Deriving fractional moments using the Moment Generating Function

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Abstract

This thesis explores a novel approach for computing moments of fractional order by combining the Moment Generating Function with various types of fractional derivatives. The study demonstrated that the Moment Generating Function in combination with the Riemann-Liouville or Grünwald-Letnikov derivative obtains accurate values of moments of fractional orders. In contrast, the Moment Generating Function in combination with the Caputo-Fabrizio derivative consistently underestimates these moments, particularly as the distribution parameters or forecasting horizons increase. By making use of moments of fractional order, statistics such as the standard deviation, skewness and kurtosis were computed to analyze and forecast volatility of stock returns in financial markets. The concept of Lower Partial Moments was extended to fractional orders, providing insights into the frequency and magnitude of downside risk. Additionally, moments of fractional order were implemented into an observation-driven regression model, reducing errors and improving prediction performance compared to traditional models. Numerical integration was required due to the absence of closed-form expressions of the Moment Generating Function. As a result, absolute moments were employed to ensure numerical stability. This solution comes at the cost of interpretability of the results, a problem that often occurs when considering moments of fractional order.

Keywords: fractional moments, moment generating function, fractional calculus, Caputo-Fabrizio, volatility forecasting, observation-driven regression models

1 Introduction

Statistical moments, defined as the n-th moment of a random variable X via its probability density function, are essential tools for characterizing data and its distribution. The first and second order moments, the mean and variance, respectively provide key insights into the average value and dispersion of a random variable. Higher-order moments offer further information about the shape and symmetry of the distribution. A less commonly discussed class of moments, however, are the fractional moments. The latter are defined in precisely the same manner as the integer moments, but now with $n \in \mathbb{R}$, or even $n \in \mathbb{C}$. From this point onward, when referring to fractional moments, we denote the order by $\alpha \in \mathbb{R}$ instead of n. While these moments may not find as much usage in comparison with the integer moments of a distribution, they can be rather valuable in specific applications.

Fractional moments play a significant role in various fields, including finance, economics, and statistics. One notable application in statistics is their use in approximating integer moments, as described by Novi Inverardi and Tagliani (2024). In such cases, evaluating a 'nearby' existing fractional moment can provide an approximation of the otherwise undefined integer moment Novi Inverardi and Tagliani (2024).

As an illustration, one can consider the student-t distribution with $\nu = 2$ degrees of freedom. This distribution only has central and raw moments of order k, where $0 < k < \nu$. This implies that its second central moment ($k = 2$) does not exist. One could however consider the central moment of order k, where $k = 1.95$, given that this order of the moment does in fact exist and interpret its value as the variance of the distribution.

Fractional moments are also used in financial modelling, particularly in the context of Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. These models are commonly applied to time series data such as financial returns and capture the dynamic volatility that changes over time. The GARCH model achieves this by modelling the volatility based on the returns and variances of previous time periods. It is useful to note that in the context of financial returns, the variable of interest often follows a distribution with heavy tails. As a consequence, not all relevant moments of integer order may exist. In such cases, fractional moments may serve as a viable alternative. Hansen and Tong (2024) propose a method for computing fractional absolute moments of the cumulative return, quantities that would otherwise be undefined using traditional integer-order techniques.

In addition, Hansen and Tong (2024) apply a Heterogenous Autoregressive Gamma Model (HARG) to model intraday stock data. The HARG model assumes the conditional distribution of the variable of interest, say X_t to be of a non-central Gamma distribution. This model is commonly used to model positive-valued time series data Gourieroux and Jasiak (2006). In particular, the volatility of the random variable is of interest, which by definition is non-negative.

In this context, X_t is the realized variance. Hansen and Tong (2024) study the conditional moments of the variance process. Specifically, they consider moments of order $\{\frac{1}{2}, \frac{3}{2}, 2\}$ which correspond to the standard deviation, skewness and kurtosis respectively. Furthermore, the moment of order $-\frac{1}{2}$, the inverse volatility has also been computed. In this context, this moment serves as an estimate of the Sharpe ratio, which is an index to measure the performance of some investment compared to a risk-free asset Sharpe (1994). These fractional moments offer valuable insights into financial return dynamics and are highly relevant for modelling and risk assessment.

In a related application, Mikosch et al. (2013) apply fractional moments to financial time series data, focusing on the stationary solution of a stochastic recurrence equation - a recursive formula that describes the evolution of a time series. This equation generalizes common time series models in econometrics such as the ARCH and GARCH and is thus of great interest in the context of financial econometrics. Notably, the GARCH(1,1) model can be represented within this one-dimensional stochastic recurrence equation framework Mikosch et al. (2013).

Similar to the case study by Hansen and Tong (2024), conditional moments of fractional order are of great interest, as is often the case in the context of (G)ARCH models. The latter can again be explained by the fact that fractional moments offer a valuable alternative for characterizing the distributional properties of financial time series.

Gzyl et al. (2013) also introduce the use of Fractional moments in risk-models, specifically insurance models. In such models, often the probability density function of total ruin, the event where an insurance company's capital becomes negative, is unknown or difficult to compute. The method of maximum entropy has been developed as a way to approximate these unknown density functions. This method uses fractional moments as input, as they have been proven to be able to characterize its distribution Lin (1992). Compared to traditional techniques, such as inverse Laplace transforms, the maximum entropy approach requires fewer moments to achieve a reliable approximation, making it more computationally efficient and practical for real-world applications.

In prior research by D'Amico et al. (2002) the same approach of using fractional moments as input for maximum entropy methods to characterize unknown distributions has been employed. One notable application is in option pricing in A Black-Scholes model. Making use of fractional moments, numerical approximations of theoretical entropies have been obtained. Remarkably, using only two fractional moments, the method achieved approximations with three-digit accuracy.

This approach outperformed traditional maximum entropy methods that rely on integer moments, both in terms of accuracy and computational efficiency. Moreover, the use of fractional moments helps to avoid numerical optimization issues that commonly arise when minimizing functions based on integer-moment constraints. Therefore, the results obtained by D'Amico et al. (2002) seem to correspond with the aforementioned results obtained by Gzyl et al. (2013). Namely, the implementation of fractional moments in the context of maximum entropy methods has great advantages when it comes to numerical stability and efficiency as compared to more traditional methods.

Beyond finance and risk modelling, fractional moments have found valuable applications in fields such as engineering and healthcare. As previously mentioned, Gzyl and Mayoral (2024) used fractional moments combined with the maximum entropy method to predict total ruin. This approach has been extended to estimating lifetime distributions, a general topic of interest in survival analysis Clark et al. (2003). Both probability density functions and survival functions were estimated using this technique. Once again, the prediction errors remained within three-digit accuracy, further supporting the method's consistency and precision across different fields of research.

Other examples in the field of engineering include optimizing signal processing and control systems as well as studying the response characteristics of random vibration systems. Wang et al. (2025) have shown that when using the concept of fractional moments for the latter, accuracy and stability is higher compared to traditional methods, such as Taylor expansions. Furthermore, in terms of simplicity and efficiency, the method of fractional moments is advantageous, as its computation steps are straightforward and avoid convergence issues, significantly reducing the resources required for computation. Implementing the usage of fractional moments has allowed Wang et al. (2025) to obtain both analytical, as well as numerical solutions to problems within their research field, which again proves its viability.

Another noteworthy application of fractional moments is in the identification of distributions in complex, non-linear systems. Di Matteo et al. (2014) demonstrate how complex fractional moments can be used to solve differential equations such as the Kolmogorov or Fokker-Planck equation, which arise in the context of continuous-time Markov processes. By transforming the system into a more agreeable form using Mellin transforms, Di Matteo et al. (2014) show that solutions can be efficiently computed and later recovered using inverse transformations. A key advantage of this method is that it preserves the entire support of the probability distribution, which traditional integer moment methods fail to achieve.

The focus of this paper is on combining the theory of fractional calculus and moment generating functions in order to obtain moments of fractional order. Comparisons between the accuracies of the moment generating function in combination with different fractional derivatives will be made. The interpretability and advantages of moments of fractional order compared to moments of integer order will also be discussed. The remainder of this paper is structured as follows. Section 2.1.1 discusses existing methods for computing fractional moments, outlining their respective advantages and disadvantages. This section concludes with an introduction to the novel approach proposed in this paper, the required techniques, and the limitations to be mindful of. Section 2.2 lays the mathematical foundation for this new method and provides a brief historical overview of the development of fractional derivatives. In section 2.3, some key definitions and properties of statistical moments and the moment generating function will be highlighted. What is more, the theory of fractional derivatives from section 2.2 will be incorporated in order to extend functionality of the moment generating function. Relevant properties are revisited in this new context, and potential analytical errors of the method are addressed. In section 3, simulation results will be analysed, which further clarify the numerical stability and potential errors of computing fractional moments via the moment generating function. Finally, in section 4, a practical implementation of this method in a financial setting will be considered. The results will be compared against those obtained using traditional methods, with a focus on the implications of potential errors in real-world applications.

2 Methodology

In this section we present the methodological framework for computing fractional moments using different approaches. We begin by reviewing existing methods before introducing an alternative approach based on fractional calculus. The comparative structure of the analysis, both theoretical and empirical, is also outlined.

2.1 Overview of existing methods and introduction to a novel approach

In this subsection we review the traditional method of computing fractional moments and a modern alternative based on the complex moment generating function (CMGF). What is more, we also introduce the motivation for using fractional derivatives applied to the moment generating function, which forms the foundation of this thesis' novel approach.

2.1.1 Existing methods of obtaining fractional moments

The formal definition of the statistical moments mentioned in the previous section is as follows: The n-th moment of a random variable X, with probability density function (PDF) $f_X(x)$

$$\mathbb{E}[X^n] = \begin{cases} \int_{-\infty}^{\infty} (x-c)^n f_X(x)\,dx & \text{if } f_X(x) \text{ is continuous,} \\ \sum_i (x_i - c_i)^n f_X(x_i) & \text{if } f_X(x) \text{ is discrete.} \end{cases}, n \in \mathbb{N}$$

Feller (1957)

The traditional method of computing fractional moments is rather straightforward. Similar to integer moments, one simply computes the summation (in the discrete case) or integral (in the continuous case) of $x^\alpha \cdot f_x(x)$, where $f_x(x)$ denotes the probability density function of the random variable X. In the context of fractional moments, $\alpha \in \mathbb{R}$ instead of $\mathbb{Z}$ (assuming that negative moments exist). Hansen and Tong (2024) introduce an alternative approach to computing fractional moments using the complex moment generating function (CMGF), which they apply in the context of the aforementioned GARCH models. One of their expressions of importance is given by:

$$\mathbb{E}\,|X-\xi|^\alpha = \frac{\Gamma(\alpha+1)}{2\pi} \int_{-\infty}^{\infty} \frac{e^{-\xi z} M_X(z) + e^{\xi z} M_X(-z)}{z^{\alpha+1}} dt$$

where $z = s + it, s \in \mathbb{N}_+, \xi \in \mathbb{R}$ and α of course the order of the moment.

This formulation extends upon the traditional moment generating function (MGF) but avoids the process of taking derivatives, making it computationally efficient. The inclusion of the Gamma function is logical, as it extends the factorial function to real values, aligning well with the computation of fractional moments. Since this method relies on integration, rather than differentiation, it avoids numerical issues that might arise when computing derivatives, such as obtaining rather great approximation errors.

2.1.2 Obtaining fractional moments by using the moment generating function

While the CMGF method provides an efficient and elegant alternative to the traditional method, this thesis explores a different approach: computing fractional moments directly by applying fractional derivatives to the MGF. The MGF is widely used for computing integer moments by differentiation around zero. Extending this approach to fractional orders requires us to take fractional derivatives. Thus, we need to define such fractional derivative operators. These fractional derivatives have a long history and often make use of the aforementioned Gamma function in combination with some integral. This means that, for continuous random variables, where we integrate the MGF, we will have to do double integration. A consequence might be that obtaining analytical expressions of these moments may not always be possible. A great number of alternative expressions of these fractional derivatives have been created, mostly based on different interpretations of the latter in the field of physics. In this thesis, we will focus on computing the MGF using the Riemann-Liouville derivative, the Caputo-Fabrizio derivative and the Grünwald-Letnikov fractional derivative. Each of these fractional derivatives in combination with the MGF might lead to different moments expressions for the same distribution and same fractional order of the moment.

Thus, it is essential to compare each of these definitions with the traditional way of computing fractional moments, to derive their accuracy and conclude which approach is most suitable for fractional moment computation. Similar to the expression of the moments of a random variable, their errors may also be hard to derive analytically, depending on its distribution.

2.1.3 Order and methods of research

In order to compare the aforementioned fractional derivatives, the order of research will be as follows. First, a mathematical groundwork for the fractional derivatives will be laid, in which a number of their respective properties will be discussed. Next, we will revise some basic definitions of statistical moments and the moment generating function and see how some of these properties change when considering fractional moments in combination with the moment generating function. If possible, analytical expressions of the errors for each fractional derivative in combination with the MGF will be computed, which will conclude the theoretical research of this thesis. We will conduct a simulation using the programming language Julia, which is well-known for its focus on data science and fast computations, to now obtain numerical errors instead of analytical errors. The simulation will evaluate each MGF-based method using statistical measures, including minimum, maximum, and average errors. Finally, we will consider a practical case; analyzing volatility and risk of the S&P 500 returns using fractional moments in which all three derivatives will once again be compared.

2.2 Fractional Calculus

In order to obtain Moment Generating Function expressions that allow us to compute moments of fractional order, we need to be able to take fractional derivatives. This section is intended to summarize the history and applications of fractional derivatives and lays the foundation of fractional calculus, as well as to provide a number of examples of fractional derivative.

2.2.1 Overview and applications of fractional derivatives

Although not the main topic of interest of this thesis, it is useful to have some knowledge about the history and applications of fractional derivatives. The study of fractional derivatives has been relevant as early as the year 1695 when the concept of such a derivative was implicitly discussed by Leibniz and Bernoulli Katugampola (2014). Since then, numerous definitions of fractional derivatives have been developed. The best-known definition of the fractional derivative is the Riemann-Liouville derivative, its upper derivative of a function $f(x)$ of order α is denoted as

$$\frac{d^n}{dx^n}\frac{1}{\Gamma(n-\alpha)}\int_a^x (x-t)^{n-\alpha-1}f(t)dt, \text{ where } n=\lceil\alpha\rceil$$

Kilbas et al. (2006). Michele Caputo (1967) defined a variation on this derivative, where instead of $\frac{d^n}{dx^n}$ in front of the integral, we have $\frac{d^n}{dt^n}$ inside the integral. Due to this adjustment, it is possible to have initial value conditions expressed as the traditional derivatives of integer-order, which made these fractional differential equation problems more intuitive. Other fractional derivatives, such as the Hadamard (1892) and Riesz (1949) derivative, have been defined to take advantage of particular beneficial properties. For example, each of the latter derivatives can be written as a Fourier transformation. As a consequence, the analytical expressions, can often be simplified. A rather unique derivative is the Grünwald-Letnikov derivative which, in contrast to all the aforementioned derivatives, is not based on integral. Instead, it generalizes the difference quotient, $\frac{f(x+h)-f(x)}{h}$, to fractional orders using binomial coefficients Atici et al. (2021). This variety of definitions emphasizes how dependent fractional derivatives are on different physical interpretations and practical applications. Beyond their theoretical significance, fractional derivatives have been of significant importance in various scientific fields since the 19th century. Examples include fractional Fourier transformations, a generalization of the regular Fourier transformations Missbauer (2012), fractional diffusion equation models, describing the motion of particles in liquids as a consequence of thermal molecular motions Einstein (1905) and the fractional Schrödinger equation, a generalization of the Schrödinger equation, often used in quantum mechanics Laskin (2002). Their applications are less common in the fields of finance or economics, as fractional derivatives are mainly used to describe natural phenomena Boulaaras et al. (2023). Yet they still offer some great potential. (Symmetric) Levy flights make use of fractional derivatives in order to solve partial differential equations which describe random walk processes in time series Scalas et al. (2000). The development of fractional derivatives also led to the notion of fractional Brownian motions, a generalization of the Brownian motion Mandelbrot and Van Ness (1968). The latter is a continuous-time stochastic process which, similar to Levy flights, may be used to model random walk processes.

2.2.2 Formal definitions of fractional derivatives

In order to obtain the expressions mentioned in 2.1.1, some advanced tools are required. We can find these in the field of fractional calculus. A formal definition of the differintegral operator, which generalizes derivatives and integrals of fractional order, can be found in A. As mentioned in section 2.2.1, quite a number of different definitions have been proposed to compute a fractional derivative. Some of these definitions are rather similar, thus, in this paper, we will focus on some of the more well known fractional derivatives. We will start with the most famous fractional derivative, which laid the foundation of the study of fractional derivatives as early as in 1832.

Definition 2.2.1. The left-side Riemann-Liouville fractional derivative of order α is defined as:

$$D^{\alpha}_{a+}f(x) = \frac{d^n}{dx^n} D_x^{-(n-\alpha)} f(x) = \frac{d^n}{dx^n} \frac{1}{\Gamma(n-\alpha)} \int_a^x (x-t)^{n-\alpha-1} f(t)dt \tag{1}$$

Joseph Liouville (1832).

Here, $n = \lceil \alpha \rceil$, the ceiling function and $\Gamma(.)$ is the Gamma function, see section Appendix A.

Note that we just defined the left-side Riemann-Liouville fractional derivative, suggesting that there also exists a right side derivative. In the case of the latter, we would evaluate the associated integral the other way around. Namely,

$$D^{\alpha}_{b-}f(x) = \frac{d^n}{dx^n} \frac{1}{\Gamma(n-\alpha)} \int_x^b (x-t)^{n-\alpha-1} f(t)dt.$$

We intend on using the left-side derivative, as is supported by Tarasov (2023). The reason is, due to the fact that many functions in probability theory, most importantly the cumulative distribution function, are defined as an integral from some constant to x.

Remark 2.2.1. For values $\alpha \in \mathbb{N}_+, n = \lceil \alpha \rceil = \alpha$, so $\Gamma(n-\alpha) = \Gamma(0)$, which is undefined. Thus for $\alpha \in \mathbb{N}_+$, we define: $D^{\alpha}f(x) = \frac{d^{\alpha}}{dx^{\alpha}} f(x)$, which is simply the regular expression for derivatives of integer order.

A modification of the Riemann-Liouville derivative is the Caputo-Fabrizio derivative, which is defined as follows:

Definition 2.2.2. The Caputo-Fabrizio fractional derivative of order $\alpha, \alpha \in [0, 1)$ is defined as:

$$D^{\alpha}f(x) = \frac{1}{1-\alpha} \int_a^x \exp\left(\frac{-\alpha}{1-\alpha}(x-t)\right) f'(t)dt \tag{2}$$

Caputo and Fabrizio (2015). With $a \in [-\infty, x)$. The Caputo-Fabrizio is always defined as the integral from some constant to the variable x. This is another reason for choosing to work with the left-side Riemann-Liouville integral. In this way, it will be more straightforward to compare the two integrals. What is more, note that for the Caputo-Fabrizio derivative, the order $\alpha \in [0, 1)$. This does not mean, however, that one can only compute fractional derivatives of order 1 or lower. There exists a rather convenient property of the differintegral operator which allows one to combine orders of derivatives, which will be discussed in a moment.

Lastly, we will define the Grünwald-Letnikov derivative, which is defined as follows:

Definition 2.2.3. The Grünwald-Letnikov fractional derivative of order α is defined as:

$$D^{\alpha} f(x) = \lim_{h \to 0} \frac{1}{h^{\alpha}} \sum_{k=0}^{\infty} (-1)^k \binom{\alpha}{k} f(x - kh) \tag{3}$$

Where $\binom{\alpha}{k}$ is the binomial coefficient, with $0 \leq k \leq \alpha$, see section Appendix A.

Zhmakin (2022). It is immediately clear, observing the summation symbol instead of the integral, that this derivative behaves quite differently from the two derivatives defined above. The Grünwald-Letnikov derivative is an extension on derivatives based of the concept of finite differences Flajolet and Sedgewick (1995).

We will consider a number of properties which come in useful when working with fractional derivatives.

Proposition 2.2.1. *The fractional derivatives above adhere to the following properties:*

(i) Linearity: Let $f(x), g(x)$ be functions and $a, b, x \in \mathbb{R}$. Then we have that $D^{\alpha}(af(x) + bg(x)) = a \cdot D^{\alpha} f(x) + b \cdot D^{\alpha} g(x)$.

(ii) $D^{\alpha} f(x) = f(x)$, for $\alpha = 0$

(iii) for sufficiently smooth functions f, we have that $D^{\alpha+\beta} f(x) = D^{\alpha}(D^{\beta} f(x)) = D^{\beta}(D^{\alpha} f(x))$, with $\alpha, \beta \in \mathbb{R}$. Note that, for definition 2.2.2, this property only holds for $\beta \in \mathbb{N}, \alpha \in [0, 1)$.

The proofs of these of the properties stated in this proposition can be found in Appendix B. Most of these proofs have been provided by myself, while some other proofs, which are outside the scope of thesis are based on other papers. Note that the third property is especially useful for the Caputo-Fabrizio derivative. This property allows one to take fractional derivatives of order greater than 1 by comparing fractional derivatives and regular integer derivatives.

We will now provide two explicit examples of these fractional derivatives. For simplicity, we will let $a = 0$:

Example 2.2.1. (i) We consider the Riemann-Liouville derivative of order $\frac{3}{2}$ for some constant $c \in \mathbb{R}$:

$$\begin{aligned} D^{\frac{3}{2}}_{RL}(c) &= \frac{d^2}{dx^2} \frac{1}{\Gamma(2 - \frac{3}{2})} \int_0^x (x - t)^{2 - \frac{3}{2} - 1} c\,dt \\ &= \frac{d^2}{dx^2} \frac{c}{\sqrt{\pi}} \int_0^x (x - t)^{-\frac{1}{2}} dt = \frac{d^2}{dx^2} \frac{-2c}{\sqrt{\pi}} \sqrt{x - t} \Big|_0^x \\ &= \frac{d^2}{dx^2} \frac{2c\sqrt{x}}{\sqrt{\pi}} = \frac{-c}{2x\sqrt{\pi x}} \neq 0. \end{aligned}$$

As stated, the fractional derivative of a constant is not equal to zero when using the Riemann-Liouville derivative. This is also the case for the Grünwald-Letnikov derivative, but not for the Caputo-Fabrizio derivative.

(ii) We compute the semi-derivative of $\frac{x}{2}$ using the Caputo-Fabrizio derivative:

$$D_{CF}^{\frac{1}{2}}\left(\frac{x}{2}\right) = \frac{1}{1-\frac{1}{2}}\int_0^x \exp\left(\frac{-\frac{1}{2}}{1-\frac{1}{2}}(x-t)\right)\frac{1}{2}dt = \int_0^x \exp(t-x)dt$$
$$= \exp(t-x)\Big|_0^x = 1-\exp(-x).$$

For $x \geq 0$, this expression is equal to the CDF of the exponential distribution with $\lambda = 1$. A remarkable result.

The observant reader might notice that no explicit examples of the Grünwald-Letnikov derivative have been provided. The latter is due to the fact that is rather difficult to obtain analytical expressions for this derivative. Thus, later on in this thesis, when computing fractional moments and their associated biases, the main focus for the Grünwald-Letnikov derivative will be on its numerical computations.

Remark 2.2.2. As shortly mentioned in the introduction, it is possible to generalize the order of derivatives even further, extending α to be in $\mathbb{C}$ instead of $\alpha \in \mathbb{R}$. This means that, when combining such derivatives with the moment generating function, we will obtain complex moments. Since statistical moments of complex order do almost not find any usage in applications, as they lack interpretability, they are not the main focus of this research. For the interested reader, Love (1971) has done some impressive research on the fundamentals of derivatives of complex order. The obtained expressions are somewhat similar to those of the fractional derivatives which have been discussed above.

2.3 The Moment Generating Function

Having defined the techniques required to compute fractional derivatives, we now turn to their application to the Moment Generating Function (MGF). Before proceeding, we will briefly review some key concepts related to statistical moments.

2.3.1 Moments

Definition 2.3.1. Let X be a random variable. The α-th moment of a X is defined as:

$$\mathbb{E}[X^\alpha] = \begin{cases} \int_{-\infty}^{\infty}(x-c)^\alpha f_X(x)\,dx & \text{if } X \text{ is continuous,} \\ \sum_i (x_i - c_i)^\alpha f_X(x_i) & \text{if } X \text{ is discrete.} \end{cases}$$

with, in the context of this paper $\alpha \in \mathbb{R}$. Here $f_X(x)$ is the probability density function if X is a continuous random variable, and the probability mass function if X is a discrete random variable Feller (1957).

If $c = \mu_x$, the first moment of $f(x)$, then our higher moments are called central moments. In the context of this research, we will focus on the case $c = 0$, corresponding to raw moments of a random variable X. This choice has been made as the Moment Generating Function, which we will soon define, only computes raw moments of higher order. A moment of order α is said to exist, if $\mathbb{E}[X^\alpha] < \infty$.

2.3.2 The Moment Generating Function

We now formally introduce the Moment Generating Function, one of the most significant subjects of this thesis.

Definition 2.3.2. The Moment Generating Function (MGF) of a variable X, is defined as

$$M_X(t) = \mathbb{E}[e^{tX}]$$

provided that $\mathbb{E}[e^{tX}] < \infty$, for all $t \in (-h, h)$, which contains 0, for some $h > 0$ Mackey (1980).

Remark 2.3.1. Deriving the expression $M_X(t) = \mathbb{E}[e^{tX}]$ is typically straightforward. Generally, it simply requires a handful of steps of analytic evaluation. This procedure is not that interesting nor relevant to this research. Thus, when making use of expressions of the Moment Generating Function, we will simply refer to the distribution table in Appendix D.

We will state the theorem which makes the MGF so useful. This theorem allows us to compute moments of higher order by taking derivatives of the given order instead of integrals.

Theorem 2.3.1. *If $M_X(t)$ exists on some interval $(-h, h)$, as defined before, we have that:*

$$\mathbb{E}[X^n] = M_X^{(n)}(0), \textit{ for } n \in \mathbb{N}$$

Casella and Berger (2002)

We introduce the following properties for the Moment Generating Function $M_X(t)$:

Proposition 2.3.1. *For X, Y random variables, we have that:*

(i) $M_X^{(0)}(t) = \mathbb{E}[e^{0X}] = 1$. *This property can be used to confirm that a given function is a valid probability density function (i.e., integrates to one).*

(ii) Location scale-transform. Assuming $M_X(t)$ exists, for constant μ, σ, we have that:

$$M_{\mu+\sigma X}(t) = e^{\mu t} \cdot M_X(\sigma t)$$

(iii) If $X \perp Y$, then $M_{X+Y}(t) = M_X(t) \cdot M_Y(t)$.

Lin (2022)

The proofs of the latter can be found in Appendix B.

There are several additional topics closely related to the MGF, including Fourier transforms, Laplace transforms, Wick rotations, and characteristic functions. While these subjects are relevant to the theoretical foundation of the MGF , they fall outside the scope of this paper and will therefore not be discussed. Readers interested in exploring these concepts further may find Kolmogorov and Fomin (1999) to be a valuable resource.

2.3.3 Computing negative moments using the Moment Generating Function

In specific cases, as were mentioned in section 1, moments of negative order can be of interest to characterize the data. Such an example was the moment of order $-\frac{1}{2}$, which in some contexts may be used to obtain the Sharpe Ratio. Thus, it is useful to understand how to compute moments of such orders. We will consider the continuous case:

$$\mathbb{E}[X^{-n}] = \int_{-\infty}^{\infty} x^{-n} f_X(x) dx = \int_{-\infty}^{\infty} \left(\frac{1}{x}\right)^n f_X(x) dx.$$

We immediately observe a rather obvious problem. This integral is undefined at $x = 0$ and diverges in a neighbourhood around zero. Khuri and Casella (2002) have stated the following corollary for the existence of a moment with negative first order:

Corollary 2.3.1. *If $f_X(x)$ is a continuous pdf defined on $(-\infty, \infty)$, and if*

$$\lim_{x \to 0} \frac{f_X(x)}{|x|^\alpha} < \infty$$

for $\alpha > 0$, then

$$\mathbb{E}[X^{-1}] \text{ exists.}$$

Most common distribution functions do not adhere to this corollary, however, the Gamma function does (see B.2).

If such a moment of negative order exists, we should be able to obtain it using the Moment Generating Function. In the 20-th century, Cressie et al. (1981) have published the following remarkable theorem:

Theorem 2.3.2. *Assuming the negative n-th raw moment exists, the negative n-th raw moment can be computed as follows:*

$$\mathbb{E}[X^{-n}] = \frac{1}{\Gamma(n)} \int_0^\infty t^{n-1} M_X(-t) dt$$

where n is a positive integer.

The proof of this Theorem can be found in Appendix B.

Since this is an extension on the regular functions of the MGF, this technique is of interest of this paper. Thus, it will be shortly be discussed. We compute the first inverse moment of the Gamma distribution, by making use of the latter theorem for Moment Generating Functions.

Example 2.3.1. Let

$$f_X(x) \sim \Gamma(\alpha, \lambda) = \frac{x^{\alpha-1} e^{-\lambda x} \lambda^\alpha}{\Gamma(\alpha)}, M_X(t) = \left(\frac{\lambda}{\lambda - t}\right)^\alpha$$

$$\mathbb{E}[X^{-1}] = \frac{1}{\Gamma(1)} \int_0^\infty t^{(1-1)} \left(\frac{\lambda}{\lambda - (-t)}\right)^\alpha dt = \int_0^\infty \left(\frac{\lambda}{\lambda + t}\right)^\alpha dt$$

$$= \lambda^\alpha \int_0^\infty (\lambda + t)^{-\alpha} dt, \text{ Let } u = \lambda + t, \frac{du}{dt} = 1, dt = du :$$

$$\lambda^\alpha \int_0^\infty u^{-\alpha} du = \lambda^\alpha \frac{u^{1-\alpha}}{1-\alpha}\Big|_0^\infty = \lambda^\alpha \frac{(\lambda + t)^{1-\alpha}}{1-\alpha}\Big|_0^\infty$$

$$= \lambda^\alpha \left(0 - \frac{\lambda^{1-\alpha}}{1-\alpha}\right) = \frac{-\lambda}{1-\alpha} = \frac{\lambda}{\alpha - 1}.$$

Which corresponds with our result from example B.2.

2.3.4 Extending the MGF to fractional order

Now that we have introduced the definitions of the MGF and discussed a number of relevant properties, we will combine these with the techniques developed in section 2.2. Therefore, we can at last obtain moments of fractional order using the MGF.

To avoid confusion regarding what fractional derivative is being used in combination with the MGF, we will from now on, work with the following notation:

Definition 2.3.3. We define the MGF of order $\alpha \in \mathbb{R}$ by ${}_{RL}M_X^{(\alpha)}, {}_{CF}M_X^{(\alpha)}, {}_{GL}M_X^{(\alpha)}$ for the MGF in combination with the Riemann-Liouville, Caputo-Fabrizio and Grünwald-Letnikov fractional derivative respectively.

Remark 2.3.2. The three properties mentioned in proposition 2.3.1 still hold for the MGF of fractional order. This is the case as the first property makes makes use of the derivative of order 0. Which has been defined to just be the original function itself as stated in the second property of proposition2.2.1. The other two properties do not involve any derivatives of any order. Thus, they are generally applicable to the MGF, regardless of its order or kind of derivative.

Before stating any results about the accuracy of these new MGF expressions, we first consider a numerical example to illustrate the interaction between fractional derivatives and the MGF.

Example 2.3.2. (i) We let $f_X(x_i) \sim Bernoulli(p)$, with $\mathbb{P}(X = 1) = p$ and with associated MGF expression: $M_X(t) = (1 - p) + p \cdot \exp(t)$, now we consider

$$ {}_{CF}M_X^{(\frac{1}{2})} = \frac{1}{1 - \frac{1}{2}} \int_{-h}^{t} \exp\left(\frac{\frac{-1}{2}}{1 - \frac{1}{2}} (t - s) \right) M'_X(s) ds. $$

In this case, the domain of $M_X(t) = (-\infty, \infty)$, so we let $-h = -\infty$, and $M'_X(s) = p \cdot \exp(s)$, thus we obtain:

$$ {}_{CF}M_X^{(\frac{1}{2})} = 2 \int_{-\infty}^{t} \exp\left((s - t)\right) \cdot (p \cdot \exp(s)) ds. $$

$$ = 2p \cdot \exp(-t) \int_{-\infty}^{t} \exp(2s) ds $$

$$ = p \cdot \exp(-t) \left(\exp(2s) \Big|_{-\infty}^{t} \right) = p \cdot \exp(t) $$

Now, all that is left to do is set $t = 0$ and we obtain that ${}_{CF}M_X^{(\frac{1}{2})} = p$.

(ii) Computing $\mathbb{E}[X^{\frac{1}{2}}]$ in the traditional fashion, we obtain:

$$ \mathbb{E}[X^{\frac{1}{2}}] = \sum_x x^{\frac{1}{2}} \mathbb{P}(X = x) = 0^{\frac{1}{2}} \cdot \mathbb{P}(X = 0) + 1^{\frac{1}{2}} \cdot \mathbb{P}(X = 1) $$

$$ = 0 \cdot (1 - p) + 1 \cdot p = p $$

It is amazing and maybe even somewhat surprising that both expressions obtain the same result. Indeed, this result is actually more of a coincidence. It is important to note that this agreement of results is coincidental and specific to the chosen distribution. Namely, all raw higher moments of a Bernoulli random variable are p. If we had taken any other distribution in combination with a moment of fractional order, it becomes highly likely that the MGF returns a different value compared to the traditional method of computing moments. What is more, if we were to take

$$ {}_{RL}M_X^{(\frac{1}{2})} = \frac{d}{dt} \frac{1}{\sqrt{\pi}} \int_{-h}^{t} (t - s)^{\frac{-1}{2}} f(s) ds $$

we obtain an integral which may diverge based on the choice of $-h$. These observations lead to the following theorem.

Theorem 2.3.3. *Consider the three MGF's as defined in definition 2.3.3. Assume ${}_{RL}M_X^{(\alpha)}$ and ${}_{GL}M_X^{(\alpha)}$ are well defined on some open interval $(-h, h)$, then the moment generating function expressions ${}_{RL}M_X^{(\alpha)}$ and ${}_{GL}M_X^{(\alpha)}$ accurately obtain moments of order $\alpha \in \mathbb{R}$*

The proof can be found in Appendix B.
Unfortunately, this result does not hold for ${}_{CF}M_X^{(\alpha)}$, which leads to the following theorem.

Theorem 2.3.4. *Consider the three MGF's as defined in definition 2.3.3. Assume ${}_{CF}M_X^{(\alpha)}$ is well defined on some open interval $(-h, h)$, then the moment generating function expression ${}_{CF}M_X^{(\alpha)}$ inaccurately approximates moments of order $\alpha \in \mathbb{R}$ with approximation error given by*

$$\begin{cases} \displaystyle\int_{-\infty}^{\infty} x^\alpha f_X(x)dx - \int_{-\infty}^{\infty} \frac{x^{n+1}}{(1-\beta)x+\beta} f_X(x)dx & \text{if } X \text{ is continuous,} \\ \displaystyle\sum_i \left(x_i^\alpha - \frac{x_i^{n+1}}{(1-\beta)x_i+\beta} \right) f_X(x_i) & \text{if } X \text{ is discrete.} \end{cases}$$

with $\alpha \in \mathbb{R}, \beta = \alpha - n$ and $n = \lfloor \alpha \rfloor$.

The proof can be found in Appendix B.

Remark 2.3.3. In the case when $\alpha \in \mathbb{N}$, we have that $n = \alpha$, and thus $\beta = 0$, therefore, ${}_{CF}M_X^{(\alpha)}$ is accurate for integer orders. This is an expected result, as the MGF for integer moments is accurate and from section 2.2 we know that $D_{CF}^{\alpha+\beta} f(x) = D_{CF}^{\alpha}(D_{CF}^{\beta} f(x))$, with $\alpha \in \mathbb{N}, \beta \in [0, 1)$. In this case, let $\beta = 0$. So we get $D_{CF}^{\alpha+0} f(x) = D_{CF}^{\alpha} f(x)$ which is just a regular derivative of integer order.

3 Error Analysis

We now focus on computing the newly obtained MGF expressions numerically. To highlight the errors of the Caputo-Fabrizio MGF, moments of various orders with different parameter configurations will be computed. However, before computing these errors involving explicit distributions, we first focus on the expression

$$E(x, \alpha) = x^\alpha - \frac{x^{n+1}}{(1-\beta)x+\beta}$$

which is of great importance in order to fully comprehend the errors discussed in section 3.3

3.1 Analysing a particular error term of interest of the Caputo-Fabrizio MGF

We explicitly focus on the term

$$E(x, \alpha) = x^\alpha - \frac{x^{n+1}}{(1-\beta)x+\beta}$$

for simplicity. The expression we analyse, denoted $E(x, \alpha)$ is not the same as the expression obtained in theorem 2.3.4. Yet, it is the part of the expression that involves the order α and is thus of great interest. What is more, considering the result obtained in theorem 2.3.4, it is easy to see that ${}_{CF}M_X^{(\alpha)}$ is accurate $\iff$ $x^\alpha = \dfrac{x^{n+1}}{(1-\beta)x+\beta}$. Thus, we consider the function $E(x, \alpha)$, to be the function of their differences and analyse when this function equals zero. Plotting this expression for different orders of α, we obtain the following figure:

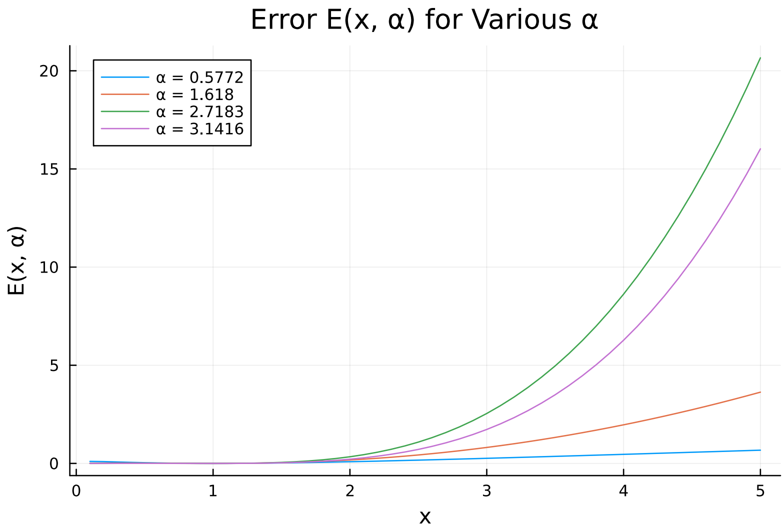

Figure 1: Error of Caputo-Fabrizio MGF

It can be observed from figure 1 above that, in general for greater orders α, the error tends to increase. However, the greatest order of α does not provide the greatest error. Instead it is the second greatest order of α that does so. This may be explained by the fact that for values of α, being exactly in the middle of two integers, the value of $(1-\beta)x+\beta$ will be the greatest. As a result, the fraction becomes small, so the error tends to increase.

This hypothesis is indeed confirmed in the following figure, which focuses on the growth rate of the error, for a fixed value of x and an increasing order α.

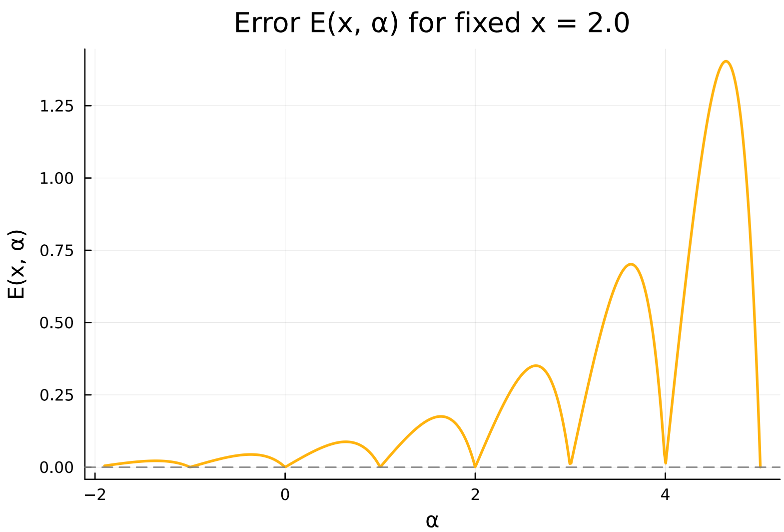

Figure 2: Error of Caputo-Fabrizio MGF, for fixed x

Figure 2 indeed seems to indicate that for some $\alpha \in (a, b)$, where $a, b \in \mathbb{Z}$ are consecutive integers that $E(x, \alpha)$ attains it maximum value for some α 'slightly greater' than $\frac{a+b}{2}$. Figure 2 also reveals that the approximation error is considerably smaller for negative fractional moments compared to the positive ones. This suggests that, when negative moments are well-defined, the Caputo-Fabrizio MGF might still offer reasonable accuracy, despite its known limitations.

Note that within each integer interval, the function $E(x, \alpha)$ appears to be concave. Thus, as is supported by figure 2, it is only possible to obtain local maxima. Ideally, one would aim to analytically determine the optimal order $\hat{\alpha}$ such that minimizes $E(x, \hat{\alpha})$. However, due to the concavity of $E(x, \hat{\alpha})$, such analytical minimization is not feasible. Figure 2 seems to suggest that order of α near integer orders yields smaller approximation errors, which makes sense intuitively. However, the latter is not rigorous evidence. Therefore, in the following section, we will analyse the numerical approximation errors of the Caputo-Fabrizio MGF by simulation. We will use numerical methods to try to obtain values α which minimize the expression from theorem 2.3.4.

We have seen in the previous section how the error $E(x, \alpha) = x^\alpha - \dfrac{x^{n+1}}{(1-\beta)x + \beta}$ changes with increasing values of α. Now, we focus on the entire expression, as stated in theorem 2.3.4.

3.2 Practical Issues

Computing these expressions poses some difficulties. In the first place, we want to compute the moment of fractional order α for a random variable X. Julia does not have any packages to compute raw moments of such an order, thus these methods will have to be created first. In order to accomplish the desired result, we directly compute $\int_{-\infty}^{\infty} x^\alpha f_X(x)dx$. If the support of the random variable is infinite, this integral is often not numerically well defined. Thus, in such cases we use a bounded support $(-1000, 1000)$ which provides a sufficient accurate approximation. What is more, for many fractional orders α in combination with negative values of x, x^α is of complex form. To avoid such expressions, given that the distribution is symmetric, we simply integrate the PDF over its non-negative support and factor the final value by 2. In this manner, it is still possible to obtain fractional moments of distributions such as the Normal distribution. If a distribution has a negative support and is not symmetric, it is possible to compute the complex or absolute moment of fractional order, which avoids any numerical issues. This approach, however, lacks interpretability, as the intuition behind absolute and complex moments is harder to grasp.
It now remains to compute the fractional moment using the Caputo-Fabrizio MGF. Unfortunately, it is rather difficult to compute the fractional derivative of an MGF expression numerically. The reason is, that programming packages often take (fractional) derivatives on a certain point x rather than over the entire function. Thus, we simply use the result obtained in theorem 2.3.4. That is, instead of the moment of order α, the Caputo-Fabrizio MGF computes the moment of order $n+1$ divided by some variables dependent on α. More explicitly, we compute ${}_{CF}M_X^{(\alpha)}(0) = \displaystyle\int_{-\infty}^{\infty} \frac{x^{n+1}}{(1-\beta)x + \beta} f_X(x)$. This integral faces the same problems as the aforementioned integral with x^α. What is more, for specific values of x and β, the denominator tends to go towards zero, which is numerically unstable. Thus, in such cases, we add a rather small ϵ in order to avoid this issue.

3.3 Accuracy Analysis

For this accuracy analysis we consider different parameter values and orders of α. We set $\alpha \in [0, 5]$ with steps of 0.01. This yields 500 errors per parameter-configuration, which provides us with a viable sample to analyse the characteristics of the errors. Whenever possible, we extend α to the interval $(-1, 0)$. We consider three distributions, namely the Exponential, Normal and Poisson distribution. This selection allows us to cover both continuous and discrete distributions, distributions with negative and positive supports and symmetric distributions. The observant reader might notice that all of the errors in the upcoming sections are non-negative and may incorrectly conclude that these are the absolute or squared errors. This is not the case. In each case we compute the expression obtained in theorem 2.3.4, for a different distribution. Since the expression $E(x, \alpha) = x^\alpha - \dfrac{x^{n+1}}{(1-\beta)x + \beta}$ is always non-negative, it follows that $x^\alpha \geq \dfrac{x^{n+1}}{(1-\beta)x + \beta}$ and thus $\int_{-\infty}^{\infty} x^{\alpha} f_X(x)dx \geq \int_{-\infty}^{\infty} \frac{x^{n+1}}{(1-\beta)x+\beta} f_X(x)dx$ for any distribution, such that the expression from theorem 2.3.4 is always non-negative.

3.3.1 Exponential Distribution

First we consider the Exponential distribution with PDF as defined in Appendix D. The support of the Exponential distribution is $[0, \infty)$, thus the integration process will avoid most numerical issues. Moreover, all relevant moments of the Exponential distribution are based on raw moments, which is precisely the kind of moments we are interested in.
We obtain the following figure:

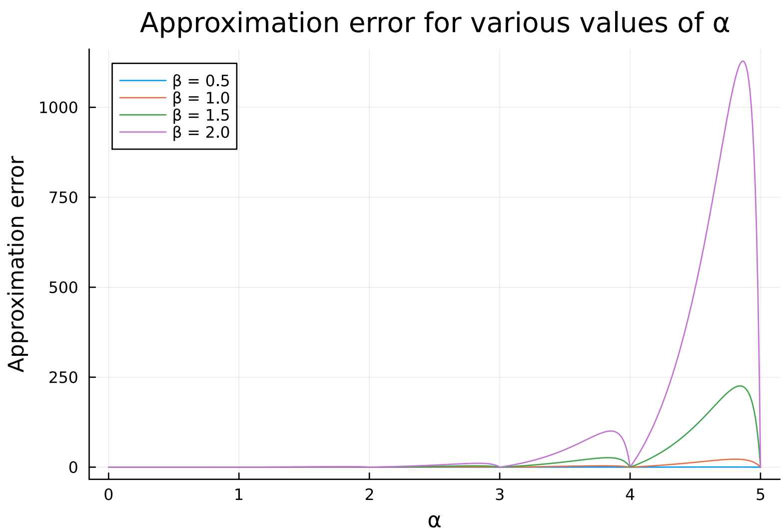

Figure 3: Approximation error for the Exponential Distribution

From figure 3, it is clear that for a greater parameter value β the approximation error increases. Namely, for moments of higher order ($\alpha \geq 3$), the approximation error increases rapidly. For smaller orders of α the approximation errors remain relatively low. In practice, moments of order $\alpha > 4$ are oftentimes not of interest. Thus, the greatest approximation errors will be avoided.

We obtain the following associated table with some core statistics:

β	**minimum**	**maximum**	**mean**	**standard deviation**	**skewness**	c_v
0.5	0.0	0.329	0.074	0.083	1.762	1.12
1.0	0.0	22.119	2.907	5.612	2.314	1.93
1.5	0.0	225.731	25.477	54.91	2.513	2.155
2.0	0.0	1128.26	115.489	265.154	2.655	2.296

Table 1: Exponential Distribution - Approximation Error Statistics

The results in table 1 align with the conclusions derived in figure 3. The greater the values of β and order of α, the greater the (average) approximation error. For all values of β, the minimum error is zero, which occurs when $\alpha \in \mathbb{N}$. An interesting observation is that for $\beta = 1.5$ the average approximation error exceeds the maximum approximation error for $\beta = 1.0$. For all values of β, the skewness is positive, implying that the distribution of the approximation errors is right-skewed. Thus, clearly the distribution of the errors is not symmetric and therefore certainly not a Normal distribution. In the last column, the Coefficient of Variation has been reported, which has been given by the formula $\frac{\sigma}{\mu}$, where μ and σ denote the sample and sample standard deviation respectively Hendricks and Robey (1936). This metric of measurement allows us to objectively compare the variability of the errors of each of the parameter configurations. The lower c_v, the lower the variability and thus the more consistent the dataset. This consistency is something we strive for, as it allows us to describe our data with greater confidence. From table 1, it is clear that the Coefficient of Variation increases as the parameter β increases. For $\beta = 0.5$ all result are reasonable. The Caputo-Fabrizio MGF in combination with the Exponential(0.5) could still be viable in practice. For Exponential(1), this conclusion may depend on the maximum order of α.

3.3.2 Normal Distribution

We now consider X to be Normally distributed with mean μ and standard deviation σ, as defined in Appendix D. This distribution is of particular interest as it has two parameters. Thus, we can analyse the differences of effect of both parameters on the approximation error. Therefore, while raw fractional moments of the Normal distribution are not commonly used in practice, we can still obtain valuable insights from this simulation. The Normal distribution is symmetric with domain $x \in \mathbb{R}$. So, we integrate the PDF over the interval $(0, 1000)$ to avoid numerical issues.

We obtain the following figure:

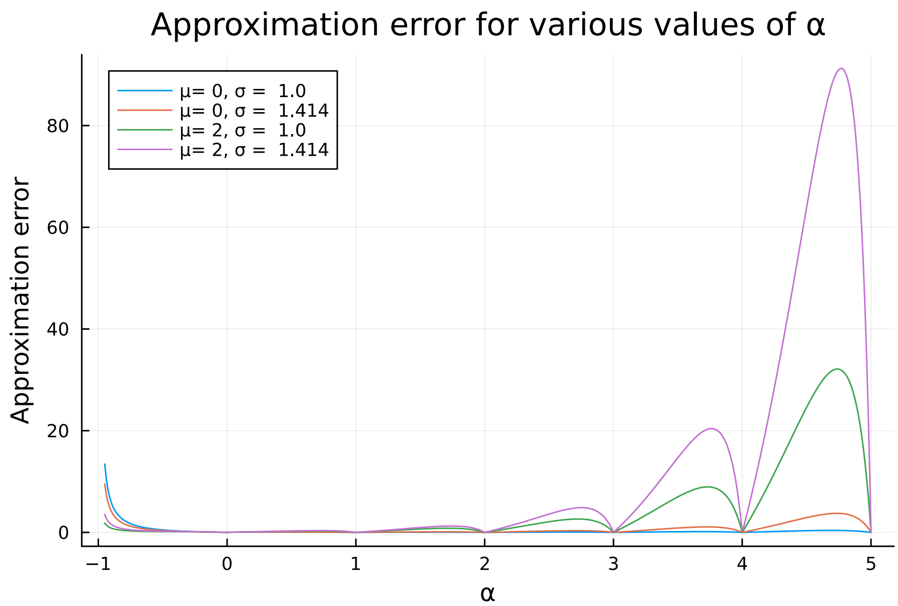

Figure 4: Approximation error for the Normal Distribution

As illustrated in figure 3, the approximation error increases with μ and σ. This result is consitent with the result obtained for the Exponential distribution. However, the magnitude of the errors of the Normal distribution is considerably smaller. Furthermore, the figure also displays the errors for order $\alpha \in (-0.95, 0)$. These errors tend to attain the same size as errors for order α near 3. Interestingly, for negative orders of α, the effect of the parameter values seems to reverse. Larger values of μ and σ are associated with smaller approximation errors.

We obtain the following associated table with some core statistics:

μ	σ	**minimum**	**maximum**	**mean**	**standard deviation**	**skewness**	c_v
0.0	1.0	0.0	13.439	0.298	1.07	7.898	3.591
0.0	1.414	0.0	9.505	0.7	1.141	2.824	1.629
2.0	1.0	0.0	32.123	4.517	8.055	2.269	1.783
2.0	1.414	0.0	91.231	11.411	22.404	2.428	1.963

Table 2: Normal Distribution - Approximation Error Statistics

The statistics in table 2 support the visuals conclusions drawn from figure 4. The average of the approximation error for $\mu = 0$ is acceptable. However, the size of its Coefficient of Variation compared to the other parameter configurations is remarkable. Indeed, configuration $(\mu, \sigma) = (0, 1)$ and configuration $(\mu, \sigma) = (0, \sqrt{2})$ have a rather similar standard deviation, however, the latter has approximately twice the average error. Except for this case, c_v again tends to increase as the parameter values increase, suggesting higher variability in approximation errors. Similar to the Exponential distribution, for all parameter-configurations, the distribution of the errors is right-skewed. Thus, the approximation errors of a Normal distribution are not Normally distributed themselves! This result is confirmed in figure 5. Even in the histogram of the parameter-configuration with the greatest parameter values, more than 50 percent of the approximation errors cluster around zero, with only a small number of observations falling in the range $(40, 80)$. As before, the average errors and variability for large parameters may be too great to be reliable depending on the context of the application.

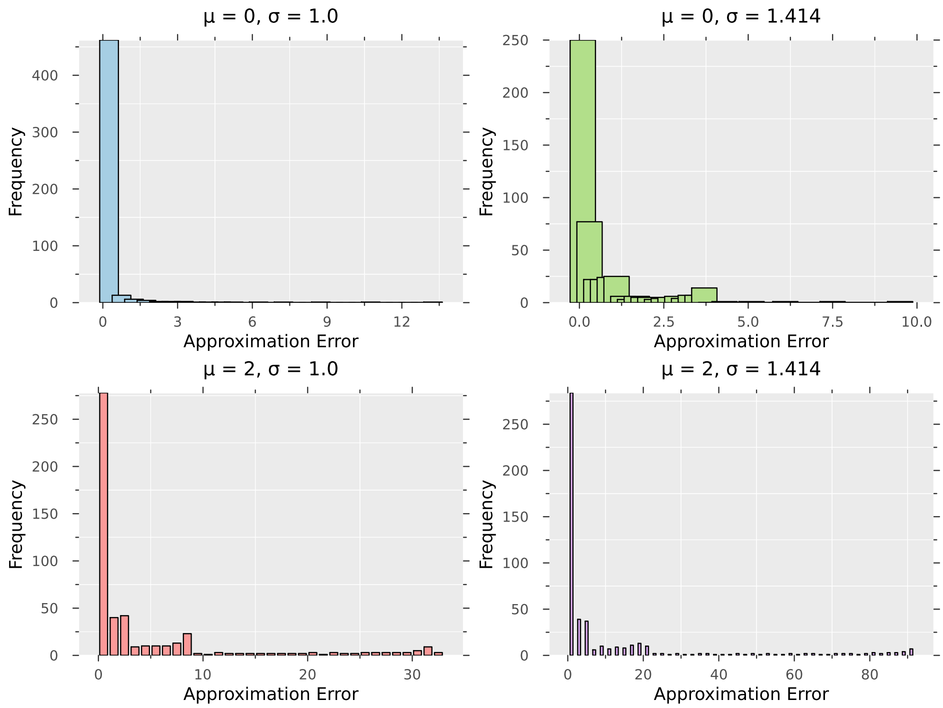

Figure 5: Error Histogram for the Normal Distribution

3.3.3 Poisson Distribution

Finally, we consider a discrete distribution to explore if these results differ from those of the continuous distributions. Specifically, we let $X \sim Poisson(\lambda)$, with the probaility mass function defined as in Appendix D. The Poisson distribution has positive support and its raw moments are given by:

$$\mathbb{E}[X^k] = \sum_{i=0}^{k} \lambda^i \left\{ {k \atop i} \right\}$$

with $k \in \mathbb{N}$ and where $\{\}$ denotes the Stirling numbers of the second kind (rather similar to the binomial coefficient) Haight (1967). This formula highlights that we cannot consider moment of negative order, as the expression relies on factorials and other combinatorial terms.

We obtain the following figure:

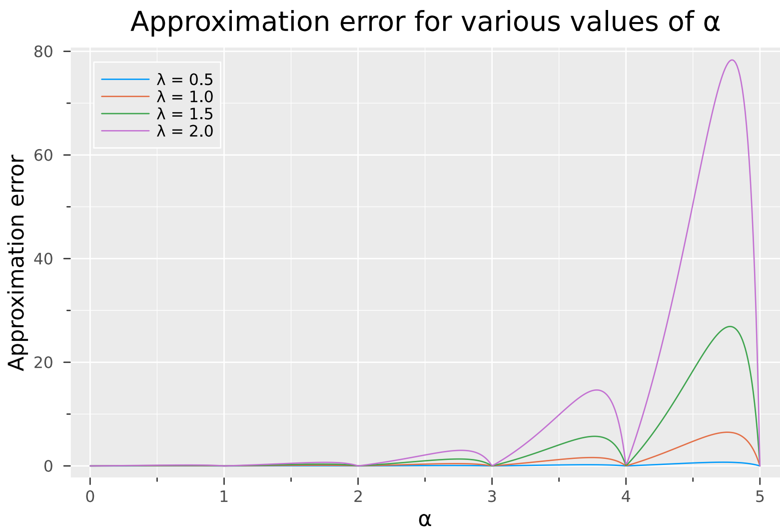

Figure 6: Approximation error for the Poisson Distribution

As shown in figure 6, the general trend of the Caputo-Fabrizio MGF errors in the case of the Poisson distribution, is consistent with that observed for continuous functions. Larger values of λ lead to greater approximation errors. The magnitude of the errors is comparable to that of the Normal distribution, and increases significantly for $\alpha \geq 3$.

λ	**minimum**	**maximum**	**mean**	**standard deviation**	**skewness**	c_v
0.5	0.0	0.715	0.128	0.191	1.915	1.494
1.0	0.0	6.5	1.021	1.713	2.075	1.679
1.5	0.0	26.904	3.895	7.001	2.176	1.797
2.0	0.0	78.34	10.687	20.143	2.251	1.885

Table 3: Poisson Distribution - Approximation Error Statistics

The statistics in table 3 further support this conclusion. As with previous distributions, the distribution of the errors is right-skewed and the Coefficient of Variation increases as the parameter, λ, grows. For $\lambda = 0.5$ and $\lambda = 1.0$, we can still obtain reliable computations. For $\lambda = 1.5$, the results are still potentially viable, depending on the application and the importance of higher-order fractional moments. In order to minimize its associated standard deviation, one can consider a smaller maximum order of α. In contrast, the configuration $\lambda = 2.0$ is likely to be too unreliable in practice, especially for order $\alpha > 3$.

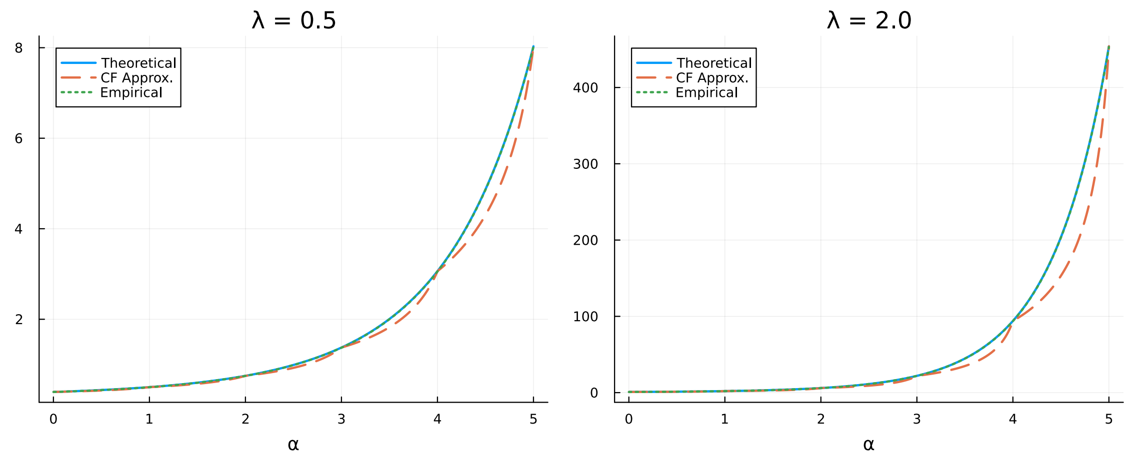

Figure 7: Comparison of different fractional moments for the Poisson Distribution

The figure above depicts the values of fractional moments for various orders α and $\lambda \in \{0.5, 2.0\}$ as computed using the Caputo-Fabrizio MGF, the two accurate MGFs and the an empirical method. The latter takes a million random samples of the Poisson distribution and computes the mean of order α. The values of the accurate MGFs (blue line) and empirical values (dashed green-line) almost completely agree, confirming the accuracy and useability of the former. The values obtained by the Caputo-Fabrizio MGF are always smaller or equal to the values of the accurate MGF expressions. This observation is in line with the result that the errors are always non-negative. Note that, when the parameter λ becomes 4 times as great, the values of the fractional moments increase by more than 50 times their size. This again confirms that the approximation errors increase as the parameter values increase.

3.4 General results

Based on the three distributions analysed, we arrive at the following general conclusions:

- As the parameter value of the underlying distribution increases, both the average and maximum approximation error tend to increase.
- For all distributions considered, higher parameter values, lead to greater standard deviations in the approximation errors.
- Furthermore, the Coefficient of Variation also increases with larger parameter values, indicating that the standard deviation increases at a higher rate than the mean - a stronger result than the increase in the standard deviation alone.
- For all considered distributions and parameter values, the distribution of the approximation errors is right-skewed. Thus, we can conclude that the latter does not follow a Normal, or any other symmetric, distribution.

These findings raise important considerations regarding the reliability of the Caputo-Fabrizio MGF in practice. While high parameter values often result in a large Coefficient of Variation, suggesting that the quality of the approximation may behaves inconsistently, figure 5 offers a different perspective. Namely, in the case of the Normal distribution, at least 50 percent of the errors are clustered around zero. Most importantly, in this section, we are considering a sample of approximation errors of 500 fractional moments. When applying moments of fractional order in practice such as in Hansen and Tong (2024), Mikosch et al. (2013) or Gzyl et al. (2013), one usually computes no more than five moments. Considering the latter, metrics such as the standard deviation and Coefficient of Variation may not always be relevant or decisive when evaluating the usability of the Caputo-Fabrizio MGF. Therefore, rejecting a parameter configuration solely based on its high variability may be too strict. In general, as long as the fractional order of the moment remains below 3 or is close to an integer, the Caputo-Fabrizio MGF tends to yield sufficiently accurate results. This supports its viability in practical cases, such as in Hansen and Tong (2024), where only fractional moments of relatively low order are of interest.

4 Practical Case

To demonstrate the usage of the Moment Generating Function for computing moments of fractional order, we consider a dataset containing the weekly S&P 500 index from the second week of January 2000 up until the last week of December 2024, provided by Wharton Research Data Services.

4.1 First look at the data

The following figure depicts the trend of the S&P 500 index over time:

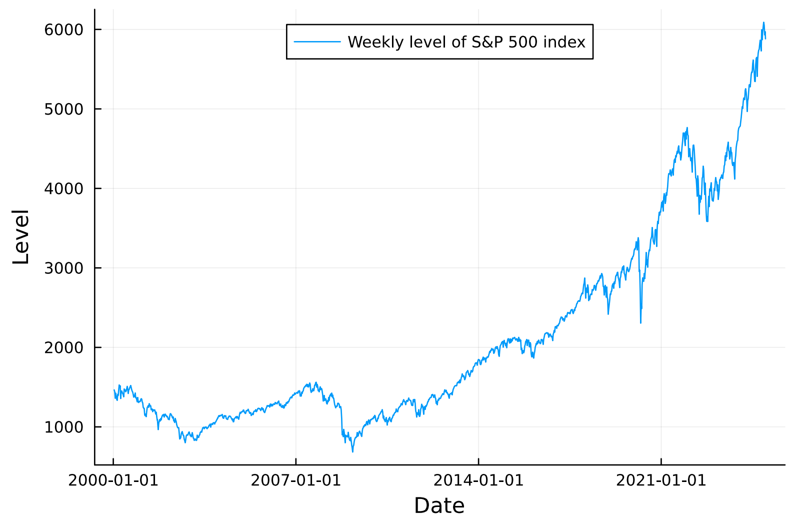

Figure 8: S&P 500 level over time

It is clear from figure 8 that the S&P 500 index is non-stationary, as the mean of the process is not constant. We prefer to work with data that is stationary, thus we consider the log-returns (variations in stock-price) as shown in figure 9. These values have been scaled by a factor of 100 to express them as percentages

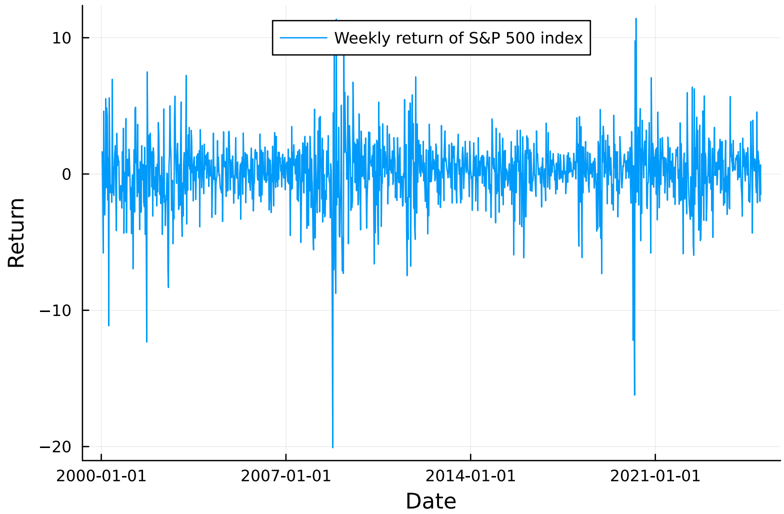

Figure 9: S&P 500 log-returns over time

The log-returns series appears more suitable for volatility analysis compared to the data displayed in figure 8. The mean of the log-returns seems to be stationary (lying around zero), the variance of the log-returns also seems to remain constant over time. Additionally, there are no signs of seasonality. Notable spikes in the log-returns around 2008 and 2021 likely correspond the global financial crisis and COVID pandemic respectively. In times of (financial) uncertainty, it is more likely that returns may take more extreme values, making them less predictable.

The following core statistics of the log-returns, as displayed in figure 9 have been computed:

Mean	**Variance**	**Skewness**	**Kurtosis**	**P-value**
0.108	6.17	-0.878	7.225	1e-99

Table 4: Summary Statistics log-returns of S&P 500

Indeed, as anticipated, the (unconditional) mean seems to be around zero. Moreover, the rather great value of the kurtosis in table 4 indicates that the log-returns of the S&P 500 are not normally distributed, as this value is far greater than 3 which is expected in the context of financial markets, due to frequent occurrence of extreme values. The normal distribution, known for its thin tails, underestimates the probability of such extremes. The p-value included in table 4 is the associated p-value of the augmented Dickey-Fuller unit root test, with null hypothesis: the log-returns of the s&P 500 stock index is a unit root process. The p-value is so small that we reject the hypothesis at any conventional significance level. Thus, we can formally conclude that the weekly log-returns of the S&P 500 index are stationary.

4.2 Modelling volatility of the log-returns

It is well known that the stock prices, as well as the mean of log-returns, cannot be predicted. Therefore, we focus on the volatility of the log-returns instead. A widely used approach is the autoregressive conditional heteroskedasticity model of order q, denoted ARCH(q), introduced by Engle (1982). With observation equation:

$$r_t = \sigma_t \cdot \epsilon_t \tag{4}$$

and updating equation:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \cdot r_{t-i}^2 \tag{5}$$

Another commonly used model is the Generalized Conditional Heteroskedasticity model of order (p, q), denoted GARCH(p, q), as proposed by Bollerslev (1986) with observation equation

$$r_t = \sigma_t \cdot \epsilon_t \tag{6}$$

and updating equation:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \beta_i \cdot \sigma_{t-i}^2 + \sum_{i=1}^{q} \alpha_i \cdot r_{t-i}^2 \tag{7}$$

To determine which model is more appropriate for monitoring volatility, we first examine the autocorrelation function (ACF) of the data. The ACF of log-returns is typically close to zero, and is therefore considered to be negligible in practice. Instead, we analyse the autocorrelation function of the squared log-returns. The following figure depicts the autocorrelation function of the squared log-returns (note that the first index at $t = 0$ has been removed as $corr(r_i, r_j)$ is always equal to 1 for $i = j$).

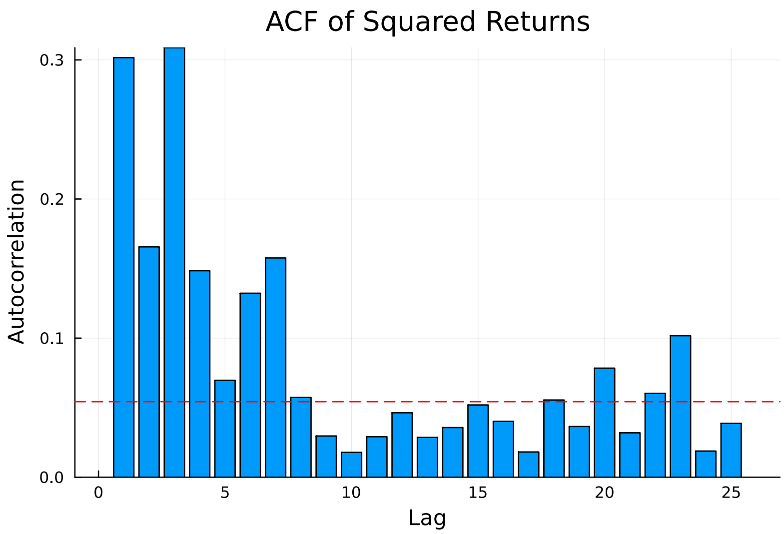

Figure 10: ACF of Squared log-returns

From figure 10 we observe that a substantial number of lags exhibit autocorrelations exceeding the 95% confidence interval (given by the red dashed line). This suggests that autocorrelation function does not decay exponentially and that an ARCH(1) model would be inadequate for describing the volatility in this dataset. Consequently, we GARCH(p, q) model. We opt for the latter, as choosing the former often leads to too many parameters to estimate.

To determine the number of parameters p and q such that the GARCH(p, q) model describes the volatility of the data the best, we compute the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). The model having both the lowest AIC and BIC value is to be preferred. We consider GARCH(p, q) models for $p, q \in \{1, 2, 3\}$.

Model	AIC	BIC
GARCH(1,1)	5699	5714
GARCH(1,2)	5700	5721
GARCH(1,3)	5697	5723
GARCH(2,1)	5700	5721
GARCH(2,2)	5702	5728
GARCH(2,3)	5699	5730
GARCH(3,1)	5702	5727
GARCH(3,2)	5703	5734
GARCH(3,3)	5699	5735

Table 5: AIC and BIC for GARCH models

From table 5 we observe that the GARCH$(1,3)$ model achieves the lowest AIC value, while the GARCH$(1,1)$ has the lowest BIC value. Both models also obtain relatively low values for the other criterion, indicating that they are good candidates for modeling volatility. For simplicity, we proceed with the GARCH$(1,1)$ model as that means we will only need to estimate three parameters instead of five, leading to more straightforward interpretability.

The parameters have been estimated using Maximum Likelihood Estimation. Link functions were applied to ensure non-negativity of the parameters and that the log-returns form a weakly stationary white noise process.

Parameter	Estimate	Standard error
ω	0.37	0.084
α	0.224	0.030
β	0.726	0.031

Table 6: Parameter Estimates of GARCH(1,1)

Indeed, $\hat{\alpha} + \hat{\beta} < 1$ confirming that the log-returns represent a weakly stationary white noise sequence. Moreover, the standard errors of the estimates are relatively small, indicating high precision.

4.3 Using fractional moments to analyse the log-returns

Now that we have described the data using core statistics, fitted appropriate models and estimated their parameters, we finally consider the usage of moments of fractional order to enhance the analysis.

4.3.1 Computing conditional absolute moments of fractional order

Following Hansen and Tong (2024), we compute the conditional expectation of the absolute variance over a given period H, specifically

$$\mathbb{E}[|X_{T+H}|^{\gamma} \mid \mathcal{F}_T],$$

where $X_{T+H} = Var(R_{T,H}) = \mathbb{E}[R_{T,H}^2] = \mathbb{E}[\sum_{t=T+1}^{T+H} r_t^2] = \sum_{t=T+1}^{T+H} \mathbb{E}[r_t^2]$. Here r_t denotes the log-return at time t and $\mathcal{F}_T$ represents the natural filtration, which is the sigma-algebra generated by the process up to time T Lowther (2009). In other words, $\mathcal{F}_T$ contains all information about log-returns observed up to time T. Note that $Var(R_{T,H})$ is indeed equal to $\mathbb{E}[R_{T,H}^2]$ as $\mathbb{E}[R_{T,H}]^2 =$

$\mathbb{E}[\sum_{t=T+1}^{T+H} r_t]^2 = \left(\sum_{t=T+1}^{T+H} \mathbb{E}[r_t]\right)^2$. We assume that $r_t \sim \mathcal{N}(0, \sigma_t^2)$ and since the autocorrelation function of log-returns is zero, we have that each r_t is independent of the observations at different time indices. So it follows that: $\left(\sum_{t=T+1}^{T+H} \mathbb{E}[r_t]\right)^2 = \left(\sum_{t=T+1}^{T+H} 0\right)^2 = 0$. To avoid confusion, we denote the order of the fractional moment by γ rather than α which is already used as a parameter in the GARCH(1,1) model. We compute moments of order $\gamma \in \{-0.5, 0.5, 1.5, 2\}$ as suggested by Hansen and Tong (2024). According to Hansen and Tong (2024) the orders of γ correspond to the following moments:

- $\gamma = -0.5$: Inverse of the volatility of the returns. May be used for Sharpe ratio forecasting
- $\gamma = 0.5$: Conditional volatility or standard deviation of returns
- $\gamma = 1.5$: Conditional skewness (of the absolute value)
- $\gamma = 2$: Conditional kurtosis

These fractional methods are computed using three different methods.

- **Empirical Simulation:** We consider the empirical value of the moments, obtained by performing 100.000 Monte Carlo simulations of the distribution of the variance (see algorithm 2) followed by averaging the results to obtain the empirical estimates.
- **Integral method:** We compute the standard integral, namely $\int_{-\infty}^{\infty} (x)^\gamma f_X(x)\, dx$, where $f_X(x)$ is the PDF of $X_{T,H}$. This PDF is acquired by performing Kernel Density Estimation on the values of $X_{T,H}$.
- **Caputo-Fabrizio MGF:** We also compute the expectations of fractional order using the inaccurate method of the Caputo-Fabrizio MGF. This integral also makes use of the same PDF obtained by Kernel Density Estimation.

We compute these moments for different time horizons, namely $H \in \{4, 8, 16\}$. That is, we compute the expectation of the absolute variance of order γ for one month, two months and four months in the future, respectively. This allows us to evaluate whether the time horizon affects the performance of the Caputo-Fabrizio method. The full procedure is detailed in algorithm 1.

We obtain the following table:

H	order	empirical	standard	CF
4	-0.5	0.25	0.255	0.138
4	0.5	4.948	4.938	1.855
4	1.5	201.653	201.763	56.748
4	2.0	1568.7	1569.69	1569.69
8	-0.5	0.164	0.164	0.06
8	0.5	7.098	7.095	1.94
8	1.5	552.323	552.142	114.85
8	2.0	5909.13	5905.96	5905.96
16	-0.5	0.113	0.113	0.028
16	0.5	10.073	10.066	1.971
16	1.5	1550.63	1547.5	230.747
16	2.0	23559.0	23482.6	23482.6

Table 7: Conditional expectations for various orders

The results from table 7 can be interpreted as follows:

- $\gamma = -0.5$: The inverse of the volatility decreases with H, implying that the volatility increases as the forecast horizon extends. All values are positive, due to use of absolute moments.

- $\gamma = 0.5$: The standard deviation of the returns indeed increase when the value of H increases. This is expected as greater time horizons lead to more uncertainty.

- $\gamma = 1.5$: The conditional skewness greatly increases when the value of H increases. However, since we examine the absolute value, all skewness values are positive, making the interpretability limited.

- $\gamma = 2$: The conditional kurtosis vastly increases as the value of H increases. For all values of H, the kurtosis is considerably greater than 3, implying that the conditional absolute cumulative returns are not normally distributed. As with skewness, the interpretability is limited due to the use of absolute values.

For all values of H and non-integer values of γ the empirical results and theoretical integral results are closely aligned. Similarly, for all values of H and $\gamma = 2$, the results of the integral method and Caputo-Fabrizio MGF are the same, as the latter is accurate for integer derivatives of the MGF. As indicated in section 3, the Caputo-Fabrizio MGF greatly under-estimates the values of fractional moments. These errors increase with H, implying that the method increasingly underestimates volatility - and hence risk - for longer horizons. We therefore conclude that the Caputo-Fabrizio MGF is unreliable for computing expectations of fractional order in forecasting applications. This conclusion is consistent with the results of section 3.3, where the size of the errors grew as the distribution parameters increased. Figure 11 emphasizes the increment of the errors of the Caputo-Fabrizio MGF.

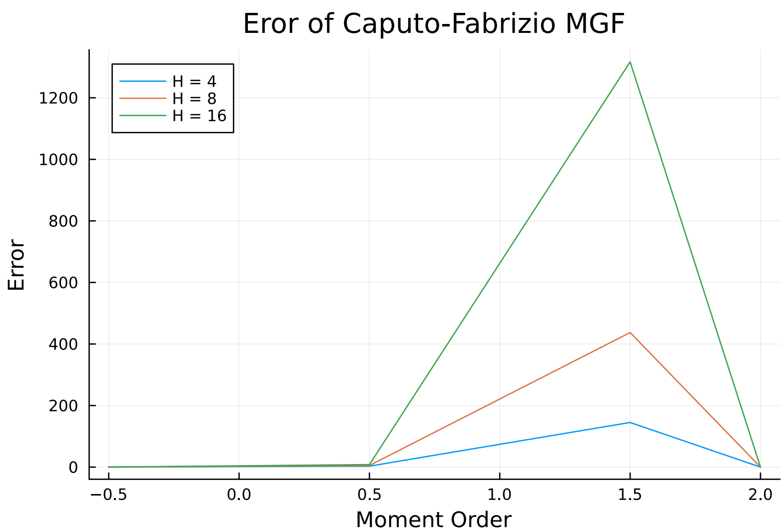

Figure 11: Error of Caputo-Fabrizio MGF for various values of H and γ

Note that figure 11 only includes discrete values of $\gamma \in \{-0.5, 0.5, 1.5, 2\}$. Therefore, the plotted functions may give a misleading impression of continuity. For instance, the error at $\gamma = 1$ should be exactly zero, yet the graph figure suggests otherwise due to the interpolation between points.

4.3.2 More about the computation and interpretability of fractional moments

An observant reader might wonder why we compute the expectation of $|X_{T+H}|$ instead of simply computing the expectation of X_{T+H}. We have that $X_{T+H} = Var(R_{T,H}) \geq 0$ so why are these absolute values necessary? The answer is twofold. When we are computing moments of negative order, i.e. $\gamma = -0.5$ we are computing a function that behaves similar to $\frac{1}{\sqrt{X_{T+H}}}$. It is quite clear that this computation will suffer from numerical issues for variances in a neighbourhood of zero. The second reason lies in the manner of how we compute the standard and CF-MGF moments. As aforementioned there exists no simple analytical expression of the MGF in this context (Hansen and Tong (2024) managed to find one, but considered a different model to monitor volatility, which seemed to be outside of the scope of this thesis). Thus we need to work with a PDF of X_{T+H}. To obtain this density, we use Kernel Density Estimation (KDE), which may occasionally produce negative values, especially around the tails of the distribution, where there are less data points. Computing negative values of fractional order is not well-defined, thus in this case, we have to include absolute values as well. As seen in table 7, this may result in values that are less intuitive or interpretable. We could also have considered to give a complex form to X_{T+H} allowing for negative values. However, these results are most likely even less intuitive. Another option would have been to square all orders to ensure that the integral is well defined for all values of the PDF. This would lead to all orders being integer orders again, which defeats the purpose of considering moments of fractional orders in the first place.

4.3.3 Analyzing risks using VaR and fractional orders of LPM

Next, we consider two different measures of risk, namely the Value-at-Risk (VaR) measure and the Lower Partial Moment (LPM). Where the former is defined as

$$\alpha\text{-VaR} = z_\alpha \cdot \sigma_{t+H} \tag{8}$$

where z_α is the quantile of level α of the standard normal distribution Holton (2013). While VaR focuses on a single quantile threshold, LPMs may provide a more complete picture of downside risk by capturing the magnitude as well as the frequency of returns falling below a specific target. The LPM is defined as follows:

$$LPM_n(\tau) = \int_{-\infty}^{\tau} (\tau - x)^n dF_X(x) \tag{9}$$

where $\tau = \alpha$-VaR and $F_X(x)$ is the distribution of a random variable X Wojt (2009). In our case X is the absolute cumulative return. The intuition of the VaR is as follows: given some portfolio with a weekly $\alpha -$ VaR of some percentage p, there is a probability of $\alpha\%$ that the value of the portfolio will fall by more than $p\%$ of its value in one week. The interpretation of the Lower Partial Moment, which is usually defined for $n \in \mathbb{N}$ is as follows. The Lower Partial Moment of order $n = 1$, is called the expected shortfall, which captures the expected downside deviation below the target value, τ. If the Lower Partial Moment is of order $n = 0$, it represent the probability of performing under the target value, τ Sorino (2001). We extend the order of the Lower Partial Moment by letting $n \in \mathbb{R}$, focusing on $n \leq 1$, as proposed by Fishburn (1977). According to the latter, the LPM of order $0 < n < 1$ emphasizes the frequency of downside incomes. The following figure depicts the Value-at-Risk with $\alpha = 5\%$, along with the Lower Partial Moment of order $n \in \{0, 1, 0.5\}$, where $LPM_{0.5}(\tau)$ has been computed using both the accurate and inaccurate expressions of the fractional MGFs. The risks are based on the forecasts of the cumulative returns up until H = 26, so half a year in advance.

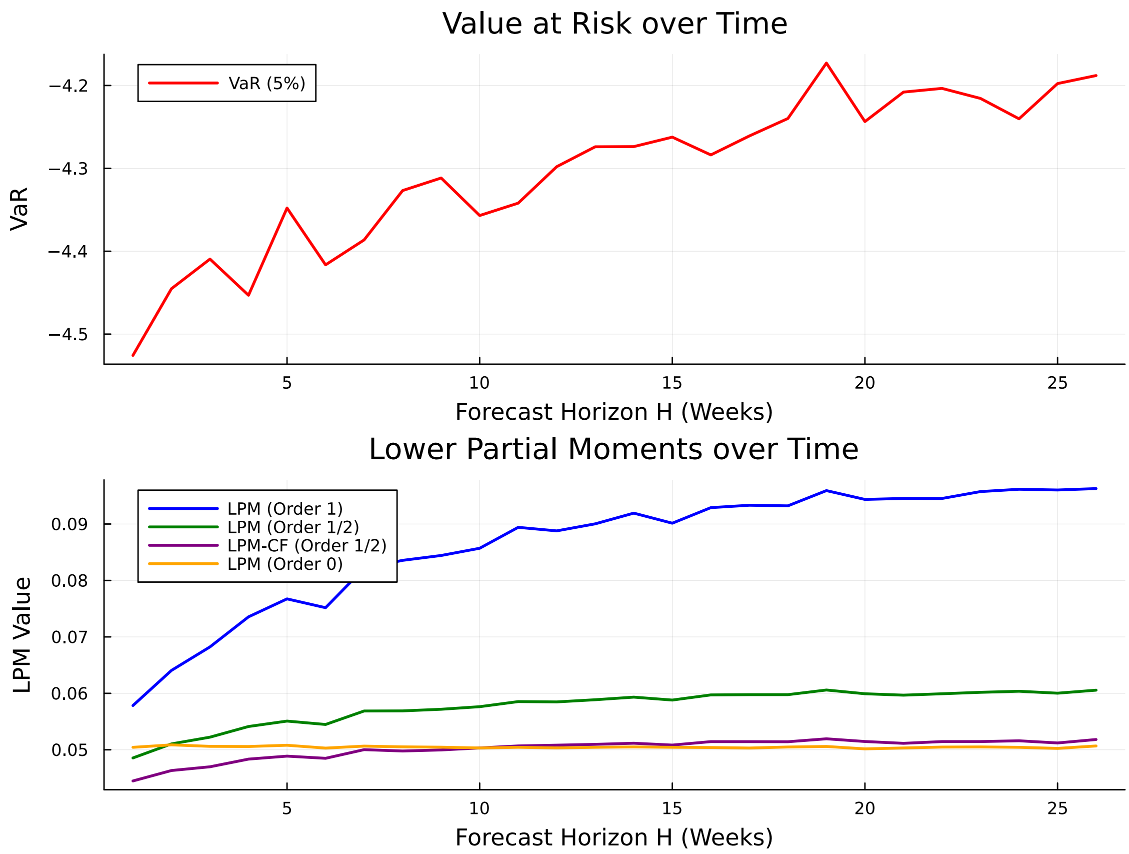

Figure 12: Comparison of VaR and LPM for various orders of LPM

- From figure 12 we observe that as H increases, the VaR quantile decreases in absolute magnitude, indicating that extreme losses become less severe relative to shorter horizons. This might seem counterintuitive at first, as stock returns may seem less predictable over larger periods of time, however this observation actually aligns theoretical expectations. That is $\lim_{h\to\infty} \sigma_T^2(h) = \omega/(1-\alpha-\beta)$. So as H increases, $\sigma_T^2(h)$ will get closer to its unconditional variance and the function will become less steep.

- As H increases, $LPM_1(\tau)$ tends to increase slightly. This suggests that, while the expected downside loss below the threshold τ may slightly increase over time, it does so at a decreasing rate. The flattening of the $LPM_1(\tau)$ function reflects the convergence of the aforementioned unconditional variance which is in line with the theory of GARCH models.

- As H increases, $LPM_0(\tau)$ seems to follow the same trends as the other orders of $LPM_n(\tau)$. The latter suggests that the downside risk grows marginally as time increases but eventually becomes constant. This is in line with the fact that return distributions converge to their long-run unconditional distribution as time increases.

- $LPM_{0.5}(\tau)$ seems to show a gradual increase, as H increases, after which it eventually flattens. This implies that the frequency and magnitude of downside deviations slowly grow over time and eventually reaching a maximum. The latter reflects the diminishing risk over long periods.

- As concluded before, fractional moments computed by the Caputo-Fabrizio MGF, inaccurately underestimated. All values of $LPM_{0.5}(\tau)$ computed via the Caputo-Fabrizio MGF are consistently lower than those computed using direct integration, once more conforming its systematic underestimation of downside risk. The Caputo-Fabrizio MGF approach does not fully capture the tail behaviour of the return distribution, especially for small values H where it even obtains smaller values compared to $LPM_0(\tau)$.

4.3.4 Modelling volatility using an observation-driven regression model

In this final section, we try forecasting volatility using a different model. Namely, we consider an observation-driven regression model, a special case of the Generalized Autoregressive Score framework Creal et al. (2013). This model has observation equation:

$$y_t = \beta_t \cdot x_t + \epsilon_t \tag{10}$$

where $\epsilon_t \sim \mathcal{N}(0, \sigma^2)$ and updating equation:

$$\beta_t = \omega + \phi \cdot \beta_{t-1} + \alpha(y_{t-1} - \beta_{t-1} \cdot x_{t-1})x_{t-1} \tag{11}$$

This model has the advantage of allowing β_t to evolve over time, in contrast to models like GARCH(1,1) which impose a constant parameter structure. Such time-varying parameters are especially useful when working with financial return series that contain extreme values or structural changes. A fixed parameter may be overly influenced by outliers, whereas a dynamic β_t allows the model to adapt flexibly to such deviations without negatively affecting prediction accuracy. In our application, we let y_t represent the variance from one-month future returns. We will consider two different versions of the model.

- Standard model: we let $x_t = |r_t|$ represent the absolute return at time t, as in Taylor (2007).
- Extended model: we let x_t represent the conditional expectation of the absolute variance over two weeks of order 0.5. That is $x_t = \mathbb{E}[|X_{T+2}|^{0.5} \mid \mathcal{F}_t]$, with X_{T+2} defined as before. This choice is motivated by section 4.3.1 where this value was interpreted as the standard deviation of the absolute returns over a period of two weeks.

The goal of this specific case study is to compare the regression performance between a model with and without a moment of fractional order serving as regressor. In order to make sure we focus on this objective and do not get lost in an array of different definitions of fractional moments, we will only consider the fractional moments computed using the expression of the accurate MGFs. It is safe to say that comparing this fractional MGF with the standard model is a lot more useful than comparing a faulty MGF with the standard model.

The dataset has been split as follows: 80% of the data has been used for the training-set and the remaining 20% functions as the test-set. Around 50% of the training-set has been reserved for estimating the parameters of the GARCH(1,1) model. We already estimated the parameters of a GARCH(1,1) model, but the estimates of those parameters were based on the entire dataset. In this case, we need parameter estimates for each different time t to obtain the most accurate computations of $\mathbb{E}[|X_{T+2}|^{0.5} \mid \mathcal{F}_t]$. We still make use of the parameters we estimated in 6 as we let $\sigma_0^2 = \hat{\omega}/(1-\hat{\alpha}-\hat{\beta})$ be the initial value of σ_t^2. We compute $\mathbb{E}[|X_{T+2}|^{0.5} \mid \mathcal{F}_t]$ for all t-values in our selected window. The computation is rather similar to those of section 4.3.1, with only a slight modification in the code (see algorithm 3). After performing Maximum Likelihood Estimation, we obtain the following estimates:

Model	$\hat{\omega}$	$\hat{\phi}$	$\hat{\alpha}$	$\hat{\sigma^2}$
Standard model	0.066	0.78	0.007	0.839
Extended model	0.08	0.812	0.219	0.683

Table 8: Parameter Estimates of the two different regression models

The two models yield similar estimates for ω and ϕ. The most notable differences appear in the parameter estimates of $\hat{\alpha}$ and $\hat{\sigma^2}$. The higher value of $\hat{\alpha}$ implies that the updates to β_t of the extended model are more responsive to the product of the past error term and regressor compared to the standard model, namely $\epsilon_{t-1} \cdot x_{t-1}$. Meanwhile, the smaller value in the extended model $\hat{\sigma^2}$ of $\epsilon_{t-1} \sim \mathcal{N}(0, 0.683)$ compared to $\epsilon_{t-1} \sim \mathcal{N}(0, 0.839)$ indicates reduced variance in the residuals, suggesting a better fit of the model.

The following plot displays the path of β_t for the standard and extended model, that is, it shows the evolution of the value of β_t over the training period (2010-2022).

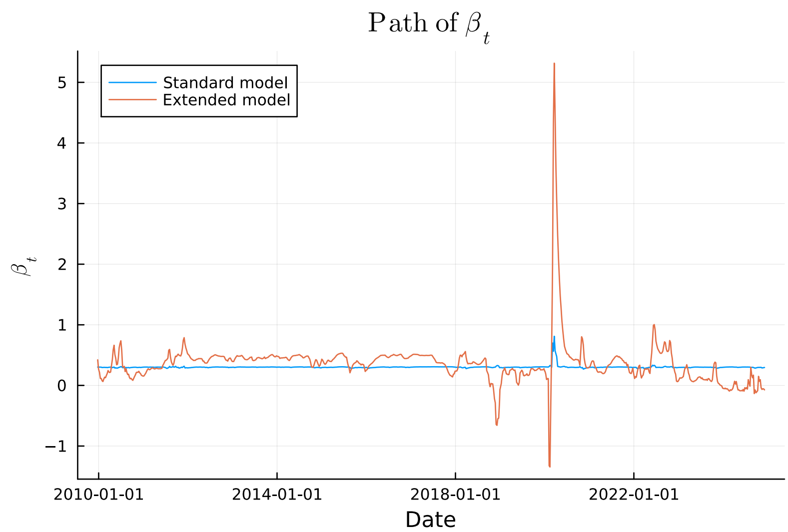

Figure 13: Path of β for different models

In the standard model β_t remains relatively stable, clustering around a value of 0.5, except for a spike around 2020 (COVID pandemic). In contrast, the extended model produces a more volatile β_t fluctuating between values around -1 and 5. This is possibly due to how β_t is updated in the extended model. Namely β_{T+2} is dependent on $\mathbb{E}[|X_{T+1}|^{0.5} \mid \mathcal{F}_t]$. We have seen in section 4.3.1 how large these fractional moments can get. Therefore, as the value of $\mathbb{E}[|X_{T+1}|^{0.5} \mid \mathcal{F}_t]$ explodes, so will the value β_t. The spike during the COVID pandemic perfectly illustrates this behaviour, where greater uncertainty drove up the value of the fractional moment and thus the value of β_t.

The table below includes some performance measures of the standard model and extended model respectively.

Model	**MSE**	**MAE**	**RMSE**	R^2
Standard model	0.275	0.387	0.524	0.023
Extended model	0.207	0.349	0.454	0.267

Table 9: Performance measures of the two different regression models

The values of the mean squared error, mean absolute error and root mean squared error of the extended model are all smaller compared to those of the standard model, indicating that the extended model is preferred. It also achieves a higher value for R^2. Note that R^2 is not always a reliable performance measure for time series data. This follows from the fact that in a time series context, there exists autocorrelation between the residuals, thus violating the assumption that residuals should be independent of each other. Using R^2 in context of time series often results in low values of R^2 indicating poor predictive performance, while this may not necessarily be the case. Yet, in table 9 we observe that the associated R^2 value of the extended model is roughly ten times the value of the associated R^2 value of the basic model. This suggests that the regressor x_t in the extended model has a much greater correlation with the variation in y_t compared to the regressor x_t in the standard model. That is, the regressor x_t in the extended model explains a greater portion of the variance in y_t. Thus, in this context, the performance measure R^2 is still found to be useful. The following figure depicts the actual variance along with the variance predicted by the two different models:

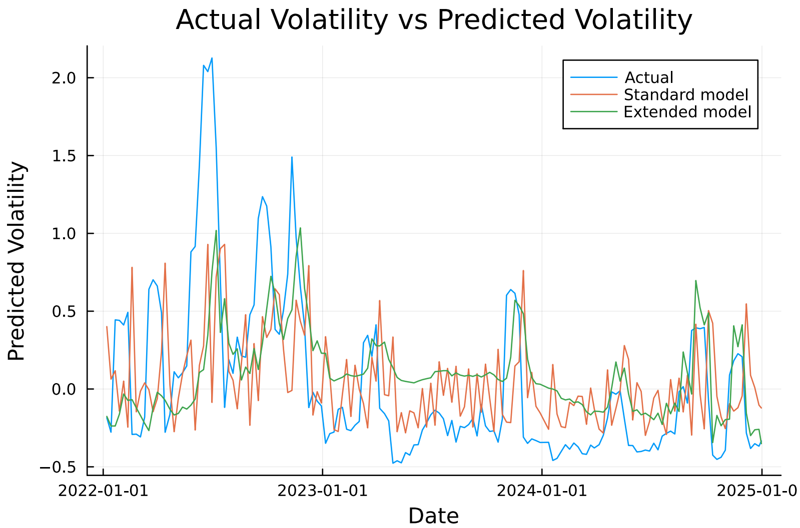

Figure 14: Actual volatility vs Predicted volatility

From figure 14 we observe that the actual variance attains more extreme values compared to the predictions. While the β_t value of the extended model was more flexible, as shown in figure 13, it is the predicted volatility of the standard model that fluctuates relatively more. The predicted volatility path of the extended model is much smoother, similar to the actual variances. This might explain the significant difference in performance measures between the two models.

In conclusion, incorporating an expression involving fractional moments as a regressor leads to an improved performance in predictions of volatility. The extended model not only obtains lower prediction errors, but also better captures the structure of the data. This comes with an increase in volatility of the coefficient path, which may be either an advantage or disadvantage depending on the specific application.

5 Conclusion

This paper has explored a relatively new method for computing moments of fractional order. This novel approach included combining Moment Generating Functions with various different fractional derivatives. It was shown that the Moment Generating Function in combination with either the Riemann-Liouville fractional derivative or the Grünwald-Letnikov fractional derivative lead

to accurate computations of fractional moments. In contrast, the Moment Generating Function in combination with the Caputo-Fabrizio fractional derivative leads to systematically underestimation of moments of fractional order.
It was shown that in general the mean and maximum error, the standard deviation, skewness and the coefficient of variation of the error increase as the parameter values of the underlying distribution grow. Nevertheless, the Caputo-Fabrizio Moment Generating Function remains accurate for integer orders and in general, most of the errors are clustered around zero.
We demonstrated the practical relevance of moments of fractional order through the application of volatility forecasting in financial markets. These moments were used to derive informative statistics for future stock returns and volatility. The values obtained using the Riemann-Liouville and Grünwald-Letnikov Moment Generating Functions aligned closely with the empirical values, thus confirming their effectiveness in real world applications.
Additionally, we extended the concept of Lower Partial Moment to fractional orders, which represent the frequency and magnitude of downside deviations. In both applications, the Caputo-Fabrizio Moment Generating Function was shown to underestimate the moments of fractional order. In particular when the forecasting horizon increased. This suggests that the Caputo-Fabrizio Moment Generating Function is not well suited for financial risk analysis, as it tends to understate volatility and associated risk.
Moreover, moments of fractional order were implemented as regressors in an observation-driven regression model. This approach allowed for a more flexible β_t compared to the β_t of the standard model, which led to reduced errors and improved forecasting accuracy compared to a standard model. In the absence of closed-form expressions of the Moment Generating Function in this setting, it was required to make use of traditional numerical integration. To ensure numerical stability we had the option to either employ absolute or complex moments. While these options are effective, they somewhat limit the interpretability of the results, compared to unrestricted fractional moments. This limitation could be avoided if closed form expressions of the Moment Generating Function are available.

Future research could include exploring Moment Generating Functions in combinations with different fractional derivatives as those proposed by Hadamard (1892), Riesz (1949) and Marchaud (1927). It would be valuable to assess which combinations obtain accurate values of moments of fractional order and whether a general theorem regarding the accuracy of the Moment Generating Function in combination with fractional derivatives can be established. Another topic of interest would be to consider computing fractional moments of multivariate distributions as briefly mentioned in Hansen and Tong (2024). This would allow us to compute fractional cross-moments to explore dependencies between different random variables. On a practical level, developing Julia packages capable of performing symbolic differentiation similar to SymPy in Python Meurer et al. (2017) would reduce reliance on manual derivation. Currently, the lack of such tools in Julia requires all derivative expressions to be computed by hand before use.

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A Appendix: Relevant functions and Identities

Definition A.0.1. Let D be the differential operator, such that $Df(x) = \frac{d}{dx}f(x)$. Then the fractional derivative of order α is defined as

$$D^\alpha f(x) = \frac{d^\alpha}{dx^\alpha} f(x)$$

Samko et al. (1993)

In this definition, α can be any real number. When taking regular derivatives, $\alpha \in \mathbb{N}$. In most of our cases, we are interested in the instance where $\alpha \in \mathbb{R}_+$. It is also possible to study derivatives of negative order, which can be used to obtain moments of negative order of a function, provided that such an order exists. A derivative of negative order is simply an integral of positive order. This is defined as follows:

Definition A.0.2. Let I be the integral operator, such that $If(x) = \int f(x)dx$. Then the fractional integral of order α is defined as

$$(I^\alpha f)(x) = \frac{1}{(\alpha-1)!}\int (x-t)^{\alpha-1} f(t)dt$$

Cauchy (1823).

Combining the previous two definitions, we obtain the following, more general, definition.

Definition A.0.3. The differintegral operator is defined as

$$R^\alpha f(x) = \begin{cases} I^{|\alpha|} f(x) & \text{if } \alpha < 0 \\ D^\alpha f(x) & \text{if } \alpha > 0 \\ f(x) & \text{if } \alpha = 0 \end{cases}, \text{ with } \alpha \in \mathbb{R}. \tag{12}$$

Oldham and Spanier (1974)

We define the (Euler-)Gamma function as follows:

Definition A.0.4. for $\Re(z) > 0$, we have the following: $\Gamma(z) = \int_0^\infty t^{z-1}e^{-t}dt$

The Gamma function can be seen as an extension of the factorial function, for non-integers. This function is defined for complex numbers and all there subsets (so also real numbers), as long as the condition above holds. For positive integers values z, we have the following identity: $\Gamma(z) = (z-1)!$ Other important identities, not necessarily for z an integer, are:

- $\Gamma(z+1) = z\Gamma(z)$
- $\Gamma(2) = \Gamma(1) = 1$
- $\Gamma(\frac{1}{2}) = \sqrt{\pi}$

Definition A.0.5. For $0 \leq k \leq n$, the Binomial Coefficient is defined as follows:

$$\binom{n}{k} = \frac{n!}{k!(n-k)!} = \frac{\Gamma(n+1)}{\Gamma(k+1)\cdot\Gamma(n-k+1)}$$

, where $n, k \in \mathbb{N}$ and $\Gamma(.)$ as defined in A.0.4.

Definition A.0.6. Vandermonde's identity: for non-negative integers, k, l, m, n, we have that

$$\sum_{k=0}^{l} \binom{m}{k} \cdot \binom{n}{l-k} = \binom{m+n}{l}$$

A modification on the latter identity has been called the Chu-Vandermonde identity. This is the same identity, but it his been proven that the identities still hold for complex values m, n as long as l is a positive integer Askey (1975).

Definition A.0.7. The binomial series is a generalization of the binomial formula, namely:

$$(1+x)^{\alpha} = \sum_{k=0}^{\infty} \binom{\alpha}{k} \cdot x^k$$

For the interchange-ability of derivatives and integrals and sums, we can apply the following two theorems:

Theorem A.0.1. *Leibnitz's Rule: Let $f(x, \theta), a(\theta), b(\theta)$ be differentiable with respect to θ, then we have that:*

$$\frac{d}{d\theta} \int_{a(\theta)}^{b(\theta)} f(x,\theta)dx = f(b(\theta),\theta)\frac{db(\theta)}{d\theta} - f(a(\theta),\theta)\frac{da(\theta)}{d\theta} + \int_{a(\theta)}^{b(\theta)} \frac{\partial f(x,\theta)}{\partial \theta} dx.$$

For the special case, where $a(\theta), b(\theta)$ are constant we have that:

$$\frac{d}{d\theta} \int_{a}^{b} f(x,\theta)dx = \int_{a}^{b} \frac{\partial f(x,\theta)}{\partial d\theta}.$$

For the interchange-ability of derivatives and summations, the following theorem has been given by Casella and Berger (2002):

Theorem A.0.2. *Suppose that the series $\sum_{x=0}^{\infty} h(\theta, x)$ converges for all θ in an interval (a, b) of real numbers and*

(i) $\frac{\partial h(\theta,x)}{\partial \theta}$ *is continuous for all x*

(ii) $\sum_{x=0}^{\infty} \frac{\partial h(\theta,x)}{\partial \theta}$ *converges uniformly on every closed bounded sub-interval of (a, b)*

Then:

$$\frac{d}{d\theta}\left(\sum_{x=0}^{\infty} h(\theta,x)\right) = \sum_{x=0}^{\infty} \frac{\partial h(\theta,x)}{\partial \theta}$$

B Appendix: Proofs of section 2

B.1 Proofs section 2.2

Proof. Proof of 2.2.1

(i) We will proof for the Riemann-Liouville derivative, the proof for the Caputo-Fabrizio derivative is very similar and the Grünwald-Letnikov derivative is a direct consequence of the linearity of the sum.

$$D^{\alpha}(af(x)+bg(x)) = \frac{d^n}{dx^n}\frac{1}{\Gamma(n-\alpha)}\int_0^x (x-t)^{n-\alpha-1}\left(af(t)+bg(t)\right)dt$$

$$= \frac{d^n}{dx^n}\left(\frac{a}{\Gamma(n-\alpha)}\int_0^x (x-t)^{n-\alpha-1}f(t)dt + \frac{b}{\Gamma(n-\alpha)}\int_0^x (x-t)^{n-\alpha-1}g(t)dt\right)$$

Where we simply split the integral and put the constants in front.

$$= \frac{d^n}{dx^n}\frac{a}{\Gamma(n-\alpha)}\int_0^x (x-t)^{n-\alpha-1}f(t)dt + \frac{d^n}{dx^n}\frac{b}{\Gamma(n-\alpha)}\int_0^x (x-t)^{n-\alpha-1}g(t)dt$$

As the regular derivative operator is linear.

$$= aD^{\alpha}f(x) + bD^{\alpha}g(x)$$

(ii) Intuitively, this makes perfect sense, as the 0-th derivative is just no derivative, so just the function $f(x)$. But for these derivatives, a little bit more effort is required to prove this rather obvious fact.
For the Grünwald-Letnikov derivative we get:

$$D^0 f(x) = \lim_{h\to 0}\frac{1}{h^0}\sum_{k=0}^{\infty}(-1)^k\binom{0}{k}f(x-kh) = \lim_{h\to 0}\frac{1}{1}\sum_{k=0}^{\infty}(-1)^k\frac{0!}{k!(0-k)!}f(x-kh).$$

The factorial identity of the binomial coefficient only holds for $0 \le k \le \alpha$. Since $\alpha = 0$ and k is always a positive integer lesser or equal to $\alpha, k = 0$. Thus, we get:

$$= \lim_{h\to 0}\sum_{k=0}^{\infty}(-1)^0\frac{0!}{0!(0-0)!}f(x-0h) = \lim_{h\to 0} f(x-0h) = f(x).$$

For the Caputo-Fabrizio derivative, we obtain the following:

$$D^0 f(x) = \frac{1}{1-0}\int_0^x \exp\left(\frac{0}{1-0}(x-t)\right)f'(t)dt = \int_0^x f'(t)dt = f(x).$$

Finally, for the Riemann-Liouville derivative, we can simply make use of 2.2.1 to note that in this context $\alpha = 0$ is included in the natural integers. So $D^{\alpha} = \frac{d^{\alpha}}{dx^{\alpha}}f(x) = d^0dx^0 f(x) = f(x)$ by the first fundamental theorem of calculus.

(iii) The proof for the Riemann-Liouville derivative is given by Koning (2015). And the proof for the Caputo-Fabrizio derivative is given by Losada and Nieto (2015).For the Grünwald-Letnikov derivative, we get:

$$D^\alpha(D^\beta f(x)) = \lim_{h\to 0}\frac{1}{h^\alpha}\sum_{k=0}^{\infty}(-1)^k\binom{\alpha}{k}\left(\frac{1}{h^\beta}\sum_{l=0}^{\infty}(-1)^l\binom{\beta}{l}f(x-lh-kh)\right)$$
$$= \lim_{h\to 0}\frac{1}{h^{\alpha+\beta}}\sum_{k=0}^{\infty}(-1)^k\binom{\alpha}{k}\sum_{l=0}^{\infty}(-1)^l\binom{\beta}{l}f(x-(k+l)h).$$

We substitute $m = k+l$ to deal with the double sums:

$$\lim_{h\to 0}\frac{1}{h^{\alpha+\beta}}\sum_{m=0}^{\infty}f(x-mh)\sum_{k=0}^{m}(-1)^k(-1)^{m-k}\binom{\alpha}{k}\binom{\beta}{m-k}$$

Now we make use of an identify from Appendix A to obtain:

$$= \lim_{h\to 0}\frac{1}{h^{\alpha+\beta}}\sum_{m=0}^{\infty}(-1)^m\binom{\alpha+\beta}{m}f(x-mh) = D^{\alpha+\beta}f(x).$$

It can be shown in an exactly similar way that the latter expression is equal to $D^\beta(D^\alpha f(x))$.

□

B.2 Proofs section 2.3

Proof. Let $f_X(x) \sim \Gamma(\alpha,\lambda) =$

$$\frac{x^{\alpha-1}e^{-\lambda x}\lambda^\alpha}{\Gamma(\alpha)}.$$

This PDF is defined on $(0,\infty)$. So the function is not defined on $\mathbb{R}$. This, however, is not a problem, as we can just evaluate the right limit. Since the Gamma function already uses α as a parameter, we will evaluate $\dfrac{f_X(x)}{|x|^\beta}, \beta > 0$:

$$\lim_{x\to 0_+}\frac{f_X(x)}{|x|^\beta} = \lim_{x\to 0_+}\frac{x^{\alpha-1-\beta}e^{-\lambda x}\lambda^\alpha}{\Gamma(\alpha)} = \lim_{x\to 0_+}\frac{x^{\alpha-(1+\beta)}e^{-\lambda x}\lambda^\alpha}{\Gamma(\alpha)}.$$

Thus for $\alpha \geq \beta+1, \lim_{x\to 0_+}\frac{f_X(x)}{|x|^\beta} < \infty$. Therefore, the first negative moment of the Gamma distribution should exist.

We compute the first negative moment:

$$\mathbb{E}[X^{-1}] = \int_0^\infty x^{-1}\frac{x^{\alpha-1}e^{-\lambda x}\lambda^\alpha}{\Gamma(\alpha)}dx = \frac{\lambda^\alpha}{\Gamma(\alpha)}\int_0^\infty x^{\alpha-2}e^{-\lambda x}dx$$

Using the substitution $u = \lambda x, \dfrac{du}{dx} = \lambda, dx = \dfrac{du}{\lambda}$, we get:

$$= \frac{\lambda^\alpha}{\Gamma(\alpha)}\int_0^\infty\left(\frac{u}{\lambda}\right)^{\alpha-2}e^{-u}du = \frac{\lambda^\alpha}{\Gamma(\alpha)\lambda^{\alpha-1}}\int_0^\infty(\frac{u}{\lambda})^{\alpha-2}e^{-u}du.$$

This integral is equal to $\Gamma(\alpha-1)$ (See Appendix A). So we get:

$$\mathbb{E}[X^{-1}] = \frac{\lambda^\alpha\Gamma(\alpha-1)}{\Gamma(\alpha)\lambda^{\alpha-1}} = \frac{\lambda\Gamma(\alpha-1)}{(\alpha-1)\Gamma(\alpha-1)} = \frac{\lambda}{(\alpha-1)}.$$

Thus, for $\alpha \neq 1, \mathbb{E}[X^{-1}] = \frac{\lambda}{(\alpha-1)}$. Fortunately, this is always the case, since we had just derived that the integral only converges when $\alpha \geq \beta + 1,$ with $\beta > 0.$ In other words, $\alpha > 1.$ So this holds. □

Proof. Proof of Proposition 2.3.1

$$M_X^{(n)}(t) = \frac{d^n}{dt^n} \int_{-\infty}^{\infty} e^{tx} f_X(x)dx = \int_{-\infty}^{\infty} \frac{d^n}{dt^n} e^{tx} f_X(x)dx$$

(We can interchange differentiation and integration since all partial derivatives of $e^{tx}f(x)$ are continuous and the absolute value of the integral converges, as we assume the n-th moment exists, see Appendix A).

$$= \int_{-\infty}^{\infty} x^n e^{tx} f_X(x)dx, \text{evaluating at } t = 0 := \int_{-\infty}^{\infty} x^n e^{0x} f_X(x)dx$$

$$= \int_{-\infty}^{\infty} x^n f_X(x)dx = \mathbb{E}[X^n]$$

The proof for the case that $f_X(x)$ is discrete is very similar. In that case, one would have to change the order of the derivative and summation, which has also been justified in Appendix A. □

Proof. Proof of Proposition 2.3.1

(i) This is trivial. For X a continuous random variable, we get:

$$M_X^{(0)}(t) = \int_{-\infty}^{\infty} x^0 \cdot e^{tx} f_X(x)dx = \int_{-\infty}^{\infty} 1 \cdot e^{0x} f_X(x)dx = \int_{-\infty}^{\infty} f_X(x)dx.$$

Assuming that $f(x)$ is a PDF, this integrates to 1 by definition. If this integral is not equal to 1, this implies that $f(x)$ is not a PDF. The proof for the discrete case is the same but with a summation instead of an integral sign.

(ii)
$$M_{\mu+\sigma X}(t) = \mathbb{E}[e^{(\mu+\sigma X)t}] = \mathbb{E}[e^{\mu t} \cdot e^{\sigma X t}].$$

Since this is the expectation of x, every term that is not dependent on x can be taken out of the summation:

$$= e^{\mu t} \cdot \mathbb{E}[e^{\sigma X t}] = e^{\mu t} \cdot M_X(\sigma t)$$

(iii)
$$M_{X+Y}(t) = \mathbb{E}[e^{(X+Y)t}] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{(x+y)t} f_{X,Y}(x,y)dxdy$$
$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{xt} \cdot e^{yt} f_{X,Y}(x,y)dxdy.$$

$f_{X,Y}(x,y)$ is the joint pdf for X, Y. But we know that the latter is equal to $f_X(x) \cdot f_Y(y)$, if X, Y are independent. Thus we get:

$$= \left(\int_{-\infty}^{\infty} e^{xt} f_X(x)dx \right) \left(\int_{-\infty}^{\infty} e^{yt} f_Y(y)dy \right) = M_X(t) \cdot M_Y(t).$$

□

Proof. Proof of Theorem 2.3.2: Suppose for the moment that X is a positive random variable. Since $x \cdot f_X(x)$ is integrable for $x > 0$, we have:

$$\mathbb{E}(X) = \int_0^\infty x \, dF(x) = \int_0^\infty \int_0^\infty e^{tx} \, dt \, dF(x).$$

We can interchange the order of integration as follows:

$$\mathbb{E}(X) = \int_0^\infty e^{tx} \, dF(x) \, dt = \int_0^\infty M_X(-t) \, dt.$$

The interchange of the order of integration is subject to $\mathbb{E}(e^{-tX})$ being integrable from $t = 0$ to $t = \infty$.

Finally, by substituting X^{-1} for X, we find:

$$\mathbb{E}(X^{-1}) = \int_0^\infty M_X^{-1}(-t) \, dt.$$

There are two natural ways to generalize (1) to $\mathbb{E}(X^{-1})$; one way gives:

$$\mathbb{E}(X^{-n}) = \int_0^\infty \int_0^\infty \cdots \int_0^\infty M_X(-t_n) \, dt_n \cdots dt_2 dt_1, \tag{2}$$

while the second way gives:

$$\mathbb{E}(X^{-n}) = \frac{1}{\Gamma(n)} \int_0^\infty t^{n-1} M_X(-t) \, dt.$$

Cressie et al. (1981) □

Proof. Proof Theorem 2.3.3 We consider X to be a continuous variable. The three MGF expressions are accurate if $\mathbb{E}[X^\alpha] - M_X^{(\alpha)}(0) = 0$, in other words, if

$$\int_{-\infty}^\infty (x^\alpha - D^\alpha e^{tx}) \cdot f_X(x) dx = 0 \iff x^\alpha = D^\alpha e^{tx}$$

where D^α the differential operator of order α. Note that we are taking derivatives w.r.t. t, not x. The proof will be shown for the Grünwald-left derivative.

(i)

$$\begin{aligned}
{}_{GL}M_X^{(\alpha)} = D_{GL}^\alpha(e^{tx}) &= \lim_{h\to 0} \frac{1}{h^\alpha} \sum_{k=0}^\infty (-1)^k \binom{\alpha}{k} \exp(x(t-kh)) \\
&= \exp(xt) \lim_{h\to 0} \frac{1}{h^\alpha} \sum_{k=0}^\infty (-1)^k \binom{\alpha}{k} \exp(-xh)^k \\
&= \exp(xt) \lim_{h\to 0} \frac{1}{h^\alpha} (1 - \exp(-xh))^\alpha
\end{aligned}$$

(where we used the binomial series identity defined in A.0.7). Now we use the Taylor expansion of $\exp(-xh) = 1 - xh + \frac{(xh)^2}{2!} - \frac{(xh)^3}{3!} + ... - ....$ Since $h \to 0$, we get: $\exp(-xh) = 1 - xh + \mathcal{O}(h^2)$ (the rest of the terms are negligible). Thus we get:

$$\exp(xt) \lim_{h\to 0} \frac{1}{h^\alpha} \left(1 - (1 - xh + \mathcal{O}(n))\right)^\alpha = \exp(xt) \lim_{h\to 0} \frac{1}{h^\alpha} \left(h(x + \mathcal{O}(h))\right)^\alpha$$

$$= \exp(xt) \lim_{h\to 0} \frac{1}{h^\alpha} \left(h^\alpha((x + \mathcal{O}(h)))^\alpha\right) = \exp(xt) \lim_{h\to 0} (x + \mathcal{O}(h))^\alpha$$

$$= \exp(xt) \cdot x^{\alpha}.$$

Finally, we take a value of t around 0 and obtain ${}_{GL}M_X^{(\alpha)}(0) = x^{\alpha}$

(ii) We consider the Riemann-Liouville derivative:

$$D_{RL}^{\alpha}(e^{tx}) = \frac{d^n}{dt^n}\frac{1}{\Gamma(n-\alpha)}\int_{-\infty}^{t}(t-s)^{n-\alpha-1}\cdot e^{sx}ds$$

Koning (2015) has shown that this derivative is equal to $x^{\alpha}e^{tx}$. Thus, if we take a value of t around 0, we get: ${}_{RL}M_X^{(\alpha)}(0) = x^{\alpha}$

The proof also holds for the case when X is a discrete random variable. □

Proof. Proof of Theorem 2.3.4 We compute

$${}_{CF}M_X^{(\alpha)} = D_{CF}^{\alpha}(e^{tx}) = \frac{d^n}{dt^n}\frac{1}{1-\beta}\int_{-\infty}^{t}\exp\left(\frac{-\beta}{1-\beta}(t-s)\right)x\exp(xs)ds$$

$$= \frac{d^n}{dt^n}\frac{x}{1-\beta}\exp\left(\frac{-\beta t}{1-\beta}\right)\int_{-\infty}^{t}\exp\left(s\left(\frac{\beta}{1-\beta}+x\right)\right)ds \text{ where } \beta = \alpha - n \text{ and } n = \lfloor\alpha\rfloor.$$

Now let $u = \dfrac{\beta}{1-\beta} + x$, so we get:

$$\frac{d^n}{dt^n}\frac{x}{1-\beta}\exp\left(\frac{-\beta t}{1-\beta}\right)\int_{-\infty}^{t}\exp(us)ds = \frac{d^n}{dt^n}\frac{x}{1-\beta}\exp\left(\frac{-\beta t}{1-\beta}\right)\frac{1}{u}exp(us)\Big|_{-\infty}^{t}$$

$$= \frac{x}{1-\beta}\exp\left(\frac{-\beta t}{1-\beta}\right)\cdot\frac{1}{u}\cdot\exp(ut) = \frac{x\exp(xt)}{(1-\beta)x+\beta}$$

Now we apply the derivative of the above expression, with respect to t, n times:

$$\frac{d^n}{dt^n}\frac{x\exp(xt)}{(1-\beta)x+\beta} = \frac{x^{n+1}\exp(xt)}{(1-\beta)x+\beta}$$

Now we take a value of t around 0 and obtain:

$${}_{CF}M_X^{(\alpha)} = D_{CF}^{\alpha}(e^{tx}) = \frac{x^{n+1}}{(1-\beta)x+\beta}.$$

The latter expression is not equal to x^{α}, thus the error of ${}_{CF}M_X^{(\alpha)}$ is:

$$\begin{cases} \displaystyle\int_{-\infty}^{\infty}x^{\alpha}f_X(x)dx - \int_{-\infty}^{\infty}\frac{x^{n+1}}{(1-\beta)x+\beta}f_X(x)dx & \text{if } X \text{ is continuous,} \\ \displaystyle\sum_i\left(x_i^{\alpha} - \frac{x_i^{n+1}}{(1-\beta)x_i+\beta}\right)f_X(x_i) & \text{if } X \text{ is discrete.} \end{cases}$$

□

C Appendix: Algorithms

Algorithm 1 Analyze Fractional Moments

Require: Parameters: ω, α, β, list of horizons: H_values, list of orders: $orders$, number of iterations: n_sim

Ensure: DataFrame of conditional moments for each H and order

```
Initialize empty results DataFrame
for each H in H_values do
    R_H^2 ← SimulateConditionalVariance(ω, α, β, H, n_sim)
    pdf_R ← KDE distribution from R_H^2
    for each order in orders do
        empirical ← mean(|R_H^2|^order)
        standard ← FractionalMoment(pdf_R, order, use_abs=true)
        CF ← FractionalMomentCF(pdf_R, order, use_abs=true)
        Append (H, order, empirical, standard, CF) to results
    end for
end for
return results
```

Algorithm 2 Simulate Conditional Variance

Require: Parameters: ω, α, β, list of horizons: H_values, number of iterations: n_sim

Ensure: Array R_H^2 of accumulated conditional variances

```
Initialize R_H^2 as a zero array of length n_sim
σ_0^2 ← ω/(1 − α − β)
for i = 1 to n_sim do
    σ^2 ← σ_0^2
    variance_R_H ← 0
    for h = 1 to H do
        σ ← √(σ^2)
        r ∼ N(0, σ)
        variance_R_H ← variance_R_H + r^2
        σ^2 ← ω + αr^2 + βσ^2
    end for
    R_H^2[i] ← variance_R_H
end for
return R_H^2
```

Algorithm 3 Compute z from returns using GARCH and fractional moments

Require: Parameters: $H \leftarrow 2$, $n_{\text{sim}} \leftarrow$ 100,000, window $\leftarrow 520$, target_length $\leftarrow$ `nothing`, returns, fractional order γ

Ensure: Computed array `z`

$n \leftarrow$ length(`returns`)
max_index $\leftarrow n - H$
if target_length $=$ `nothing` **then**
    range $\leftarrow$ window : max_index
else
    range $\leftarrow$ (max_index $-$ target_length $+ 1)$: max_index
end if
Initialize empty array z
for each t in `range` **do**
    $r_{\text{window}} \leftarrow$ `returns`$[(t -$ window $+ 1) : t]$
    Fit GARCH(1,1) model to r_{window}
    Extract parameters ω, α, β from model
    $R_H^2 \leftarrow$ simulate_conditional_variance$(\omega, \alpha, \beta, H, n_{\text{sim}})$
    distribution$_R \leftarrow$ kde(R_H^2)
    pdf$_R \leftarrow$ KDEDistribution(distribution$_R$)
    moment $\leftarrow$ fractional_moment(pdf$_R, \gamma$; use_abs $=$ true)
    Append `moment` to `z`
end for
return z

D Appendix: Table of Common Distributions

Distribution	PDF / PMF	MGF $M_X(t)$	Restrictions
Bernoulli(p)	$f(x) = p^x(1-p)^{1-x}$	$M_X(t) = (1-p) + pe^t$	$0 \le p \le 1,\ x \in \{0,1\}$
Binomial(n,p)	$f(x) = \binom{n}{x} p^x(1-p)^{n-x}$	$M_X(t) = (1-p+pe^t)^n$	$n \in \mathbb{N},\ 0 \le p \le 1$
Poisson(λ)	$f(x) = \dfrac{\lambda^x e^{-\lambda}}{x!}$	$M_X(t) = \exp(\lambda(e^t-1))$	$\lambda > 0,\ x \ge 0$
Exponential(β)	$f(x) = \dfrac{1}{\beta}e^{-x/\beta}$	$M_X(t) = \frac{1}{1-\beta t},\ t < 1/\beta$	$\beta > 0,\ x > 0$
Gamma(α,β)	$f(x) = \dfrac{1}{\Gamma(\alpha)\beta^\alpha} x^{\alpha-1} e^{-x/\beta}$	$M_X(t) = (1-\beta t)^{-\alpha},\ t < 1/\beta$	$\alpha, \beta > 0,\ x > 0$
$\mathcal{N}(\mu,\sigma^2)$	$f(x) = \dfrac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$	$M_X(t) = \exp\left(\mu t + \frac{\sigma^2 t^2}{2}\right)$	$\sigma > 0$

Table 10: Common distributions and their moment generating functions

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