LUND UNIVERSITY

DEPT. OF ECONOMICS

Leverage and Volatility

Master Thesis Financial Economics (1st yr)

Author: Ola Lithman

Thesis Advisor: Prof. Hossein Asgharian

Presentation Date: September 3rd 2010

Opponent: Arash Sani

ABSTRACT

This paper attempts to contribute to existing knowledge through an explicit threefold purpose. Initially, the importance of leverage in explaining equity return volatility is determined through two fixed effects panel data estimations. The panel dataset runs from 1990-2009 and includes 20 years worth of observations for the 45 firms on the Stockholm stock exchange for which data is available.

The second purpose is to evaluate the main explanations of asymmetric volatility. This is done for equity return volatility in its totality and for its component parts. The panel dataset is expanded through the addition of the three variables that arise from decomposing volatility into its three constituent parts (firm, industry and market specific volatility) and an approximated measure of risk premium. This leads into the implementation of a VAR-approach in a panel data setting.

The last segment sees the construction of five portfolios that are based on the return series of all 45 firms sorted from low to high leverage. Each portfolio return series corresponds to the 9 return-series associated with each leverage quintile for each year, i.e., the portfolio composition changes year-to-year in order to consistently represent the return series of each leverage quintile. This is the operationalization of the third and final purpose which is to determine if the persistence in volatility and degree of volatility asymmetry is higher for higher leverage quintile portfolios.

The main findings are that leverage is an important determinant of equity return volatility. However, the evidence is mixed for the idea that leverage influences the persistence of volatility and aggravates asymmetries. Further, special dynamics are at work during periods of financial crisis since certain relations are reversed and/or intensified during these periods. In complement to the purposes expressly pursued, central relations and processes not discussed in the literature are uncovered and recommended for future research.

Keywords: Leverage, volatility, asymmetric volatility, leverage effect, leverage hypothesis, volatility feedback, VAR, PVAR, risk premium, GARCH, APARCH, Conditional CAPM, volatility decomposition

Table of Contents

1. Introduction

The role of leverage in understanding the dynamics of financial crises is presently receiving attention through various research efforts. The aftermath of the recent financial crisis has witnessed proposals to link financial economics and macroeconomics more closely in order to understand what has gone wrong and how to prevent future episodes. It is the author´s belief that the concept of leverage represents one such connection that holds promise in the areas of explaining certain statistical observations, understanding asset valuation, modeling financial risk and ensuring financial stability.

A simple inspection of the stock market development over the past 20 years and the extraordinary market events of the past 2-3 years suggests it is now a more volatile environment. The development of microeconomic models, such as the leverage cycle (Geanakoplos 2009) to explain this new found volatility, seem to make intuitive sense from the buy-side. Consider the development of leveraged buyouts where at the height of the boom deals in the tens of billions could be 100% financed by debt, the dizzying pace of housing price rises and the development of the credit culture in the western world and the need for alternative models that look beyond interest rates as the final arbiter of credit supply and demand becomes clear. However, these are developments on the buy-side of financial assets that due to lack of data are difficult to investigate. As far as empirical research goes, there is only a staff report from the Federal Reserve (Adrian & Shin 2008) which shows that leverage and volatility are pro-cyclical.

The relation between corporate leverage and asset volatility has received a great deal of focus in the research literature. One reason for this is the inability to reach a consensus on the exact workings of asymmetric volatility (bad news impacts volatility more than good news). Many questions remain unanswered, e.g. the respective validity of the proposed explanations (discussed below), whether this effect is more pronounced in certain type of market environments, and the effect of leverage on the various types of volatility components. Given the recent interest in leverage as a risk measure[1] and the extreme movements in leveraging and de-leveraging over the past 2-3- years, a deeper look at leverage and volatility is motivated.

[1] E.g. a Financial Times article on 11 Sep. 2009 discussed using leverage ratios instead of VaR. Indeed, the newly arrived bank capital requirement rules from the Bank of International Settlements impose such a leverage ratio (Murphy and Jenkins 2010).

There is an established empirical finding that stock return volatility and negative returns are correlated. This is an empirical finding and has nothing to do with leverage, in any sense of the word. The word *leverage effect* refers to the notion that return volatility increases more as a result of negative returns than it does as a result of positive returns (i.e. asymmetric volatility). Confusingly, this is sometimes called the leverage effect hypothesis (see Ericsson et al. 2007). The two main proposed explanations for this are the *leverage hypothesis* (no less confusing is the fact that this hypothesis is sometimes called the leverage effect, (see Brooks 2008)), and the *volatility-feedback hypothesis*. In the leverage hypothesis, due originally to Black (1976), it is the capital structure that leverage refers to. It is explained in detail below but essentially says that after a market downturn, the nominal volatility (i.e. the risk of the firm which is assumed to be constant), is shouldered by equity that is after the drop a smaller share of the total, therefore the percentage volatility should rise. The volatility-feedback hypothesis states that if returns increase when volatility increases, the expectation of such an increase in volatility should cause prices to drop so investors can be compensated for the extra risk that such volatility entails. It is therefore also known as the *hypothesis of time-varying risk premia*. This second hypothesis proposes a reversed order of causality from the leverage hypothesis. As a final note on terminology, it can be mentioned that according to the second Modigliani-Miller theorem, expected return increases with leverage, what Asgharian (2003) calls the *pure leverage effect*.

This study examines the interaction between leverage and volatility using Swedish data, and the introduction of a new case has its own merit.

The four main points of inquiry are:

1. ***Do the stock return series of more highly leveraged firms display greater volatility than the return series of less leveraged firms? This initial step seeks to establish whether leverage affects volatility.***

2. ***If leverage is important in explaining total equity return volatility, what empirical support exists for the two main explanations of asymmetric volatility?***

3. ***Is the impact of leverage on asymmetric volatility constant across the three volatility components (market, industry and firm specific volatility)?***

4. *If leverage is important, do high frequency return series display the properties expected of theory? In other words, are the properties of leverage-sorted portfolio return series consistent with the findings above? In theory, the higher leverage-sorted portfolios should display greater returns, greater volatility, greater persistence in volatility, and greater sensitivity to asymmetric effects.*

This thesis comprises three main sections that together seek to answer these questions. The first section investigates the role of corporate leverage as a factor in explaining stock return volatility. This is done through fixed-effects estimation in an original panel data setup and demonstrates that leverage has a positive and significant effect on volatility.

The second section employs a panel vector autoregressive approach (PVAR) in two parts. The first part of this section consists of a bi-variate PVAR model to establish the causal relationship between leverage and volatility. The second part of the PVAR section consists of two tri-variate subsections. In the first tri-variate analysis, total return volatility and leverage are coupled with a risk premium approximation to evaluate the leverage hypothesis versus the volatility feedback hypothesis as explanations of asymmetric volatility. The second tri-variate PVAR estimation employs a volatility decomposition methodology that reduces the total return volatility into firm, industry and market specific volatility. These are linked to leverage and risk premia in order to ascertain whether the main explanations of "leverage effects" are equally valid across the three volatility constituents.

The third and final section assumes a portfolio approach in applying recent research that finds leverage is important in explaining asymmetric volatility. To do so, the return series properties of leverage-sorted portfolios are investigated via established models of changing volatility.

The differences from other studies and new contributions are as follows:

1. *The measure used for risk premia follows expected return more closely over time and the overlap is accelerated during market upturns. There exists no theoretically informed expectation of such a result.*
2. *No known studies have addressed the issue of whether the main explanations of asymmetric volatility carry equal weight for each volatility component. Indeed, there exists no theory on which to base such an approach.*

3. *The presence of studies that examine, even cursory, the possibility of a corporate leverage cycle is lacking.*
4. *As far as the author is aware, the importance of leverage in explaining equity return volatility in the context of Swedish data has not previously been examined.*
5. *What properties are revealed when estimating the equity return series of leverage-sorted portfolios with models of changing volatility using Swedish data?*
6. *Consider the validity of each asymmetric volatility explanation for Swedish data.*
7. *Illustrating the importance of improving the understanding of the special dynamics that are at work during financial crises.*

It seems that the whole asymmetric volatility discussion is underdeveloped. Indeed, Ericsson et al. (2007) point out that the importance of the leverage hypothesis as expounded by Black (1976) is still not fully understood and that no consensus on the relative importance of various return volatility components (depending on chosen method of decomposition) has been reached.

To the author's knowledge, this is the first paper examining these phenomena on Swedish data and the first to dissect return volatility when seeking to validate or disprove the main asymmetric volatility explanations. No other known articles dissect return volatility to investigate whether the effect of leverage on volatility is constant on these the components (FIRM, IND and MKT). Since theory in this regard is incomplete, an exploratory and testing approach is employed. Several areas are examined without loss of precision in each separately. However, to reach generalized conclusions, more research is needed.

2. Previous Research

In financial economics, the role of leverage has traditionally been cast as a factor in explaining asymmetric volatility (see e.g. Black 1976), and as a risk factor not priced by the capital asset pricing model (Fama and French 1992). In finance, the focus has been on optimizing capital structure within the business cycle. It is possible that the present author's focus on leverage represents a key component linking financial economics and macroeconomics. This linkage has been suggested by several economists (e.g. Krugman 2009) as the next challenge facing economics as a discipline.

Studies are generally performed on US equities because of the greater availability of data and the fact that leverage exists as a monthly observation which allows the empirically verified properties of high-frequency financial data to manifest themselves. However, findings in US data may not be mirrored in European or Swedish data for various cultural and institutional reasons.

Asgharian (2003) seeks to answer the question whether more highly leveraged firms lose a greater market share than their less leveraged rivals. Since, in theory, a leveraged firms yields a greater return on equity than a less leveraged firm when it does well, it is therefore necessary to estimate firm performance.

Asgharian and Hansson (2000) test the ability of beta and other explanatory variables to explain cross-sectional differences in expected returns on Swedish data spanning 1983-1996. The explanatory variables are those in Fama and French (1992) which are proxies for dimensions of risk not captured by beta. The authors find that leverage (as a proxy for financial risk) is only significant from zero when the entire sample is considered but loses significance once the three years of financial crisis are excluded. The sample-wide estimate generates a negative coefficient which would imply that firms with greater financial risk offer a smaller risk premium (i.e. excess return). This is primarily related to an industry factor since heavily leveraged firms were found in those industries that suffered the most during the crisis years. However, the authors main purpose is to remedy the errors-in-variables problem that results from first regressing excess asset return on excess market return via OLS and then employing that estimate in generating a parameter that should explain (according to CAPM) fully differences in cross-sectional returns.

Chen et al. (2010) estimate the idiosyncratic return volatility using the return volatility decomposition of Campbell et al. (2001) and run a regression to show that this firm specific risk is related to managerial discretion and certain macroeconomic variables.

Black (1976) proposes the leverage hypothesis to explain the empirical finding that volatility increases after negative returns materialize. In this view, it is the reduced equity that bears the full, constant nominal risk, which results in a higher percentage volatility. However, since the leverage effect is manifest in other non-firm financial time series, it is perhaps an explanation that is not wholly valid.

Ericsson et al. (2007) estimate a panel vector autoregressive (PVAR) model to add empirical evidence to the debate about the importance of capital structure in determining equity return volatility. In this dynamic model, leverage, return volatility and an estimated stock specific risk-premium are synthesized to allow the authors to study the interaction effects between the three. In this study the authors find strong empirical support for the leverage effect hypothesis, that leverage is an important component of equity volatility, and that its effect accumulates over time.

Figlewski and Wang (2000) find, on the other hand, that asymmetries in return data should be thought of as a "*down market effect*" rather than something that can be traced back to capital structure. This seems more in line with a view that what causes volatility is trading itself. To support such a conclusion, market volume must be examined, since trading should therefore increase after market drops.

Schwert (1989) estimates the ability of market-wide leverage to explain the volatility of the market portfolio using a generalized least squares estimation. This estimation shows that the volatility of returns is positively correlated with leverage. To compensate for the strong residual autocorrelation the residuals from this equation are modeled with an ARMA (1,3) process. Schwert interprets this residual autocorrelation as the volatility of the value of the firm not remaining constant throughout time and that there is some omitted variable that yields the large estimates of the leverage coefficient. As can be expected, Schwert finds that leverage alone cannot account for stock market volatility.

Choi and Richardsson (2008) construct five portfolios conforming to each leverage quintile of their dataset and then run various volatility models to investigate whether the portfolios of higher leverage suffer a greater persistence in volatility and are more susceptible to asymmetric volatility effects. They compare the various coefficients for these equity return portfolios with the coefficients for asset return portfolios. Both portfolio series are sorted according to leverage but one is a series of equity returns and the other is of asset returns. However, since asset returns are estimated as a weighted combination of, among other things equity returns, it must be seen as introducing an error that reduces the validity of their conclusion. The results indicate that these portfolios retain their properties regardless of equal or market weighting. They run a one-factor EGARCH estimation using the Black-Scholes formula to investigate the merits of the leverage hypothesis versus the volatility feedback effect. The authors find that leverage plays an important and hitherto largely undocumented role in explaining the severity of asymmetric volatility effects. The volatility of the estimated measure of firm value (i.e. asset value) is then found to determine *both* leverage and equity volatility. Finally, the effect of leverage on volatility is partitioned into transient and permanent components.

Sivaprisad and Muradoglu (2010) attempt to extend the study of leverage and incorporate it as a factor in asset pricing. To do so, the well-known Fama, French and Carhart (Carhart 1997) four-factor model of explaining the cross section of expected returns is extended to include a factor mimicking portfolio, that captures leverage as a risk factor in returns. This portfolio is formed by the difference in average monthly returns between the 30% most levered firms and the 30% least levered firms, re-sorted each year as leverage ratios change. It is not altogether clear how the authors can ascertain that their HLMLL (high leverage minus low leverage) portfolio represents the risk effect of leverage on returns and not some underlying factor, e.g. change in asset value as suggested by Choi and Richardsson (2008).

3. Theoretical Framework

The several issues dealt with in this investigation requires an engagement with several theoretical loci.

3.1 Beta and Modigliani-Miller (MM)

The beta of a stock measures the non-diversifiable risk of a stock, i.e. the systemic risk, and is understood as the covariance of the asset´s return with the market portfolio´s return (Rubinstein 1973). Hamada (1972) points out that in both the capital asset pricing model (CAPM) and the Modigliani-Miller (MM) theory increasing the leverage increase the inherent risk of the investment. The two MM propositions are as follows (cf. Modigliani and Miller 1958 and Berk and DeMarzo 2008).

MM I - In a perfect world, the total value of a firm is equal to the market value of the total cash flows generated by its assets and is not affected by its choice of capital structure. Regardless of financing, the total market value of the firm´s securities is equal to the market value of its assets.

In the first part of the present essay, it is shown that the choice of capital structure has implications for the strength and speed of the change in perceived firm value, if the share price can be seen as a discounted cash flow "per asset".

MM II - The expected equity return increases with leverage. This is presented in Asgharian (2003) as

$$E[R_e] = E[R_\alpha] + \frac{d}{e}(E[R_\alpha] - E[R_d]) \quad (1)$$

where $E[R]$ is the expected return, e is equity, α refers to total assets and d is debt.

3.2 The Leverage Hypothesis

This section furthers the exposition of Black´s leverage hypothesis where the nominal risk of the firm is assumed to be constant. However, the risk of a firm cannot reasonably be regarded the same before and after a stock price fall. If the equity return fluctuation is a perfect proxy for the risk in the firms asset then, if this bandwidth is 1 SEK before the stock price fall it should reasonably be greater after the fall because the future cash-flow stream is perceived as more risky (cf. Brooks 2008). This cash-flow stream should be considered even more risky for the leveraged firm and so the effect should be even stronger for the leveraged firm. Since debt is considered to be riskless, equity bears the full risk of the firm. The increase in risk comes even if in absolute terms the risk of the firm is the same. This risk should actually increase given a stock price fall which amplifies the leverage effect. For a company that has a greater degree of original leverage this effect also has a third component, since the percentage increase in the risk should be larger.

Consider the present author's presentation below where the risk is considered to be 1. With respect to the second firm, the equity has lost a proportional value due to the negative shock.

Table 1. The Leverage Hypothesis for two Firms with equal Risk but different Leverage

	Firm 1			Firm 2	
	Equity	*Debt*		*Equity*	*Debt*
Before Shock	10	10	**Before Shock**	5	15
σ=1	10%		**σ=1**	20%	
After Shock	6	10	**After Shock**	3	15
σ=1	16.6%		**σ=1**	33.3%	

It is important to note that the risk is the same but the *percentage* volatility of equity has risen (Campbell et al. 1997). Although the risk is assumed to be the same for both firms before and after the negative shock, it is more realistic to assume that the initial risk in the levered firm is greater (since such a firm has a higher expected return on equity). The risk should also increase for both companies after the shock but even more so for the levered firm. If the leverage hypothesis is correct, the asymmetric volatility effect should be larger for more leveraged firms (see table 3). If this third component, which may be called the *leverage risk effect,* is included, the asymmetric volatility effect is even more pronounced.

Table 2. The Leverage Hypothesis for two Firms with the same Value of total Assets but with different Risk as a Result of Different Leverage. Sigma has increased by 50% for both Firms as a Result of the negative Shock.

	Firm 1			Firm 2	
	Equity	*Debt*		*Equity*	*Debt*
Before Shock	10	10	**Before Shock**	5	15
σ=1	10%		**σ=1.5**	30%	
After Shock	6	10	**After Shock**	3	15
σ=1.5	25%		**σ=2.25**	75%	

Table 3. Illustrating the Leverage Risk Effect. The Percentage increase in sigma is greater for Firm 2, since it has a greater Level of initial Leverage.

	Firm 1			**Firm 2**	
	Equity	*Debt*		*Equity*	*Debt*
Before Shock	10	10	**Before Shock**	5	15
σ=1	10%		**σ=1.5**	30%	
After Shock	6	10	**After Shock**	3	15
σ=1.5	25%		**σ=3**	100%	

3.3 The Leverage Cycle

The original leverage cycle theory of Geanakoplos (2009), posits that highly leveraged buyers are willing to pay more than an unleveraged buyer in a market upturn. This class of buyers becomes forced to divest at a lower price than unlevered buyers in order to meet margin calls in a market downturn.[2] This aggravates "normal" business cycle volatility. Since data on buyer leverage cannot be found, although some attempts have been made to estimate, for example, hedge fund leverage (McGuire and Tsatsaronis 2008), the relation between leverage and volatility must be approached from a corporate finance perspective, although this thesis is not a corporate finance specific inquiry.

Below are presented three graphs that plot mean of volatility of returns, average leverage and yearly change in Swedish GDP over a 20 yr period. It seems that corporate leverage was built up during the dot-com boom and then underwent a continual drop even though the economy had already started growing strongly again in the mid 2000´s. It seems that the rapid increase in leverage in the second half of the last decade strongly correlated with the rapid drop in GDP and it could be argued that heavily levered companies took the brunt of stock market decline. If that were true, then it could explain the equally drastic reversal in leverage as the financial crisis took hold. The last section of the three graphs is very interesting, since a drop in GDP, a rise in leverage, and a forceful rise in volatility seem to go hand in hand. When the financial crisis had cemented itself, all the three variables move jointly downward. It seems

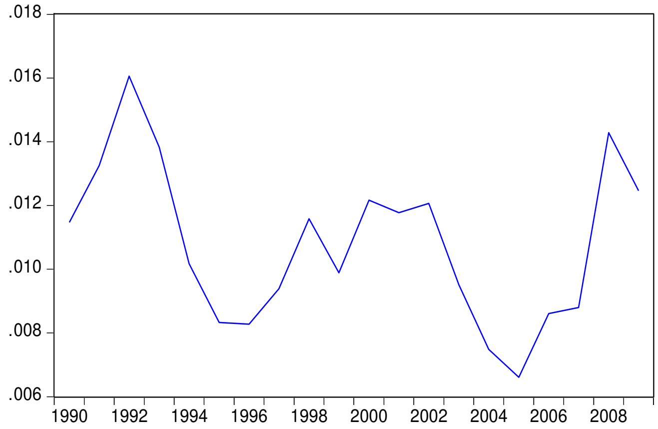
[2] A possible theoretical connection between the leverage cycle on the buy-side and corporate finance on the other side would have to be this: since a highly leveraged firm can generate a higher return on levered equity (what Asgharian (2003) calls the *pure leverage effect)* the buyers of this stock are less sensitive to its price. However, this seems counterintuitive and flies in the face of prevailing theory.

that initial negative shocks drive up volatility but that their effect ebbs out as market participants get used to a new environment of rapid price changes. Disregarding 1990 and 1991, leverage and volatility go hand in hand aside from the sharp drop in volatility in 1998 (perhaps because the market was almost wholly accustomed to a bullish sentiment when the Russian default and LTCM debacle materialized itself), which does not have an equivalent in the leverage graph. The crisis periods suggest that the relations are more complex than suggested by a simple order of causality between two or three variables.

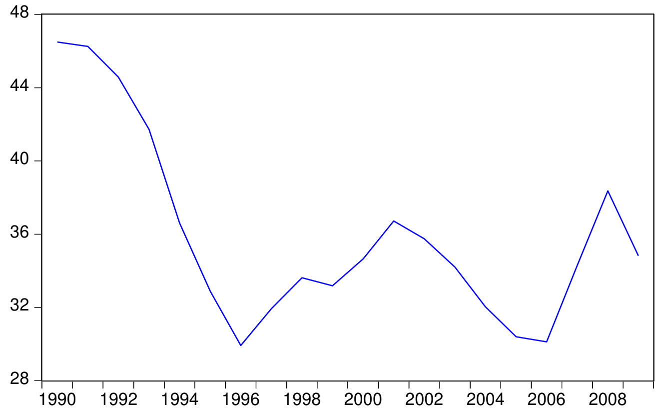
There are macroeconomic factors beyond the scope of this essay at play here as well. In a report on leverage and volatility from JP Morgan (Loeys and Panigirtzoglouin 2005), investor leverage is presented as the generally acknowledged evil force behind volatility. The dramatic buildup of investor leverage has been made possible in part by the unsustainably low interest rates (this was well-known during the recent economic boom of the mid to late 2000´s) which in part were possible because inflation did not materialize itself (to what extent this was related to enormous imports of cheap Chinese goods is another interesting question). The point is that the extrapolation from this period in history with low interest rates may be unusually unrepresentative.

Even when viewed from the perspective of corporate leverage, there seems to be some anecdotal evidence for the leverage cycle. The big departure from this theory in these graphs is the drastic fall in volatility 2002-2004, although it seems as if it returned with a vengeance 2006-2007, right before the bust.

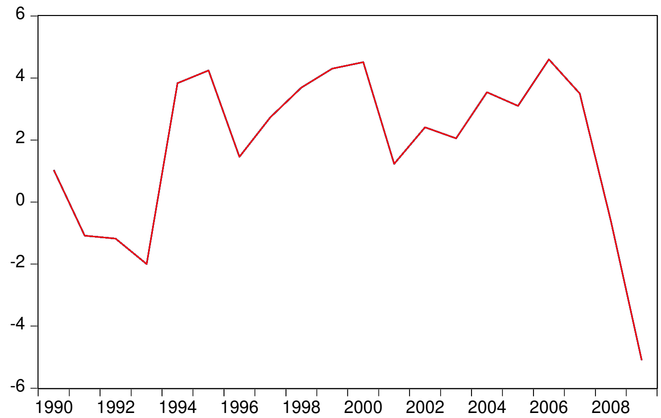
Graph 1. Mean volatility of sample returns 1990-2009



Graph 2. Average sample leverage 1990-2009



Graph 3. % Change in real GDP Sweden 1990-2009



3.4 Models of Changing Volatility

Two prominent features of return series are leptokurtosis (fatter tails than normal) and volatility clustering (the return series passes through periods of high and low volatility).

3.4.1 ARCH

As an introduction to the modeling of dynamics in the return data consider the Engle (1982, 2004) ARCH specification, where a standard AR (1) process

$$y_t = \mu + \rho y_{t-1} + u_t \tag{2}$$

is not posited to contain an error term that is white noise. Rather the error term is modeled with the following properties

$$u_t = \varepsilon_t \sqrt{h_t} \qquad \varepsilon_t \sim IID(0,1) \tag{3}$$

where h_t is generated according to

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 \tag{4}$$

for an ARCH (1) model. For an ARCH (2) model y_t is still generated by an AR (1) process but h_t is generated according to the following process

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 \tag{5}$$

In a generalized autoregressive conditional heteroskedastic, in this case a GARCH (1,1) framework, the following process generates h_t

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} \tag{6}$$

The GARCH framework can be extended to any number of lags of the squared residuals (labeled *q*) and conditional variances (denoted *p*). In the GARCH framework the inclusion of lagged conditional variances allows the model to "learn" the changing nature of a time series. If q and p are both zero, then the errors are white noise. This way of representing the error terms accurately models many financial time series. These models are estimated with maximum likelihood where a normal distribution of the errors is assumed as the basis for the log-likelihood function.

$$\varepsilon_t|\Omega_{t-1} \sim N(0,\sigma_t^2) \tag{7}$$

However, as a way of incorporating the excess kurtosis (kurtosis in excess of 3) present in many financial time series, a t-distribution may also be assumed for the error terms. This distribution has a greater mass in the extreme tail region (Dowd 2005).

$$\varepsilon_t|\Omega_{t-1} \sim t(0,\sigma_t^2,\text{d.f}) \tag{8}$$

3.4.2 Conditional and Unconditional Variance

Given what is known at time t, the forecast error for time t+1 is referred to as volatility (or conditional variance). For an ARCH (1) process this conditional variance can be written as follows

$$var(u_t|\Omega_{t-1}) = \alpha_0 + \alpha_1 u_{t-1}^2 \tag{9}$$

The conditional heteroskedasticity is of course dependent on t. Using the law of total variance the unconditional variance of u_t is (for an ARCH (1) process)

$$var[u_t] = \frac{\alpha_0}{1-\alpha_1} \tag{10}$$

A change in t does not impact the right-hand-side (RHS) of this expression. It is tempting to think that a series displaying heteroskedastic second moments must be non-stationary (by definition non-constant 1st, 2nd and 3rd moments). However, as long as the unconditional moments are stationary (i.e. independent of time), a series may display heteroskedastic conditional variance and still be stationary (Harris and Sollis 2003).

3.4.3 Asymmetric Models of Changing Volatility

There are several extensions of the general heteroskedastic modeling framework. These typically try to free themselves from the imposition of symmetry on the return series response to exogenous shocks. One is the asymmetric power ARCH (APARCH), that tries to capture the leverage effect (bad news has a greater effect on volatility than good news), while at the same time allowing for greater flexibility from a varying exponent. This is an often observed effect in high-frequency financial data.

If y_t is assumed to be generated by an AR (1) process, then the residuals from such a process are, in an APARCH (1,1,1) model, due to Ding et al. (1993), generated by

$$\varepsilon_t = \sigma_t e_t \tag{11}$$

where

$$\sigma_t^\delta = \eta + \alpha(|\varepsilon_{t-1}| - \gamma\varepsilon_{t-1})^\delta + \beta\sigma_{t-1}^\delta \tag{12}$$

When $\gamma > 0$, negative shocks cause a greater degree of volatility than positive shocks. When $\gamma < 0$, positive shocks cause greater volatility than negative ones.

Below is a summary of how this model differs from the standard ARCH & GARCH specifications given different values for the parameters.

$\gamma = 0 \; and \; \delta = 2$ yields a GARCH (1,1) model

$\beta = 0, \gamma = 0 \; and \; \delta = 2$ yields an ARCH (1,1) model.

In a second attempt to capture the asymmetric volatility relation, the exponential GARCH (EGARCH) model of Nelson (1991), is also tested on the return data. The variance equation of an EGARCH (1,1,1) may be specified as follows

$$\log(\sigma_t^2) = \omega + \beta\log(\sigma_{t-1}^2) + \alpha\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| \tag{13}$$

After the model is estimated, ARCH-LM (autoregressive conditional heteroskedasticity Lagrange multiplier due to Engle (1982)), tests were run to see if there were any remaining ARCH effects in the residuals. In this test, the squared residuals are regressed on a constant and their own lags

$$\hat{\varepsilon}_t^2 = \alpha + \alpha_1 \hat{\varepsilon}_{t-1}^2 + \alpha_q \hat{\varepsilon}_{t-q}^2 + v_t \tag{14}$$

If there are no ARCH effects the estimated coefficients should all be zero. Under the null hypothesis of no ARCH effects, sample size multiplied by R^2 follows a χ^2 distribution with q degrees of freedom.

4. Data

For the first part of the research effort, a panel data set was constructed consisting of various explanatory variables for the 45 of the AFGX (Affärsvärldens Generalindex) constituent firms for which 20 yr data is available. All data comes from the Datastream/Worldscope database except the Swedish 5 year Treasury note series which is from the Swedish central bank homepage.[3] The financial firms and utilities are not excluded from the sample in this exploratory approach, although exclusion is occasionally recommended in the literature (see e.g. Cai and Zhang, 2006). Financials display a particular corporate finance structure that may render them unsuitable and utilities are usually highly regulated.

The firms included in the study are the same throughout, so the panel is consistent. The panel is balanced, meaning it contains the same number of cross-sectional units at each point in time. It is possible, however, that certain firms have dropped out over the course of these two decades as a result of their high leverage raising the possibility, albeit remote, of a certain survivorship bias in the data. It seems likely, if they existed, that such highly leveraged and subsequently bankrupted companies displayed greater equity return volatility in the period leading up to their delisting. In table 4 and 5, the relevant descriptive statistics are presented for the chosen variables. GDP refers to the percentage change in real gross domestic product,

[3] http://www.riksbank.se/templates/stat.aspx?id=16740

L is leverage[4] and is defined as total debt as a percentage of total capital, MV is market value of equity. ER is expected return and RP is risk premium.

Table 4. Descriptive Statistics for the five explanatory Variables

	Mean	*Maximum*	*Minimum*	*Std. Dev.*	*Skewness*	*Kurtosis*	*Jarque-Bera*	*Prob.*
L	35.92770	97.46000	0.000000	22.86261	0.252713	2.370542	24.43773	0.000005
GDP	1.813000	4.600000	-5.100000	2.550953	-1.064304	3.450346	177.5169	0.000000
MV	19205.69	1433200.	0.550000	66563.44	12.58505	236.7843	2073324.	0.000000
ER	8.75E-05	0.003975	-0.005356	0.000852	-0.536194	6.582602	524.4393	0.000000
RP	-0.000149	0.003538	-0.005283	0.000735	-1.026689	7.393412	881.9411	0.000000

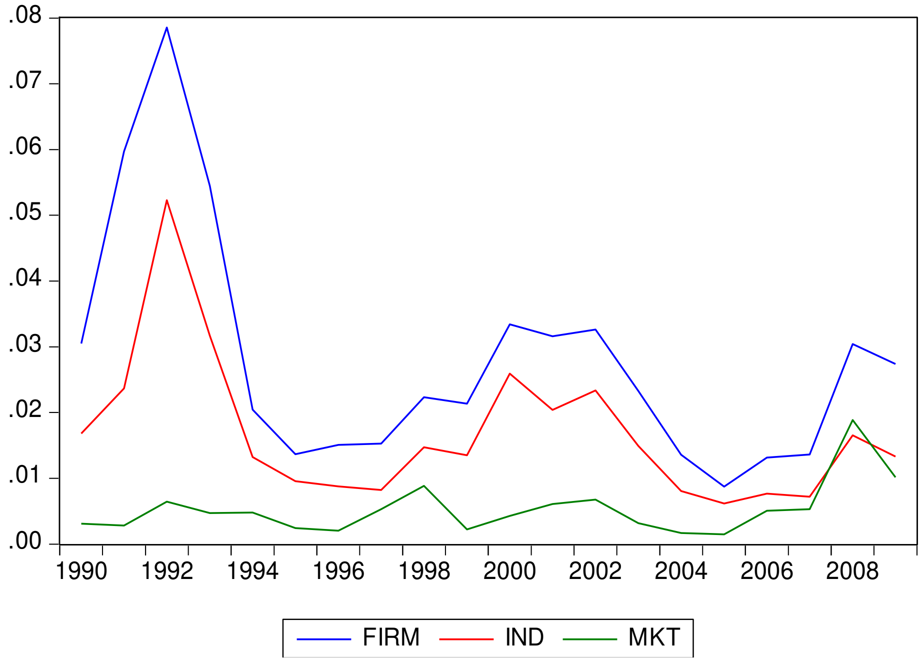
RVOL is the annual standard deviation of the daily returns. The three remaining volatility measures are defined more closely in the chapter devoted to methodology, but represent the variance of daily returns attributable to market, industry and firm specific factors. The second line of inquiry uses these volatility measures together with leverage and risk premium.

Table 5. Descriptive Statistics for the four volatility Measures

	Mean	*Maximum*	*Minimum*	*Std. Dev.*	*Skewness*	*Kurtosis*	*Jarque-Bera*	*Prob.*
RVOL	0.010802	0.055682	0.004218	0.004974	3.094111	21.03804	13637.43	0.000000
FIRM	0.027961	0.078550	0.008731	0.017381	1.488818	4.631107	432.2560	0.000000
IND	0.016806	0.052285	0.006164	0.010650	1.831677	6.588246	986.0878	0.000000
MKT	0.005282	0.018848	0.001491	0.003855	2.134288	8.017245	1627.256	0.000000

[4] Datastream Code: wc08221

Graph 4. FIRM, IND and MKT 1990-2009



The plots above show the evolution of these three volatility components over time. It is interesting how, during the recent financial crisis, market factors overtook industry-specific factors in importance for determining the total volatility. That this phenomenon is not documented in the literature could be due to the bias of only using US data. During this crisis diversification as a guiding investing principle took a heavy blow. This is not explained by the fact that the market volatility was a larger component of total volatility, which rose abruptly.

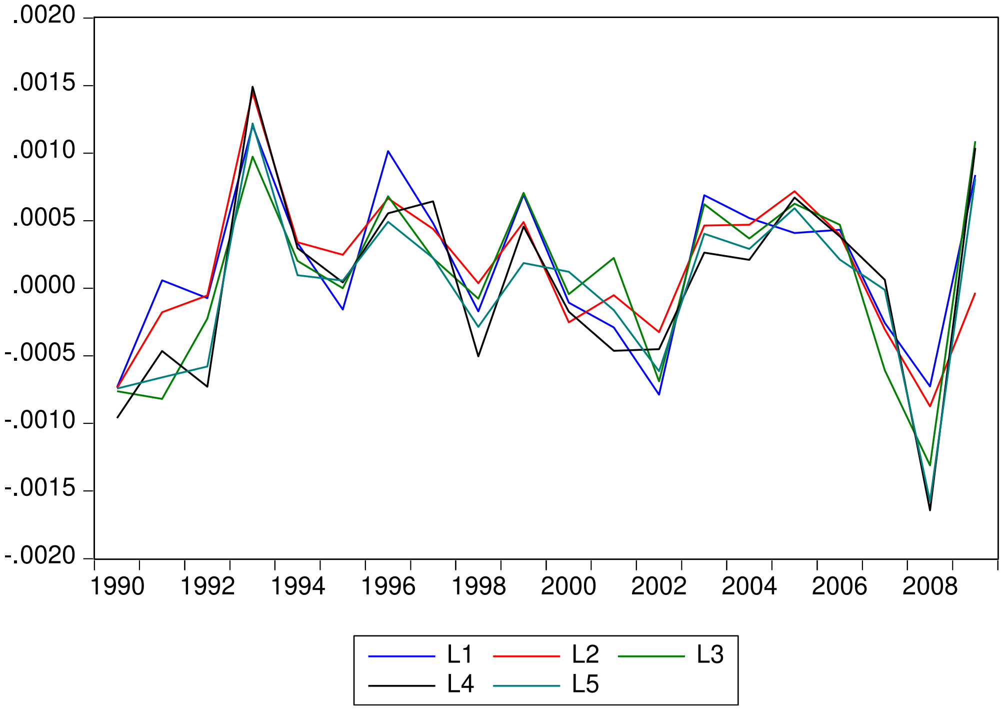
The extreme volatility of the early 90´s was heavily firm and industry specific. To a large extent, these two go hand in hand with MKT increasing firmly in 1998 and only really taking off in the last part of the graph. It is conceivable that the deepening integration of the financial sector over the last two decades has made MKT a larger share in this crisis than it otherwise would be.

Since leverage plays an important part in explaining equity volatility (see e.g. section 6.1 below) it is also of interest to investigate how leverage affects the properties of financial time series. The third line of inquiry required a dataset that somehow incorporated leverage and stock volatility but retained the large number of observations required of the return data to display the characteristics of interest. Following the portfolio approach of Choi and Richardson (2008), five leverage-sorted portfolios were held throughout the 20 years. These five portfolios were resorted for each year (interval of reported leverage) so as to always correspond to each leverage quintile of the forty-five firm dataset. Each portfolio therefore contains 9 firms but the composition of the portfolios is different for each of the twenty years. The individual equity return is the continuously compounded daily return according to

$$R_t = lnp_t - lnp_{t-1} \qquad (15)$$

where p is the closing price at time t. Since the return on any portfolio is equal to the weighted average of the return on the component securities, the return on each leverage quintile portfolio at any t represents an equal-weighted (for simplicity´s sake) average of the 9 constituent equity returns.[5] The plots of the return series for each leverage quintile portfolio can be found in appendix J. Table 6 presents their respective descriptive statistics.

Graph 5. Yearly mean of daily returns for each portfolio



[5] It was considered to create a zero-leverage equity return portfolio, but no clear way to construct such a portfolio was found. An assumption regarding the functional form of the relationship between leverage and return would have to be made. However, since it is this relation that is being explored it does not make sense to make such an assumption *a priori*.

One very discernable feature in graph 5 is how the least leveraged portfolio outperformed all others during the crisis periods that characterize the beginning and end of the sample period. Aside from the dot-com bust of the early 2000´s, the more leveraged portfolios generate a worse rate of return in a crisis than the less leveraged portfolios.

Table 6 shows that the higher leverage quintile portfolios yield a lower expected rate of return than the lower leverage quintile portfolios. If all companies were performing poorly, this result would conform to the second Modigliani-Miller proposition. It is beyond the scope of this essay to estimate firm performance, as in Asgharian (2003), and confirm or disconfirm the theory that leverage increases return on levered equity if the firm does well, and decreases it if the firm does poorly.

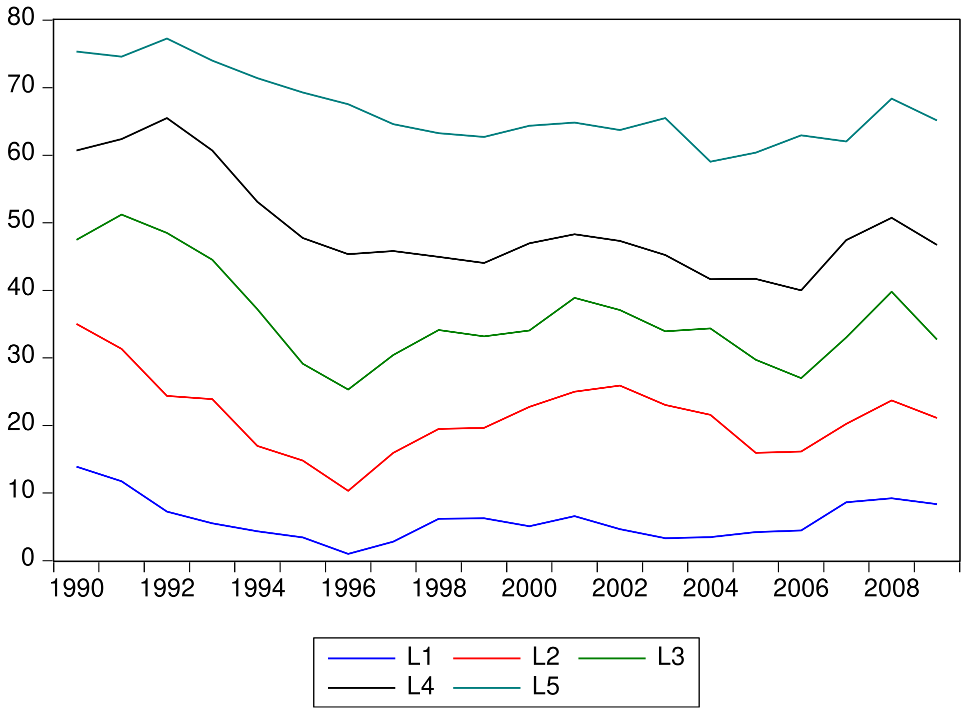
Table 6. Descriptive Statistics for the Return Series of Each of the five Leverage Quintile Portfolios

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.
L1	0.000169	0.043855	-0.039661	0.005489	-0.062918	8.520182	6628.653	0.000000
L2	0.000145	0.047493	-0.031117	0.005262	-0.148827	8.611086	6864.471	0.000000
L3	8.38E-05	0.039079	-0.069759	0.005925	-0.512067	12.85041	21324.11	0.000000
L4	3.62E-05	0.041704	-0.054315	0.005827	-0.262677	9.454686	9118.232	0.000000
L5	1.18E-06	0.077156	-0.043337	0.005520	0.291715	16.07763	37257.55	0.000000

In contrast to Choi and Richardsson (2008), the higher leverage quintile portfolios yield a lower expected rate of return. Kurtosis is higher for the higher leveraged portfolios but not uniformly so. The highest leverage quintile portfolio has by far the "fattest tail". The skewness changes from negative to positive with the increasing degree of leverage. Inspecting the standard deviation of the portfolios, it is not clear that the higher leverage portfolios display a greater standard deviation. The assumption of normality is rejected for all return series.

Graph 6 shows the evolution of the average leverage of each quintile portfolio over time.

Graph 6. Average Leverage for each Leverage Quintile Portfolio 1990-2009



The general picture that emerges from graph 6 is how L1 (the least leveraged portfolio) and L5 (the most leveraged portfolio) dampen the general pro-cyclical trend of increasing leverage in periods of high growth and decreasing leverage in periods of slow or negative growth. L2, L3, and L4 display this pattern much more clearly than L1 and L5. This suggests that the highest and lowest leverage portfolio consist of firms that maintain a relatively constant degree of leverage throughout the business cycle, thus diminishing the effect of leverage on volatility.

5. Methodology

5.1 Unit Roots

Two types of panel unit root tests were run on all variables. Both tests take the null hypothesis to be the presence of a unit root, i.e. non-stationarity. The first panel unit root test employed is the Levin and Lin (LL) test, which assumes a parameter persistence that is the same for all cross-sections. Secondly, the IPS (Im, Pesaran and Shin) test that drops assumption of homogeneity by estimating a separate ADF-regression and averages the relevant t-statistics, was run for all variables.

The null is rejected for all variables except MKT, but this exclusive quality only holds when lag length is user specified rather than determined automatically according to some information criterion. (For specific panel unit root test results, see appendix F)

When estimating the PVAR model, Ericsson et al. (2007) find evidence of leverage being a unit root process and therefore employs a quasi-maximum likelihood estimation due to Binder et al. (2005) that allows for unit roots. Regarding stationarity in VAR estimation, it is posited in Brooks (2008), that if the purpose is hypothesis testing, it is vital that all variables are stationary. However, inducing stationarity via differencing is argued by some researchers to waste useful information on long-run relationships (cf. Brooks 2008).

The only variable that is not stationary is MKT and one could estimate PVAR with first differences of *all* variables. However, it seems like a disproportionate loss of data to take first differences of all variables when only one may be non-stationary. I have therefore "sided" with the proponents of VAR in opting out of a VECM estimation setting.

5.2 Panel Regression

The panel data was modeled on the following equation:

$$\sigma_{it} = \alpha + \beta_1 Tr + \beta_2 gdp_t + \beta_3 l_{it} + \beta_4 mv_{it} + \beta_5 \sigma_{it-1} + \beta_6 \sigma_{it-2} + u_{it} \tag{16}$$

where *i* denotes cross section and *t* denotes the time period. Tr is trend, gdp refers to the percentage change in real GDP, l is leverage[6] and is defined as total debt as a percentage of total capital, $mv$is market value of equity. The dependent variable is the annual standard deviation of the daily returns as defined by equation 15.

When estimating the historical return volatility, closing prices form the basis for return calculations, as suggested by Hull (2009), and also employed by Sivaprasad and Muradoglu (2010). As in Christie (1982), lags of volatility are included to compensate for

[6] Datastream Code: wc08221

autocorrelation. Following Chen et al. (2010), real change in GDP is included as a "business-cycle variable" since it can reasonably be assumed that a change in GDP will affect volatility in the stock market. In Chen et al. (2010), market value is found to influence idiosyncratic volatility and is included as an explanatory variable, not because the inquiry is in the determinants of idiosyncratic equity return volatility as such, but because idiosyncratic equity return volatility is a part of total equity return volatility and it is the dynamics of volatility as it relates to leverage that is the focus of this study.

A second specification was run according to

$$\sigma_{it} = \alpha + \theta_1 E[r]_{it} + \theta_2 l_{it} + \theta_3 \pi_{it} + \theta_4 gdp_t + \theta_5 \sigma_{it-1} \qquad (17)$$

where $E[r]$ denotes expected return and π denotes risk premium.

A test was conducted to determine whether to employ a fixed or random effects model. In the fixed effects model the parameter β is computed by OLS since this estimator fulfills the standard requirements, but it is calculated given that the intercept is allowed to vary across the components groups of the panel (cf. Verbeek 2008). The null hypothesis of equal intercepts is tested. If this null is rejected the fixed effects estimator is used. The effects test shows clearly the presence of fixed effects (see appendix B) and that the chosen panel estimation method is correct. The fixed effects model controls for the heterogeneity of the included firms (Ericsson et al. 2007).

A time-fixed effects model is not used because the average value of σ is thought to vary cross-sectionally. Therefore a cross-sectional fixed effects model is used to estimate the above equations.

A regression of residuals on lagged residuals (see appendix C) and a Wald test (see appendix D) to confirm a parameter restriction both indicate remaining autocorrelation. These results hold for the second specification as well.

5.3 Vector Autoregression

Before proceeding, a simple Granger causality test was run to add some weight to the hypothesis that leverage should affect volatility.

This is essentially a bi-variate VAR model that simultaneously estimates the following equations:

$$\sigma_t = \alpha_0 + \alpha_1 \sigma_{t-1} + \alpha_1 l_{t-1} + \varepsilon_{1t} \tag{18}$$

$$l_t = \omega_0 + \beta_1 \sigma_{t-1} + \beta_2 l_{t-1} + \varepsilon_{2t} \tag{19}$$

where $\begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix} \sim IID \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_{11}^2 & \sigma_{12} \\ \sigma_{21} & \sigma_{22}^2 \end{bmatrix} \right)$

Table 7. Granger Causality Test Results

Null Hypothesis:	Obs	F-Statistic	Prob.
L does not Granger Cause RVOL	855	7.86954	0.0051
RVOL does not Granger Cause L		0.11782	0.7315

The first hypothesis can clearly be rejected and the expected direction of causality is reinforced.

In the VAR estimation it is necessary to make a collective assessment of the estimation results, the block exogeneity tests, impulse-response graphs and the variance decompositions. The ordering for the Cholesky decomposition has implications for the results, and so the variables are ordered in the same manner throughout. The standard errors are estimated via Monte Carlo simulation. A significant parameter does not necessarily imply causation but rather a chronological ordering. Formal inquiries into proper selection of VAR lag-length shows dynamics at work even in higher-order lags, but the PVAR estimation was consciously restricted to one lag in order to facilitate analysis. The lack of theoretical underpinning in understanding higher-order lag dynamics in the context of asymmetric volatility was also a factor in this decision.

5.4 Risk Measure

The next step is to extend this analysis of causality to include a measure of risk premium. The starting point for this analysis is the conditional capital asset pricing model. In the modeling environment of the conditional CAPM, the appropriate measure of individual firm risk is the covariance of the stock with the market. This allows the required returns to be written as

$$E_{t-1}[r_{i,t}] = \frac{E_{t-1}[r_{m,t}]}{Var_{t-1}[r_{m,t}]} Cov_{t-1}[r_{i,t} r_{m,t}] \qquad (20)$$

where r denotes excess return, i denotes *asset,* m denotes market, t denotes time and E is the expectation operator conditional on the available information set. In the article, Ericsson et al. (2007), the required returns are approximated by the actual returns, henceforth denoted by $\bar{r}_{i,t}$. This variable is best understood in the words of Ericsson et al. (2007:8) as "essentially an *ex post* [emphasis mine] measure of the required return based on the conditional CAPM." If the conditional CAPM had held at time t, then $\bar{r}_{i,t}$ is the return that asset i would have generated.

The authors note that the two important advantages of this risk measure are 1) it does not need to be estimated, but is based on actual data, and 2), more importantly, it can vary as result of a change in any of its three constituent variables.

5.5 Testing the Measure of Risk Premium

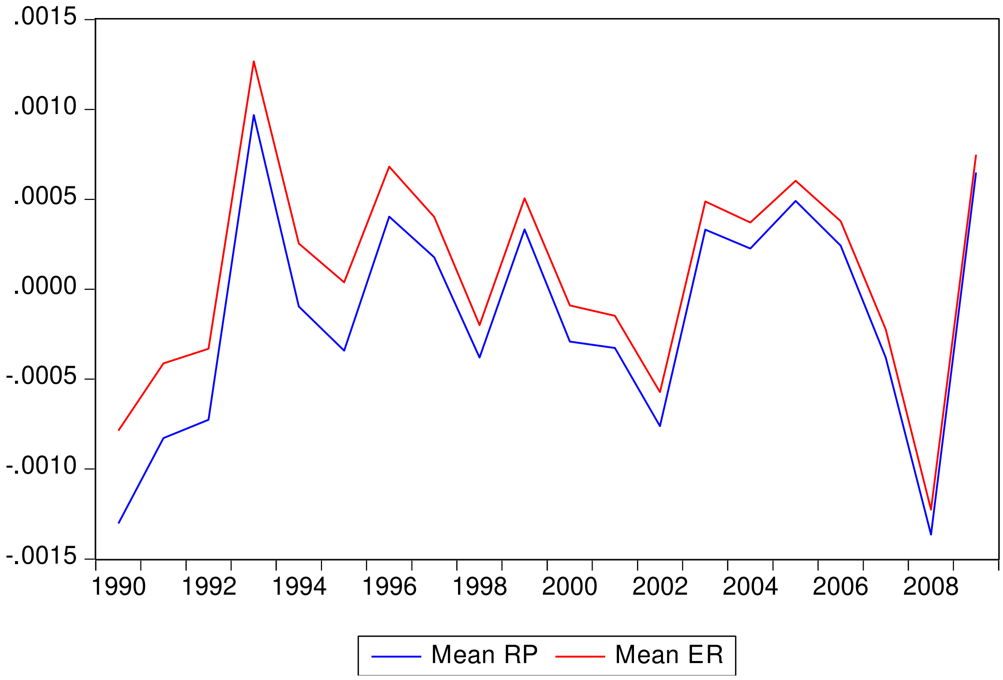
In order to test time-varying risk premia as an explanation of asymmetric volatility, the measure of risk premium that was developed above is needed. Here the suitability of that measure is tested. (See appendix E for specific estimation results).

Under the null that $\bar{r}_{i,t}$ is a suitable proxy for the risk premium, the intercept should be zero and the beta coefficient 1 when regressing the risk premium on the actual market returns for asset i

$$r_{i,t} = \alpha + \beta \bar{r}_{i,t} + \varepsilon_{i,t} \qquad (21)$$

The intercept is close to, but not zero, and the beta coefficient is less than 1 (0.75), which means that the risk premium measure may be an upwardly biased measure of the required returns.

Graph 7. Mean Risk Premium and Mean expected Returns 1990-2009.



Graph 7 plots mean risk premium and mean expected excess return over the sample period. They follow each other closely but are virtually identical from mid 2008 onward. Viewing each business cycle separately, the two lines lie closer on the way up than they do on the way down. Why excess expected return should more accurately represent risk premia (as implied by the conditional CAPM) in strong upturns is not clear. This conjoined movement has also fallen closer in sync over time to the point where they overlap.

5.6 Tri-variate Panel Vector Autoregression

This risk measure (here denoted by π) is now included in a tri-variate fixed effects PVAR (1) model on the sample data at hand.

$$l_{i,t} = \alpha_1 + \alpha_{11} l_{i,t-1} + \alpha_{12} \sigma_{i,t-1} + \alpha_{13} \pi_{i,t-1} + \varepsilon_{1i,t} \quad (22)$$

$$\sigma_{i,t} = \alpha_2 + \alpha_{21} l_{i,t-1} + \alpha_{22} \sigma_{i,t-1} + \alpha_{23} \pi_{i,t-1} + \varepsilon_{2i,t} \quad (23)$$

$$\pi_{i,t} = \alpha_3 + \alpha_{31} l_{i,t-1} + \alpha_{32} \sigma_{i,t-1} + \alpha_{33} \pi_{i,t-1} + \varepsilon_{3i,t} \quad (24)$$

This modeling methodology is then extended to include measures of volatility components. Why is this important? If leverage increases volatility, it has implications. First, it is of interest in a financial stability perspective whether this impact is limited to idiosyncratic volatility, or whether it also impacts the degree of volatility arising solely from industry and market factors.

This article follows Ericsson et al. (2007) in using a PVAR framework to evaluate the relative merits of the leverage hypothesis versus the volatility feedback hypothesis, but in a volatility decomposition framework proposed by Campbell et al. (2001), albeit not for this purpose. In Campbell et al. (2001), the total return volatility is decomposed into several parts and this volatility decomposition is employed in a PVAR framework to see if the two explanations for asymmetric volatility carry different validity for different parts of the total volatility.

Since the market portfolio of all assets is unobservable (Roll 1977), an index proxy is usually used that corresponds to some well-known stock index. I have used the equal weighted market return based on the assets in my sample as the basis on which to calculate excess market return.

5.7 Volatility Decomposition

Since the asymmetric volatility effect is present in many other time series not related to firm leverage, it is of interest to investigate whether the effect of leverage on volatility is constant across the three volatility measures.

In the volatility decomposition of Campbell et al. (2001), the volatility of the stock return is reduced to its three components without the need to estimate firm-specific betas or including co-variances of returns.[7] The errors-in-variables problem of beta estimation and subsequent use in regression is overcome. The initial step is to identify the CAPM as

$$R_{it} = \beta_{im} R_{mt} + \varepsilon_{it} \tag{25}$$

for industry returns, where R denotes excess return, i denotes industry, m denotes market and t denotes period t, and

$$R_{jit} = \beta_{ji} R_{it} + \eta_{it} \tag{26}$$

for firm returns where j denotes firm. Excess return is the return above the Swedish 5-year treasury notes. Dropping the industry beta from equation 25 and the stock beta from equation 26 yields

$$R_{it} = R_{mt} + \varepsilon_{it} \tag{27}$$

$$R_{jit} = R_{it} + \eta_{it} \tag{28}$$

MKT_t is the notation for the sample market return volatility in period t and is defined as

$$MKT_t = \hat{\sigma}_{mt}^2 = \sum_{s \in t} (R_{ms} - \mu_m)^2 \tag{29}$$

where μ is the mean of the market return in the sample, s refers to the return interval (daily) and t refers to interval of volatility construction (yearly). Throughout this essay an equal weighting approach is used and the market return is also calculated this way. Since the weighting across industries does not matter as long as the market return is weighted the same way, I have chosen an equal weighting scheme (for simplicity) for both the market and industry return series. This is possible since the decomposition methodology is valid for any weighting scheme.

[7] For the specific methodology, the reader is referred to Campbell et al. (2001:4-7).

Volatility in industry *i* during period t is calculated by summing the squared residuals from equation (27) according to

$$\hat{\sigma}_{\varepsilon it}^{2} = \sum_{s \in t} \varepsilon_{is}^{2} \tag{30}$$

In accordance with the Campbell methodology, the covariances are eliminated by averaging over industries which yields the final expression for average industry volatility

$$IND_t = \sum_{i} w_{it} \hat{\sigma}_{\varepsilon it}^{2} \tag{31}$$

In this measure an equal-weighted approach is also used. The industry classification is based on AFGX (Affärsvärldens Generalindex).

Firm level volatility is estimated by summing the residuals from equation (28) for each firm

$$\hat{\sigma}_{\eta jit}^{2} = \sum_{s \in t} \eta_{jis}^{2} \tag{32}$$

The second step involves averaging the firm-level volatility within an industry

$$\hat{\sigma}_{\eta it}^{2} = \sum_{j \in i} w_{jit} \hat{\sigma}_{\eta jit}^{2} \tag{33}$$

And finally averaging over industries to yield average idiosyncratic volatility, $FIRM_t$

$$FIRM_t = \sum_{i} w_{it} \hat{\sigma}_{\eta it}^{2} \tag{34}$$

Note that these variables are measures of variance, not standard deviation.

5.8 Tri-variate PVAR with Volatility Decomposition

The final step is extending the PVAR analysis to the various volatility components via the volatility decomposition of Campbell et al. (2001). Consequently, three new sets of PVAR equations, each containing three equations, are estimated.

For *FIRM*:

$$l_{i,t} = \alpha_1 + \alpha_{11} l_{i,t-1} + \alpha_{12} FIRM_{t-1} + \alpha_{13} \pi_{i,t-1} + \varepsilon_{1i,t} \quad (35)$$

$$FIRM_t = \alpha_2 + \alpha_{21} l_{i,t-1} + \alpha_{22} FIRM_{t-1} + \alpha_{23} \pi_{i,t-1} + \varepsilon_{2i,t} \quad (36)$$

$$\pi_{i,t} = \alpha_3 + \alpha_{31} l_{i,t-1} + \alpha_{32} FIRM_{t-1} + \alpha_{33} \pi_{i,t-1} + \varepsilon_{3i,t} \quad (37)$$

For *IND*:

$$l_{i,t} = \alpha_1 + \alpha_{11} l_{i,t-1} + \alpha_{12} IND_{t-1} + \alpha_{13} \pi_{i,t-1} + \varepsilon_{1i,t} \quad (38)$$

$$IND_t = \alpha_2 + \alpha_{21} l_{i,t-1} + \alpha_{22} IND_{t-1} + \alpha_{23} \pi_{i,t-1} + \varepsilon_{2i,t} \quad (39)$$

$$\pi_{i,t} = \alpha_3 + \alpha_{31} l_{i,t-1} + \alpha_{32} IND_{t-1} + \alpha_{33} \pi_{i,t-1} + \varepsilon_{3i,t} \quad (40)$$

For *MKT*:

$$l_{i,t} = \alpha_1 + \alpha_{11} l_{i,t-1} + \alpha_{12} MKT_{t-1} + \alpha_{13} \pi_{i,t-1} + \varepsilon_{1i,t} \quad (41)$$

$$MKT_t = \alpha_2 + \alpha_{21} l_{i,t-1} + \alpha_{22} MKT_{t-1} + \alpha_{23} \pi_{i,t-1} + \varepsilon_{2i,t} \quad (42)$$

$$\pi_{i,t} = \alpha_3 + \alpha_{31} l_{i,t-1} + \alpha_{32} MKT_{t-1} + \alpha_{33} \pi_{i,t-1} + \varepsilon_{3i,t} \quad (43)$$

6. Analysis

In this section the results from the three main sections (fixed effects estimation, PVAR, and portfolio) are presented and discussed.

6.1 Panel Regression Results

The relevant estimation results from the fixed effects estimation of equation 16 and 17 are presented in table 8 and table 9. A negative correlation between GDP and volatility exists, which is in line with Officer (1973), who finds market volatility is higher in economic downturns. The reported intercept is the average value of α_i. All variables are very significant in explaining volatility. Leverage and negative change in GDP are found to increase volatility. The greater degree of leverage the greater the risk and subsequent volatility whereas growth in GDP decreases uncertainty and reduces volatility.

Table 8. Results from fixed Effects Estimation of Equation 16

	Coefficient	**Std. Error**	**t-Statistic**	**P-Value**
Variable				
C	0.006990	0.000601	11.62206	0.0000
TREND	-6.82E-05	2.48E-05	-2.751640	0.0061
GDP	-0.000302	5.07E-05	-5.957239	0.0000
L	3.00E-05	8.57E-06	3.497103	0.0005
MV	6.52E-09	2.46E-09	2.652443	0.0082
RVOL(-1)	0.509303	0.034688	14.68230	0.0000
RVOL(-2)	-0.156918	0.033870	-4.632887	0.0000
Adj. R-squared	0.492521			

Oddly, market value is also positively correlated with volatility but this parameter is very small. The adj. R^2 of 49.2 % must be considered high.

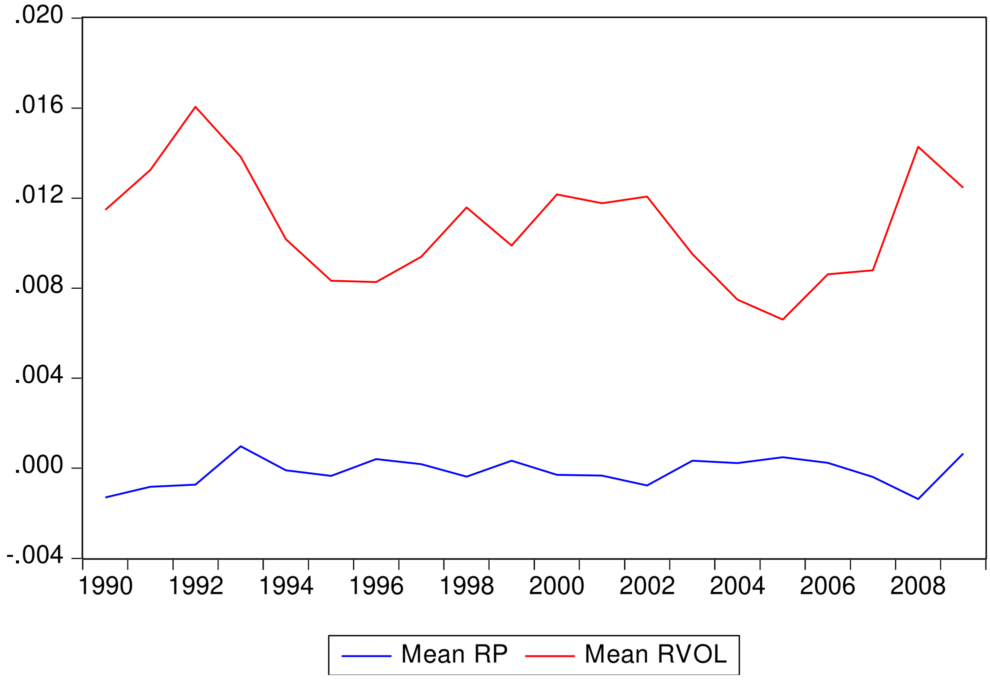
Table 9. Results from fixed Effects Estimation of Equation 17

	Coefficient	Std. Error	t-Statistic	P-Value
Variable				
C	0.005343	0.000415	12.87203	0.0000
ER	-0.873898	0.177243	-4.930518	0.0000
L	2.10E-05	8.03E-06	2.614858	0.0091
RP	-1.707193	0.220606	-7.738643	0.0000
GDP	-0.000352	4.57E-05	-7.700565	0.0000
RVOL(-1)	0.494585	0.027857	17.75416	0.0000
Adj. R-squared	0.575032			

In the second specification (table 9), a higher R^2 is obtained and all coefficients are significant at 99%. Nearly all have the sign that one would expect. An increase in expected return should lower volatility and an increase in GDP should also lower volatility. As in the previous specification, leverage is found to increase volatility.

However, risk premium (RP) should have the opposite sign. A rise in risk premium should be associated with higher volatility. This holds against the hypothesis of time-varying risk premia, for investors are not compensated (with a premium) for the extra volatility. Graph 8 shows the development of these two variables over time and it seems they move in opposite directions. A clear inverse relation is especially present during periods of financial turmoil.

Graph 8. Mean Risk Premium and Mean Return Volatility 1990-2009



6.2 PVAR Parameter Results

After estimating this VAR (eq. 18 and 19), a formal test of lead-lag relationships is undertaken, and it is evident that at the 1% level only interactions from leverage and risk premium to return volatility exist.

The α_{12} coefficient corresponds to the volatility feedback hypothesis and it only significant at 99% for the PVAR equation with FIRM as the volatility variable. It is a positive coefficient which is in agreement with the volatility feedback hypothesis. For three out of the four sets of equations (eq. 22-24, 35-37, 38-40 and 41-43) this coefficient is either of the wrong sign or insignificant, lending support to the idea that this hypothesis perhaps has some bearing on idiosyncratic volatility, but not much more. Inspecting the impulse-response functions (see appendix H) for the PVAR equation with FIRM as volatility variable, it is clear that this effect is not constant but rather shifts to a negative one during the fourth lag after the shock to FIRM.

α_{21}corresponds to the leverage hypothesis. It says that leverage causes volatility. This coefficient is positive and 99% significant for three of the five PVAR equations. It loses significance in explaining IND and FIRM which suggests that leverage is a greater factor in explaining market volatility as well as asymmetric volatility. For all impulse response functions, the effect of leverage on volatility is positive for all future periods except MKT, where the effect reverses during the third period. It is also interesting to note that on RVOL a shock to leverage takes a long time to die out. This is the first arrow in fig. 2 which together with fig. 1 is the present author's generalized presentation of the main theories of asymmetric volatility.

α_{31} captures the relation between risk premia (required returns) and leverage. This coefficient is negative for all equations which means that an increase in leverage is followed by a decrease in required returns. This is inconsistent with the volatility feedback hypothesis. This coefficient is significant at 99% or 95% for all equations. On the impulse-response functions the effect can be seen to die out quickly. This corresponds to the second arrow in fig. 1.

α_{32} is positive for all equations but insignificant only for FIRM which indicates that industry and market specific volatility affect risk premia. This corresponds to the first arrow in the first figure (fig. 1). Intuitively, this does not make sense. There is no conceivable reason why FIRM volatility should not influence risk premia.

α_{23} should be positive and significant for the leverage hypothesis to hold because a drop in price (negative news) should mean a greater risk premium which causes volatility, i.e. leverage and risk premia should jointly contribute to volatility. However, this coefficient is negative for all equations with varying degrees of significance.

Inspecting the variance decomposition graphs (see appendix I), two things stand out. A general feature is the small degree of variation in one variable that can be attributed to variation in the other. The other notable feature is the degree to which variation in risk premia can be attributed to MKT, IND and FIRM respectively. Since the variable α_{32} is only significant for IND and MKT it seems reasonable to conclude that MKT and IND play an important role in determining risk premia. However, as shown above, the statistics do not support the second part required for the hypothesis to hold.

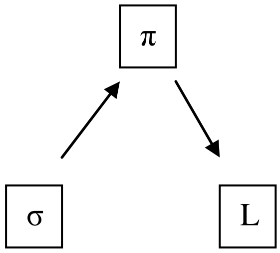


Fig. 1 Volatility Feedback. The figure shows volatility, risk premium and leverage respectively.

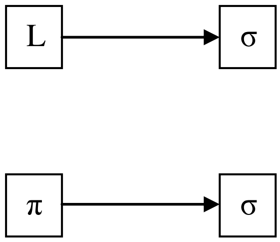


Fig.2 Leverage Hypothesis. The figure shows leverage to volatility, and risk premium to volatility, respectively.

6.3 Portfolio Results

The leverage quintile portfolios were estimated with GARCH (1,1) and APARCH (1,1,1) models, because the idea that this specification correctly models many financial time series is documented in the literature (cf. e.g. Brooks 2008:394). They are estimated with Bollerslev-Wooldridge standard errors.

Here the focus is on whether the theoretical arguments put forth in the theory section, namely that volatility, asymmetries and expected returns should increase with leverage, hold for leverage-sorted portfolios. Since it is the inter-portfolio comparisons that are of interest, the results for each conditional volatility model are allotted a separate table. In table 10 and 11, the estimation results garnered from running conventional models of changing volatility on the five portfolios are presented.

Table 10. GARCH (1,1) Estimation Results for each Leverage Quintile Portfolio

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5
Mean Eq.					
C	0.000353	0.000332	0.000262	0.000217	0.000134
	(5.88E-05)	(5.86E-05)	(6.90E-05)	(6.37E-05)	(6.65E-05)
AR(1)	0.059641	0.044095	0.071785	0.069540	0.044690
	(0.015714)	(0.015680)	(0.015913)	(0.015263)	(0.016894)
Variance Eq.					
ω	5.76E-07	4.13E-07	8.36E-07	8.28E-07	2.74E-07
	(9.76E-08)	(8.10E-08)	(1.79E-07)	(1.38E-07)	(1.25E-07)
α	0.095122	0.081742	0.093137	0.116069	0.056446
	(0.011382)	(0.009486)	(0.014970)	(0.014590)	(0.008966)
β	0.886939	0.904022	0.885600	0.861974	0.936678
	(0.010755)	(0.008550)	(0.016314)	(0.015074)	(0.009905)
α+β	0.982061	0.985764	0.978737	0.978043	0.993124

Table 11. APARCH (1,1,1) Estimation Results for the Return Series of each Leverage Quintile Portfolio

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5
Mean Eq.					
C	0.000280	0.000243	0.000175	0.000148	8.01E-05
	(6.55E-05)	(6.17E-05)	(6.84E-05)	(6.70E-05)	(6.57E-05)
AR(1)	0.064766	0.046615	0.075554	0.067768	0.042809
	(0.014552)	(0.015246)	(0.015892)	(0.015039)	(0.013354)
Variance Eq.					
ω	1.53E-05	4.89E-06	3.80E-05	3.18E-05	1.22E-06
	(9.55E-06)	(6.35E-06)	(3.90E-05)	(3.19E-05)	(4.55E-07)
α	0.101040	0.072751	0.084875	0.104105	0.048786
	(0.005552)	(0.010074)	(0.012255)	(0.012302)	(0.002801)
γ	0.251161	0.313563	0.458158	0.233423	0.210110
	(0.028892)	(0.083697)	(0.133136)	(0.072228)	(0.028559)
δ	1.429748	1.556948	1.249484	1.280671	1.690536
	(0.111621)	(0.236201)	(0.188998)	(0.190549)	(0.074029)
β	0.888122	0.916255	0.908470	0.892654	0.948855
	(0.006048)	(0.009927)	(0.015269)	(0.013812)	(0.002272)

In Cai and Zhang (2006), and Asgharian (2003), a negative relationship between leverage and stock return is found and this is in line with the portfolio results where the return is lower for each higher leverage quintile portfolio.

The persistence of volatility is high for all portfolios but it is the highest for the fifth portfolio. In fact, it could be categorized as a portfolio with a unit autoregressive root. The beta parameter is the highest for this fifth portfolio.

For the APARCH estimation, the asymmetric parameter increases from portfolio 1 (least leveraged portfolio) to portfolio 3, but then decreases again for portfolio 4 and portfolio 5 (most leveraged).

Inspecting the conditional standard deviation graphs (appendix L and appendix K), it is remarkable how much less volatile the highest leverage portfolio is. Compare the L5 APARCH graph with any of the others, and notice how much less volatility is present in the middle of the sample period. If this were an effect of the focus on technology stocks in the late 90´s, and the L5 portfolio being unrepresentative in its concentration of financials, then L5 should manifest a greater volatility in the early 90´s as the Swedish banking crisis unfolded. When viewing the GARCH graphs for the first years of the sample period, that does not appear to hold. In fact, what is happening is that when the asymmetric component is included, the conditional volatility of the highest leverage quintile portfolio falls drastically.

This suggests two things. One is that special dynamics are at work during crises. The second is that the theoretical concept of leverage aggravating asymmetric volatility seems to be finding support in these graphs. Perhaps this later relation is more pronounced during a financial crisis.

EGARCH estimation yields similar results. For all models the ARCH-LM test implies remaining ARCH effects.

7. Conclusion

This paper has investigated the relation between leverage and volatility in a panel data and portfolio setting and evaluated the relative importance of the two main theoretical explanations of asymmetric volatility.

Several results emerge. The fixed effects estimation shows leverage to have a strong and significant influence on equity return volatility. This section shows that additional research on volatility should focus on leverage and not risk-premia.

From the PVAR estimation it is clear that leverage contributes to return volatility. However, asymmetric volatility cannot be explained by one of the two proposed explanations alone. Rather, some combination of the leverage hypothesis and volatility feedback hypothesis are at work. There is some evidence that leverage influences market-specific volatility. This is important, because it goes to the heart of the matter, i.e. how the swings in leverage endanger overall stability. If leverage only affected the firm specific volatility, that could be a factor in the pricing. However, if leverage is something that increases MKT volatility, how should that be dealt with from a stability perspective?

From the portfolio analysis it seems that leverage is important for several reasons. The expected return is lower for each higher leveraged quintile portfolio and the persistence in volatility is high for all portfolios but highest for L5. There is some evidence of a positive relation between leverage and asymmetric volatility, but it is difficult to know how much of it to ascribe to leverage. In the portfolio estimation, asymmetries increase with each portfolio but then taper off for the higher leverage quintile portfolios. The pro-cyclical evolution of leverage, a la the leverage cycle, is more apparent when L1 and L5 are excluded.

Some additional results also emerge. Consider e.g. graph 7, where risk premia and expected return are represented. None of the three empirical divergences form the CAPM can help explain why expected excess return and risk premia should fall closer in line over time, nor why they should follow each other more closely in upturns.

There are some points to note regarding the divergence in results from other studies. The average leverage is smaller in this dataset than in Choi and Richardsson (2008), and a further analysis would remove the first and last quintile portfolio in the dataset, and repeat the analysis. A second point would be to investigate if the results would differ depending on weighting. If the leverage dispersion between the portfolios had been greater, perhaps a general trend of pro-cyclical change in leverage would have emerged clearer. Since this dataset contains two periods of financial crises, the intra-variable dynamics are especially interesting. It is the author´s belief that leverage increases asymmetric volatility, but especially so in a crisis. However, this will have to be left for future research.

It is possible that the coefficient of asymmetric volatility will increase in the future, similar to how the implied volatility in options pricing has become less dependent on the underlying strike price after the 1987 stock market crash. Since the markets have recently emerged from a crash of historical proportions, a new appreciation for how low stock prices can go should mean that future declines should increase volatility even more.

8. References

Adrian, Tobias, and Hyun S. Shin, 2008, "Liquidity and leverage," *Technical Report 328*, New York: Federal Reserve Bank of New York.

Alloway, Tracy, 2009, "Leverage ratios are the new VaR?," *Financial Times Alphaville*, Sep.11. http://ftalphaville.ft.com/blog/2009/09/11/71381/leverage-ratios-are-the-new-var/

Asgharian, Hossein, 2003, "Are highly leveraged firms more sensitive to an economic downturn?," *The European Journal of Finance* 9 (3), 219-241.

Asgharian, Hossein and Björn Hansson, 2000, "Cross-sectional analysis of Swedish stock returns with time-varying beta: the Swedish stock market 1983-96," *European Financial Management* 6 (2), 213-233.

Baekert, Geert, and Guojun Wu, 2000, "Asymmetric volatility and risk in equity markets," *The Review of Financial Studies* 13 (1), 1-42.

Berk, Jonathan, and Peter DeMarzo, 2008, *Corporate Finance*, Boston: Pearson Education.

Binder, Michael, Cheng Hsiao, and Hashem M. Pesaran, 2005, "Estimation And Inference In Short Panel Vector Autoregressions With Unit Roots And Cointegration," *Econometric Theory* 21 (04), 795-837.

Black, Fischer, 1976, "Studies of stock price volatility changes," *Proceedings of the 1976 Meetings of the Business and Economic Statistics Section*," pp. 177-181, Alexandria, VA.: American Statistical Association.

Bollerslev, Tim, 1986, "Generalized autoregressive conditional heteroskedasticity," *Journal of Econometrics* 31 (3), 307-327.

Brooks, Chris, 2008, *Introductory econometrics for finance*, Cambridge: Cambridge University Press.

Cai, Jie and Zhe Zhang, 2006, "Capital structure dynamics and stock returns." http://papers.ssrn.com/sol3/papers.cfm?abstract_id=685462

Campbell, John, Andrew W. Lo, and A. Craig MacKinlay, 1997, *The econometrics of financial markets*, Princeton: Princeton University Press.

Campbell, John Y., Martin Lettau, Burton G. Malkiel, and Yexiao Xu, 2001, “Have individual stocks become more volatile?,” *The Journal of Finance* 56 (1), 1-43.

Carhart, Mark M., 1997, “On persistence in mutual fund performance,” *The Journal of Finance* 52 (1), 57-82.

Chen, Changling, Alan Guoming Huang, and Ranjini Jha, 2010, “Trends in earnings volatility, earnings quality and idiosyncratic return volatility: managerial opportunism or economic activity.” http://ssrn.com/abstract=1108641

Choi, Jaewon, and Matthew Richardson, 2008, “The volatility of the firm’s assets.” http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1359368##

Christie, Andrew, 1982, “The stochastic behaviour of common stock variances: Value, leverage and interest rate effects,” *Journal of Financial Economics* 10 (4), 407-432.

Ding, Zhuanxin, Clive Granger, and Robert F. Engle, 1993, “A long memory property of stock returns and a new model,” *Journal of Empirical Finance* 1 (1), 83-106.

Dowd, Kevin, 2005, *Measuring market risk*, 2nd Edition, New York: John Wiley and Sons.

Engle, Robert F., 1982, “Autoregressive conditional heteroskedasticity with estimates of variance of United Kingdom inflation," *Econometrica* 50 (4), 987-1008.

Engle, Robert F., 2004, “Risk and volatility: Econometric models and financial practice” (Nobel Lecture), *The American Economic Review* 94 (3), 405-420.

Ericsson, Jan, Xiao Huang, and Stefano Mazzotta, 2007, ” Leverage and asymmetric volatility: the firm level evidence.” http://papers.ssrn.com/sol3/papers.cfm?abstract_id=964447

Fama, Eugene F., and Kenneth R. French, 1992, “The cross-section of expected stock returns,” *The Journal of Finance* 47 (2), 427-465.

Figlewski, Stephen, and Xiaozu Wang, 2000, “Is the ‘leverage effect’ a leverage effect?,” *NYU Working Paper No. S-CDM-00-09.* http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1295834

French, Kenneth R., William G. Schwert, and Robert F. Stambaugh, 1987, “Expected stock return and volatility,” *Journal of Financial Economics* 19 (1), 3-29.

Geanakoplos, John, 2009, “The leverage cycle,” *Cowles Foundation Discussion Paper No. 1715*. http://cowles.econ.yale.edu/P/cd/d17a/d1715.pdf

Hamada, Robert S., 1972, “The effect of the firm´s capital structure on the systematic risk of common stocks,” *The Journal of Finance* 27 (2), 435-452.

Harris, Richard, and Robert Sollis, 2003, *Applied time series modelling and forecasting*, New York: John Wiley and Sons.

Hull, John, C., 2009, *Options, futures and other derivatives*, Upper Saddle River, NJ: Pearson, Prentice Hall.

Krugman, Paul, “How did economists get it so wrong?,” *International Herald Tribune*, Sep. 2, 2009.

Loeys, Jan, and Nikolaus Panigirtzoglou, 2005, “Volatility, leverage and returns,” Research Brief, Oct. 19, *Global Market Strategy*, J.P. Morgan Securities Ltd., London.

McGuire, Patrick, and Kostas Tsatsaronis, 2008, “Estimating hedge fund leverage,” *BIS Working Papers No. 260*, Basel: Monetary and Economic Department, Bank of International Settlements.

Modigliani, Franco, and Merton H. Miller, 1958, “The cost of capital, corporation finance, and the theory of investment,” *American Investment Review* 48 (3), 261-297.

Murphy, Megan, and Patrick Jenkins, 2010, “The Basel Meetings: Key Changes,” *Financial Times*, July 28, p.3.

Nelson, Daniel B., 1991, “Conditional heteroskedasticity in asset returns: A new approach,” *Econometrica* 59 (2), 347-370.

Officer, Robert R., 1973, “The variability of the market factor of the New York Stock Exchange,” *Journal of Business* 46 (3), 434-453.

Roll, Richard, 1977, “A critique of the asset pricing theory's tests. Part I: On past and potential testability of the theory,” *Journal of Financial Economics* 4 (2), 129–176.

Rubinstein, Mark E., 1973, “A mean-variance synthesis of corporate financial theory,” *The Journal of Finance* 28 (1), 167-181.

Schwert, G. William, 1989, “Why does stock market volatility change over time?,” *The Journal of Finance* 44 (5), 1115-1153.

Sivaprasad, Sheeja, and Yaz Gulnur Muradoglu, 2010, “Using leverage as a risk factor in explaining the cross section of stock returns.” http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1101504

Thurner, Stefan, J. Doyne Farmer, and John Geanakoplos, 2010, “Leverage causes fat tails and clustered volatility.” http://cowles.econ.yale.edu/P/cd/d17a/d1745.pdf

Verbeek, Marno, 2008, *A guide to modern econometrics*, 3rd Edition, New York: John Wiley and Sons.

9. APPENDIX

App. A List of Firms in Sample

ACTIVE BIOTECH	IBS 'B'
AF 'B'	INDUSTRIVARDEN 'A'
ATLAS COPCO 'A'	INVESTOR 'B'
B&B TOOLS 'B'	JM
BEIJER ALMA 'B'	LATOUR INVESTMENT 'B'
BERGS TIMBER 'B'	MIDWAY HOLDINGS 'B'
BILIA 'A'	NCC 'A'
BONG LJUNGDAHL	OEM INTERNATIONAL 'B'
BORAS WAFVERI 'B'	ORESUND INVESTMENT
BRIO 'B'	PEAB 'B'
CONCORDIA MARITIME 'B'	RATOS 'B'
ELANDERS 'B'	SANDVIK
ELECTROLUX 'B'	SCA 'B'
ELEKTRONIKGRUPPEN BK 'B'	SEB 'A'
ELOS 'B'	SECO TOOLS 'B'
ENEA	SKANSKA 'B'
ERICSSON 'B'	SKF 'B'
FENIX OUTDOOR	SSAB 'A'
G & L BEIJER	TRELLEBORG 'B'
HENNES & MAURITZ 'B'	VBG GROUP
HALDEX	VOLVO 'B'
HOLMEN 'B'	XANO INDUSTRI 'B'
HUFVUDSTADEN 'A'	

App. B Test for Presence of Fixed Effects

Redundant Fixed Effects Tests			
Equation: EQ01			
Test cross-section fixed effects			
Effects Test	Statistic	d.f.	Prob.
Cross-section F	2.229919	-44,759	0.0000
Cross-section Chi-square	98.473314	44	0.0000

App. C Regression of Residuals on Lagged Residuals

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESID07(-1)	-0.089110	0.032318	-2.757280	0.0060

App. D Wald Test

Wald Test:			
Equation: Untitled			
Test Statistic	Value	df	Probability
t-statistic	12.71389	764	0.0000
F-statistic	161.6429	(1, 764)	0.0000
Chi-square	161.6429	1	0.0000
Null Hypothesis: C(1)=-0.5			
Null Hypothesis Summary:			
Normalized Restriction (= 0)	Value	Std. Err.	
0.5 + C(1)		0.410890	0.032318

App. E Estimation of Expected Return on Risk Premium

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000200	2.23E-05	8.989201	0.0000
RP	0.759551	0.030068	25.26086	0.0000
Adj. R-squared	0.408336			

App. F Unit Root Test Results

GDP	Statistic	Prob.**
Levin, Lin & Chu t*	-10.2990	0.0000
Im, Pesaran and Shin W-stat	-3.64956	0.0001
FIRM		
Levin, Lin & Chu t*	-15.2862	0.0000
Im, Pesaran and Shin W-stat	-16.7650	0.0000
L		
Levin, Lin & Chu t*	-2.06868	0.0193
Im, Pesaran and Shin W-stat	-2.33451	0.0098
ER		
Levin, Lin & Chu t*	-12.4357	0.0000
Im, Pesaran and Shin W-stat	-14.0868	0.0000
MKT		
Levin, Lin & Chu t*	5.93201	1.0000
Im, Pesaran and Shin W-stat	1.31798	0.9062
MV		
Levin, Lin & Chu t*	-3.19934	0.0007
Im, Pesaran and Shin W-stat	-3.17314	0.0008
RP		
Levin, Lin & Chu t*	-11.0929	0.0000
Im, Pesaran and Shin W-stat	-11.1149	0.0000
RVOL		
Levin, Lin & Chu t*	-3.72200	0.0001
Im, Pesaran and Shin W-stat	-6.37301	0.0000
IND		
Levin, Lin & Chu t*	-9.11091	0.0000
Im, Pesaran and Shin W-stat	-6.77788	0.0000

App. G Block Exogeneity Tests

Dependent variable: L			
Excluded	Chi-sq	df	Prob.
RVOL	9.843031	2	0.0073
All	9.843031	2	0.0073
Dependent variable: RVOL			
Excluded	Chi-sq	df	Prob.
L	18.91366	2	0.0001
All	18.91366	2	0.0001

Dependent variable: L			
Excluded	Chi-sq	df	Prob.
RVOL	8.416564	2	0.0149
RP	6.113355	2	0.0470
All	16.00668	4	0.0030
Dependent variable: RVOL			
Excluded	Chi-sq	df	Prob.
L	16.88181	2	0.0002
RP	16.29026	2	0.0003
All	35.53967	4	0.0000
Dependent variable: RP			
Excluded	Chi-sq	df	Prob.
L	8.347313	2	0.0154
RVOL	5.221716	2	0.0735
All	12.79562	4	0.0123
Dependent variable: L			
Excluded	Chi-sq	df	Prob.
MKT	5.045242	2	0.0802
RP	5.844814	2	0.0538

All	12.60382	4	0.0134

Dependent variable: MKT

Excluded	Chi-sq	df	Prob.
L	17.03244	2	0.0002
RP	2.746561	2	0.2533
All	20.21123	4	0.0005

Dependent variable: RP

Excluded	Chi-sq	df	Prob.
L	12.20215	2	0.0022
MKT	51.48910	2	0.0000
All	59.49658	4	0.0000

Dependent variable: L

Excluded	Chi-sq	df	Prob.
IND	16.77499	2	0.0002
RP	5.882801	2	0.0528
All	24.44329	4	0.0001

Dependent variable: IND

Excluded	Chi-sq	df	Prob.
L	3.668474	2	0.1597
RP	132.0333	2	0.0000
All	140.0589	4	0.0000

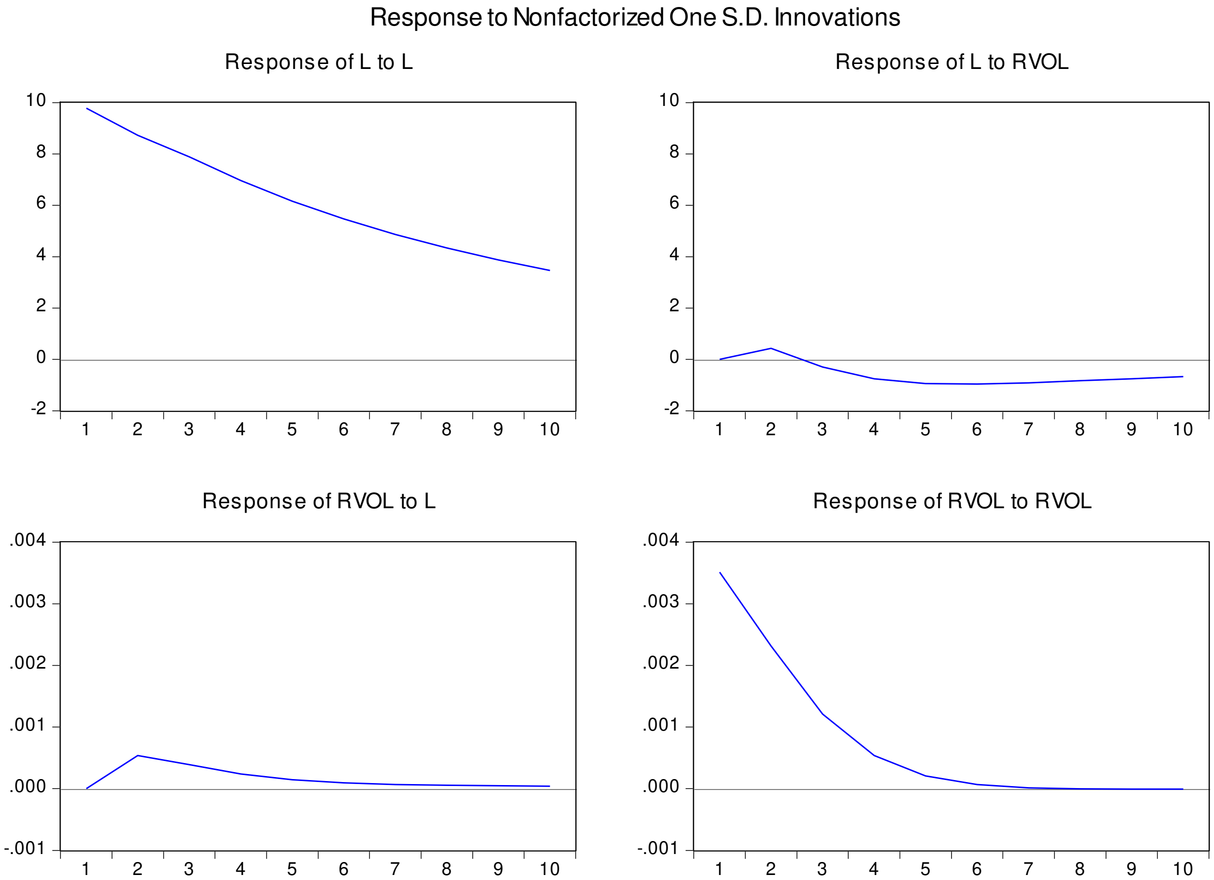
Dependent variable: RP

Excluded	Chi-sq	df	Prob.
L	8.157136	2	0.0169
IND	81.50573	2	0.0000
All	89.79449	4	0.0000

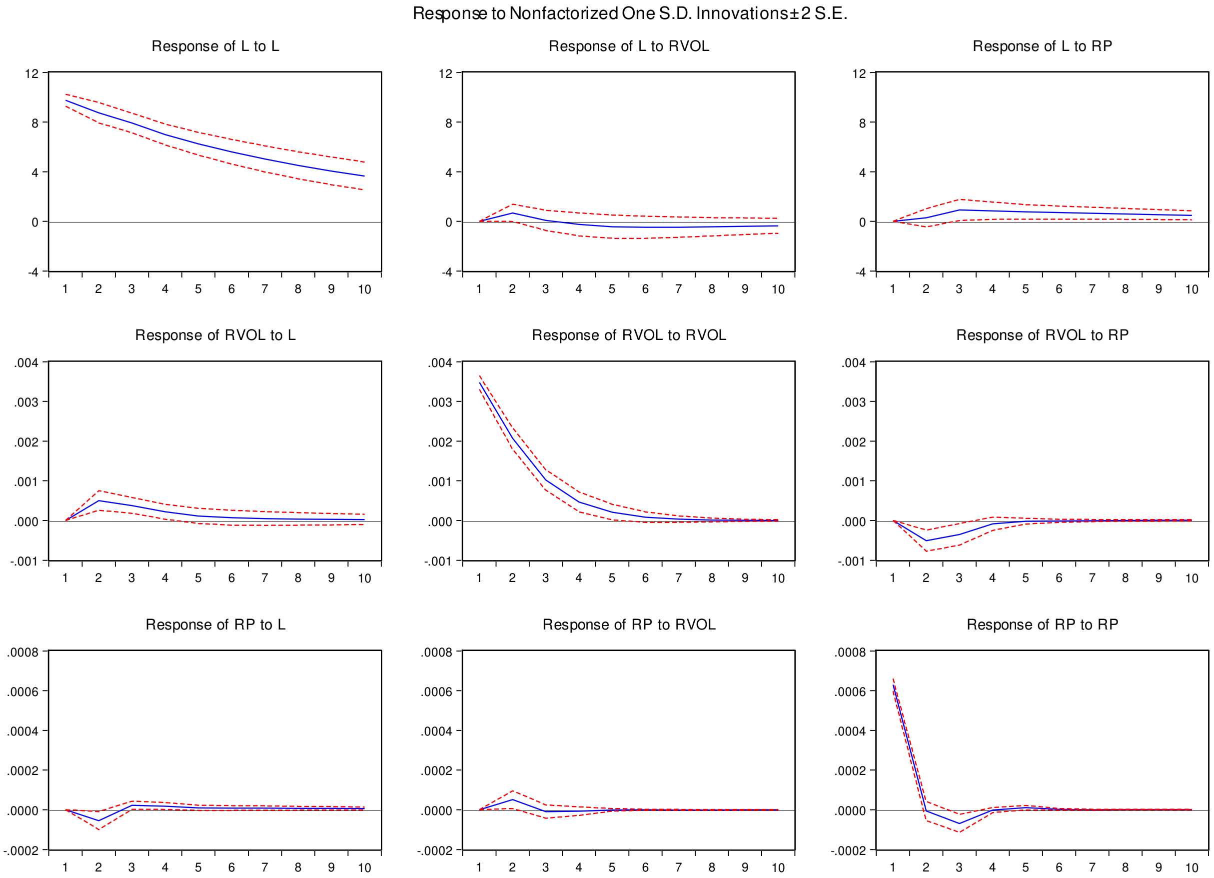
Dependent variable: L			
Excluded	Chi-sq	df	Prob.
FIRM	22.26654	2	0.0000
RP	9.840978	2	0.0073
All	29.98621	4	0.0000
Dependent variable: FIRM			
Excluded	Chi-sq	df	Prob.
L	1.585005	2	0.4527
RP	5.655286	2	0.0592
All	7.534757	4	0.1102
Dependent variable: RP			
Excluded	Chi-sq	df	Prob.
L	5.827818	2	0.0543
FIRM	8.135035	2	0.0171
All	15.73624	4	0.0034

App. H PVAR Estimation Results and Impulse-Response Graphs

	L	RVOL
L(-1)	0.892050	5.50E-05
	(0.03565)	(1.3E-05)
	[25.0242]	[4.29626]
L(-2)	0.003243	-4.56E-05
	(0.03541)	(1.3E-05)
	[0.09159]	[-3.58504]
RVOL(-1)	122.1726	0.659527
	(89.2607)	(0.03203)
	[1.36872]	[20.5896]
RVOL(-2)	-274.8639	-0.097181
	(89.9444)	(0.03228)
	[-3.05593]	[-3.01081]
C	4.656361	0.004299
	(0.95566)	(0.00034)
	[4.87240]	[12.5359]
Adj. R-squared	0.812699	0.451012

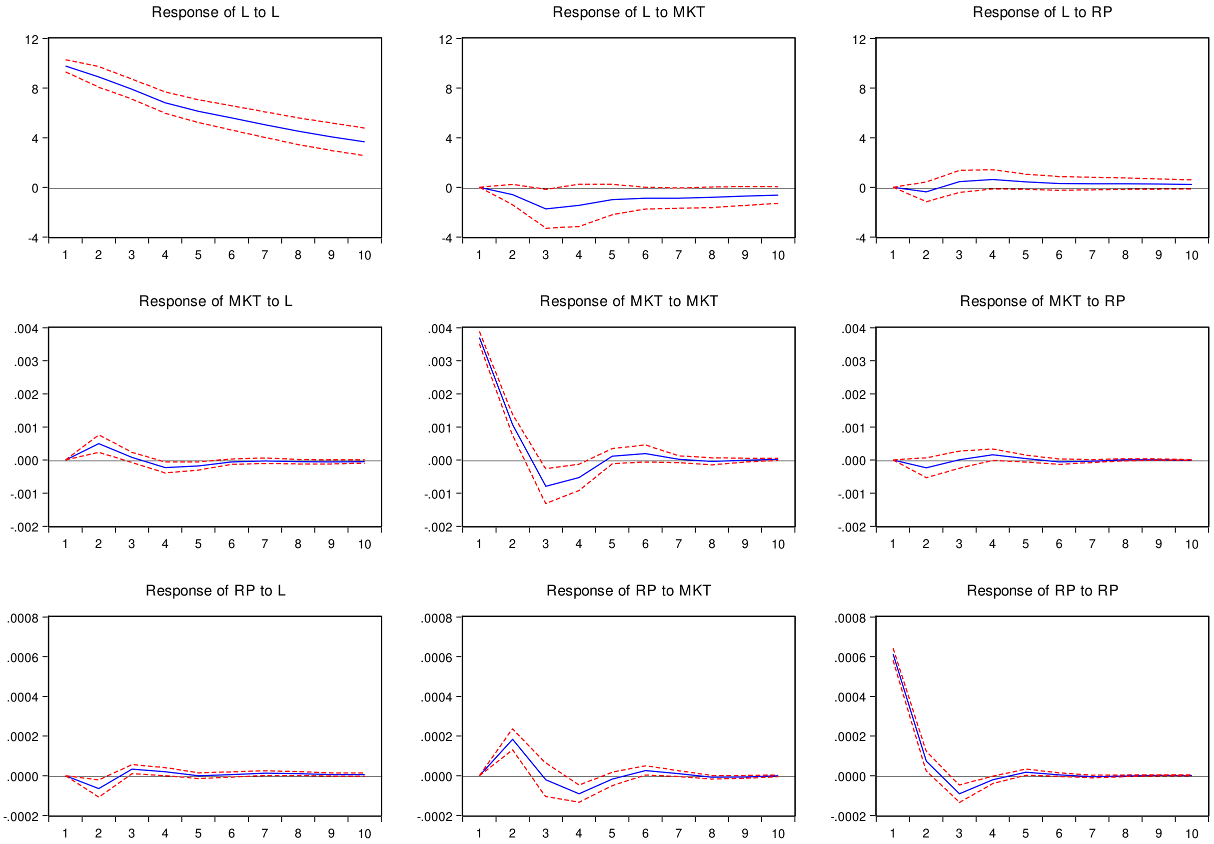

Response to Nonfactorized One S.D. Innovations
Response of L to L
Response of L to RVOL
Response of RVOL to L
Response of RVOL to RVOL
10
8
6
4
2
0
-2
.004
.003
.002
.001
.000
-.001
1 2 3 4 5 6 7 8 9 10

	L	RVOL	RP
L(-1)	0.895497	5.16E-05	-5.65E-06
	(0.03563)	(1.3E-05)	(2.3E-06)
	[25.1300]	[4.05840]	[-2.45368]
L(-2)	0.001919	-4.27E-05	6.56E-06
	(0.03538)	(1.3E-05)	(2.3E-06)
	[0.05425]	[-3.38554]	[2.87155]
RVOL(-1)	194.5174	0.595408	0.014591
	(99.6578)	(0.03554)	(0.00644)
	[1.95185]	[16.7530]	[2.26687]
RVOL(-2)	-276.0875	-0.059127	-0.010343
	(95.2321)	(0.03396)	(0.00615)
	[-2.89910]	[-1.74098]	[-1.68159]
RP(-1)	444.1536	-0.808510	-0.010458
	(588.140)	(0.20974)	(0.03799)
	[0.75518]	[-3.85473]	[-0.27532]
RP(-2)	1205.408	-0.105793	-0.095537
	(548.777)	(0.19571)	(0.03544)
	[2.19653]	[-0.54057]	[-2.69544]
C	4.031173	0.004484	-0.000143
	(0.98641)	(0.00035)	(6.4E-05)
	[4.08672]	[12.7463]	[-2.23727]
Adj. R-squared	0.813652	0.457908	0.024368

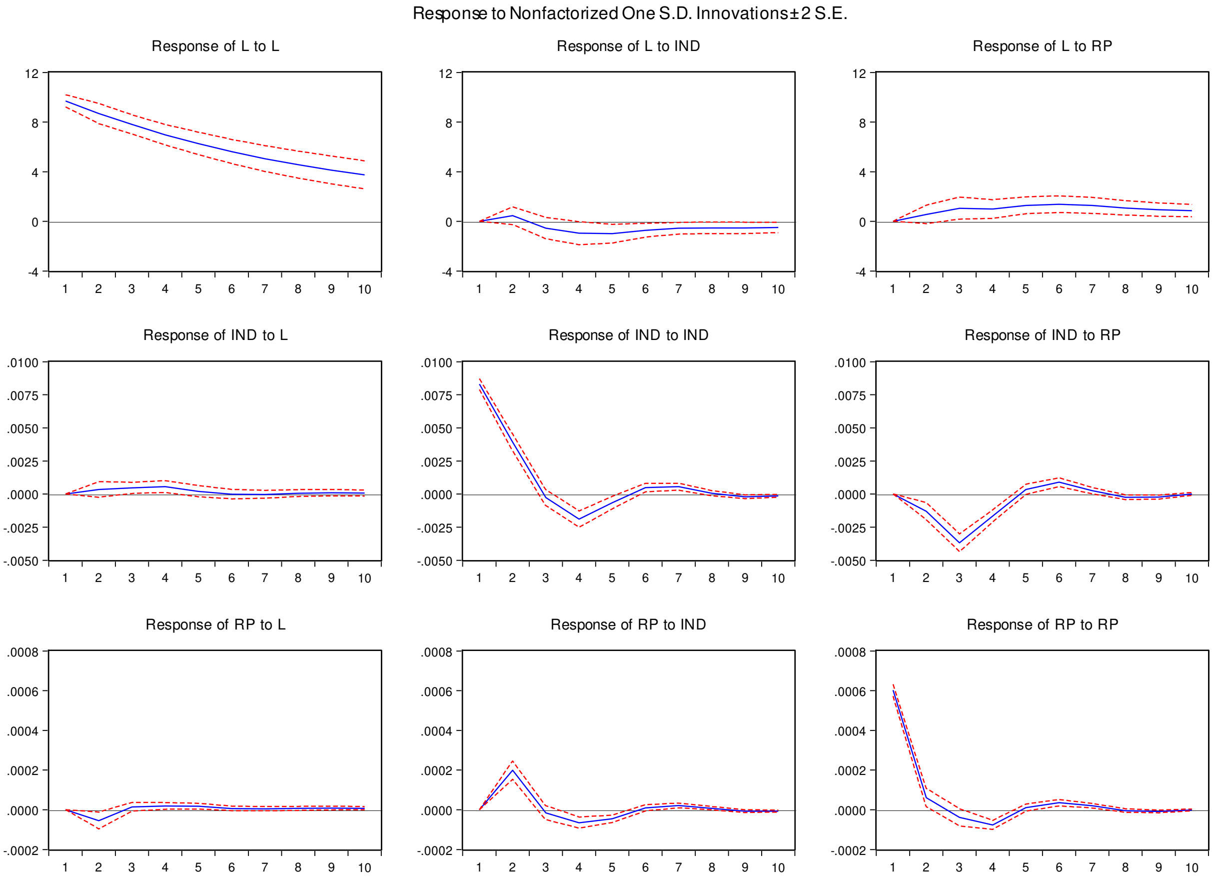

Response to Nonfactorized One S.D. Innovations ± 2 S.E.
Response of L to L
Response of L to RVOL
Response of L to RP
Response of RVOL to L
Response of RVOL to RVOL
Response of RVOL to RP
Response of RP to L
Response of RP to RVOL
Response of RP to RP

	L	MKT	RP
L(-1)	0.909304	5.07E-05	-6.65E-06
	(0.03568)	(1.4E-05)	(2.2E-06)
	[25.4856]	[3.74955]	[-2.97237]
L(-2)	-0.014610	-5.53E-05	7.70E-06
	(0.03541)	(1.3E-05)	(2.2E-06)
	[-0.41266]	[-4.12689]	[3.47061]
MKT(-1)	-161.0446	0.287814	0.049554
	(110.741)	(0.04194)	(0.00694)
	[-1.45425]	[6.86191]	[7.13858]
MKT(-2)	-247.4951	-0.269442	-0.026913
	(184.858)	(0.07002)	(0.01159)
	[-1.33884]	[-3.84830]	[-2.32255]
RP(-1)	-604.1491	-0.385854	0.119777
	(650.748)	(0.24647)	(0.04079)
	[-0.92839]	[-1.56550]	[2.93634]
RP(-2)	1319.439	0.198423	-0.147146
	(549.421)	(0.20810)	(0.03444)
	[2.40151]	[0.95351]	[-4.27257]
C	5.067051	0.005375	-0.000230
	(1.05360)	(0.00040)	(6.6E-05)
	[4.80927]	[13.4687]	[-3.48977]
Adj. R-squared	0.812874	0.134471	0.077195

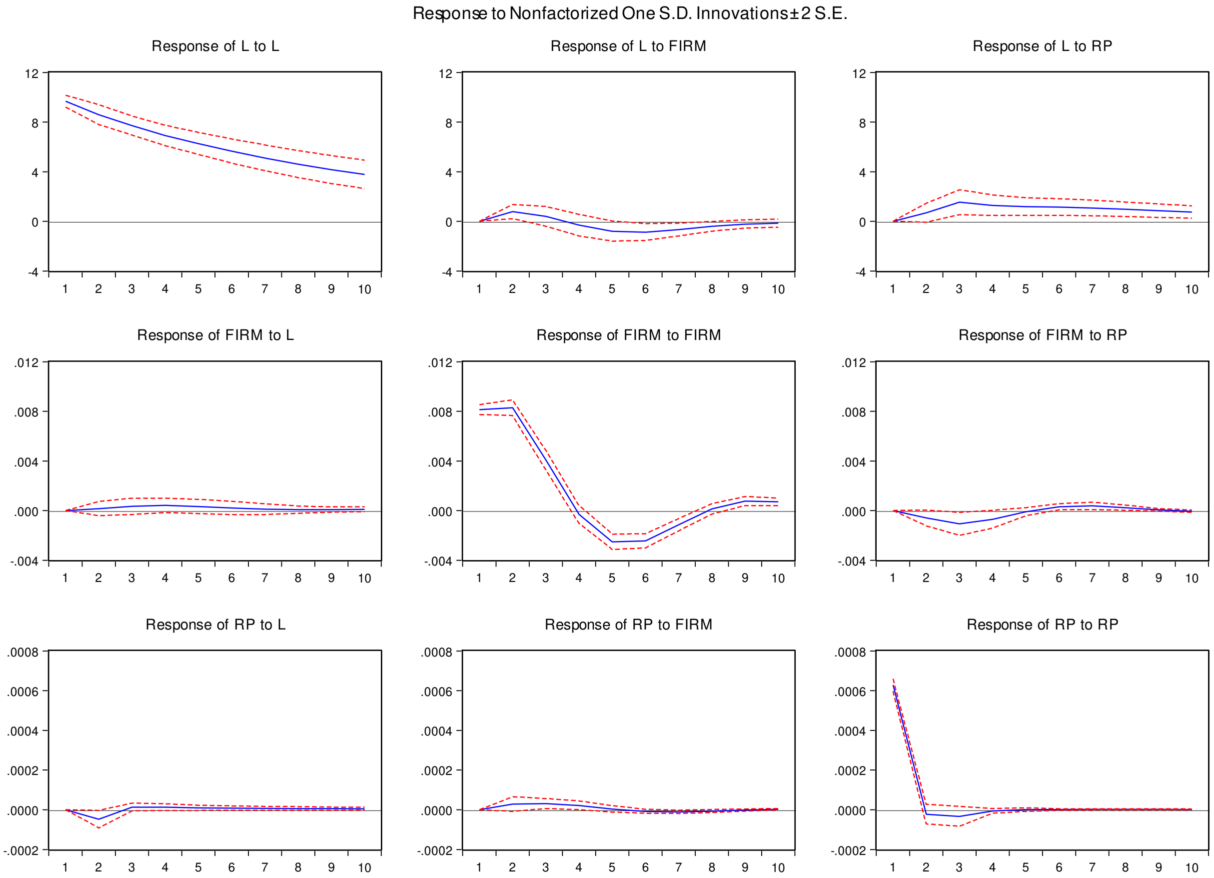
Response to Nonfactorized One S.D. Innovations ±2 S.E.



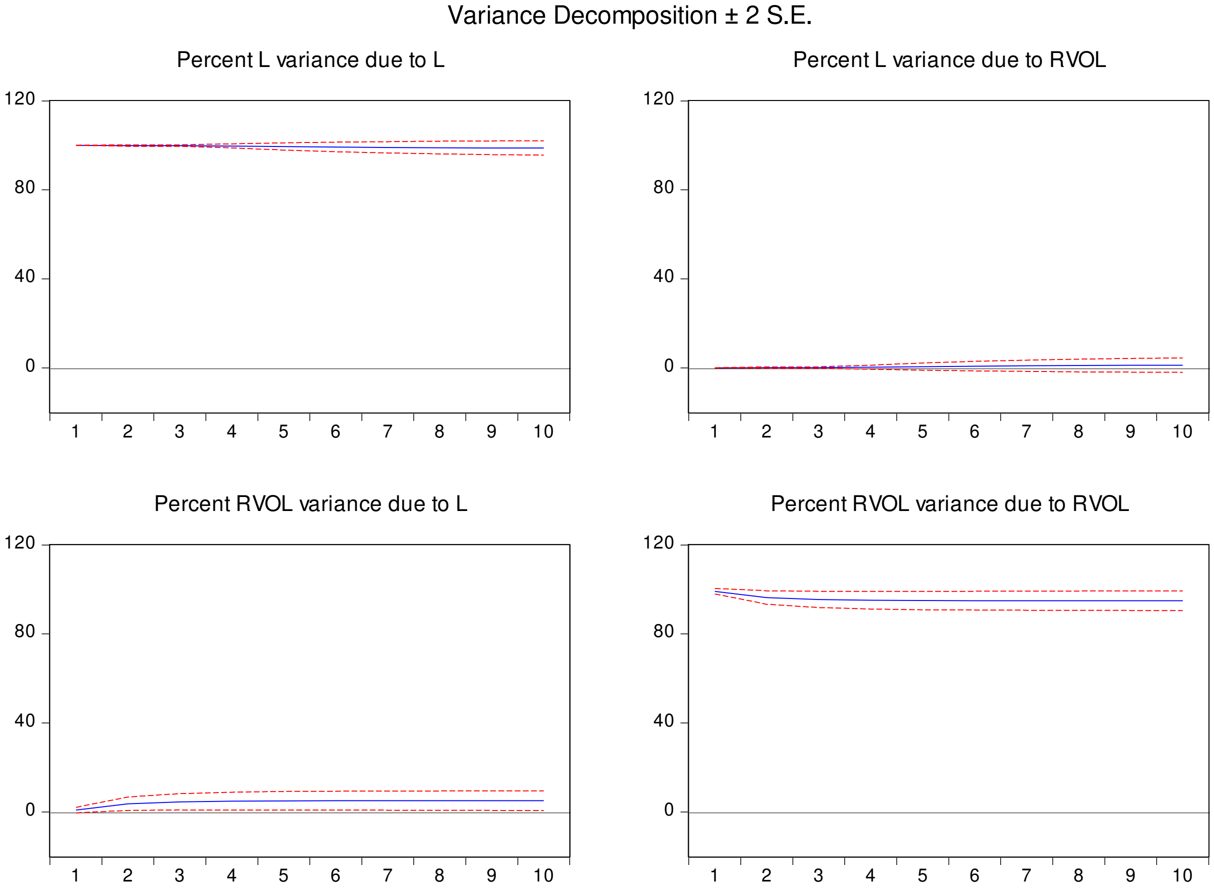
	L	IND	RP
L(-1)	0.894743	3.50E-05	-5.61E-06
	(0.03533)	(3.0E-05)	(2.2E-06)
	[25.3264]	[1.15729]	[-2.55807]
L(-2)	0.006400	-1.17E-05	6.24E-06
	(0.03523)	(3.0E-05)	(2.2E-06)
	[0.18167]	[-0.38940]	[2.85567]
IND(-1)	54.35099	0.470833	0.024024
	(43.0778)	(0.03689)	(0.00267)
	[1.26169]	[12.7628]	[8.98660]
IND(-2)	-162.2495	-0.204314	-0.015271
	(41.5505)	(0.03558)	(0.00258)
	[-3.90487]	[-5.74190]	[-5.92231]
RP(-1)	915.4244	-2.161662	0.101495
	(614.887)	(0.52658)	(0.03816)
	[1.48877]	[-4.10512]	[2.65987]
RP(-2)	961.3910	-4.917653	-0.017779
	(573.090)	(0.49078)	(0.03556)
	[1.67756]	[-10.0200]	[-0.49992]
C	4.936785	0.010182	-0.000210
	(0.85130)	(0.00073)	(5.3E-05)
	[5.79914]	[13.9670]	[-3.97226]
Adj. R-squared	0.815552	0.439369	0.108511

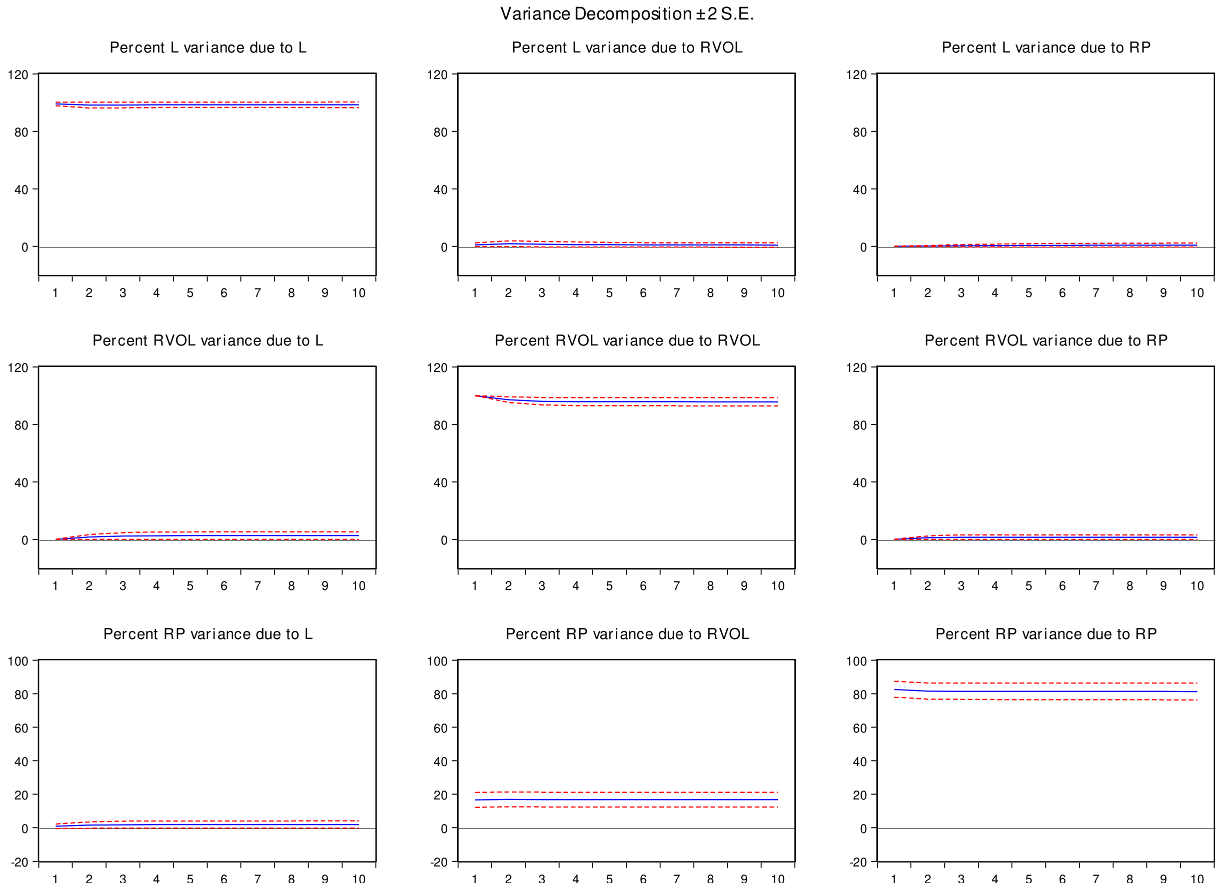

Response to Nonfactorized One S.D. Innovations ± 2 S.E.
Response of L to L
Response of L to IND
Response of L to RP
Response of IND to L
Response of IND to IND
Response of IND to RP
Response of RP to L
Response of RP to IND
Response of RP to RP

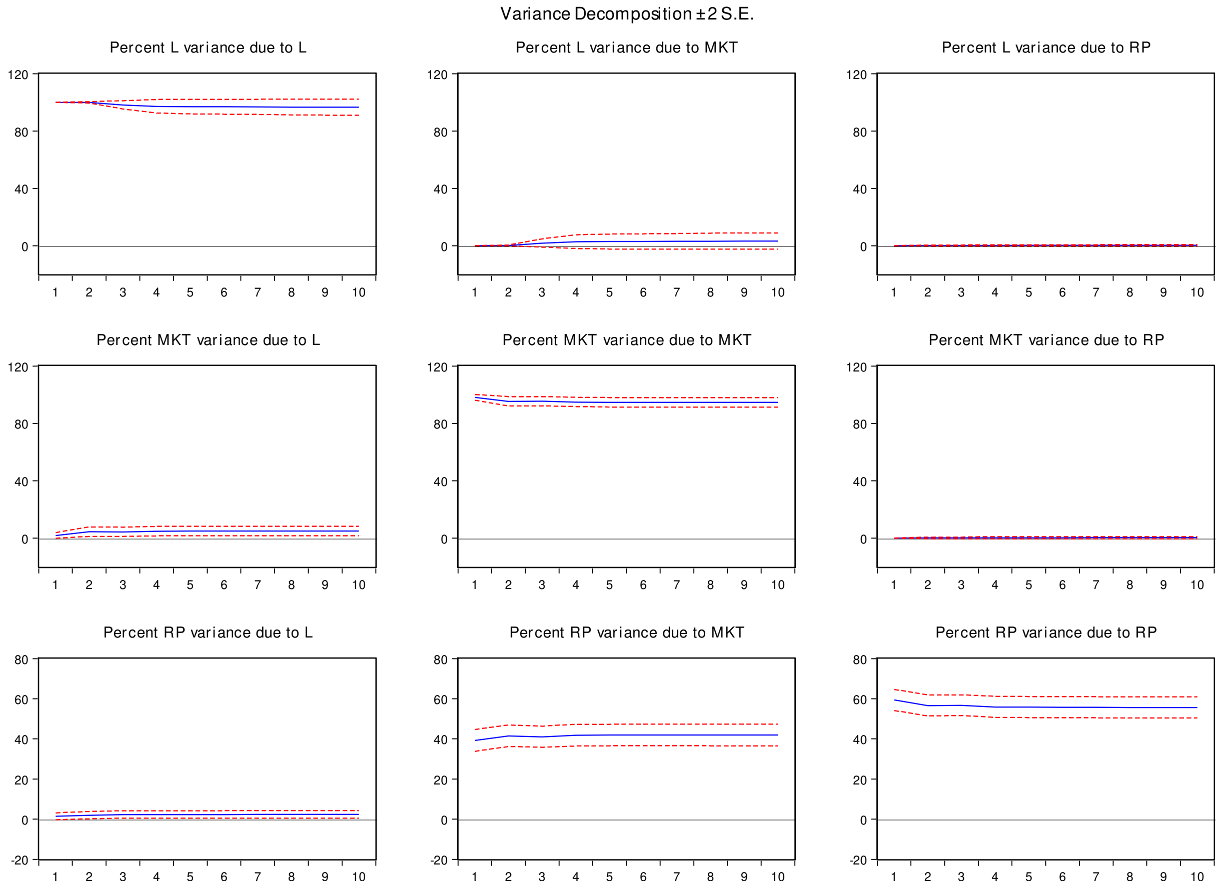
	L	FIRM	RP
L(-1)	0.888094	1.52E-05	-4.92E-06
	(0.03530)	(3.0E-05)	(2.3E-06)
	[25.1570]	[0.51161]	[-2.14429]
L(-2)	0.012810	9.47E-07	5.53E-06
	(0.03523)	(3.0E-05)	(2.3E-06)
	[0.36364]	[0.03198]	[2.41274]
FIRM(-1)	96.30441	1.017838	0.003527
	(34.7159)	(0.02920)	(0.00226)
	[2.77407]	[34.8628]	[1.56249]
FIRM(-2)	-138.8095	-0.532245	0.000849
	(30.0756)	(0.02529)	(0.00196)
	[-4.61536]	[-21.0431]	[0.43437]
RP(-1)	1086.047	-0.955225	-0.035615
	(609.714)	(0.51276)	(0.03964)
	[1.78124]	[-1.86291]	[-0.89840]
RP(-2)	1617.485	-0.784560	-0.045010
	(620.678)	(0.52198)	(0.04036)
	[2.60600]	[-1.50304]	[-1.11532]
C	4.394388	0.011740	-0.000203
	(0.83062)	(0.00070)	(5.4E-05)
	[5.29048]	[16.8066]	[-3.75724]
Adj. R-squared	0.816779	0.759742	0.027872

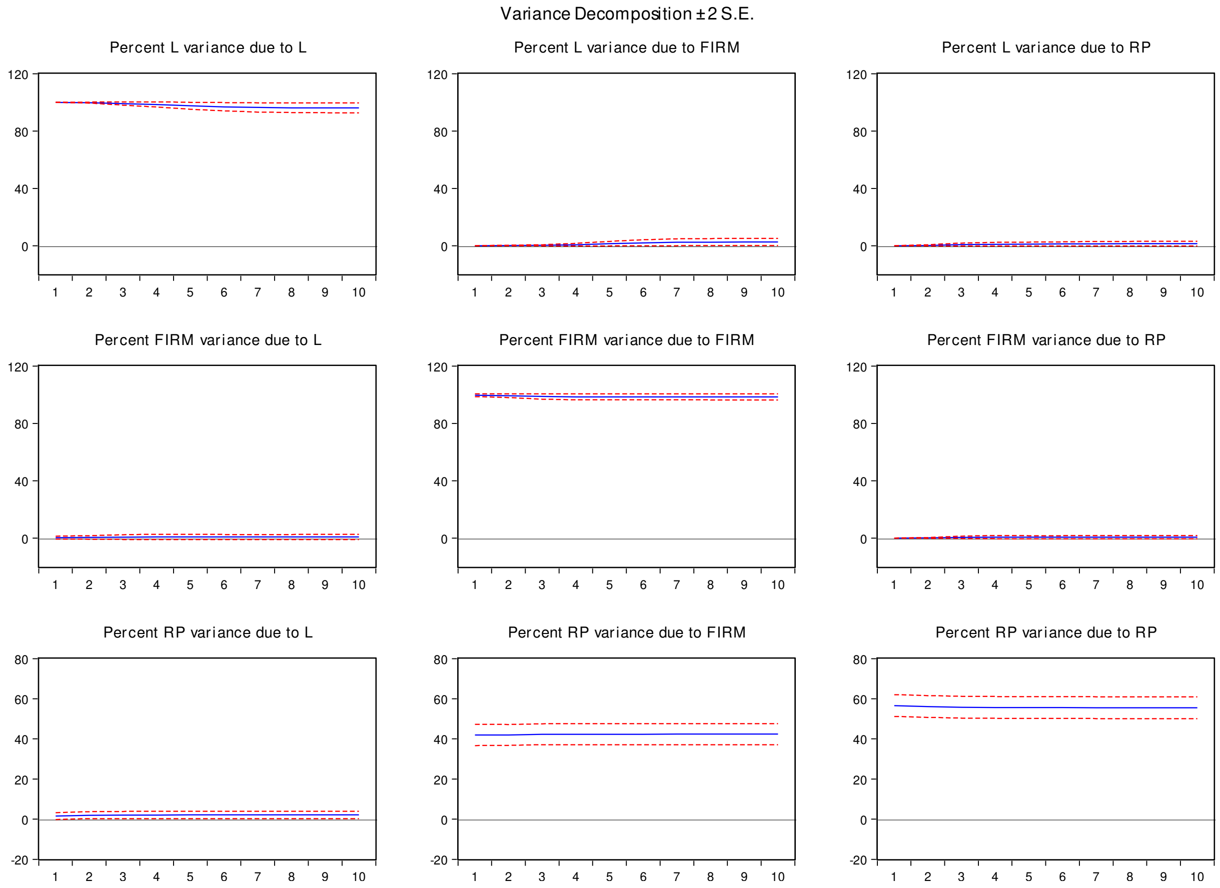

Response to Nonfactorized One S.D. Innovations ±2 S.E.
Response of L to L
Response of L to FIRM
Response of L to RP
Response of FIRM to L
Response of FIRM to FIRM
Response of FIRM to RP
Response of RP to L
Response of RP to FIRM
Response of RP to RP

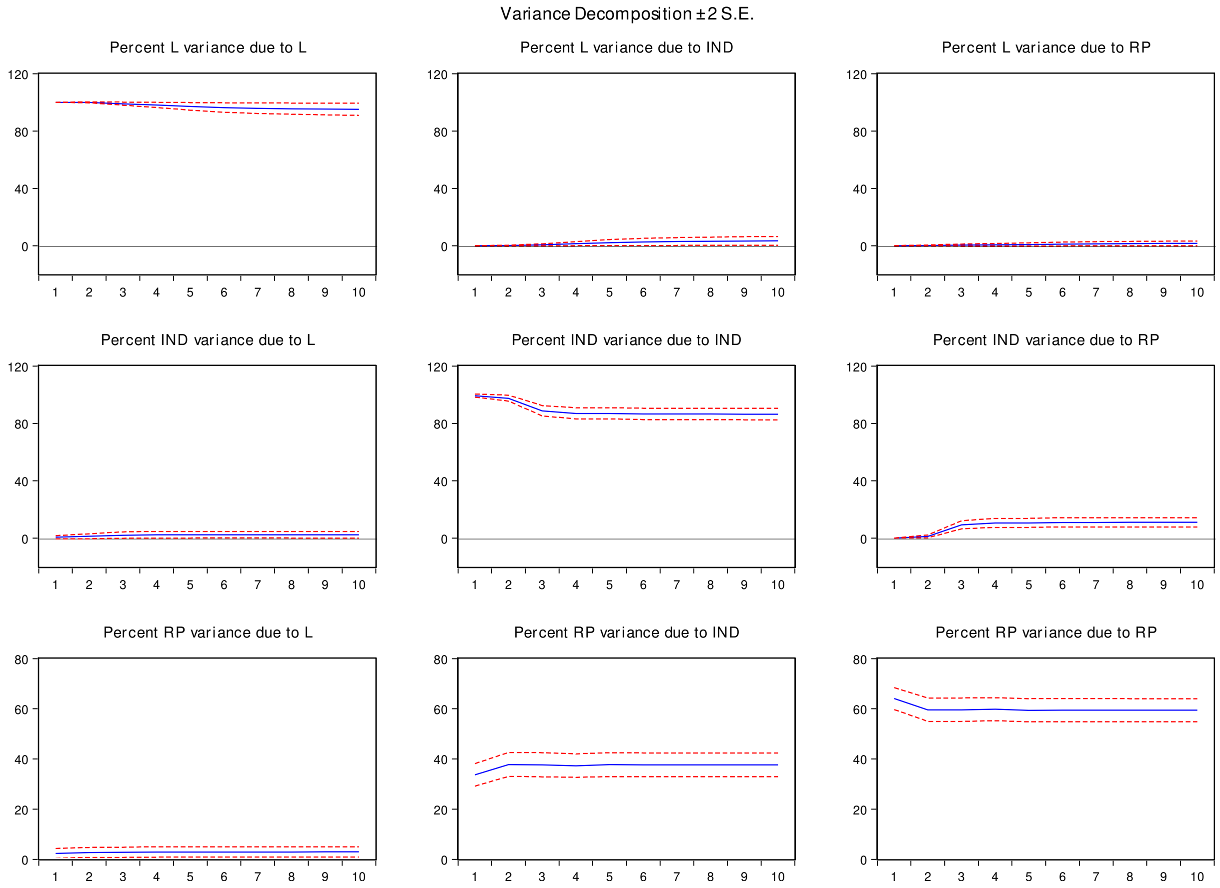
App. I Variance Decomposition



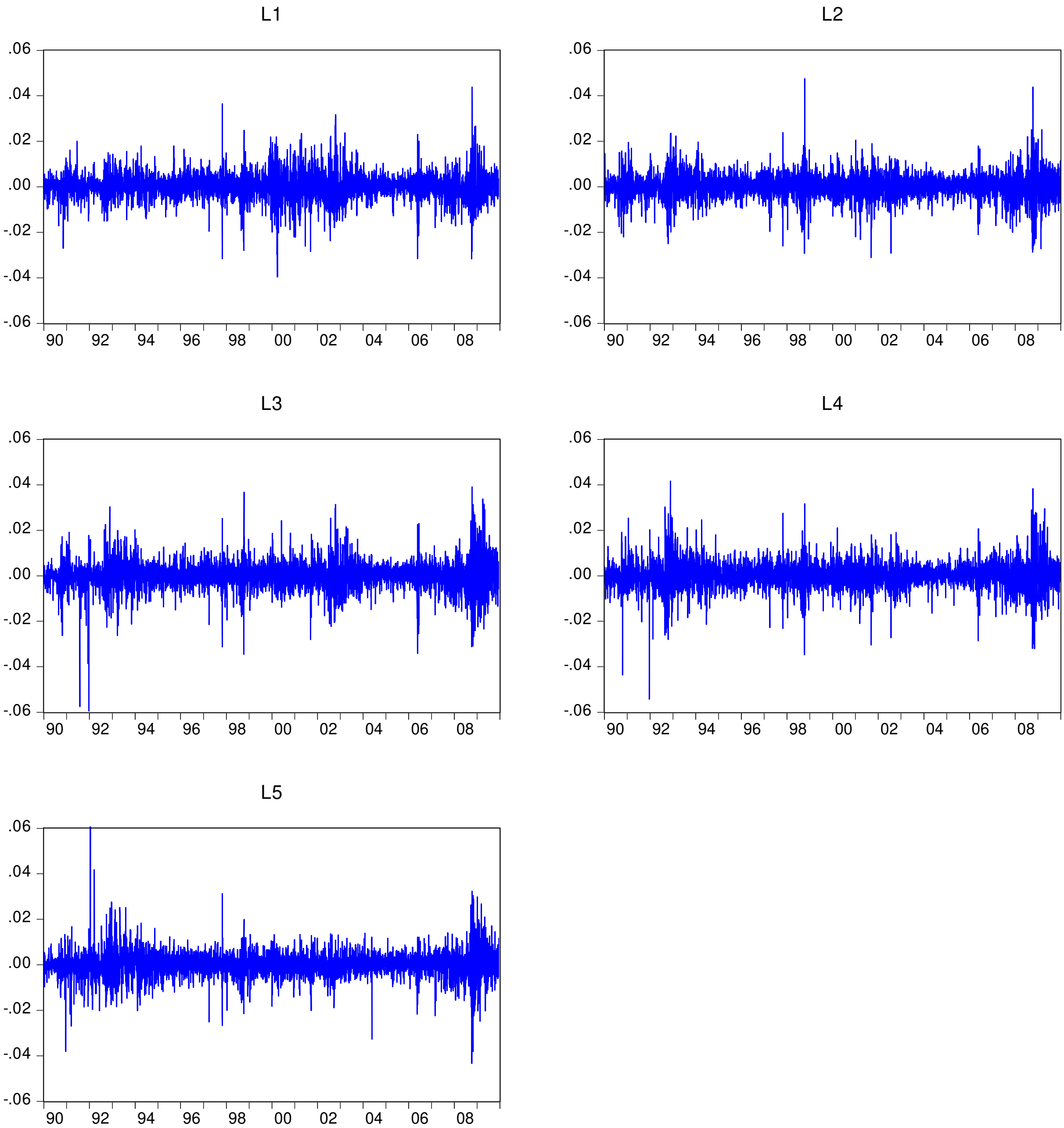

Variance Decomposition ± 2 S.E.
Percent L variance due to L
Percent L variance due to RVOL
Percent L variance due to RP
Percent RVOL variance due to L
Percent RVOL variance due to RVOL
Percent RVOL variance due to RP
Percent RP variance due to L
Percent RP variance due to RVOL
Percent RP variance due to RP


Variance Decomposition ± 2 S.E.
Percent L variance due to L
Percent L variance due to MKT
Percent L variance due to RP
Percent MKT variance due to L
Percent MKT variance due to MKT
Percent MKT variance due to RP
Percent RP variance due to L
Percent RP variance due to MKT
Percent RP variance due to RP


Variance Decomposition ± 2 S.E.
Percent L variance due to L
Percent L variance due to FIRM
Percent L variance due to RP
Percent FIRM variance due to L
Percent FIRM variance due to FIRM
Percent FIRM variance due to RP
Percent RP variance due to L
Percent RP variance due to FIRM
Percent RP variance due to RP

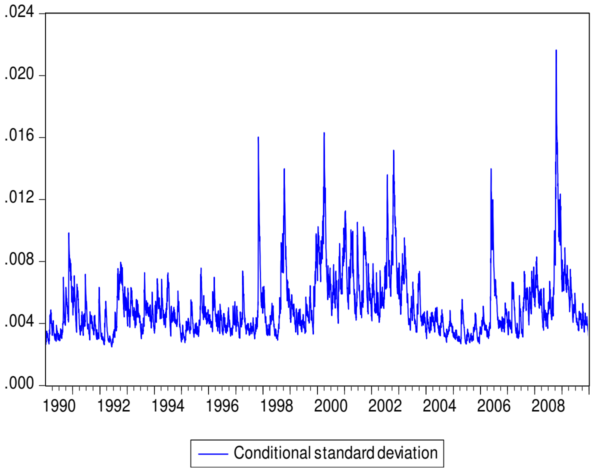

Variance Decomposition ± 2 S.E.
Percent L variance due to L
Percent L variance due to IND
Percent L variance due to RP
Percent IND variance due to L
Percent IND variance due to IND
Percent IND variance due to RP
Percent RP variance due to L
Percent RP variance due to IND
Percent RP variance due to RP

App. J Daily Return Plots for each Leverage Quintile Portfolio

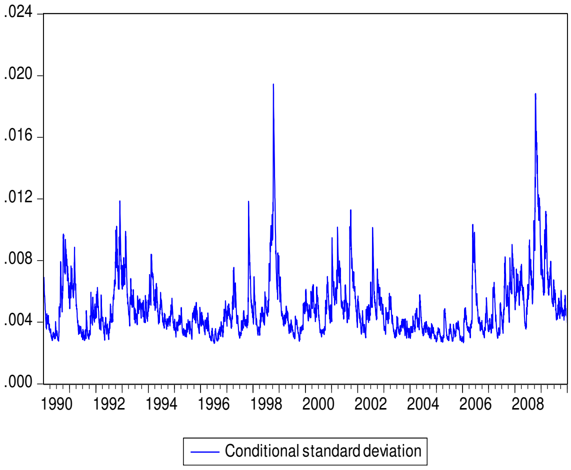


App. K GARCH Conditional Standard Deviation Plot for each Leverage Quintile Portfolio

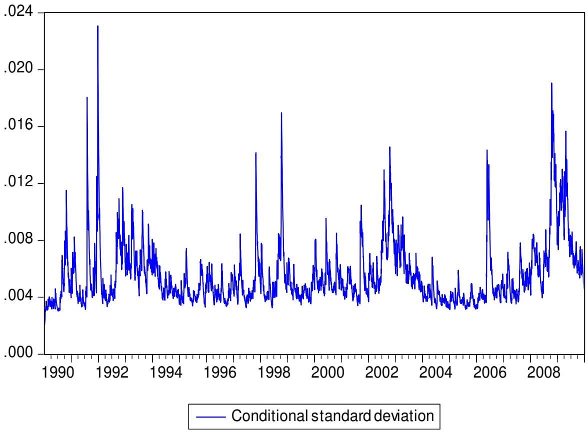
L1



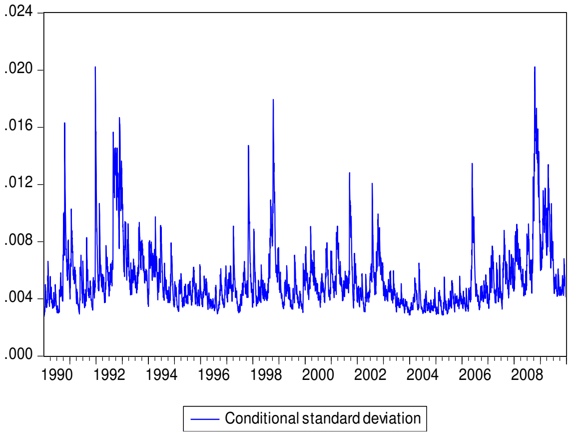
L2



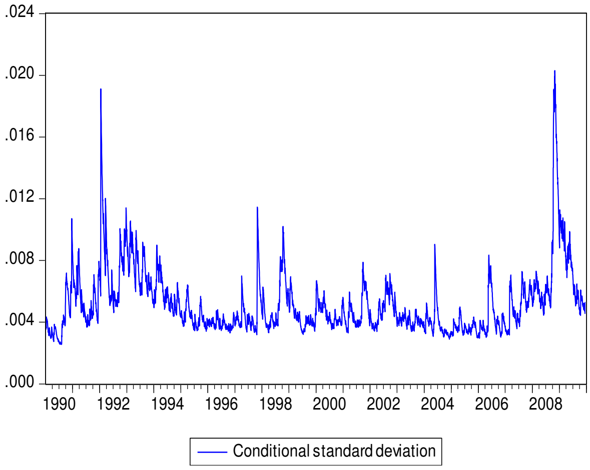
L3



L4

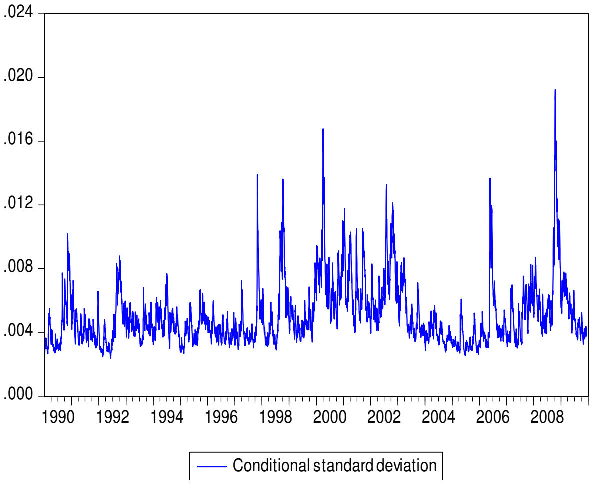


L5

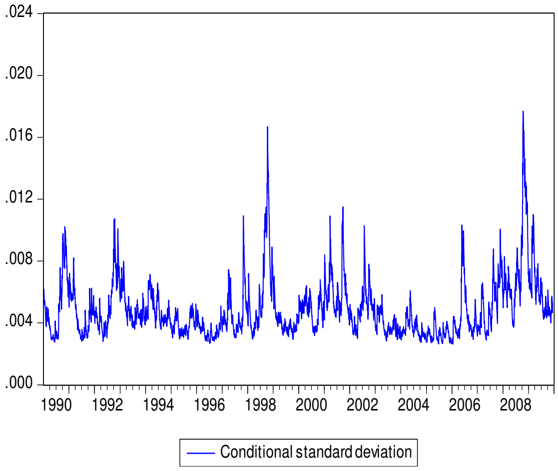


App. L APARCH Conditional Standard Deviation Plot for each Leverage Quintile Portfolio

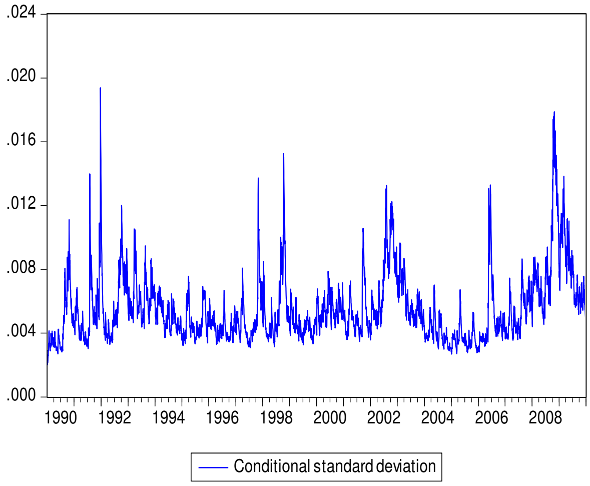
L1



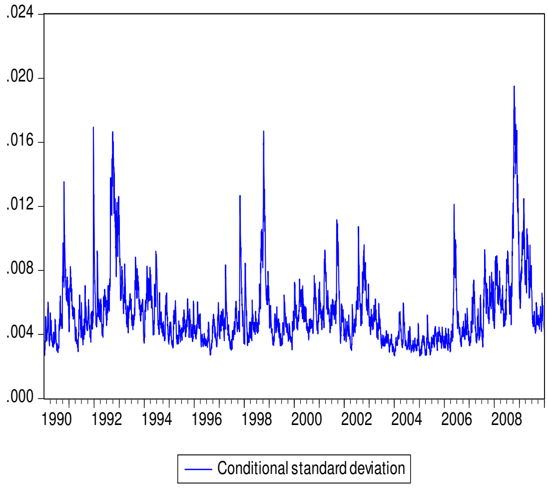
L2



L3



L4



L5