Guaranteed stop orders as portfolio insurance – An analysis for the German stock market

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ABSTRACT **In this study, we analyze the effects of Guaranteed Stop Orders (GSOs) on stocks in the German stock index DAX. We briefly explain how GSOs work and then we develop a jump process, based on a Variance Gamma Process, to model the share prices. We show through simulations that the payoff of a GSO is primarily governed by volatility in the underlying stocks' intraday and overnight movements. We also demonstrate that the common linear approach to price-GSOs is too general and needs to be refined in order to show adequately differences between stocks. We show that recent turbulence in stock markets around the world has made the GSO more interesting and that, further during normal periods, this order type was nearly irrelevant.**

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INTRODUCTION

There are many different forms of portfolio insurance, all having certain advantages and disadvantages. A common portfolio insurance is the Protective Put Option. This simple tool avoids losses below a certain barrier, but has the drawback of not providing continuous protection (see Bodie *et al*, 1996). Dynamic insurance tools, such as synthetic puts, are used to ensure that a portfolio never drops below a certain level. However, they have the drawback of requiring continuous trades. Therefore, the investor must invest considerable effort in order to use them. In addition, Basseer (1991) discovered that dynamic portfolio insurances work best in orderly markets, but become impractical during periods of high volatility. Risk management orders are basic tools to avoid losses. The most common one is the Stop or Stop Loss Order (SO). Unlike most other tools, the investor does must not pay a premium when placing SOs – as a result, it is a widespread tool. One problem with SOs as to protection is that they do not guarantee a selling price equal to their barrier. If liquidity is tight and if it is therefore difficult to find a counterparty willing to execute the SO, the selling price may drop significantly. Many studies have shown that SOs can reinforce sudden share price drops, a phenomenon that is often referred to as 'price cascades' (see Genotte and Leland, 1990; Easley and O'Hara, 1991). These price cascades occur when many investors have set Stop Orders with similar barriers and a price drop triggers them simultaneously. These sudden sell orders encourage other market participants to sell, or worse, they force investors to sell owing to loss limits.

The Guaranteed Stop Order (GSO) was created to counteract this vulnerability to sudden share price jumps. Basically, it is an SO with the additional benefit of guaranteeing a selling price equal to the barrier. If an investor uses a GSO instead of an SO, he still contributes to the above-mentioned problem, but he has the distinct advantage of not being affected by sudden price jumps. Because there is no free lunch, the GSO has a major drawback. A GSO is not always superior to a simple SO, as the investor pays a premium in order to be insured against price jumps. Such share price jumps are often neglected when looking at SOs and, for major firms, this may be appropriate in quiet and orderly times. However, the recent financial crisis has caused considerable turbulence and has dramatically increased stock price volatility. Under these conditions, we consider it to be necessary to take a closer look at GSOs and to evaluate if their pricing is justified.

The purpose of this essay is to make readers aware of the valuation of GSOs, an instrument that has received very little scientific attention so far. A jump process is used to account for the discontinuities in the stock market, which are the sole reasons for the existence of GSOs. We establish, by means of share price, simulations to determine whether the method of pricing GSOs as used, for example, by CMC Markets (2005) is appropriate and reflects their true value. We analyze which factors determine the value of a GSO and how to price them accordingly.

This essay is organized as follows. In the next two sections, a model for share prices and GSOs is developed. Then the data is presented and the fitting process is described. Afterwards the simulation process and its results are explained. The following section provides a closer analysis, determines the major influences on GSOs and outlines a new pricing approach. Hence, the two penultimate sections are dedicated to robustness, and check the stability of previous findings regarding the modeling assumptions and the stability of the most relevant parameters. Finally, the last section summarizes the results and by giving an outlook on possible future research on GSOs.

MODEL

As already defined, GSO were created to circumvent the problem of an SO, when a sudden price jump occurs. To clarify how a GSO works, we give the following real-life example: Let us assume we are short in Volkswagen shares on 28 October 2008. We placed an SO at a level of €525. This means that in case the share price of Volkswagen is €525 or higher, we cut the losses of our bearish strategy, because we close the position at the next price. At some point this occurred, and the next obtainable price was €595. With respect to our SO we lost an additional amount of €70 per stock. If we had placed a GSO instead of an SO, the price at which our order would have been executed would have exactly been the guaranteed €525. Compared with the SO we would have gained €70. We set up the following model to answer the question, 'what should an investor pay in order to be insured against price jumps?'.

First, we must decide on a model for the underlying stocks in order to evaluate GSOs. The most common approach would be to assume that the stock prices follow a Brownian motion. One characteristic of Brownian motion is the fact that its paths are almost surely continuous. In simpler terms, a Brownian motion does not jump. On the other hand, GSOs are instruments specifically developed to protect investors against jumps in the stock markets. Therefore, it would be desirable to use a stochastic process that focuses on such events. According to Cont and Tankov (2004) there are two basic categories of jump processes to choose from: jump-diffusion models and infinitely active models. The former consist of a Brownian component and rare jumps, and the latter of an infinite number of jumps in each interval. In this article, we use a Variance Gamma Process (VGP), a process of infinite activity, as a starting point for our model. Carr *et al* (2002), Geman (2002) and Madan (2001) confirm that this category provides a better representation of historical share price processes than the Brownian motion. Furthermore, the VGP is a well-established model, as several authors have shown that it fits stock market data relatively well and can also be easily simulated (see Madan and Seneta, 1990). Alternative models are the jump-diffusion as well as the hyperbolic process, which are tested relatively often and positively evaluated. The latter process is used especially for the German market (see Eberlein *et al*, 1998; Rathgeber, 2007). We will discuss this further in the robustness checks section.

In the basic model (compare Schoutens, 2003; Cont and Tankov, 2004; Seneta, 2004), the share price S_t over time $t \geqslant 0$ is given by:

$$S_t = S_0 \exp(X_t) \tag{1}$$

where S_0 is the initial share price and the exponent X_t is defined as:

$$X_t = ct + \theta G_t + \sigma W(G_t) \tag{2}$$

with the parameters c, θ, σ and the Brownian motion W. G_t is a random process independent of the Brownian motion $W(\bullet)$. G_t follows a gamma process, is a positive increasing random process and can be interpreted as an 'economically relevant measure of time' (Geman *et al*, 2001). The expected economically relevant time change per calendar time unit is, without loss of generality, normalized to 1.

$$E(G_t - G_{t-1}) = 1 \tag{3}$$

Hence, the expected activity time change over unit calendar time equals 1. This normalization is contained within θ and σ. The change in the exponent X_t over one unit of calendar time, denoted by ΔX_t, can be written as:

$$\begin{aligned}\Delta X_t &= X_t - X_{t-1} \\ &= c + \theta(G_t - G_{t-1}) + \sigma\sqrt{G_t - G_{t-1}}W(1)\end{aligned} \tag{4}$$

Consequently, the time change can be transformed in a variance change according to Seneta (2004). The model, as it stands now, requires that the expected price change from one time step to the next is constant. However, in reference to GSOs, it is important to consider the fact that the expected change between the last share price of any given day and the next will not be the same as it would between two adjacent intraday prices. This is taken into consideration by defining S_t as follows:

$$S_t = S_0 \exp(ID_t + ON_t) \tag{5}$$

In this definition, there are two independent stochastic processes ID_t and ON_t. ID_t controls the intraday share movement and ON_t the overnight movement. This model is based on the assumption that each jump is independent of previous jumps, and that especially overnight jumps are independent of intraday jumps. This assumption is not entirely true. There is evidence that an over- or under-performance in the last few share prices of a day is related to an over- or under-performance in the overnight jumps. This dependence lends itself to further research but is ignored in the present model. To be able to formally define ID_t and ON_t, we create a set T containing all points in time which coincide with the first price fixing of each day. The change in ID_t is now defined similar to ΔX_t in.

$$\Delta ID_t = \begin{cases} 0, & \text{if } t \in T \\ c_{ID} + \theta_{ID}(G_t(\kappa_{ID}) - G_{t-1}(\kappa_{ID})) \\ \quad + \sigma_{ID}\sqrt{G_t(\kappa_{ID}) - G_{t-1}(\kappa_{ID})}W(1) & \text{otherwise} \end{cases} \tag{6}$$

This definition shows that the intraday movement follows a VGP that does not affect the overnight movement. ON_t adds a jump between the closing and the opening price with the jump being distributed according to the marginal distribution of the VGP:

$$\Delta ON_t = \begin{cases} c_{ON} + \theta_{ON}(G_t(\kappa_{ON}) - G_{t-1}(\kappa_{ON})) \\ \quad + \sigma_{ON}\sqrt{G_t(\kappa_{ON}) - G_{t-1}(\kappa_{ON})}W(1), & \text{if } t \in T \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Furthermore, the overnight jump does not affect intraday movement.

GUARANTEED STOP ORDERS

As mentioned before, GSOs are similar to standard Stop Orders. The difference is that a GSO guarantees a selling price which is equal to the chosen barrier, whereas the SO only provides the next selling price after the barrier has been broken. Basically, a GSO can be seen as an insurance that pays the difference between the barrier and the next possible selling price. We evaluate GSOs using the share price model. The payoff P_B is defined as:

$$P_B = |B - S_\tau| \tag{8}$$

It is assumed that τ is the first point in time for the share price S_τ, which can be less than or equal to or, if it is short selling, exceed the barrier B.
The model considers a time frame T of 1 year between GSO placement and cancellation. If the barrier is not reached within this time frame, the payoff P_B is 0. It is extremely uncommon to place (guaranteed) stop orders for a longer period. Many brokerage services do not even permit it. Unlike an SO, an insurance premium must be paid when placing a GSO to reflect the offered protection. This fee is calculated according to CMC Markets (2005). For stocks in the German

stock index DAX, the premium is set to be 0.3 per cent of the GSOs' barrier by CMC (similar also Macquarie, 2011; IG, 2012) and must be paid immediately. Stocks in other indices have different premium rates, but they follow the same structure. Therefore, the premium R is defined as:

$$R = cB \tag{9}$$

with $c = 0.003$ in our case. This definition is intuitive for long positions, but seems counter-intuitive for short positions, where the premium rises farther away from the initial share price where the barrier is set. This structure is probably due to the fact that the expected relative jump sizes are assumed to be constant and the absolute jumps, therefore, are expected to increase in case of higher share prices. An additional rule is that a GSO cannot be set within 5 per cent limit of the current price of a share. For example, if a share is listed at 100, one can set a GSO at 95 and pay a premium of 0.285. In this article, we focus on long positions, where the barrier is consequently below the initial stock price.

In order to be able to price the GSO we need to calculate the expected payoff. Therefore, we can define the stopping time, when the price process crosses the barrier:

$$\tau = \min\{t \in [0; T] | S_t \leqslant B\} \tag{10}$$

Consequently, the expected payoff with regard to the new measure (c_{new}) discounted by the riskless rate r is:

$$E_{c_{new}}(P_B(\tau) \cdot 1(\tau \leqslant T)) \cdot \exp(-r\tau) - cB \tag{11}$$

To price the contingent claim according to Equation (11), we had to find an equivalent martingale measure; as Chan (1999) points out, this must be done even if the market is incomplete. As there is no unique measure in incomplete markets, we had to choose among the different possibilities. For the sake of simplicity, we use the mean correcting measure according to Schoutens (2003, p. 79). Within our robustness checks we stress this choice by applying another measure transformation: by following Schoutens (2003, p. 80) and applying the parameter transformation in Schoutnes (2003, p. 57), the mean corrected measure c_{new} is

$$c_{new} = r + \frac{1}{\kappa}\ln\left(\frac{(M-1)(G+1)}{MG}\right) \tag{12}$$

whereby

$$M = \left(\sqrt{\frac{1}{4}\theta^2\kappa^2 + \frac{1}{2}\sigma^2\kappa} - \frac{1}{2}\theta\kappa\right)^{-1} \quad \text{and}$$

$$G = \left(\sqrt{\frac{1}{4}\theta^2\kappa^2 + \frac{1}{2}\sigma^2\kappa} + \frac{1}{2}\theta\kappa\right)^{-1}$$

Last but not least, in order to solve Equation (11) the first passage time must be evaluated. Owing to the overshoot problem of the general Lévy Processes, there exist only rare cases where analytical solutions are feasible (see Kou and Wang, 2003). Because of the special structure of the different parameters for overnight and intraday returns, we faced the problem that we could not apply any of these rare cases. Hence, we chose a simulation framework to evaluate the Equation (11).

DATA

The next step is to obtain data to fit the model to. We adjusted our parameters to the stock prices of the 35 firms, which have been listed on the Deutscher Aktienindex (DAX), the most important German stock index, since 2005. As we intend to simulate stock prices at a tick level, we require share price data of the same level. The stock exchange in Stuttgart provided us with the necessary time series of quotes for each tick in the stock market. In order to fit the intraday aspect of our model, we collected quotes ranging from 1 January 2010 to 31 October 2010. Two hundred trading days may seem to be a very short period of time, but since we use tick data we have an average of 8265 data points per firm. Deutsche Bank AG shows the highest activity with 28 172 data points. Metro AG, the firm with the least activity in this period, still provides 875 data points. Therefore, we believe these 200 trading days to be sufficient for the intraday fit of our model. This time period provides us with only 200 overnight returns, which do not suffice for an adequate fit of the model's overnight aspect. As we assume the overnight returns to be independent of the intraday returns, we can extend the time period to gain additional data points, by using overnight returns ranging from 1 January 2003 to 31 October 2010. This period amounts to more than 2000 returns, which should enable an adequate fit. The overnight returns corresponding to dividend payment dates were removed from this series. As a result there is one less data point for most firms. Intraday returns are not directly affected by the dividend payments; therefore none had to be removed. To check the robustness of our results, we applied our model first to quotes ranging from 1 April 2009 to 14 May 2009 (intraday) as well as 1 January 2008 to 14 May 2009 (overnight). These periods were chosen due to the high volatility during the financial crisis. Second, we analyzed how the model results change, if we look at mid- or small-cap stocks. To this end, we used a time series of the 20 most important (index weights) MDAX and SDAX stocks, which spans from 1 September 2010 to 31 October 2010 (intraday) as well as 1 July 2009 to 31 December 2011 (overnight).

FITTING THE PARAMETERS

After obtaining the data, the next step is to decide on a method to fit the model to the data. Following Cont and Tankov (2004), there are two main approaches: the method of moments (MoM) and the maximum likelihood estimation. Recently, Finlay and Seneta (2008) have shown that the minimum χ^2 procedure produces an acceptable approximation of the marginal distribution in connection with a low calculation time. The χ^2 procedure corresponds to the goodness-of-fit test of the same name and tries to minimize the squared difference between observed absolute frequency and the number of observations derived from the theoretical probability. Mathematically speaking, we had to numerically minimize the χ^2 value with respect to the distribution parameters, whereby the χ^2 value can be expressed by the following sum:

$$\chi^2(c_\bullet, \theta_\bullet, \kappa_\bullet, \sigma_\bullet) = \sum_{n=1}^{m} \frac{(O_n - E_n)^2}{E_n} \tag{13}$$

Here, O_n is the total number of observations in the data set divided by the number of sample bands m, and E_n is the expected number of observations falling within the n-th sample quantile band. According to Finlay and Seneta (2008), we split the data set into 100 equal-sized sample bands. Owing to the different time series, we fitted the overnight parameters (c_{ON}, θ_{ON}, κ_{ON}, σ_{ON}) and the intraday parameters (c_{ID}, θ_{ID}, κ_{ID}, σ_{ID}) separately (for example, the dot at c stands for either ON or ID) (Table 1).

The minimum χ^2 procedure requires a starting value for the parameters. Therefore, following Seneta (2004), we use an MoM approach. The overnight and intraday parameters are fitted to the first four moments of the Variance Gamma Distribution (VGD) (Seneta, 2004). Then we use these estimated parameters as starting values for

Table 1: Goodness-of-fit test statistics (base case)

Firm	*Reuters code*	χ^2 *statistics*	
		Intraday	*Overnight*
Addidas	ADS	6.21	2.68
Allianz	ALV	7.06	5.03
BASF	BAS	6.69	3.69
Bayer	BAY	4.87	2.30
Beiersdorf	BEI	2.30	1.59
BMW	BMW	5.16	3.06
CBK	CBK	12.01	2.15
Continental	CON	9.51	1.97
Daimler	DAI	10.46	4.64
Deutsche Boerse	DB1	177.84***	2.54
Deutsche Bank	DBK	7.62	5.27
Deutsche Postbank	DPB	8.27	1.70
Deutsche Post	DPW	12.49	2.72
Deutsche Telekom	DTE	8.08	3.01
EON	EOAN	17.11	2.71
Fresenius Medical Care	FME	2.34	1.57
Fresenius	FRE3	19.96	1.51
Henkel	HEN3	5.90	3.16
Hannover Rück	HNR1	5.13	2.06
Infineon	IFX	9.58	2.31
Lufthansa	LHA	5.56	2.43
Linde	LIN	3.36	2.23
Lanxess	LXS	2.30	2.11
MAN	MAN	3.98	2.58
Metro	MEO	4.25	1.53
Merck	MRK	4.17	2.94
Münchner Rück	MUV2	5.84	2.38
RWE	RWE	8.93	2.82
SAP	SAP	6.54	1.68
Kali und Salz	SDF	4.65	5.70
Siemens	SIE	5.49	2.68
Salzgitter	SZG	4.06	1.57
Thyssen-Krupp	TKA	2.77	1.78
TUI	TUI1	5.14	2.62
Volkswagen	VOW	107.57***	3.13

Notes: Table 1 presents the goodness-of-fit χ^2 statistics for the returns of the 35 different stocks in our data sample (base case, period January–October 2010). The χ^2 method was applied to intraday (Column 3) and overnight returns (Column 4) separately. The values for which the null hypothesis (drawn from VGD) are rejected on a 1 per cent significance level are indicated by three stars ***. In Column 2, the Reuters instrument code is also depicted.

the minimum χ^2 procedure produces. Table 2 shows the fitted parameters for overnight and intraday returns separately. Furthermore, Table 1 comprises the χ^2 statistics to test the goodness of fit.

The null hypothesis that the samples are drawn from the reference distribution at a level of 1 per cent can be rejected for two cases. Deutsche Boerse AG (DB1) goes up to a test statistic of 177.84 regarding overnight returns, and Volkswagen AG (VOW) goes up to 107.57. Therefore, we remove Deutsche Boerse as well as Volkswagen from our further observation, as the error is too large and the simulation results with these parameters cannot be trusted. In addition, we tested whether the overnight and intraday distribution can be drawn from the same distribution. A closer look at the first three parameters proves that it is not possible.

SIMULATION PROCESS

Having fitted the parameters of our model to the data, we must now decide on a simulation process. In order to be able to simulate the price process, a time grid has to be chosen. The payoff of a GSO is determined by the first obtainable stock price after the relevant barrier has been broken. Therefore, one calendar time unit is defined as one tick. A problem with this definition is that the number of ticks per day varies for each stock and day. In the base model, we will assume that the number of ticks per day N_S is constant for a given stock but may be different for different firms. For each stock S the average number of ticks per day is calculated and defined as N_S. To determine the value of the GSOs, we run 10 000 simulations for each stock in our sample. During these simulation runs, we evaluate GSOs for 10 different barrier levels, ranging from 50 to 95 per cent in 5 per cent intervals. We simulate a period of 1 year, which is assumed to have 250 trading days. If a GSO is not triggered in the course of 1 year, it is canceled and has a payoff of 0. The simulation algorithm is based on Cont and Tankov (2004, p. 184) and is modified to fit our specific model.

SIMULATION RESULTS

Table 3 shows the simulated GSO payoff. Every second GSO barrier is omitted in order to keep the table at a reasonable size. Payoffs that exceed the costs are in bold type and underlined. One can observe that, at the highest possible barrier, over 10 per cent of the firms (15 per cent) have a payoff which is higher than the costs. This figure decreases steadily, down to 0 per cent at the lowest barrier.

Table 4 takes a closer look at the difference between the payoffs and costs of GSOs. The numbers in the table indicate the percentage of firms with a payoff to cost ratio at a certain barrier in the respective interval. We can observe that, at the highest barrier, half of the firms have a payoff to cost ratio between 75 and 125 per cent. As the barrier decreases, fewer and fewer firms remain at moderate ratios. At the 85 per cent barrier and below, over 25 out of 33 firms have ratios of either less than 50 per cent or more than 150 per cent. This clearly shows that the proposed approach to pricing GSOs does not reflect their true value. In addition, we can observe that the payoff decreases at a rate significantly higher than the cost and, with a barrier of 85 per cent or lower, most results show a payoff to cost ratio of less than 50 per cent.

The payoff of a GSO depends on two factors: the probability that the stock reaches the barrier and the amount at which it breaks the barrier.

Table 2: Fitted parameters (base case)

Firm	*Intraday*				*Overnight*			
	$c_{ID} \times 10^{-5}$	$\theta_{ID} \times 10^{-5}$	$\sigma_{ID} \times 10^{-3}$	$\kappa_{ID} \times 1$	$c_{ON} \times 10^{-5}$	$\theta_{ON} \times 10^{-5}$	$\sigma_{ON} \times 10^{-3}$	$\kappa_{ON} \times 1$
ADS	2.94	−2.00	4.17	2.92	−119.89	46.44	11.08	1.43
ALV	−7.89	4.58	1.74	1.96	−242.41	171.37	12.01	1.33
BAS	11.03	9.78	1.71	2.10	−93.16	22.47	8.60	1.24
BAY	6.89	0.62	2.39	2.04	−107.48	30.07	10.16	1.13
BEI	2.78	−39.61	4.09	3.21	−108.67	28.39	9.61	0.97
BMW	−3.32	−1.12	3.28	2.52	−182.85	97.10	11.64	1.43
CBK	8.15	−7.80	2.29	2.23	−154.96	−28.36	18.05	12.01
CON	6.46	7.16	6.56	3.14	−70.97	−147.83	15.43	1.83
DAI	7.76	−9.27	1.75	2.21	−104.88	21.00	9.99	0.95
DB1	−18.27	17.02	2.82	2.12	−94.01	66.47	21.36	177.84
DBK	5.31	−3.85	1.77	2.13	−184.77	102.09	13.35	1.52
DPB	20.94	−20.92	4.61	2.73	−205.53	114.63	13.71	1.71
DPW	38.38	−32.42	2.44	2.20	−173.80	73.16	12.90	11.24
DTE	5.33	1.71	0.97	2.48	−78.44	20.30	6.90	1.18
EOAN	10.67	−10.29	1.33	1.74	−31.87	29.11	11.34	17.11
FME	11.45	−0.86	2.50	1.94	−104.19	82.16	8.34	1.08
FRE3	−18.07	16.07	2.73	1.95	−73.33	63.12	11.40	19.96
HEN3	4.78	−8.93	2.90	1.93	−89.25	22.16	9.75	1.42
HNR1	13.34	−0.98	3.33	2.94	19.42	−115.17	14.95	1.77
IFX	−0.01	0.25	2.24	2.07	−258.96	78.77	16.14	1.25
LHA	−16.06	18.84	2.50	1.76	−271.74	220.82	10.29	1.19
LIN	11.71	−14.56	2.29	2.54	−98.70	39.59	9.45	1.26
LXS	5.91	−8.97	5.58	2.69	−221.75	50.12	17.06	1.54
MAN	9.17	10.80	3.23	2.63	−171.22	78.13	13.66	1.42
MEO	−3.03	−44.16	4.41	2.70	−128.42	51.46	12.13	1.43
MRK	16.64	6.01	2.13	2.43	−102.47	107.36	11.91	1.03
MUV2	0.16	1.34	1.69	1.56	−174.62	118.57	11.09	1.33
RWE	5.41	−5.79	1.52	2.01	−175.14	138.62	8.52	1.11
SAP	13.89	−10.05	2.15	2.13	−144.75	102.62	10.18	1.22
SDF	10.97	15.59	2.71	2.32	−119.61	16.99	14.15	1.50
SIE	13.35	−7.98	2.00	2.07	−113.30	−2.92	11.30	1.22
SZG	9.54	−20.96	3.54	2.03	−253.54	119.25	16.84	1.36
TKA	18.03	−22.54	2.54	1.86	−192.47	93.10	12.60	1.23
TUI1	8.80	23.53	7.41	3.35	−134.53	59.26	14.95	1.82
VOW	13.90	−37.04	3.64	3.20	−19.18	20.09	22.30	107.57

Notes: The four parameters determining the VGP and governing the intraday returns are depicted in Columns 2–5 (period January–October 2010). The four parameters determining the VGP and governing the overnight returns are depicted in Columns 6–9. For the purpose of a more convenient reading, $c_\bullet$ as well as $\theta_\bullet$ are depicted in 10^{-5} and σ is depicted in 10^{-3}.

Table 3: Simulated and discounted GSO payoff (base case)

Firm	*Barrier*				
	95%	*85%*	*75%*	*65%*	*55%*
ADS	0.244	0.070	0.010	0.000	0.000
ALV	0.235	0.209	0.180	0.154	0.112
BAS	0.143	0.128	0.113	0.097	0.080
BAY	0.250	0.118	0.033	0.005	0.000
BEI	0.052	0.000	0.000	0.000	0.000
BMW	0.248	0.115	0.032	0.003	0.000
CBK	0.000	0.000	0.000	0.000	0.000
CON	0.279	0.121	0.033	0.004	0.000
DAI	0.005	0.000	0.000	0.000	0.000
DBK	0.027	0.000	0.000	0.000	0.000
DPB	0.078	0.002	0.000	0.000	0.000
DPW	0.000	0.000	0.000	0.000	0.000
DTE	0.153	0.138	0.110	0.057	0.007
EOAN	0.000	0.000	0.000	0.000	0.000
FME	0.196	0.051	0.006	0.000	0.000
FRE3	0.098	0.084	0.069	0.017	0.000
HEN3	0.077	0.004	0.000	0.000	0.000
HNR1	0.135	0.010	0.000	0.000	0.000
IFX	**<u>0.328</u>**	0.237	0.140	0.060	0.020
LHA	0.233	0.202	0.181	0.148	0.125
LIN	0.015	0.000	0.000	0.000	0.000
LXS	**<u>0.316</u>**	0.093	0.018	0.002	0.000
MAN	**<u>0.345</u>**	**<u>0.300</u>**	**<u>0.253</u>**	**<u>0.203</u>**	0.125
MEO	0.079	0.001	0.000	0.000	0.000
MRK	**<u>0.475</u>**	**<u>0.337</u>**	0.174	0.056	0.007
MUV2	0.254	0.163	0.069	0.013	0.001
RWE	0.023	0.000	0.000	0.000	0.000
SAP	0.055	0.001	0.000	0.000	0.000
SDF	0.253	0.227	0.200	0.172	0.141
SIE	0.026	0.000	0.000	0.000	0.000
SZG	0.133	0.006	0.000	0.000	0.000
TKA	0.006	0.000	0.000	0.000	0.000
TUI1	**<u>0.329</u>**	**<u>0.294</u>**	**<u>0.256</u>**	**<u>0.201</u>**	0.115

Notes: The table depicts the discounted and expected payoffs (in percentage) of the price for the 33 different stocks at different barriers ranging from 95 to 55 per cent (period January–October 2010). In case the discounted and expected payoff is higher than the costs (see also Table 5), the value is bold faced and underlined.

Table 4: GSO payoff buckets (base case)

Payoff/cost	*Barrier*									
	95%	*90%*	*85%*	*80%*	*75%*	*70%*	*65%*	*60%*	*55%*	*50%*
<50%	52	61	76	79	82	85	85	91	100	100
50–75%	9	21	9	12	12	9	15	9	0	0
75–100%	24	9	6	9	6	6	0	0	0	0
100–125%	12	6	9	0	0	0	0	0	0	0
125–150%	0	3	0	0	0	0	0	0	0	0
>150%	3	0	0	0	0	0	0	0	0	0

Notes: The table describes the relative frequency of different payoff to cost ratios depending on the 10 different barrier levels and the 33 different stocks (period January–October 2010).

Table 5: Averages of all simulations (base case)

Average	*Barrier*									
	95%	*90%*	*85%*	*80%*	*75%*	*70%*	*65%*	*60%*	*55%*	*50%*
Cost	0.285	0.270	0.255	0.240	0.225	0.210	0.195	0.180	0.165	0.150
Payoff	0.154	0.112	0.088	0.071	0.057	0.046	0.036	0.029	0.022	0.017
Payoff when triggered	0.343	0.309	0.339	0.293	0.222	0.246	0.191	0.178	0.170	0.151
Trigger probability	51.1	41.9	36.6	32.5	29.0	25.5	21.7	18.6	16.1	13.7
Overnight probability	47.0	50.3	48.3	48.9	39.7	46.3	36.9	37.9	35.6	37.1

Notes: The first three lines indicate the relative values of costs, payoffs and payoffs when triggered (in percentage) of the price for the 33 different stocks at different barriers ranging from 95 to 50 per cent (period January–October 2010). The fourth line comprises the trigger probability as relative frequency of paths where the GSO was executed in relation to 10 000. In the last line the overnight probability is depicted, which is defined as the relative frequency of barrier breaches by overnight jumps in relation to barrier breaches overall. Averages were calculated in two steps. Step 1: For each firm: average of all simulations. Step 2: Average of each firm's average. In the case of 'payoff when triggered' and 'overnight probability', only those firms were considered that reached the respective barrier in at least one simulation run.

Table 5 shows averages, across all firms, for the payoff, the payoff under the condition that the barrier is reached (payoff when triggered), the trigger probability and the percentage of overnight jumps that break the barrier. In addition, the cost of the GSO is shown for comparative purposes. When considering the average payoff among the DAX firms, only barriers of 90 per cent or higher have an acceptable return. This is evidence that the linear pricing structure is not adequate for low barriers. The decline in 'payoff when triggered' is due to the fact that the expected relative jump size is constant, and the expected absolute jump size is

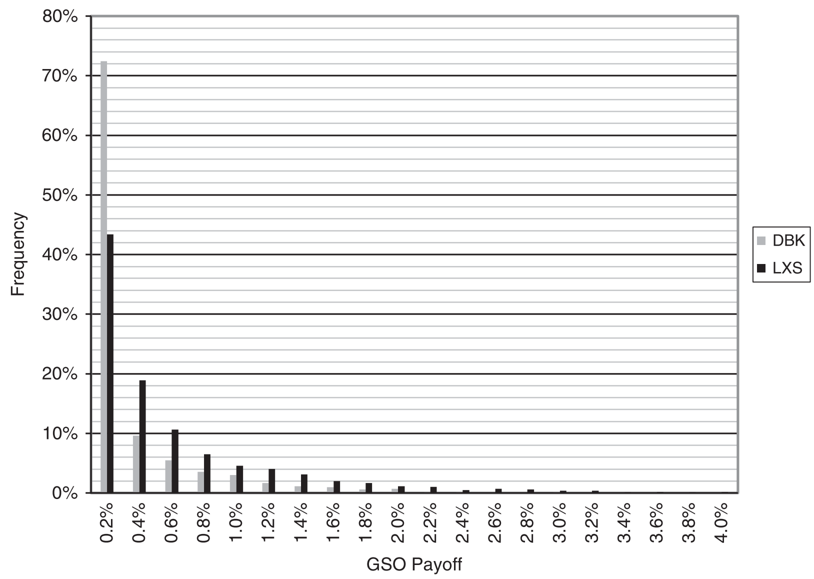

Figure 1: Payoff histogram for Deutsche Bank and Lanxess at 95 per cent barrier (base case). *Notes:* The graph describes the relative frequency of the GSO payoff under the condition that the barrier was broken (in percentage of the share price), when the order was submitted (period January–October 2010). The black bars stand for Lanxess (LXS), whereas the gray bars represent Deutsche Bank (DBK).

not. Hence, the payoff when triggered should be proportional to the share price, and therefore to the barrier. The simulation results reflect this relation with the exception of the two barriers. Here a not-marginal increase is observable. This increase can be explained easily when considering that not all of the firms reach these barriers. Firms with little movement and small jumps will not reach the lower barriers, whereas firms with much movement and the largest jumps will. Therefore, the weights of the most active firms increase at low barriers and the average is biased upwards. As expected, the probability of reaching a barrier decreases as the barrier goes down. The percentages of barrier passages that occur overnight are evidently constant at about 50 per cent and seem to be independent of the barrier. As overnight movements are independent of the intraday movements in our model, they are also independent of the share prices. Hence, the simulated all-in-all constant percentage is in accordance with the model.

ANALYSIS

The goal of this section is to analyze what determines the value of a GSO, and by using this information to analyze how to price GSOs adequately on different stocks. Two important questions arise: Is the value driven by overnight movement or by intraday movement? Which parameter of the VGP is the major determinant of the payoff?

Figure 1 compares two typical ‘payoff when triggered’ histograms with a barrier of 95 per cent. Lanxess is a company with a very high simulated payoff, Deutsche Bank has a very low simulated payoff. It is obvious that the distribution of payoffs is very different. Lanxess's payoff has much more weight regarding the tail than that of Deutsche Bank. Deutsche Bank shows only a few simulation runs with a payoff of more than 2 per cent. Lanxess has several runs of more than 2 per cent up to payoffs of nearly 4 per cent. The variance in these payoffs is 0.46 for Lanxess and 0.18 for Deutsche Bank. These results are typical for firms with high and low payoffs, respectively, and they show that the value of a GSO is strongly driven by the distribution of this conditional payoff. This indicates that payoff, when triggered, might be the relevant factor.

Table 6 is an excerpt from a correlation matrix of the 95 per cent barrier that aims to answer the previous questions. It uses the simulation inputs and results of all 33 firms. The hypothesis, that they are 0 at the 99 per cent confidence level, can be rejected for all correlations with an absolute value above 44.21 per cent. This was determined by using a *t*-test, which, according to Zimmermann (1986), performs well even for small, non-normally distributed samples. When looking at the GSO payoff, we see that it has a small correlation with the 'payoff when triggered' (4.68 per cent), but an extremely high correlation of 83.34 per cent with the trigger probability. This clearly shows that, when calculating the value as the product of trigger probability and 'payoff when triggered', the first factor in our sample is of much greater importance. Columns 4–9 of the first line of Table 6 show that intraday moments and overnight moments are only partly correlated with the GSO payoff. This is not astonishing due to the measure change that the expected value seems not to be influential.
A closer look at intraday and overnight variances and payoff reveals that larger variances lead to

Table 6: Correlations (base case)

	Trigger probability	*Payoff when triggered*	*Variance of the payoff when triggered*	*Moments of the log returns*							
				Intraday				*Overnight overall*			
				Expected value	*Variance*	*Skewness*	*Kurtosis*	*Expected value*	*Variance*	*Skewness*	*Kurtosis*
Simulated payoff	83.33%***	4.68%	12.69%	14.36%	33.57%**	47.49%***	5.58%	−10.11%	32.44%**	−3.95%	−33.45%**
Trigger probability	—	−38.78%**	−27.55%	27.18%	14.14%	61.58%***	18.16%	9.07%	6.71%	18.38%	−8.56%
Payoff when triggered	—	—	92.00%***	−49.71%***	29.13%*	−49.90%***	−21.40%	−16.09%	18.69%	−38.64%**	−47.89%***
Variance of the payoff when triggered	—	—	—	−28.01%	13.87%	−33.73%**	−4.86%	−27.57%	31.75%*	−37.32%**	−32.42%*

Notes: The correlogram depicts the correlation in percentage between the simulated payoff, the trigger probability, the payoff when triggered (see also Table 5), as well as the variance of the payoff when triggered and the moments of the four intraday and four overnight log returns, as well as (the correlation) with themselves (period January–October 2010). Here * represents a significance level of 10 per cent, ** a significance level of 5 per cent and *** a significance level of 1 per cent.

larger payoffs. Hence, we can conclude that variance is the most important parameter in comparison with the other moments.

In addition, the intraday skewness as well as the overnight kurtosis plays an important role. Positively skewed and therefore right skewed returns lead to a more pronounced right tail but also to a more rounded peak at the left of the mean and therefore higher intermediate values on the left. The latter seems to be responsible for the observed positive relationship. If we look at the trigger probability, there is only one highly significant factor. A huge intraday skewness is responsible for a high trigger probability. This is not astonishing because a high probability is in line with higher intermediate values on the left of the mean.

The overnight kurtosis is negatively related to the expected payoff, whereby a lower kurtosis leads to a higher payoff when triggered. Before the simulation, one might have expected the kurtosis to play the most significant role instead of the variance. The importance of the variance is due to the VGD used for the stock log returns. Cont and Tankov (2004) show that parameter $\kappa_\bullet$ basically defines the kurtosis and parameter $\sigma_\bullet$ defines the variance. In the VGD, the rate of decay in case of the negative tail is governed by:

$$\lambda_- = \frac{\theta_\bullet + \sqrt{\theta_\bullet^2 + 2\frac{\sigma_\bullet^2}{\kappa_\bullet}}}{\sigma_\bullet^2} \tag{14}$$

Therefore, an increase in both $\kappa_\bullet$ or $\sigma_\bullet$ leads to a smaller λ_-, which means a slower decay in the tail. But an increase in $\kappa_\bullet$ also means a less rounded peak. If combined, this means that a decrease in $\kappa_\bullet$, which represents an decrease of the kurtosis, will decrease probabilities near the peak value and in the tail, but it will increase intermediate values (see also Madan and Seneta, 1990). The latter leads to the higher payoffs when triggered. By contrast, an increase in $\sigma_\bullet$, which represents an increase of the variance, will increase probabilities in the tail and it will increase symmetry, which implies the dominating influence.

As mentioned earlier, the pricing method that uses the linear formula (9) does not reflect the payoff structure of GSOs adequately. As the empirical study shows, the payoff decreases more rapidly with decreasing barriers. The reason for this can be found in the fact that, on the one hand, costs are proportional to the barrier (see also Table 5). On the other hand, the expected value is the product of the 'payoff when triggered' – which is, as we have seen, proportional to the barrier – and the trigger probability, which exponentially decays due to the distribution function. Consequently, in contrast to the costs, the expected value decreases exponentially. Therefore, overpricing is especially high at low barriers. Furthermore, the payoff is greatly dependent on the underlying stocks' intraday volatility.

The fact that an exponential pricing approach better represents the payoff, as well as the fact that the most important driver for the payoff is the intraday volatility, could be included in a better approach to finding an adequate GSO premium.

ROBUSTNESS CHECKS I: METHODOLOGY

First, we want to relax some assumptions. To this end, we use a different change in measurement to price the GSO. In addition, we add a stochastic clock, which implies that the number of ticks

Table 7: Averages of all simulations (Esscher transform)

Average	*Barrier*									
	95%	*90%*	*85%*	*80%*	*75%*	*70%*	*65%*	*60%*	*55%*	*50%*
Cost	0.285	0.270	0.255	0.240	0.225	0.210	0.195	0.180	0.165	0.150
Payoff	0.149	0.115	0.092	0.072	0.054	0.039	0.027	0.019	0.013	0.009
Payoff when triggered	0.369	0.344	0.276	0.278	0.251	0.239	0.236	0.166	0.163	0.128
Trigger probability	45.2	38.3	33.7	29.4	25.4	21.7	18.5	15.8	11.8	9.0
Overnight probability	60.6	58.6	49.2	50.2	48.9	46.1	49.0	39.4	44.9	40.4

Notes: The first three lines indicate the relative values of costs, payoffs and payoffs when triggered (in percentage) of the price for the 33 different stocks at different barriers ranging from 95 to 50 per cent, whereby the Esscher transform is used to generate the equivalent martingale measure (period January–October 2010). The fourth line comprises the trigger probability as relative frequency of paths where the GSO was executed in relation to 10 000. Overnight probability is depicted in the last line, defined as the relative frequency of barrier breaches by overnight jumps in relation to barrier breaches overall. Averages were calculated in two steps. Step 1: For each firm: average of all simulations. Step 2: average of each firm's average. In the case of 'payoff when triggered' and 'overnight probability', only those firms were considered which reached the respective barrier in at least one simulation run (see also Table 5). The Esscher transform is according to Hubalek and Sgarra (2006) and transformed according to Madan and Seneta (1990).

$$\sigma_{new} = \frac{\sqrt{2\lambda}}{\gamma_{new}}, \theta_{new} = \frac{2\beta_{new}\lambda}{\gamma_{new}^2},$$
$$\gamma_{new} = \gamma - \beta\xi - \frac{\xi^2}{2}, \beta_{new} = \beta + \xi,$$
$$\xi = -\beta - \frac{1}{\varepsilon} + \frac{1}{\varepsilon}\sqrt{1 + \beta^2\varepsilon^2 - \varepsilon + 2\gamma^2\varepsilon^2},$$

with

$$\varepsilon = 1 - \exp\left(\frac{c}{\lambda}\right), \lambda = \frac{1}{\kappa}, \beta = \frac{\theta}{\sigma^2}, \gamma = \frac{\sqrt{2}}{\sigma\sqrt{\kappa}}$$

per day is an independent lognormally distributed random variable with a mean and variance, which correspond to the means and variances of the number of ticks per day in the sample. The concept of a stochastic clock is introduced by means of simulating a random number at the beginning of the day which determines the ticks per day. Furthermore, we applied different Lévy processes to stress the choice of the VGP. Lastly, we tried to estimate the influence of price cascades on the value of the GSO.

With regard to the martingale approach, there are several possibilities to change the measure. To test the robustness of our choice, we use the Esscher transformation according to Schoutens (2003, p. 77) in connection with Hubalek and Sgarra (2006) as alternative. According to Table 7, the values are in general lower than in the base case. The payoff hardly exceeds the costs. This can rarely be observed, especially at low barriers. Thereby, the ranking of GSO values is similar in both the Esscher and the base case. The major driving force is again the intraday volatility as well as the overnight volatility followed by intraday skewness and overnight kurtosis. If we look at the results with a stochastic clock, there is nearly no change in comparison with the base case (not reported). The reason for this can be found in the relatively stable trade frequency from day-to-day and the fact that the expected value only has a slightly negative correlation of -0.1 with the ticks per day (not reported).

To check the robustness with respect to the process, we fitted two additional processes, which are often discussed in the literature especially with regard to the German market. In addition, these processes should be conveniently simulated due to the size of the study. We therefore choose the jump-diffusion as well as the hyperbolic process (see Schoutens, 2003, p. 80, for the measure transformation). For both processes the four parameter version seems to be in the line the VG process. The results are similar using the jump-diffusion as well as the hyperbolic model (not reported). Even after changing the underlying process the main findings remain the same. The overall results do not change dramatically, although values at high barriers increase and at low barriers decrease. Furthermore, there is still an exponential decay in the values and they strictly depend on the corresponding stocks (not reported).

So far we have estimated the prices and therefore the payoff of the GSO by simulating the stock prices. Thereby the random numbers were drawn from a distribution, which was fitted to the historic traded quotes. In doing so, we could not include resulting price cascades. For example, imagine that the price drops sharply and many investors place market orders. Then the execution price of a corresponding SO may not be the next quote due to the existence of other competing market orders. In this case, the execution price of the corresponding SO is lower than the price we obtained from the historical data and the payoff of the GSO is higher.

Because it is difficult to measure the cascade effect, we tried to proxy it by taking the second negative return after the price process crossed the barrier.[1] For the latter, we used the same procedure as in the base case. However, instead of taking the stock price after crossing the barrier we used the second stock price, if it was lower than the first one. The results of this procedure lead to slightly higher values for the GSO (not reported). As can be seen, the trigger probability as well as the overnight probability are almost the same as in the base case. However, the payoff when triggered rises and the expected payoff logically increases. All in all, the effect is relatively small and the overall observation remain the same.

ROBUSTNESS CHECKS II: SMALL AND MEDIUM CAPS AND CRISES

In the previous sections we have shown how GSOs on DAX stocks perform during normal, volatile periods. Here two questions arise. First, does the result change if we look at medium- and small-cap stocks? Due to the lower trading activity, medium- and small-cap stocks show in general higher volatility on tick data, and volatility was the most influential parameter according to the previous sections.

Second, the question arises as to how GSO perform in periods of relatively high volatility, and how large the change in the parameters must

Table 8: Averages of all simulations (mid- and small-cap stocks)

	Barrier									
	95%	*90%*	*85%*	*80%*	*75%*	*70%*	*65%*	*60%*	*55%*	*50%*
Average mid-cap										
Cost	0.285	0.270	0.255	0.240	0.225	0.210	0.195	0.180	0.165	0.150
Payoff	0.561	0.441	0.366	0.312	0.269	0.231	0.199	0.167	0.138	0.112
Payoff when triggered	0.782	0.828	0.790	0.751	0.689	0.613	0.524	0.427	0.331	0.328
Trigger probability	68.4	58.5	49.9	44.0	39.4	35.7	32.4	29.3	26.2	23.0
Overnight probability	83.4	88.4	88.6	89.1	90.4	79.2	80.6	62.6	50.7	53.1
Average small-cap										
Payoff	0.537	0.409	0.320	0.247	0.194	0.153	0.118	0.090	0.067	0.049
Payoff when triggered	0.774	0.717	0.686	0.656	0.600	0.511	0.422	0.321	0.308	0.286
Trigger probability	58.7	46.6	37.4	30.2	24.9	20.9	17.6	14.8	12.3	10.0
Overnight probability	79.3	74.7	74.9	74.3	75.1	65.2	62.1	46.2	46.1	43.8

Notes: The first three lines of sub-Table 1 (upper part) indicate the relative values of costs, payoffs and payoffs when triggered (in percentage) of the price for the 19 different mid-cap stocks (max χ^2 test statistic 4.4) at different barriers ranging from 95 to 50 per cent (period September–October 2010). The first two lines of sub-Table 2 (lower part) indicate the relative values, payoffs and payoffs when triggered (in percentage) of the price for the 19 different small-cap stocks (max χ^2 test statistic 8.1). The fourth line of sub-Table 1 and the third line of sub-Table 2 comprise the trigger probability as relative frequency of paths where the GSO was executed in relation to 10 000. In the last line of both sub-tables the overnight probability is depicted, which is defined as the relative frequency of barrier breaches by overnight jumps in relation to barrier breaches overall. Averages were calculated in two steps. Step 1: For each firm: average of all simulations. Step 2: average of each firm's average. In the case of 'payoff when triggered' and 'overnight probability', only those firms were considered that reached the respective barrier in at least one simulation run (see also Table 5, Ticker symbols of mid-cap stocks inspected: CLS1, EAD, FPE3, FRA, G1A, GBF, HOT, KCO, MTX, NDA, PSM, PUM, RHK (excluded), RHM, SAZ, SGL, SY1, SZU, WCH, WIN; Ticker symbols of small-cap stocks inspected: 2HR, AOX (excluded), COM, DBA, DEX, DEZ, DWNI, EVD, GFK, GLJ, GWI1, HBH3, INH, JUN3, KU2, KWS, MDN, MLP, MVV1, WAC).

be so GSOs are attractive to buyers. To answer this question, we evaluate two additional simulations. For the first, we obtained the parameters for a second sample period, when the financial crisis was still active and volatility was very high. For the second, we looked at how high the most influential parameters must be so that the GSO's value is equal to its cost.

With regard to the medium- and small-cap stocks, we applied the model to 20 MDAX and 20 SDAX stocks (which have the highest weights in the index). Again we had to exclude one MDAX as well as one SDAX stock due to high χ^2 test statistics, leaving 38 stocks. As we expected, the value of the GSO was higher for both types of stocks than for DAX stocks (see Table 8).

Table 9: Averages of all simulations (financial crises)

Average	*Barrier*									
	95%	*90%*	*85%*	*80%*	*75%*	*70%*	*65%*	*60%*	*55%*	*50%*
Cost	0.285	0.270	0.255	0.240	0.225	0.210	0.195	0.180	0.165	0.150
Payoff	0.462	0.399	0.353	0.313	0.278	0.247	0.216	0.190	0.166	0.143
Payoff when triggered	0.682	0.690	0.666	0.562	0.492	0.395	0.348	0.306	0.271	0.254
Trigger probability	77.4	72.8	69.8	67.2	64.7	62.4	60.2	58.2	56.2	54.1
Overnight probability	47.4	48.4	46.8	47.8	41.4	37.6	37.1	34.0	33.4	35.8

Notes: The first three lines indicate the relative values of costs, payoffs and payoffs when triggered (in percentage) of the price for the 25 different stocks (max χ^2 test statistic 12.7) at different barriers ranging from 95 to 50 per cent, when the data of the financial crisis is used (period April–May 2009). The fourth line comprises the trigger probability as relative frequency of paths where the GSO was executed in relation to 10 000. In the last line the overnight probability is depicted, which is defined as the relative frequency of barrier breaches by overnight jumps in relation to barrier breaches at all. Averages were calculated in two steps. Step 1: For each firm: average of all simulations. Step 2: average of each firm's average. In the case of 'payoff when triggered' and 'overnight probability', only those firms were considered that reached the respective barrier in at least one simulation run (see also Table 5).

This held true for every barrier applied, and was driven by a higher trigger probability and a more pronounced payoff when triggered. In particular, the more than doubled payoff when triggered is responsible for the higher value, which might be the result of higher price changes in case of lower trading activity (MDAX at 21.1 and SDAX at 3.4 trades per day). In addition, the overnight changes play a more important role, even if the overnight price changes account only for 5 per cent (mid-cap) and 22 per cent (small-cap, for comparison DAX<2 per cent), respectively, of all price changes. The latter is also the result of lower trading activity. Furthermore, there is nearly no difference between medium and small caps. All in all, prices for high and especially middle barriers seem to be more adequate in this case, but the linear pricing method still does not reflect the payoff structure of GSOs.

Regarding the second question, we use the same model, but fit it to data from early 2009 while using the same algorithms. To be precise, we use intraday data on 25 stocks out of 30 stocks after performing the χ^2 test. The average payoff is now much higher than the cost at high barriers (see Table 9). This implies that, in volatile periods, the guarantee of the GSO may be necessary. Even at the lowest barrier, three firms (12 per cent) have a positive GSO value, and at the highest barrier about half of the firms have GSO payoffs of more than half the cost. All in all, this confirms our findings that the proportional costs are inadequate. The intraday as well as the overnight volatility is again the most influential parameter. Altogether, even in the case of high volatility regimes, the intraday as well as the overnight volatility are adequate to justify the costs. This result is, for example, in line with

Table 10: Implied parameters

Firm	*Intraday*					*Overnight*				
	$\sigma \times 10^{-3}$				*Annualized*	$\sigma \times 10^{-3}$				*Annualized*
Barrier	*Historical estimate*	*95%*	*75%*	*50%*	*50%*	*Historical estimate*	*95%*	*75%*	*50%*	*50%*
ADS	4.17	8.63	15.32	21.63	112	11.08	12.33	23.49	39.73	63
ALV	1.74	6.79	7.07	7.84	104	12.01	13.60	13.52	17.12	27
BAS	1.71	7.71	7.71	7.71	111	8.60	13.82	13.74	13.91	22
BAY	2.39	6.79	9.27	12.37	116	10.16	11.08	19.02	32.18	51
BEI	4.09	17.50	27.87	36.38	141	9.61	14.69	27.00	39.80	63
BMW	3.28	7.80	11.06	14.92	116	11.64	12.72	22.08	37.70	60
CBK	2.29	9.30	11.33	12.95	206	18.05	104.37	118.88	131.42	208
CON	6.56	7.04	14.48	20.20	120	15.43	15.48	28.40	46.32	73
DAI	1.75	9.22	11.51	13.17	230	9.99	24.49	44.27	60.80	96
DBK	1.77	7.86	8.91	10.29	193	13.35	26.64	45.34	62.26	98
DPB	4.61	11.80	18.05	23.55	130	13.71	20.87	37.14	54.66	86
DPW	2.44	12.83	18.00	21.71	175	12.90	98.98	113.38	127.49	202
DTE	0.97	8.59	8.71	9.16	161	6.90	9.94	10.94	22.63	36
EOAN	1.33	8.02	10.20	12.02	191	11.34	111.02	122.00	133.76	211
FME	2.5	7.57	11.79	16.62	102	8.34	10.44	19.53	32.78	52
FRE3	2.73	7.60	8.88	14.82	75	11.40	103.97	99.65	99.65	158
HEN3	2.9	8.96	13.43	18.30	111	9.75	16.49	29.58	45.18	71
HNR1	3.33	10.46	17.03	23.02	126	14.95	19.19	34.72	52.66	83
IFX	2.24	6.19	7.20	8.61	143	16.14	14.83	20.15	32.60	52
LHA	2.5	6.13	6.29	7.04	59	10.29	12.09	12.17	12.87	20
LIN	2.29	11.66	16.53	20.85	138	9.45	18.39	32.71	47.83	76
LXS	5.58	3.70	14.88	20.94	119	17.06	16.19	29.61	46.05	73
MAN	3.23	6.30	5.30	9.90	79	13.66	12.23	12.23	19.14	30
MEO	4.41	15.55	27.50	38.37	127	12.13	17.71	32.64	49.37	78

Table 10: (*Continued*)

Firm	*Intraday*					*Overnight*				
	$\sigma \times 10^{-3}$				*Annualized*	$\sigma \times 10^{-3}$				*Annualized*
Barrier	*Historical estimate*	*95%*	*75%*	*50%*	*50%*	*Historical estimate*	*95%*	*75%*	*50%*	*50%*
MRK	2.13		8.63	14.49	96	11.91	8.06	13.59	26.28	42
MUV2	1.69	5.87	7.64	10.51	95	11.09	11.83	18.65	33.23	53
RWE	1.52	8.22	10.62	13.15	144	8.52	16.43	28.98	42.29	67
SAP	2.15	9.03	13.08	17.00	128	10.18	16.27	29.56	43.33	69
SDF	2.71	6.95	7.05	7.32	76	14.15	15.20	15.37	15.54	25
SIE	2	8.59	11.24	13.87	160	11.30	20.91	36.76	51.66	82
SZG	3.54	8.78	14.44	18.68	137	16.84	21.96	38.77	54.68	86
TKA	2.54	9.81	13.96	16.86	181	12.60	27.91	49.98	66.71	105
TUI1	7.41			14.52	74	14.95	12.69	13.03	24.00	38
Average	2.92	8.75	12.34	16.02	130	12.11	26.75	36.57	48.96	77

Notes: Historical estimates are taken from Table 1. For the calculation of the implied parameters at the barriers of 95, 75 and 50 per cent, a bisection method was applied with one bound at the historical estimation and one bound at 0.2 or 10^{-3}. The procedure was applied until the payoff differentiates at a maximum of 3 per cent of the cost by means of a martingale approach (mean correcting measure). The latter was chosen due to the numerical exactness of the Monte Carlo method. In case of an antitone payoff function in σ the procedure was repeated with a new bound to obtain the nearest intersection value. The intraday value at the 95 per cent barrier for MRK as well as the two intraday values for TUI1 were excluded due to bad convergence. For comparative purposes, the parameters at the 50 per cent barrier were annualized by using 250 days for the overnight parameter and the average yearly trading activity for the intraday parameters.

Walker (2009), who details the application of GSO in financial crises.

In addition, we look at those implied parameters, which can balance the value of the GSO with costs in the base case. As the payoff is not always an isotonic function in σ, σ must be increased in order to find appropriate values. In case of non-uniqueness we use the parameter which is closer to the actual one. This is in line with the concept of parameter stability.

At first sight, there seem to be huge differences between the historical parameters and the implied parameters (see Table 10). Especially at low barriers, these differences are enormous. In that case σ, which can be interpreted as implied volatility, is by far higher than historically estimated. As to the overnight parameter, the difference between estimated and implied parameters at a 50 per cent barrier was less than 70 per cent only in the case of Lufthansa (LHA). To clarify, this σ is annualized as well. According to Table 7, the overnight as well as the intraday volatilities very often exceed 100 per cent per year. This is more the case for intraday than for overnight parameters, which is the result of neglecting the complete intraday movement. All in all, the requested parameters differ greatly from historical parameters in normal times, and the absolute difference is, with the exception Salzgitter (SZG), always higher if the barrier is lower.

Altogether, we can conclude that in quiet periods, a Stop Order is sufficient to protect shares against sudden losses, and the guarantee of a GSO is not necessary. In other words, the current pricing model renders GSOs uninteresting to investors, as it does not factor in volatilities.

CONCLUSION

We have analyzed the effects of GSOs on shares by means of our modified VGP. We have shown that the pricing of GSOs poorly reflects their expected payoffs. The pricing performs best in turbulent stock markets with GSO barriers close to the share price. Furthermore, the payoff exceeds costs when mid- and small-cap stocks with high GSO barriers are inspected. Barriers that are farther from the share price cause a drop in the payoff which is larger than the drop in the price of GSOs. A better illustration of this decrease would probably make GSOs more attractive to investors, what can only be in the interest of the issuing stock exchange. Further, we have shown that the variance of the underlying shares' log-returns is the main factor in forecasting the payoff of a GSO and determining an adequate premium. The pricing, therefore, needs to be linked to volatility in order to ensure that GSOs, as a product, remain interesting to investors. In addition, in contrast to the actual pricing model, which implies a proportional decline with a lower barrier, the pricing should imply an exponential decay with a decreasing barrier.

Future research may develop a pricing approach which is more precise than the linear one, maybe by means of a σ-dependent exponential behavior, as proposed earlier. In addition, it may be interesting to see how GSOs behave in a more flexible model, which considers dependencies between returns, especially overnight returns, which are dependent on intraday movement. Finally, one could take a closer look at the value of GSOs when they are being sold short.

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NOTE

1 The measurement builds on the effect that SO is normally placed just above or below round numbers. Hence, trends after crossing round numbers should be relatively rapid and occasionally cause price cascades (see Osler, 2005).

References

Basseer, P. (1991) Reducing market exposure with portfolio insurance. *Risk Management* 38(4): 36–45.

Bodie, Z., Kane, A. and Marcus, A. (1996) *Investments*. 3rd edn. Irwin, CA: Mcgraw-Hill Publications.

Carr, P., Geman, H., Madan, D. and Yor, M. (2002) The fine structure of asset returns: An empirical investigation. *Journal of Business* 75(2): 305–332.

Chan, K. (1999) Pricing contingent claims on stocks driven by Lévy processes. *Annals of Applied Probability* 9(2): 504–528.

CMC Markets. (2005) Guaranteed stop loss order. London, http://www.cmcmarkets.co.uk/en/trading-platforms/executing-a-trade, accessed 19 May 2012.

Cont, R. and Tankov, P. (2004) *Financial Modelling with Jump Processes*. London: Chapman & Hall/CRC.

Easley, D. and O'Hara, M. (1991) Order form and information in securities markets. *Journal of Finance* 46(3): 905–927.

Eberlein, E., Keller, E. and Prause, K. (1998) New insights into smile, mispricing, and value at risk: The hyperbolic model. *Journal of Business* 71(3): 371–405.

Finlay, R. and Seneta, E. (2008) Stationary-increment variance-gamma and *t* models: Simulation and parameter estimation. *International Statistical Review* 76(2): 167–186.

Geman, H. (2002) Pure jump Lévy processes for asset price modeling. *Journal of Banking and Finance* 26(7): 1297–1316.

Geman, H., Madan, D. and Yor, M. (2001) Time changes for Lévy processes. *Mathematical Finance* 11(1): 79–96.

Gennote, G. and Leland, H. (1990) Market liquidity, hedging and crashes. *American Economic Review* 80(5): 999–1021.

Hubalek, F. and Sgarra, C. (2006) Esscher transforms and the minimal entropy martingale measure for exponential Lévy models. *Quantitative Finance* 6(2): 125–145.

IG. (2012) Risk management. London, http://www.ig.com/au/risk-management, accessed 10 August 2014.

Kou, S.G. and Wang, H. (2003) First passage times for a jump diffusion process. *Advances in Applied Probability* 35(2): 504–531.

Macquarie. (2011) Stop loss and guaranteed stop loss orders. Sydney, http://www.macquarie.com.au, accessed 8 August 2014.

Madan, D. (2001) Financial modeling with discontinuous price processes. In: O. Barndorff-Nielson, T. Mikosch and S. Resnik (eds.) *Lévy Processes – Theory and Applications*. Boston, MA: Birkhäuser.

Madan, D. and Seneta, E. (1990) The Variance Gamma (V.G.) model for share market returns. *Journal of Business* 63(4): 511–524.

Osler, C.L. (2005) Stop-loss orders and price cascades in currency markets. *Journal of International Money and Finance* 24(2): 219–241.

Rathgeber, A. (2007) Optionsbewertung unter Lévy-Prozessen. *Credit and Capital Markets* 40(3): 451–484.

Schoutens, W. (2003) *Lévy Processes in Finance*. Chichester, UK: John Wiley & Sons.

Seneta, E. (2004) Fitting the Variance-Gamma model to financial data. *Journal of Applied Probability* 41A(special issue): 177–187.

Walker, C. (2009) How to limit losses on your shares. *Money Magazine*: December.

Zimmermann, D. (1986) Tests of significance of correlation coefficients in the absence of bivariate normal populations. *Journal of Experimental Education* 54(4): 223–227.