	0.08**	0.00	-0.11**	0.00	p	0.97**
MKT	0.95**	0.00	0.97**	0.02	q	0.95**
SMB	-0.03	0.85	0.42	0.47	ρ_{St}	0.01**
HML	0.41**	0.02	-0.52	0.38	ρ_{St}	0.02**
Silliq	-0.03*	0.06	-0.06	0.27		
σ_i	0.01**					

Regime 2

	Low IVOL		High IVOL	
	Coefficient	p-val	Coefficient	p-val
Constant	0.00	0.77	0.078**	0.01
MKT	0.74**	0.00	1.37**	0.03
SMB	0.06	0.75	2.20**	0.01
HML	0.66**	0.00	2.10**	0.02
Silliq	-0.06**	0.00	-0.23**	0.01
σ_i	0.15**			

Table 4 – *Continued*

Panel B: Wald tests for differences in coefficients between regime 1 and regime 2

	Low IVOL		High IVOL	
	χ^2	p-val	χ^2	p-val
Constant	30.59	0.00	187.93	0.00
MKT	0.49	0.48	1.69	0.19
SMB	0.042	0.84	16.75	0.00
HML	0.28	0.59	31.2	0.00
Silliq	0.31	0.57	16.78	0.00

Panel C: Wald tests for differences in coefficients between low and high volatility stocks

	Regime 1		Regime 2	
	χ^2	p-val	χ^2	p-val
Constant	1531	0.00	15.64	0.00
MKT	0.02	0.88	2.24	0.13
SMB	8.52	0.00	12.89	0.00
HML	31.63	0.00	5.04	0.02
Silliq	3.72	0.05	9.48	0.00

Table 5: Returns of portfolios sorted by idiosyncratic risk after recessions

This table reports the results we obtain by forming quintile portfolios according to idiosyncratic risk and considering only periods after recessions. Quintile 1 corresponds to the lowest idiosyncratic risk portfolio and quintile 5 to the highest idiosyncratic risk. In Panel A months are classified into these two regimes according to the NBER Business Cycle Data and covers the sample period from January 1964 to December 2009. In Panel B months are classified into the two regimes according to the Kansas City Financial Stress Index so that any month having a value higher than the 75th percentile of the index is considered as a recession period. It covers the sample period from February 1990 to December 2009. In Panel C the classification is done following the CNFAI. Any month for which the value of the Index is lower than one standard deviation is considered as a recession month. Using this index the sample covers the period from May 1967 to December 2009. In all tables, returns and Alphas are reported in monthly percentage. The row [5-1] is the difference between portfolio 5 and portfolio. Alphas correspond to the Fama and French (1993) model. Newey-West t-statistics are reported in brackets. * denotes significance at 10% level, ** significance at 5% level and *** significance at 1% level.

Panel A: Quintiles by Idiosyncratic Risk after Recessions (NBER)						
	1 month after recession		2 months after recession		5 months after recession	
	Returns	Alphas	Returns	Alphas	Returns	Alphas
Low IVOL 1	3.08	0.04	2.91	-0.01	2.22	0.34
		[0.46]		[-0.03]		[1.62]
2	3.91	-0.26*	4.01	0.07	2.92	0.01
		[-1.84]		[0.29]		[0.08]
3	4.25	-0.05	4.83	0.09	2.89	-0.78*
		[-0.08]		[0.20]		[-1.86]
4	5.63	0.40	5.99	-0.36	2.85	-1.69*
		[1.12]		[-0.28]		[-1.82]
High IVOL 5	5.14	-0.34	6.98	-0.03	2.99	-2.09**
		[-0.31]		[-0.02]		[-2.00]
[5-1]	2.06	-0.38	4.08***	-0.02	0.77	-2.44**
	[1.30]	*[-0.35]*	*[3.16]*	*[-0.01]*	*[1.00]*	*[-2.13]*

Table 5 – *continued*

Panel B: Quintiles by Idiosyncratic Risk in differing Financial stress regimes (Kansas Index)						
	1 month after recession		2 months after recession		10 months after recession	
	Returns	Alphas	Returns	Alphas	Returns	Alphas
Low IVOL 1	1.84	-0.06 [-0.31]	1.27	-0.14* [-1.74]	0.53	0.23*** [2.75]
2	2.91	0.54 [0.95]	2.12	0.15 [0.26]	1.09	-0.18 [-0.79]
3	3.52	-1.28** [-1.99]	4.11	0.00 [-0.01]	2.21	-0.27 [-0.88]
4	5.67	-0.82 [-1.05]	4.76	-0.54 [-0.66]	2.31	-1.30* [-1.92]
High IVOL 5	7.71	2.38 [0.76]	8.06	1.75 [0.97]	2.58	-1.91** [-2.10]
[5-1]	5.87* *[1.94]*	2.43 [0.83]	6.79* *[1.90]*	1.89 *[1.06]*	2.05 *[1.00]*	-2.13** *[-2.30]*

Panel C: Quintiles by Idiosyncratic Risk in differing Financial stress regimes (CFNAI Index)						
	1 months after recession		2 months after recession		4 months after recession	
	Returns	Alphas	Returns	Alphas	Returns	Alphas
Low IVOL 1	2.01	0.57** [2.68]	0.81	0.49** [2.32]	1.37	0.62*** [3.46]
2	2.74	1.09*** [6.02]	1.33	1.14*** [3.46]	1.83	0.82*** [3.44]
3	2.85	0.47*** [2.74]	0.95	0.10 [0.20]	1.38	0.02 [0.05]
4	2.16	-2.06 [-1.49]	0.17	-1.65 [-0.99]	0.37	-1.33* [-1.72]
High IVOL 5	2.85	-1.98 [-0.87]	0.50	-2.47 [-1.04]	0.46	-1.47* [-1.70]
[5-1]	0.85 *[0.29]*	-2.54 *[-1.03]*	-0.31 *[-0.16]*	-2.96 *[-1.16]*	-0.91 *[-0.78]*	-2.09** *[-2.25]*

Table 6: Returns of portfolios sorted by idiosyncratic risk for different economic classifications

This table reports the results we obtain by forming quintile portfolios according to idiosyncratic risk and separating the sample months into "after recessions", "during recessions" and "not classified" periods. Quintile 1 corresponds to the lowest idiosyncratic risk portfolio and quintile 5 to the highest idiosyncratic risk. The classification of months in each of the categories is done following the procedure described in the previous table. In all tables, returns and Alphas are reported in monthly percentage. The row labeled "Spread high-low" is the difference between portfolio 5 and portfolio 1. Alphas correspond to the Fama and French (1993) model. Newey-West t-statistics are reported in brackets. * denotes significance at 10% level, ** significance at 5% level and *** significance at 1% level.

	Return		Alpha		Return	
NBER						
	During recessions		*2 months after recession*		*During not classified months*	
High IVOL stocks	-1.81	-1.37*	6.98	-0.03	0.3	-1.12***
Low IVOL stocks	-0.03	0.13	2.91	-0.01	1.04	0.07
Spread High-low	*-1.78**	*-1.50**	*4.07****	*-0.02*	*-0.74**	*-1.18****
	During recessions		*4 months after recession*		*During not classified months*	
High IVOL stocks	-1.81	-1.37*	-1.81	-2.00	0.28	-1.05***
Low IVOL stocks	-0.03	0.13	-0.03	0.15	1.01	0.06*
Spread High-low	*-1.78**	*-1.50**	*-1.78**	*-2.15*	*-0.74**	*-1.11****
KANSAS INDEX						
	During recessions		*2 months after recession*		*During not classified months*	
High IVOL stocks	-0.56	0.23	8.06	1.75	-0.04	-1.53***
Low IVOL stocks	0.66	0.38	1.27	-0.14*	0.93	0.04
Spread High-low	*-1.22*	*-0.15*	*6.79**	*1.89*	*-0.97*	*-1.57****
	During recessions		*9 months after recession*		*During not classified months*	
High IVOL stocks	-0.56	0.23	-0.56	-1.37	0.06	-0.86***
Low IVOL stocks	0.66	0.38	0.66	0.16**	1.17	0.03
Spread High-low	*-1.22*	*-0.15*	*-1.23*	*-1.53*	*-1.11***	*-0.89****
CFNAI INDEX						
	During recessions		*2 months after recession*		*During not classified months*	
High IVOL stocks	0.73	-1.86**	0.5	-2.47	-0.14	-0.53***
Low IVOL stocks	1.49	0.90***	0.81	0.49**	0.84	0.51***
Spread High-low	*-0.76*	*-2.76****	*-0.31*	*-2.96*	*-0.98***	*-1.04****
	During recessions		*3 months after recession*		*During not classified months*	
High IVOL stocks	0.73	-1.86**	0.46	-1.15	-0.15	-0.53**
Low IVOL stocks	1.49	0.90***	1.04	0.42***	0.83	0.51***
Spread High-low	*-0.76*	*-2.76****	*-0.57*	*-1.57*	*-0.98***	*-1.04****