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Risk Management for Private Equity Investors - a VaR Approach

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Judge Business School, University of Cambridge

April 1, 2021

Abstract

Value at Risk in private equity funds can be estimated using stochastic cash flow models, as first done by Buchner (2014). This paper uses additional model parameters to account for fees and return skews, following a stochastic model. Fees are given a similar structure to call options and are allowed to vary with portfolio performance. Return skews are generated through a Poisson jump parameter, which provides a non-standard representation of fund dynamics. I show that VaR approximately doubles when fees are introduced and dynamics change significantly when accounting for skews in private equity returns. This result was robust at all VaR confidence levels. In the latter sections, I present additional calibration methods and potential improvements to the model.

Keywords: Private equity; Risk management; Stochastic models.

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1 Introduction

Private market assets under management have grown by $4 trillion over the past decade, representing an increase of 170% (McKinsey, 2020). The majority of this growth has come from private equity (PE) which includes leveraged buyout funds, venture capital, and growth equity, and has the potential to deliver outsized, uncorrelated returns. Institutional investors rely on such asset classes to diversify their exposure to public markets and are increasingly likely to either invest in GP-led intermediary funds or engage in direct PE investments (such as the Canada Pension Plan Investment Board's recent investments into Petco and Merlin Entertainments). However, there continues to be insufficient understanding of the risks posed by this illiquid, segmented market (Diller and Kaserer, 2015), which is caused by an incomplete risk management framework for both originators and investors.

This paper, drawing largely on the work of Buchner and Wagner (2017), attempts to mitigate this problem by presenting a Value at Risk (VaR) model which accounts for both fees and the characteristic skew of PE returns. I employ a stochastic cash flow model which incorporates Gaussian noise, Poisson jump diffusion, and stock market correlations to ensure empirical validity. The model was also developed without access to PE datasets (due to funding constraints) and therefore, I propose additional calibration methods in the latter sections. These methods are easily implemented using a conditional least squares (CLS) model, which results in consistent and asymptotically normal estimators.

2 Literature review

This section presents a brief review of existing research on PE risk management, which can be divided into stochastic models, factor pricing models, and corporate finance-based models. Stochastic cash flow models form the largest part of the academic research, with Buchner and Wagner (2017) presenting a continuous time model which shows that PE fees create risk-taking incentives that are not fully priced by investors. This leads to excessive risk-taking by GPs and a lack of transparency regarding the pricing of fees, which are also often ignored by other PE models. An interesting application of this research relates to their lifetime valuation of PE fees, which could be used to derive fundamental values for GP stake investments (an investment strategy adopted by Goldman Sachs' Petershill group). Buchner (2014) also presents a framework for VaR modelling, but does not incorporate adjustments for PE fees, an research area in which I hope to contribute. Their research methodology relies heavily on the use of geometric Brownian motions, which imposes parametric restrictions on PE returns, ignoring the positive skew characteristic of PE investments. Ungsgard (2020) adopts a similar approach but focuses on portfolio data from multiple PE funds and also considers cash flow dynamics in greater detail. His study finds that these types of differential equation models explain fund distributions more accurately than capital calls due to observed lags in the speed of capital contributions at the start of a fund's lifetime. A generalisation of this widely accepted stochastic model is the Yale Endowment Model, which incorporates an exogenous growth term and a bowing factor for return distributions (Harte and Buchner, 2017). Bongaerts and Charlier (2009) use a similar model, yet focus on risk weightings and capital requirements for PE investments, providing an implicit risk management tool for regulated banks looking to invest in private assets. Although this paper focuses on bank risk weightings, it provides a useful time-series analysis of the risks generated by private equity investments and this method has also been extended by Buchner (2014) to measure cash flow risks from PE investments dynamically.

Factor pricing models provide a comprehensive understanding of risk through a pricing lens rather than a bottom-up cash flow methodology, relying on standard pricing restrictions to determine risk premia. Driessen et al (2007) present a Generalised Method of Moments (GMM) framework to assess risk exposure to a non-traded asset. The estimation strategy uses cash flow data rather than self-reported net asset values (NAV), in an attempt to mitigate bias or measurement error. They find that PE returns are surprisingly uncorrelated with public markets, casting doubt on the inclusion of a stock market correlation parameter, which is currently an accepted practice in most empirical papers. They also conclude that risk-adjusted PE returns are surprisingly low (particularly in the longer term), suggesting that investors may achieve greater alpha elsewhere. This paper builds on work by Kaplan and Schoar (2005) who assess abnormal performance of PE funds using public market equivalents, and Jones and Rhodes-Kropf (2004), who regress NAV-based returns on various risk factors. The main advantage of this GMM specification is the lack of parametric or distributional assumptions for factor returns, avoiding any problems with p-hacking or data mining. Diller and Kaserer (2007) extend this pricing factor model using a weighted least squares (WLS) regression, concluding that total fund inflows, GP skills, and investment risk are all significant in explaining returns. Jegadeesh et al (2009) employ a novel approach, estimating risk and expected returns based on market prices of exchange-traded funds (ETFs), which invest in unlisted PE funds. They find that the liquid market equivalents price in an expected abnormal return greater than 0.25% but less than 2.25% (after fees). They also find that markets do not expect PE funds to earn extreme abnormal returns in the long-term. This proves inconsistent with various historical observations that show extreme positive abnormal returns in a significant proportion of funds due to positive skew and excess kurtosis.

Corporate finance-based risk management literature is predominantly generated by practitioners, who present both analytical and qualitative solutions to PE risk management. Diller et al (2015) provide a summary of this research and focus specifically on risk management from the perspective of GPs (both ex ante when originating investments and ex post when mitigating risks from existing investments). They find that if an investor holds a portfolio of 20 funds, the probability of losing any capital (over a 22 year period) is 1.4%, falling to 1% in 50 funds, signalling the diversification advantages of PE. They also state that VaR metrics which measure market risk alone are not useful when quantifying PE risks and thus VaR measures must consider both liquidity and cash flow risks. This form of research provides a qualitative perspective on GP risk and also includes theoretical accounting and corporate finance-based methodologies.

3 The model

I base my theoretical model on the work of Buchner and Wagner (2017), employing a similar specification for drawdowns, distributions, and fund value dynamics. The general functional form is given by:

$$P_t = V_t + C_t \tag{1}$$

where V_t is the NAV of the fund and C_t is the cash balance. I assume that drawdowns and distributions move between these two entities, producing a closed portfolio. The first model is summarised by the following SDEs:

$$dV_t = V_t(\mu_V dt + \beta_V \sigma_M dB_{M,t} + \sigma_\epsilon dB_{\epsilon,t}) + dD_t - dR_t \tag{2}$$

$$dC_t = C_t r_f dt - dD_t + dR_t \tag{3}$$

where μ_V is the fund growth rate (which is calibrated to exclude PE fees), β_V is the stock market beta, σ_M is the market variance, r_f is the risk-free rate, and dt is a change in continuous time. I introduce randomness into the model by including two standard Brownian motions ($dB_{M,t}$, $dB_{\eta,t}$), which display the desirable mean-variance properties leading to an overall GBM. Drawdown and distribution dynamics are summarised by dD_t and dR_t respectively, which follow similar specifications to the Buchner model, but I remove the stock market correlations here to reduce model complexity. Essentially, drawdowns follow an exogenous rate but have a degree of randomness introduced by a third Brownian motion. This leads to a concentration of drawdowns in the investment period (as expected) and an exponential decrease over time, which accounts for the harvesting period. Distributions are organised in a similar way with a constant, deterministic mean term and a random component; they are also derived from fund value as distributions are performance-linked, leading to smaller payouts at the start of the fund and greater payouts as investments are sold.

The second model introduces fee dynamics, with the GP entitled to a management fee (as a percentage of committed capital) and performance fee (carried interest). This is paid as a fraction of net cash flow (subject to certain conditions). The fee structure is summarised as:

$$dF_t = c_m C_0 dt + c_p max(dP_t - dD_t - c_m C_0 dt) \cdot 1_{(IRR_t > h)} \tag{4}$$

where c_m is the management fee parameter, C_0 is committed capital, c_p is the performance fee parameter, and h is the hurdle rate required for a performance fee to be paid (Buchner and Wagner, 2017). The management fee component is constant in each period and can, in practice, be ignored since one can specify that μ_V accounts for management fees. The performance fee component creates non-linearity in the fee variable which also feeds into the final portfolio variable. Intuitively, if all other variables are kept constant, fees will only be paid when the fund is in profit (and producing an internal rate of return (IRR_t) greater than the required hurdle). This means that fees reduce upside gain without affecting the left-hand side of the distribution of returns, implying that performance fees will have minimal effect on VaR except in specific cases when initial performance is strong followed by a reversal in gains during the harvesting period. This would lead to fee outflows initially (as the IRR is above the hurdle) but this would stop when performance deteriorates. However, when such a point is reached, fees have already been paid out and the fund value path has been 'shifted' downwards, leading to greater VaR figures. In practice, this is mitigated by carry clawbacks but I assume they are not present in this model.

Despite clawback provisions, there is still a mismatch in incentives when fees are introduced, as the GP (who is in control of the fund) looks to maximise their own payoff. This leads to excessive risk-taking as shown by Buchner and Wagner (2017), leading to a significant increase in VaR (which was not explored in their paper). I attempt to quantify this effect by making assumptions on the alpha generation of PE funds, thus showing that GPs always choose PE investments with greater idiosyncratic variance, even if the expected returns (and alpha) are identical (this will be explained further in the Calibration section). A final consideration regarding fee structure is that equation (4) is only valid for carried interest without catch-up or clawbacks provisions, since this reduces the model's complexity. I also impose a European fee structure, which calculates carry on a whole-fund basis (ensuring model tractability), as opposed to an American waterfall, which allows carried interest to accrue on a deal-by-deal basis.

The third model in consideration is a stochastic model with Merton jump diffusion (1976), which generates positive skew in the fund value distribution and the subsequent distribution of IRRs. The Merton jump model utilises a Poisson intensity parameter to determine the frequency of each jump and a Gaussian variable to determine the size of the jump. The model is summarised below:

$$dV_t = V_t((\mu_V - \lambda\mu_j)dt + \beta_V\sigma_M dB_{M,t} + \sigma_\epsilon dB_{\epsilon,t} + J_t dP_t) + dD_t - dR_t \tag{5}$$

where λ is the Poisson intensity parameter, J_t is a random percentage jump size, which follows a lognormal distribution, μ_J is the mean of J_t, and dP_t is the Poisson process generator. This formulation is based on Lambrecht and Tse's research on bank insolvency (2019), which utilises a similar - but negative - Poisson jump process, and Bayraktar and Egami's research on optimising venture capital investments in jump diffusion models (2007). The additional parameter modifies the standard GBM assumption to fit PE return distributions more precisely, leading to improved maximum loss predictions. Naturally, this is still a parametric assumption, which introduces the possibility of functional form misspecification. However, given that the standard GBM is known to be violated in practice, including a skew term provides some progress on existing distributional assumptions.

To conclude the section, I present the final VaR metric, which focuses on quantifying market risk. I define VaR in a similar way to Buchner with respect to a certain time horizon h, as the worst loss expected given a certain probability. In the context of my model, this translates into the following expression:

$$Prob(P_t - P_{t+h} \geq VaR_{t,h}(\alpha)) = 1 - \alpha. \tag{6}$$

Given the various critiques of using VaR in PE risk management, this model can also be adjusted to measure Liquidity-at-Risk and Cash-Flow-at-Risk (Buchner, 2014), however, for the sake of brevity, I do not consider these models in this paper. An advantage of Buchner's VaR model is its use of a discrete ranking, which avoids any biases from skew or kurtosis. This means VaR is robust to changes in distributional assumptions, unlike a standard symmetric confidence interval.

4 Model calibration

To calibrate the first model, I follow a similar process to Buchner (2014) and Ungsgard (2020), in assuming that the PE fund is an efficient portfolio which lies on the security market line (following the Sharpe-Lintner CAPM). I then assume the fund has a market beta of 1.3 (Ang et al, 2013) and risk-free rate of 0.01. From this, I derive the PE fund's expected return, which is μ_V in the model and also assume that the fund has an idiosyncratic variance of 0.35 as in Buchner's specification. The remaining model parameters (including drawdown and distribution parameters) are summarised in Table 1 in the Appendix.

The second model (incorporating fees) has three additional parameters which need to be set. I first assume that there are no management fees ($c_m = 0$) to ensure simplicity, since the growth rate can be augmented to account for this constant cash outflow. This also simplifies comparisons as I can focus on the more interesting carry effect, which introduces further dynamics into the PE risk management structure. I assume carry fees are charged at 20% of net cash flow, which comes from anecdotal evidence in the literature and the empirical bunching seen at this level (Choi et al, 2011). Therefore, I impose the restriction that carry will only be paid if the hurdle IRR is met, which is set at 8%.

Finally, I introduce endogeneity into the idiosyncratic volatility parameter (σ_ϵ), which was previously assumed to be constant and equal to 0.35 in the Buchner model. Assuming the GP manages this fund in isolation (although this can easily be generalised to multiple follow-on funds), it can be shown that the GP will maximise the risk-neutral expectation of its fees over the fund's lifetime. Looking at the equation denoting total fees earned, the management fees are constant, so the only variables which can be changed are the fund return, market beta, and the idiosyncratic volatility. I also assume that the fund return and market beta are kept constant (which can be relaxed if necessary), implying that the GP does not have direct control over either the alpha of the fund or the fund's correlation with the stock market. In this case, the GP will maximise total carry with respect to σ_ϵ. This is because carry fees are structured in a similar way to call options, with an asymmetric payoff which is increasing in volatility. However, given that the hurdle rate condition also needs to be fulfilled, the GP will not choose an infinite volatility, leading to a global maximum. A closed-form, analytical solution is not available for this function. Therefore, to find the maximum, I implement Euler discretisation and solve numerically through Monte Carlo simulation to find the idiosyncratic volatility which maximises total carry.

After implementing a maximisation algorithm, I find that the σ_ϵ which maximises carry fees for the GP is equal to 1.4. However, this introduces excessive volatility into the fund value dynamics and creates a distribution of IRRs not observed empirically. A reason for this observation may be due to the assumption that the fund operates in isolation, whereas in reality GPs raise multiple funds in sequence, which is likely to reduce risk appetite for each individual fund. This is due to the reputational risk that may be incurred when an individual fund experiences large losses, jeopardising any future fundraises. Another factor to consider is that it may be impossible to increase idiosyncratic volatility by such an amount. An extension of the model would be to introduce endogenous debt and equity funding, as this could link portfolio company debt levels with total fund volatility. One could use borrowing constraints to find an empirical upper bound on total fund volatility, but at this stage, I assume an idiosyncratic volatility of 0.7, which produces an acceptable IRR distribution.

To conclude the calibration section, I set the parameters in the third Merton jump model. There are three additional parameters to calibrate in this model, which are the jump intensity, the mean of the jump process, and the volatility of the jump. The most unbiased method to calibrate these parameters would have been to implement a CLS model using data from Cepres. This would have generated strong consistency, asymptotic normality, and strong convergence. However, given funding constraints and lack of PE data, I have instead resorted to calibrating the model by studying the distribution of IRRs for a set of private equity funds. Kupperman and Griffiths (2001) show that distributions of US and European

PE returns are similar in shape with a moderate bias towards higher returns. They also find that 15% of managers have a final IRR of below zero with European returns 400bps less than US PE funds. Finally, they show that approximately 10% of funds generate in excess of 20% net IRR and a significant number of cases in excess of 100%, providing evidence for positive skew. This is corroborated by Jacobson (2020) who, using the Venture Economics dataset, finds that buyout funds generate a positive skew of 1.55 and a kurtosis of 3.38. He asserts that this skew comes from exposure to large outlier returns, manager expertise (which limit downside losses), and the strategy of targeting undervalued companies. Using this information, I iteratively generate Monte Carlo simulations for different values of the parameters and find that setting λ equal to 0.1, μ_j equal to 0.2, and σ_j equal to 0.2 provides an acceptable IRR distribution and fund value dynamics. However, given these parameters have not been derived using a consistent estimator, they will likely contain bias and therefore, the results must be interpreted with this in mind.

5 Results

The final set of results come from a Monte Carlo simulation with 10,000 iterations and 1000 time steps (which divide up a fund life of 12 years). The convergence of results is robust, yet noise and fractal-like behaviour persisted in the VaR output, which led me to apply non-parametric Loess smoothing. This can be avoided by increasing the number of iterations and time steps but due to computer processing constraints, this was not possible.

Figure 1 illustrates the various dynamics generated by the fund under the Buchner model. The graphs bear resemblance to Buchner's original paper, which is to be expected given that the model is almost identical, and this provides confidence that my subsequent analysis is comparable to previous research. The graphs are consistent with PE theory, in which capital drawdowns increase at their fastest rate at the beginning of the fund. Distributions also behave as expected, ramping up rapidly at the beginning of the harvesting period and subsequently plateauing. The fund value dynamics illustrate a peak in the fund value immediately before the harvesting period. Following this, total value held within the fund (as opposed to the investor's portfolio position) gradually trends downwards and is eventually liquidated. This relates to the boundary condition between distributions and fund value, as cumulated distributions at fund maturity must adjust for liquidation values.

Figure 2 compares the fund value dynamics for the first and third models, demonstrating the effect of introducing a jump parameter. The mean path of fund value peaks higher under this new specification, however the median path is not significantly affected. The confidence intervals are also greater but this is misleading given the distribution of fund values is now skewed (and so confidence intervals must be adjusted). Given the Poisson jump process generates higher fund values in expectation, this leads to lower VaR figures nearer the end of the fund's life since a greater proportion of value paths are de-risked over time. This is because a greater proportion of paths have delivered abnormally positive returns, meaning there is very little chance of a reversal large enough to result in a final investment value below the VaR threshold.

Figures 3, 4, and 5 present VaR graphs at fund initiation for standard confidence intervals of 10%, 5%, and 1%, and shows that all three specifications share some common traits. They all display a steep increase in VaR initially, which comes from capital being drawndown from the cash pool and invested in risky assets. This continues to grow until the fund enters the harvesting period, leading to a flattening of all curves. The Buchner and Poisson jump models exhibit similar dynamics with only a small divergence (which does widen over time). The absolute VaR for the Poisson jump model is approximately 10% lower at liquidation and has a steeper downward trend during the harvesting period. This is likely to come from the compounding effect in fund returns, which is stronger when there is positive skew present. An interesting difference between these two models is that as the confidence level changes, the divergence point comes later, with the VaR dynamics at 1% almost identical for both models until year 5.

There is a stark divergence in the fee-based model compared to the other two models, arising from a change in GP incentives. The absolute level of risk at fund liquidation is more than double the Buchner model under all confidence levels and there is a noticeably smaller downward trend in the latter period of the fund lifetime. This is related to intermediate capital distributions, which limit the compounding effects in fund returns (Buchner, 2014). Introducing fees exacerbates this further as they have a similar effect to distributions but are not even paid into the investor's portfolio - they are just a leakage from the fund. This leads to a broadly constant risk level from the beginning of the harvesting period until full liquidation. The ramping up of risk is also much steeper at the beginning of the fund for the third model but the levelling off point is similar between all three models. However, this levelling off point does change for different confidence levels: for high confidence levels, the VaR peaks more quickly and then falls, whereas for lower confidence levels, the peak comes later. These results are corroborated when looking at VaR dynamics over shorter time horizons, with risk increasing as funds are drawndown, peaking at maximum fund value, and trending downwards during harvesting period. The changing risk levels require additional risk management by investors such as setting capital aside during peak risk taking, to compensate for the amount of risk, particularly if investors have their own liabilities to service. This is where a dynamic VaR framework (which considers fees and a new distribution) can assist investors with more accurate risk forecasting.

6 Concluding remarks

This paper attempts to build on existing research to address the shortcomings of existing risk management processes in private equity funds through focusing on a framework from an investor's perspective. The use of novel specifications aims to aid investors in both understand risk dynamics and exposure at different periods in a fund's lifetime, which can be used practically by investors when deciding on how much capital to set aside when planning out their own liability-driven investment strategies. However as stated in previous sections, the estimation strategy has only considered a select few numerical methods, which are easily improved through the use of granular PE return data. Therefore, this is only a preliminary study of a problem facing investors who aim to understand the exact portfolio risks presented by private investments. The framework is also easily adapted to different types of sector- and geography-specific funds through modifications to the functional form and calibration methods based on historical data, presenting an opportunity for further research into PE risk management.

Appendix

Table 1: Summary of key inputs

Input	Notation	Value	Input	Notation	Value
Riskless rate	r_f	0.01	Average distribution rate	ν	0.08
Expected stock market return	μ_M	0.11	Volatility of distribution rate	σ_ν	0.80
Stock market volatility	σ_M	0.15	Management fee percentage	c_m	0.0
PE return volatility	σ_M	0.4	Carried interest percentage	c_p	0.2
Market beta of PE funds	β_V	1.30	Hurdle rate	h	0.0
Alpha of PE funds	α	0.04	Poisson jump parameter	λ	0.1
Idiosyncratic volatility	σ_ϵ	0.35	Mean of jump parameter	μ_J	0.2
Drawdown rate of PE funds	δ	0.41	Volatility of jump parameter	σ_J	0.2
e Volatility of drawdown rate	σ_δ	0.21	Initial committed capital	C_0	100

Figure 1: Fund dynamics

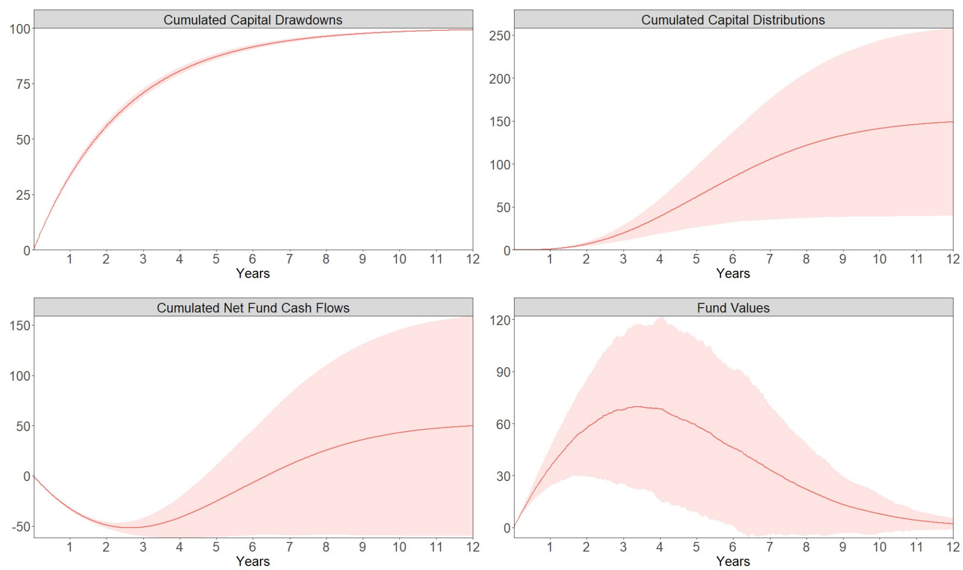


Figure 2: Comparison of fund value dynamics

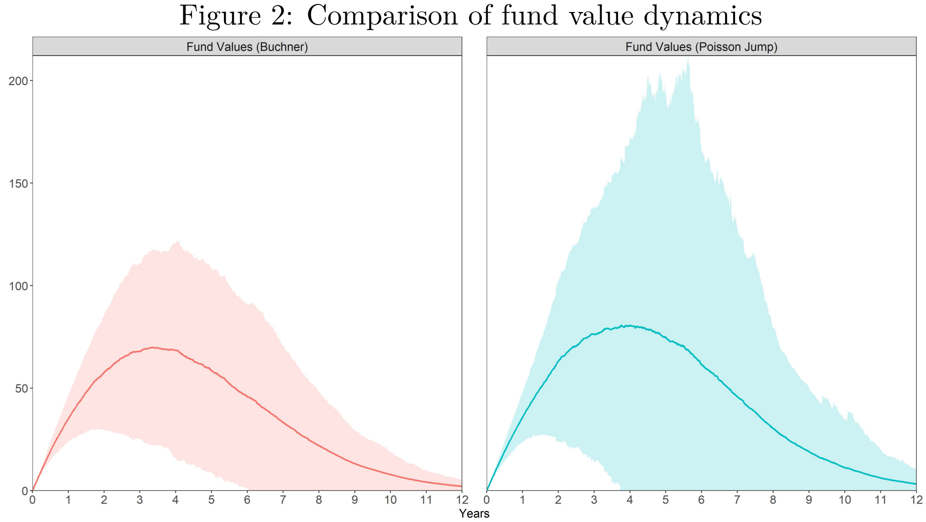


Figure 3: VaR(10%) at fund initiation

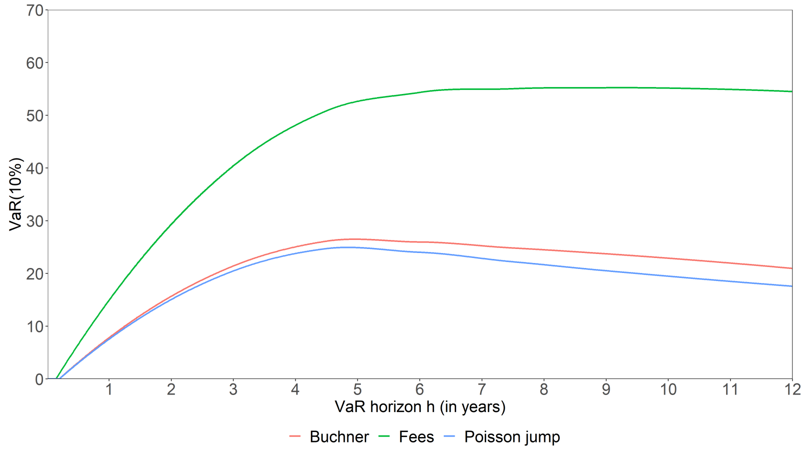


Figure 4: VaR(5%) at fund initiation

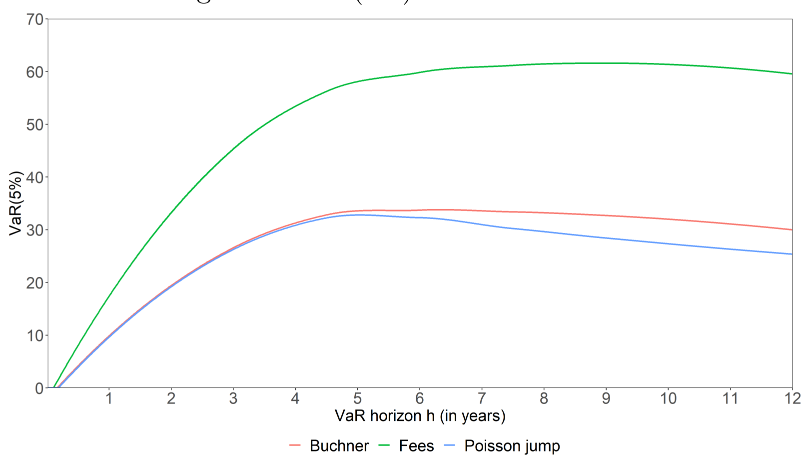
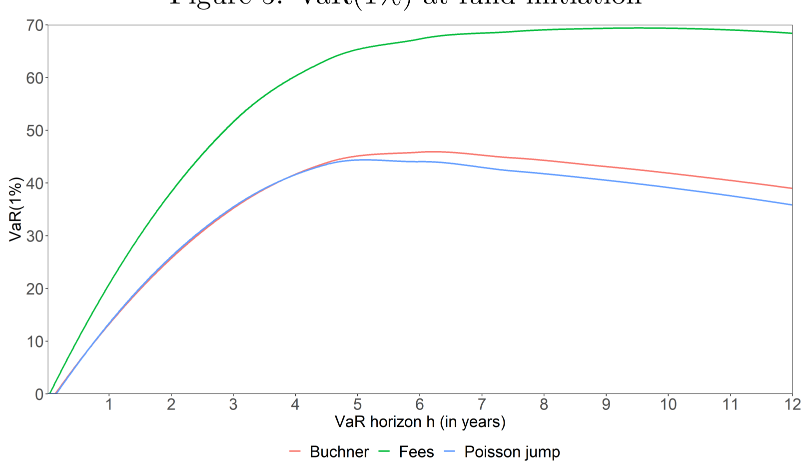


Figure 5: VaR(1%) at fund initiation



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