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Literature review

1.1 Stylized facts of returns

When analyzing returns as a time-series, we look at log returns. The log returns are similar to simple returns, so the stylized facts of returns apply to both. One assumption that is made often in financial applications is that returns are i.i.d., or independently and identically distributed. Another assumption is that they are normally distributed. These assumptions might not be reasonable in reality. Below the stylized facts¹ following Annaert [1] for returns are given.

- Returns are *small and volatile* (with the standard deviation being larger than the mean on average).
- Returns have very *little serial correlation*, as mentioned by for example Bollerslev [2].
- Returns exhibit conditional heteroskedasticity, or *volatility clustering*. This effect goes back to Mandelbrot [3]. There is no constant variance (homoskedasticity). Instead it is time-varying. Bollerslev [2] describes this phenomenon as “rates of return data are characterized by volatile and tranquil periods”. Alexander [4] argues this to have implications for risk models: following a

¹Stylized facts are the statistical properties that appear to be present in many empirical asset returns (across time and markets)

large shock to the market, the volatility changes and the probability of another large shock is increased significantly.

- Returns exhibit *asymmetric volatility*, in the sense that volatility increases more after a negative return shock than after a large positive return shock. This is also called the *leverage effect*. Alexander [4] mentions that this leverage effect is most pronounced in equity markets: usually there is a strong negative correlation between equity returns and the change in volatility.
- Returns are *not normally distributed*, as found by early work of Fama [5]. Returns have tails fatter than a normal distribution (they are leptokurtotic) and thus carry more risk. Log returns however **can** be assumed to be normally distributed. We will examine this in our empirical analysis. This makes that simple returns follow a log-normal distribution, a skewed density distribution. A good summary is given by Alexander [4] : “In general, we need to know more about the distribution of returns than its expected return and its volatility. Volatility tells us the *scale* and the mean tells us the *location*, but the dispersion also depends on the *shape* of the distribution. The best dispersion metric would be based on the entire distribution function of returns.”

Firms holding a portfolio of various stocks or other investments have a lot of things to consider: expected return of a portfolio, the probability to get a return lower than some threshold, the probability that an asset in the portfolio drops in value when the market crashes. All the previous requires information about the return distribution or so called density function of returns. What we know from the stylized facts of returns that the normal distribution is not appropriate for returns. In appendix part ?? we summarize some alternative distributions (SGT, SGED, GED, Skewed Student-t, and Symmetric Student-t) that might better approximate the actual distribution of returns than the normal one.

1.2 Volatility modeling

1.2.1 Rolling volatility

When volatility needs to be estimated on a specific trading day, the method used as a descriptive tool would be to use rolling standard deviations. Engle [6] explains the calculation of rolling standard deviations, as the standard deviation over a fixed number of the most recent observations². Engle regards this formulation as the first ARCH model.

1.2.2 From ARCH to GARCH models

Autoregressive Conditional Heteroscedasticity (ARCH) models, proposed by Engle [7], were in the first case not used in financial markets but on inflation. Since then, it has been used as one of the workhorses of volatility modeling.

There are three building blocks of the ARCH model: returns, the innovation process and the variance process (or volatility function), written out for an ARCH(1) in respectively equation (1.1), (1.2) and (1.3). Returns are written as a constant part (α_0) and an unexpected part, called noise or the innovation process ($\alpha_1 \times \varepsilon_t$). The innovation process is the volatility (σ_t) times z_t , which is an independent identically distributed random variable with a mean of 0 (zero-mean) and a variance of 1 (unit-variance). The independent (iid), notes the fact that the z -values are not correlated, but completely independent of each other. The distribution is one of the distributions listed in appendix part ???. The third component is the variance process or the expression for the volatility. The variance is given by a constant β_0 , plus the random part which depends on the return shock of the previous period squared (ε_{t-1}^2). In that sense when the uncertainty or surprise in the last period increases, then the variance becomes larger in the next period. The element σ_t^2

²For example, for the past month it would then be calculated as the equally weighted average of the squared deviations from the mean from the last 22 observations (the average amount of trading or business days in a month). All these deviations are thus given an equal weight. Also, only a fixed number of past recent observations is examined.

is thus known at time $t - 1$, while it is a deterministic function of a random variable observed at time $t - 1$ (i.e. ε_{t-1}^2).

$$y_t = \alpha_0 + \alpha_1 \times \varepsilon_t \quad (1.1)$$

$$\varepsilon_t = \sigma_t \times z_t, \text{ where } z_t \stackrel{iid}{\sim} (0, 1) \quad (1.2)$$

$$\sigma_t^2 = \beta_0 + \beta_1 \times \varepsilon_{t-1}^2 \quad (1.3)$$

The full description of the ARCH model is given in appendix part ??.

An improvement of the ARCH model is the Generalized Autoregressive Conditional Heteroscedasticity (GARCH)³. This model and its variants come in to play because of the fact that calculating standard deviations through rolling periods, gives an equal weight to distant and nearby periods, by such not taking into account empirical evidence of volatility clustering, which can be identified as positive autocorrelation in the absolute returns. GARCH models are an extension to ARCH models, as they incorporate both a novel moving average term (not included in ARCH) and the autoregressive component. Furthermore, a second extension is changing the assumption of the underlying distribution. As already explained, the normal distribution is an unrealistic assumption, so other distributions which are described in part ?? will be used. As Alexander [4] explains, this does not change the formulae of computing the volatility forecasts but it changes the functional form of the likelihood function⁴. An overview (of a selection) of investigated GARCH models is given in the following table.

³*Generalized* as it is a generalization by Bollerslev [8] of the ARCH model of Engle [7]. *Autoregressive*, as it is a time series model with an autoregressive form (regression on itself). *Conditional heteroscedasticity*, while time variation in conditional variance is built into the model [4].

⁴which makes the maximum likelihood estimation explained in part ?? complex with more parameters that have to be estimated.

Table 1.1: GARCH models, the founders

Author(s)	Model
Engle [7]	ARCH model
Bollerslev [8]	GARCH model
Bollerslev [8]	IGARCH model
Nelson [9]	EGARCH model
Glosten, Jagannathan, and Runkle [10]	GJRGARCH model
Engle and Ng [11]	NAGARCH model
Zakoian [12]	TGARCH model
Taylor [13] and Schwert [14]	AVGARCH model
Morgan Guaranty Trust Company [15]	EWMA or RiskMetrics model

1.3 ACD models

An extension to GARCH models was proposed by Hansen [16], namely the autoregressive conditional density estimation model (referred to as ACD model, sometimes ARCD). It focuses on time variation in higher moments (skewness and kurtosis), because the degree and frequency of extreme events seem to be not expected by traditional models. Some GARCH models are already able to capture the dynamics by relying on a different unconditional distribution than the normal distribution (for example skewed distributions like the SGED or SGT), or a model that allows to incorporate these higher moments. However, Ghalanos [17] mentions that these models also assume the shape and skewness parameters to be constant (not time-varying). As Ghalanos mentions: “the research on time-varying higher moments has mostly explored different parametrizations in terms of dynamics and distributions with little attention to the performance of the models out-of-sample and ability to outperform a GARCH model with respect to VaR.” Also one could question the marginal benefits of the ACD, while the estimation procedure is rather sophisticated (nonlinear bounding specification of higher moment distribution parameters and interaction). So, are skew (skewness parameter) and kurtosis (shape parameter or parameters) time-varying? The literature investigating higher moments has arguments for and against this statement. In part ?? the specification is given.

1.4 Value at Risk

Value at Risk (VaR) is a risk metric developed simultaneously by Markowitz [18] and Roy [19] to calculate how much money an investment, portfolio, department or institution such as a bank could lose in a market downturn, though in this period it remained mostly a theoretical discussion due to lacking processing power and industry demand for risk management measures. Another important document in literature is the *1996 RiskMetrics Technical Document*, composed by RiskMetrics⁵ (Morgan Guaranty Trust Company [15], part of JP Morgan), which gives a good overview of the computation, but also made use of the name “value-at-risk” over equivalents like “dollars-at-risk” (DaR), “capital-at-risk” (CaR), “income-at-risk” (IaR) and “earnings-at-risk” (EaR). According to Holton [20] VaR gained traction in the last decade of the 20th century when financial institutions started using it to determine their regulatory capital requirements. A VaR_{99} finds the amount that would be the greatest possible loss in 99% of cases. It can be defined as the threshold value F . Put differently, in 1% of cases the loss would be greater than this amount. It is specified as in (1.4). Christoffersen, Hahn, and Inoue [21] puts forth a general framework for specifying VaR models and comparing between two alternatives models.

$$Pr(y_t \leq F | \Omega_{t-1}) \equiv \alpha \quad (1.4)$$

With y_t expected returns in period t , Ω_{t-1} the information set available in the previous period and ϕ the chosen confidence level.

1.5 Conditional Value at Risk

One major shortcoming of the VaR is that it does not provide information on the probability distribution of losses beyond the threshold amount. As VaR lacks

⁵RiskMetrics Group was the market leader in market and credit risk data and modeling for banks, corporate asset managers and financial intermediaries [4].

subadditivity of different percentile outcomes, [Artzner1998] reject it as a coherent measure of risk. This is problematic, as losses beyond this amount would be more problematic if there is a large probability distribution of extreme losses, than if losses follow say a normal distribution. To solve this issue, they provide a conceptual idea of a Conditional VaR (CVaR) which quantifies the average loss one would expect if the threshold is breached, thereby taking the distribution of the tail into account. Mathematically, a $cVaR_{99}$ is the average of all the VaR with a confidence level equal to or higher than 99. It is commonly referred to as expected shortfall (ES) sometimes and was written out in the form it is used by today by [22]. It is specified as in (1.5).

To calculate α , VaR and CVaR require information on the expected distribution mean, variance and other parameters, to be calculated using the previously discussed GARCH models and distributions.

$$Pr(y_t \leq \alpha | \Omega_{t-1}) \equiv \int_{-\infty}^{\alpha} f(y_t | \Omega_{t-1}) dy_t = \phi \quad (1.5)$$

With the same notations as before, and f the (conditional) probability density function of y_t .

According to the BIS framework, banks need to calculate both VaR_{99} and $VaR_{97.5}$ daily to determine capital requirements for equity, using a minimum of one year of daily observations [23]. Whenever a daily loss is recorded, this has to be registered as an exception. Banks can use an internal model to calculate their VaRs, but if they have more than 12 exceptions for their VaR_{99} or 30 exceptions for their $VaR_{97.5}$ they have to follow a standardized approach. Similarly, banks must calculate $CVaR_{97.5}$.

1.6 Past literature on the consequences of higher moments for VaR determination

Here comes the discussion about studies that have looked at higher moments and VaR determination. Also a summary of studies that discusses time-varying higher

moments, but not a big part, while it is also only a small part of the empirical findings (couple of GARCH-ACD models).

Table 1.2: Higher moments and VaR

Author	Higher moments
Hansen [16]	Skewness and kurtosis extended ARCH-model
Harvey and Siddique [24]	Skewness, Effect of higher moments on lower moments
Brooks et al. [25]	Kurtosis, Time varying degrees of freedom

While it is relatively straightforward to include unconditional higher-moments in VaR and CVaR calculations, it is less simple to do so when the higher moments (in addition to the variance) are time-varying. Hansen [16] extends the ARCH model to include time-varying moments beyond mean and variance. While mean returns and variance are usually the parameters of most interest, disregarding these higher moments could provide an incomplete description of a conditional distribution. The model proposed by Hansen [16] allows for skewness and shape parameters to vary in a skewed-t density function through specifying them as functions of their errors in previous periods (in an similar way how variance is estimated). Applications on U.S. Treasuries and exchange rates are discussed. \

Harvey and Siddique [24] extends a GARCH(1,1) model to include time varying skewness by estimating it jointly with time varying variance using a skewed Student-t distribution. They find a significant impact of skewness on conditional volatility, suggesting that these moments should be jointly estimated for efficiency. Changes in conditional skewness have an impact on the persistence of volatility shocks. They also find that including skewness causes the leverage effects of variance to disappear. They apply their methods on different stock indices (both developed and emerging) at daily, weekly and monthly frequency. \

Brooks et al. [25] proposes a model based on a Student-t distribution that allows for both the variance and the degrees of freedom to be time-varying, independently from each other. Their model allows for both asymmetric variance and kurtosis through an indicator function (which has a positive effect on these moments only

when the shock is in the right tail). They apply their model on different financial assets in the U.S. and U.K. at daily frequency.

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