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Robustness of stable volatility strategies

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ABSTRACT

The paper analyzes the robustness of stable volatility strategies, i.e. strategies in which the portfolio weight of the stock is inversely proportional to its local volatility. These strategies are optimal for a CRRA investor if the stock follows a diffusion process, the expected excess return is proportional to its volatility, and the hedging demand is zero. We assess the performance of stable volatility strategies when these restrictive assumptions do not hold, in particular, when the risk premium is not proportional to volatility and when the stock price is subject to jumps. We find that stable volatility strategies are indeed robust or close to robust under a maxmin decision rule. In addition to our theoretical results, we perform a simulation analysis to evaluate strategies that scale the portfolio weight by the volatility, variance or a constant portfolio weight, and also analyze the strategies using empirical excess returns. Both analyses confirm the robustness of stable volatility strategies.

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1. Introduction

The overall level of uncertainty in the market is time-varying. Dating back to Schwert (1989) and Campbell and Hentschel (1992) it is a stylized fact that the volatilities of stock returns change substantially over time.[1] In general, this is also true for the volatility of portfolios. If an investor is interested in holding a portfolio with a (close to) constant volatility, she can rely on a stable volatility strategy in which the portfolio weight of the stock is inversely proportional to the volatility of the stock.[2]

The basic idea to achieve a constant volatility of the portfolio value is appealing. However, the question is whether this choice is also optimal, i.e. whether the portfolio value really should have a constant volatility. It can be shown that this is indeed the case if the investor has CRRA preferences and maximizes the expected utility of terminal wealth, there is no hedging demand, the stock price follows a diffusion process, and the expected excess stock return is proportional to the volatility of the stock. In reality, these restrictive conditions will most likely not be met, and the stable volatility strategy is

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[1] Recent empirical studies about uncertainties in the market comprise e.g. Connolly et al. (2005), Beber et al. (2009), Baele et al. (2010), Bollerslev and Todorov (2011) and Wachter (2013).

[2] If the stock price follows a diffusion process, this strategy implies that the volatility of the resulting portfolio value is indeed constant. Scaling the portfolio to have constant volatility over time is widely applied in the asset management industry. Targeting an ex ante volatility is more common in practice than running constant leverage, cf. Barroso and Santa-Clara (2015).

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suboptimal. The decisive question, however, is how good the strategy still is, or stated differently, how robust it is to model mis-specification. Indeed, recent empirical literature finds a rather good performance of stable volatility strategies.[3]

In this paper we analyze whether stable volatility strategies are robust or close to robust under model risk. It is well known that the solution to an optimization problem can lead to a very poor performance even if the true parameters differ only slightly from the parameters under which the optimal solution has been derived. This problem is highly relevant in portfolio optimization, as shown for example by DeMiguel and Nogales (2009) who find that optimal portfolios rarely outperform a naive benchmark. Since neither the true model nor the true parameters are known for sure, robust strategies which perform well in a whole class of models and/or for a whole set of parameters are particularly attractive.

The specification of a robust strategy starts with the set of models to take into account. In this paper, we rely on jump-diffusion models for the stock with stochastic volatility and stochastic jump intensity.[4] They capture both the risk of sudden large (usually downward) jumps and time-varying uncertainty. The models differ with respect to the assumptions on the expected excess return (constant, proportional to the diffusive return volatility, or proportional to the diffusive return variance) and on the jump intensity (zero, constant, proportional to the diffusive variance, or independent of the diffusive variance). The optimal strategies in the resulting twelve models follow by (numerically) solving the respective asset allocation problems. They are conditional on the specific models and thus subject to model risk.

One intuitive way to cope with model risk, that is, with the uncertainty about the true data-generating process, is robust portfolio optimization. In line with the classical robustness definition that mother nature plays against the investor, we rank the candidate strategies by the worst case certainty equivalent across all possible models. Our candidate strategies comprise the overall optimal strategies in the twelve models. We focus on simplified and easy-to-describe strategies and thus ignore the (highly model-dependent) hedging demand and rely on the (much less model-dependent) myopic demand only.[5] The myopic demand is based on the local risk-return trade-off, but no longer on the dynamics of the state variables. In a second step, we furthermore ignore the differences between jump and diffusion risk[6] and capture the risk by the local variance of the stock only. This results in an approximate myopic demand which is proportional to the ratio of the expected excess return and the local variance of the stock return. It can be interpreted as the 'common' component of the optimal strategies which they share across the different models. If the risk premium is proportional to the local volatility, the resulting strategy is indeed a stable volatility strategy. Taken together, our candidate strategies are given by the myopic strategies and the approximate myopic strategies.

We take the characterization of the uncertainty set as given, i.e. we start with a given set of models. Our robust strategies depend on the choice of this set of models. They are thus subject to the same criticism as optimal strategies which depend on the choice of a specific model. A robust strategy may fail to be robust if the 'true' model is not included in this set of models. The question *how robust is robustness?* is highly relevant. To answer this question, we do not only assess the robustness of the strategies (the assumption on the risk premium, respectively) with respect to diffusion models but also w.r.t. more general jump diffusion models.

The contribution of our paper can be summarized as follows. We show analytically that stable volatility strategies are robust (w.r.t. a meaningful set of relevant models) in diffusion models if the investor has log utility. In this case, strategies which rely on a constant portfolio weight perform equally well and are thus also robust. For a relative risk aversion larger than one, the correlation between the stock and the variance matters. If the correlation is zero, both strategies are still (close to) robust. In the empirically relevant case of a negative correlation, portfolio strategies with a constant portfolio weight cease to be robust, while stable volatility strategies still are.

To shed further light on the robust optimization problem and on the impact of jumps, we perform a simulation study. We assume a negative correlation between stock prices and the variance. Overall, the losses due to incorrect assumptions on the risk premium are in line with our theoretical findings for diffusion models. Stable volatility strategies which are based on a risk premium that is proportional to volatility are also robust across all models that allow for jumps. For low levels of risk aversion, however, the differences between the strategies become small as soon as there are jumps, while they become more pronounced in pure diffusion models. The reason is that the strategies are capped at their upper bound of one in case of jumps, which happens more often for small values of the risk aversion, for which the strategies thus differ less. Furthermore, the assumptions on the structure of the jump intensity turn out to have much less of an impact than the assumptions on the risk premium. While strategies that incorrectly ignore jumps can be prohibitively bad, the exact specification of the jump intensity does not matter too much. When we turn to the approximate myopic strategy based on the realized variance, the argument for stable volatility strategies becomes even stronger. Again, they perform best in the

[3] For example, Barroso and Santa-Clara (2015) find that a stable volatility momentum strategy virtually eliminates crashes and nearly doubles the Sharpe ratio of the momentum strategy. Zieling and Mahayni (2014) find that time-varying multiple portfolio insurance strategies based on a rolling window of historical volatility estimates give a significant improvement of CPPI strategies.

[4] Empirical evidence supporting such a model setup comprises Bakshi et al. (1997), Bates (2000); Eraker et al. (2003), and Pan (2002).

[5] While, in sample, Sangvinatsos and Wachter (2005), Jurek and Viceira (2011), and Larsen and Munk (2012) find utility gains resulting from accounting for the hedging demand, Diris et al. (2015) find the opposite in an out of sample analysis. Feldhütter et al. (2012) find that an investor with typical risk aversion is better off following a portfolio strategy implied by a misspecified but parsimonious model than a correctly specified but difficult to estimate model. To justify our restriction to myopic strategies, we also look at the strategies including the hedging demand in our simulation study. We find that the utility gain due to accounting for the hedging demand when the true model is known is very small and around 1 bp in our example. In case of model risk, the inclusion of the hedging demand can lead to a higher, but also to a lower utility, with potential gains and losses around 5–10 bp.

[6] Liu et al. (2003) provide a detailed discussion of how jump and diffusion risk differ when it comes to finding the optimal strategy.

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