A Jumping Index of Jumping Stocks? An MCMC Analysis of Continuous-Time Models for Individual Stocks

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This paper examines continuous-time models for the price and volatility processes of individual stocks and the S&P 100 index via Markov Chain Monte Carlo estimation. We find that the stochastic processes governing individual stocks are rather heterogeneous. A key result of our investigation is that index jumps are not necessarily accompanied by jumps in a large number of individual stocks when we apply the same critical values for a posteriori jump probabilities to the index and the stocks. Albeit on a generally lower level of jump probabilities we can nevertheless distinguish between index jump days where the majority of industrial sectors have high jump probabilities and those where this is not the case. We therefore interpret index jumps in the first scenario as 'macro driven', and as 'statistical jumps' otherwise. Concerning diffusive volatility innovations we find that the first principal component is highly correlated with index variance innovations and can therefore be interpreted as a variance market factor.

Keywords: Stochastic volatility, individual stocks, MCMC, volatility factors

JEL: G11, G12

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This paper examines continuous-time models for the price and volatility processes of individual stocks and the S&P 100 index via Markov Chain Monte Carlo estimation. We find that the stochastic processes governing individual stocks are rather heterogeneous. A key result of our investigation is that index jumps are not necessarily accompanied by jumps in a large number of individual stocks when we apply the same critical values for a posteriori jump probabilities to the index and the stocks. Albeit on a generally lower level of jump probabilities we can nevertheless distinguish between index jump days where the majority of industrial sectors have high jump probabilities and those where this is not the case. We therefore interpret index jumps in the first scenario as 'macro driven', and as 'statistical jumps' otherwise. Concerning diffusive volatility innovations we find that the first principal component is highly correlated with index variance innovations and can therefore be interpreted as a variance market factor.

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1 Introduction

The analysis of the statistical properties of stock returns has been one of the centerpieces in financial research. Building on the empirical properties of stock returns, there is a large body of literature trying to derive continuous time models that are able to capture essential features of observed stock price movements. Starting with fairly strict specifications as a geometric Brownian motion with constant volatility the model setup has evolved to more realistic models as stochastic volatility models and models with jump components. These model specifications are also capable of capturing features such as stock market crashes. Empirical testing of these continuous time equity price models has been one of the main research questions of numerous studies in recent years. Starting with models with stochastic volatility (see, e.g. Jacquier, Polson, and Rossi (1994) and Jacquier, Polson, and Rossi (2004)) the literature has evolved to models with jump components in returns (see, e.g. Bakshi, Cao, and Chen (1997) and Pan (2002)) and to models containing jumps in returns and in volatility (see, among others, Eraker, Johannes, and Polson (2003), Eraker (2004)).

A major innovation in econometric technique relates to the usage of Bayesian estimation methods. By using Markov Chain Monte Carlo (MCMC) methods it is possible to estimate models of very high dimensionality that need not to be in the conjugate model class, i.e. have no closed form solution for the moments of the resulting posterior distribution. Furthermore, this estimation technique allows us to determine not only estimators for the model parameters but give also the smoothing distribution of the latent variables as a by product.

Empirical investigations of equity asset pricing models have been carried out with major equity market indices like the S&P 500 or the NASDAQ 100 as the main economic object of investigation. From the literature one can identify certain characteristics of stock price models that can be termed as stylized facts. First, models with just a stochastic volatility component, but without jumps, appear to be significantly mis-specified. Second, when jumps are included in the model, they turn out to be rare, negative and large in absolute value. Third, there is a negative correlation between the innovations in the return and the variance process. Since all these findings were made exclusively for indices, the big question is if they also remain valid for individual stocks.

To the best of our knowledge our paper represents the first detailed study of stochastic volatility models with jumps for individual stocks in the context of Bayesian estimation. An analysis of a rather small set of selected stocks was performed by Maheu and McCurdy (2004), who estimate the parameters of their discrete-time GARCH model with jumps using maximum likelihood. They attribute jumps to corporate news events and show that this hypothesis is supported by the data. In contrast to their approach we estimate a pure stochastic volatility model (SV), an SV including jumps in prices (SVJ), and an SV model featuring correlated jumps in the stock price and the conditional variance (SVCJ), using the MCMC approach developed in Eraker, Johannes, and Polson (2003).

Our results show that the stochastic processes for the 'typical' (i.e., average) individual stock is significantly different from that for the market index, represented by the S&P 100. The average size of the jumps in the stock price is smaller in absolute terms than for the index. It is even in many cases positive showing that the stylized facts found in studies on indices do not carry over to individual stocks. The frequency of jumps in prices is much higher for the representative stock than for the index, so, although jumps are still somewhat rare, they tend to occur more than twice as often for the average stock than for the S&P 100. Furthermore, the correlation between stock returns and volatility changes is estimated at values which are much less negative than for the index. This last result was, of course, derived under the physical probability measure in our investigation, but is nevertheless related to empirical findings concerning the pricing of options on indices and individual stocks. As shown by Bollen and Whaley (2004) the implied volatility curves for stock market indices tend to be negatively sloped and much steeper than those for the component stocks. So, in line with this result from empirical option pricing research, we again provide evidence that one cannot simply extend the results from the analyses of major market indices to single stocks.

The main contribution of our empirical analysis concerns the behavior of the individual stocks on the days when the index exhibits a jump. Surprisingly, only very few stocks also jump on these days. Out of a sample of 83 stocks, the highest number of jumping stocks we observe on any of the index jump days is 22, i.e., just one fourth of the stocks in our sample. This immediately yields the question of whether the models estimated for the index and the individual stocks are compatible at all. The solution to this apparent 'puzzle' lies in a detailed analysis of the mechanics of the models employed in our study. A jump is considered likely (in terms of posterior probability), if the price move of an asset on a given day is large relative to the conditional variance for that day. The index as a diversified portfolio of stocks then naturally jumps on days when most of the component stocks exhibit large *returns* (not necessarily jumps) in the same direction. Since the average local variance of the stocks in our sample is pretty stable around index jump days, at least some of these jumps must be caused by the correlation between the stocks moving towards one, thus generating the large and negative index return, which is ultimately identified as a jump. We call these jumps 'statistical jumps'. The remaining jumps, which we call 'macro-driven', are more interesting from an economic point of view. They are characterized by a large number of sectors exhibiting high jump probabilities simultaneously and we can clearly link them to important macroeconomic events. Interestingly there are significant differences between the SVJ and the SVCJ model when it comes to the identification of index jump days. In our sample period the SVJ model primarily identifies macro-driven jumps and none of the statistical jumps we see for the SVCJ model.

Another issue we are interested in is the co-movement of diffusive variance components between the individual stocks and the relation of some common variance innovation factor to the variance innovations in the S&P 100. Existing empirical research tends to focus on volatility modeling for indices rather than for individual stocks. Nevertheless, there are several papers in the literature which are concerned with the estimation of common and idiosyncratic volatility components. Examples include Connor, Korajczyk, and Linton (2006), who employ a dynamic factor model with GARCH-type components to filter out the idiosyncratic part of volatility, while Campbell, Lettau, Malkiel, and Xu (2001) investigate the issue of diversification in the sense of how many stocks are necessary to form a well-diversified portfolio. Goyal and Santa-Clara (2003) and subsequently Guo and Savickas (2003) study the question of whether idiosyncratic volatility can serve as a useful predictor for stock returns, while Malkiel and Xu (2004) empirically test the hypothesis that not only systematic but also idiosyncratic risk is priced in a CAPM-style model. We find that there is indeed such a common factor, explaining roughly 30% of the variability in diffusive variance innovation across stocks. The correlation of this factor with index variance innovations is rather high at about 0.8 for both the SVJ and the SVCJ model. This result has important implications for the specification and estimation of two factor stochastic volatility models of the type introduced by Chernov (2003).

The rest of the paper is structured as follwows. In Section 2 we present the model and describe our estimation approach. The results are then discussed in Section 3. Section 4 concludes.

2 Models and Estimation Approach

2.1 Model

There are several papers which investigate the empirical performance of equity price models (see, e.g. Christoffersen, Jacobs, and Mimouni (2008), Bakshi, Cao, and Chen (1997), Eraker, Johannes, and Polson (2003) and Eraker (2004)). Besides the paper written by Christoffersen, Jacobs, and Mimouni (2008) all papers consider stochastic processes with jump components. Our model specification follows the analysis in Eraker, Johannes, and Polson (2003), which offers the most flexible model structure by not only considering jumps in returns but by also allowing a jump component in the volatility process.

Therefore we consider a stochastic volatility model for the stock price with jumps in returns and volatility. We assume the following stochastic specification for the stock price and the volatility processes

$$\begin{pmatrix} dY_t \\ dV_t \end{pmatrix} = \begin{pmatrix} \mu \\ \kappa(\theta - V_t) \end{pmatrix} dt + \sqrt{V_t} \begin{pmatrix} 1 & 0 \\ \rho\sigma_v & \sqrt{(1-\rho^2)}\sigma_v \end{pmatrix} d\mathbf{W}_t + \begin{pmatrix} \xi^y dN_t \\ \xi^v dN_t \end{pmatrix} \quad (1)$$

with $Y_t = \ln S_t$ denoting the logarithm of the asset price and where $\mathbf{W}_t$ is a standard bivariate Brownian motion, N_t is a Poisson process with constant intensity λ and ξ^y and ξ^v are jump sizes in returns and volatility, respectively.

We consider three special cases of the general representation in Equation (1) in our estimations. By setting $\lambda = 0$ the model reduces to the well known specification given in Heston (1993), denoted by SV. The second model (SVJ) incorporates jumps in returns only. For this model we set $\xi^v = 0$ and we assume that the jumps in returns are normally distributed with mean μ_y and variance σ_y^2. This model was considered first in Bates (1996). The third model incorporates jumps in return and volatility, and is denoted by SVCJ. This model assumes contemporaneous jumps in returns and volatility, and assumes correlated jump sizes. In detail, we assume exponential distributed jump sizes in volatility ($\xi^v \sim \exp(\mu_v)$ and normally distributed jumps in returns ($\xi^y \sim \mathcal{N}(\mu_y + \rho_j \xi^v, \sigma_y^2)$). This model was the preferred model in Eraker, Johannes, and Polson (2003).

In order to carry out estimation we first use a Euler discretization scheme for the model given in (1) and use $\Delta = 1$ (where, since we use daily data, $\Delta =$ one day) as discretization step. For our empirical analysis we will use the following three discretized versions of the general model specification. The SV model is given by

$$\begin{aligned} Y_{t+1} - Y_t = R_{t+1} &= \mu + \sqrt{V_t}\varepsilon^y_{t+1} \\ V_{t+1} - V_t &= \kappa(\theta - V_t) + \sigma_v \sqrt{V_t}\varepsilon^v_{t+1} \end{aligned} \tag{2}$$

where $\varepsilon^y_{t+1} = W^y_{(t+1)} - W^y_t$ and $\varepsilon^v_{t+1} = W^v_{(t+1)} - W^v_t$ follow a bivariate normal distribution with zero expectation, unit variance and correlation ρ. For this model we have a data set of T returns $\{R_t\}^T_{t=1}$ and the set of latent variables is given by $\{V_t\}_{t=1}T$. The unknown parameters are given by ρ, κ, θ, σ_v, and μ.

Generalizing the SV model by introducing jumps into the equation for y yields the SVJ (stochastic volatility and jumps) which is characterized by the system of SDEs

$$\begin{aligned} Y_{t+1} - Y_t = R_{t+1} &= \mu + \sqrt{V_t}\varepsilon^y_{t+1} + J_{t+1}\xi^y_{t+1} \\ V_{t+1} - V_t &= \kappa(\theta - V_t) + \sigma_v \sqrt{V_t}\varepsilon^v_{t+1} \end{aligned} \tag{3}$$

where $\varepsilon^y_{t+1} = W^y_{(t+1)} - W^y_t$ and $\varepsilon^v_{t+1} = W^v_{(t+1)} - W^v_t$ follow a bivariate normal distribution with zero expectation, unit variance and correlation ρ. For the jump process we assume that there is at most one jump per time period, so that $N_{(t+1)} - N_t = J_{t+1}$ with equals one if a jump occurs and equals zero else. For the jump size we assume that $\xi^y_{t+1} \sim \mathcal{N}(\mu_y, \sigma_y)$. For this model the set of latent variables comprises the time series of the jump indicator $\{J_t\}^T_{t=1}$, the time series of jump sizes in returns $\{\xi^y_t\}^T_{t=1}$ and the variances $\{V_t\}^T_{T=1}$. The unknown parameters are given by ρ, κ, θ, σ_v, μ, λ, μ_y and σ_y.

Finally, adding jumps in the conditional variance yields the so-called SVCJ model (stochastic volatility with correlated jumps) with the discretization

$$\begin{aligned} Y_{t+1} - Y_t = R_{t+1} &= \mu + \sqrt{V_t}\varepsilon^y_{t+1} + J_{t+1}\xi^y_{t+1} \\ V_{t+1} - V_t &= \kappa(\theta - V_t) + \sigma_v \sqrt{V_t}\varepsilon^v_{t+1} + J_{t+1}\xi^v_{t+1} \end{aligned} \tag{4}$$

where $\varepsilon^y_{t+1} = W^y_{(t+1)} - W^y_t$ and $\varepsilon^v_{t+1} = W^v_{(t+1)} - W^v_t$ follow a bivariate normal distribution with zero expectation, unit variance and correlation ρ. For the jump process we assume that there is at most one jump per time period, so that $N_{(t+1)} - N_t = J_{t+1}$ with equals one if a jump occurs and equals zero else. For the jump size in volatility we assume $\xi^v_{t+1} \sim \exp(\mu_v)$ and for the jump size in returns we assume that $\xi^y_{t+1}|\xi^v_{t+1} \sim \mathcal{N}(\mu_y + \rho_j \xi^v_{t+1}, \sigma_y)$. This yields $\{J_t, \xi^y_t, \xi^v_t, V_t\}^T_{t=1}$ as the set of latent variables and ρ, κ, θ, σ_v, μ, λ, μ_v, μ_y, ρ_j and σ_y as unknown parameters to estimate.

Since the discretization scheme assumes only one jump per time period the indicator J_{t+1} is a binomial distributed random variable witch equals one with probability λ. Although this assumption makes the estimation of the model easier, it could introduce some disctretization bias. But since jumps are rare events and we use daily data, this bias is typically very small. To see why this is the case assume that the jump intensity for a day is given by $\lambda = 0.1$, which is much higher than the intensities we found. Given that

$$P(N_{t+1} - N_t = j) = \frac{e^{-\lambda}\lambda^j}{j!}$$

the probability for observing more than one jump per day would be 0.0045. This shows that the discretization bias is very small.

2.2 Econometric Specification

Since neither the volatility nor the jump components are observable variables our estimation procedure has to deal with the problem of latent variables. Several estimation methods have been developed to tackle this problem. For example Singleton (2001), Pan (2002) or Viceira and Chacko (1999) develop GMM procedures using the known characteristic functions for affine models. Simulation based methods like simulated methods of moments or the efficient methods of moments where used, e.g. in Duffie and Singleton (1993) and Gallant and Tauchen (1996), respectively. Estimation of asset price models with latent variables using a bayesian framework was introduced in Jacquier, Polson, and Rossi (1994) and extended in the papers by Jacquier, Polson, and Rossi (2004) and Eraker, Johannes, and Polson (2003). That a bayesian framework using MCMC methods is particular suited for the problem at hand was shown in a Monte Carlo study by Andersen, Chung, and Sørensen (1999).

We carry out the estimation of the model using bayesian estimation methods. Based on the discretization schemes given in equation (2) - (4) we construct an hierarchical model in order to determine the posterior distribution of the parameters and the latent variables. Since the posterior distribution is of very high dimensionality we have to rely on MCMC methods to compute its moments. MCMC methods allow us to perform a Monte Carlo integration by constructing a Markov Chain that converges to the desired target distribution. After convergence is attained we run the chain until the sample is large enough to compute the desired moments by Monte Carlo integration.

We now give a brief description of the econometric methodology used, and we restrict our discussion to the SVCJ model since it is the most general one. In a bayesian setting the likelihood function and the prior distribution is combined into the posterior distribution. The posterior distribution is given by (up to a constant of proportionality)

$$p(\mathbf{\Theta}, \mathbf{J}, \boldsymbol{\xi}^y, \boldsymbol{\xi}^v, \mathbf{V}|\mathbf{R}) \propto p(\mathbf{R}|\mathbf{\Theta}, \mathbf{J}, \boldsymbol{\xi}^y, \boldsymbol{\xi}^v, \mathbf{V})p(\mathbf{\Theta}, \mathbf{J}, \boldsymbol{\xi}^y, \boldsymbol{\xi}^v, \mathbf{V}) \tag{5}$$

where $\mathbf{\Theta} = (\mu, \kappa, \theta, \sigma_v^2, \lambda, \mu_y, \sigma_y^2, \mu_v, \rho_j)'$, $\boldsymbol{\xi}^k = \{\xi_t^k\}_{t=1}^T$, $k = y, v$, $\mathbf{V} = \{V_t\}_{t=1}^T$, $\mathbf{J} = \{J_t\}_{t=1}^T$ and $\mathbf{R} = \{R_t\}_{t=1}^T$. Due to the hierarchical structure the joint prior of the latent variables and the parameters can be rewritten as

$$p(\mathbf{\Theta}, \mathbf{J}, \boldsymbol{\xi}^y, \boldsymbol{\xi}^v, \mathbf{V}) = p(\mathbf{V}|\mathbf{\Theta}, \mathbf{J}, \boldsymbol{\xi}^v)p(\mathbf{J}|\lambda)p(\boldsymbol{\xi}^y|\boldsymbol{\xi}^v, \mathbf{\Theta})p(\boldsymbol{\xi}^v|\mathbf{\Theta})p(\mathbf{\Theta}) \tag{6}$$

The discretized versions of the underlying models allow us to easily determine the likelihood function $p(\mathbf{R}|\mathbf{\Theta}, \mathbf{J}, \boldsymbol{\xi}^y, \boldsymbol{\xi}^v\mathbf{V})$ and the conditional prior for the variances $p(\mathbf{V}|\mathbf{\Theta}, \mathbf{J}, \boldsymbol{\xi}^v)$. The likelihood can be rewritten as

$$p(\mathbf{R}|\mathbf{\Theta}, \mathbf{J}, \boldsymbol{\xi}^y, \boldsymbol{\xi}^v\mathbf{V}) = \prod_{t=1}^T p(R_t|\mathbf{\Theta}, J_t, \xi_t^y, \xi_t^v, V_{t-1}) \tag{7}$$

and the second expression can be rewritten as

$$p(\mathbf{V}|\mathbf{\Theta}, \mathbf{J}, \boldsymbol{\xi}^v) \propto \prod_{t=1}^T p(V_t|V_{t-1}, \mathbf{\Theta}, J_t, \xi_t^v) \tag{8}$$

where each component is given by a normal density. Furthermore, the assumptions concerning the jump times and the jup sizes allows us to determine the components $p(\mathbf{J}|\lambda)$, $p(\boldsymbol{\xi}^y|\boldsymbol{\xi}^v, \mathbf{\Theta})$ and $p(\boldsymbol{\xi}^v|\mathbf{\Theta})$ in the prior distribution. These expressions are given by the product of binomial distribution with success probability λ, a product of normal distribution and a product of exponential distributions, respectively. For the remaining parameters we use the same priors as in Eraker, Johannes, and Polson (2003), i.e. $\mu \sim \mathcal{N}(1, 25)$, $\kappa\theta \sim \mathcal{N}(0, 1)$, $\kappa \sim \mathcal{N}(0, 1)$, $\sigma_v^2 \sim \mathcal{IG}(2.5, 0.1)$, $\lambda \sim \mathcal{B}(2, 40)$, $\mu_y \sim \mathcal{N}(0, 100)$, $\sigma_y^2 \sim \mathcal{IG}(5.0, 20)$, $\mu_v \sim \mathcal{G}(20, 10)$, $\rho_j \sim \mathcal{N}(0, 4)$ and $\rho \sim \mathcal{U}(-1, 1)$, where $\mathcal{IG}$ denotes the inverse gamma distribution, $\mathcal{B}$ is a beta distribution, $\mathcal{N}$ denotes the normal distribution, $\mathcal{G}$ a gamma distribution and $\mathcal{U}$ denotes a uniform distribution.

The MCMC algorithm draws iteratively from the following complete conditional posterior distributions (see Gilks (1995) for a general discussion on how to compute complete conditional distributions)

$$
\begin{array}{ll}
\text{Parameters :} & p(\boldsymbol{\Theta}_i|\boldsymbol{\Theta}_{-i}, \mathbf{J}, \boldsymbol{\xi}^y, \boldsymbol{\xi}^v, \mathbf{V}, \mathbf{R}),\ i = 1, \ldots, k \\
\text{Jump times :} & p(J_t|\boldsymbol{\Theta}, \mathbf{J}_{-t}, \boldsymbol{\xi}^y, \boldsymbol{\xi}^v, \mathbf{V}, \mathbf{R}),\ t = 1, \ldots, T \\
\text{Jump sizes :} & p(\xi_t^y|\boldsymbol{\Theta}, \mathbf{J}, \boldsymbol{\xi}^y_{-t}, \boldsymbol{\xi}^v, \mathbf{V}, \mathbf{R}),\ t = 1, \ldots, T \\
 & p(\xi_t^v|\boldsymbol{\Theta}, \mathbf{J}, \boldsymbol{\xi}^v_{-t}, \boldsymbol{\xi}^y, \mathbf{V}, \mathbf{R}),\ t = 1, \ldots, T \\
\text{Volatility :} & p(V_t|\boldsymbol{\Theta}, V_{t+1}, V_{t-1}, \mathbf{J}, \boldsymbol{\xi}^v, \boldsymbol{\xi}^y, \mathbf{R}),\ t = 1, \ldots, T
\end{array}
$$

where $\boldsymbol{\Theta}_{-i}$ denotes the vector $\boldsymbol{\Theta}$ without the element i. The meaning of an index $-t$ is analogous. A derivation of the complete conditional distributions used can be found in Eraker, Johannes, and Polson (2003). It can be seen that the algorithm solves the dimensionality problem by reducing the posterior to a series of one dimensional distributions. Given the model specification and our conjugate prior assumptions almost all distributions we have to sample from are of a known form. The parameters of the conjugate complete conditionals can be found in bayesian textbooks, i.e. Bernardo and Smith (1995). The only exceptions are the complete conditionals for the variance and the correlation parameter, where we use a Metropolis step. We run the algorithm for 200,000 iterations and discard the first 100,000 as burn-in period.

Note that the MCMC approach yields a straightforward estimator for the latent variables $\{V_t, J_t, \xi_t^y, \xi_t^v\}_{t=1}^T$ by using the non-discarded samples generated by the algorithm. As a point estimator we chose the expected value of the latent variable given the data, e.g. $E(L_t|\mathbf{R})$ where L_t stands for one of the latent variables. This quantity can be estimated by simply taking the average of the draws from the MCMC algorithm, e.g. $\sum_{g=1}^G L_t^g$, where G denotes the number of non-discarded samples. Two points are worth mentioning with respect to this estimator. First, since we only condition on the data set we are automatically taking parameter uncertainty into account, e.g. we are not using $E(L_t|\mathbf{R}, \hat{\boldsymbol{\Theta}})$. The second estimator bases inference on a point estimator of the parameters, whereas the MCMC estimator integrates out all parameter uncertainty. Second, the conditioning information is over the entire return series. This yields a smoothing estimator for the latent variables, in contrast to a filter estimator which only uses information up to the period t.

3 Empirical Analysis

3.1 Data

Estimation is carried out using time series of continuously compounded daily returns spanning from January 3, 1995 until December 31, 2007. We analyze the S&P 100 index and 83 stocks contained in the index where our sample contains the entire sample period. The data set is obtained from the Center for Research in Security Prices (CRSP) database and contains 3273 daily return observations. In order to be consistent with the previous literature we use returns data scaled by 100, i.e. we use percentage returns and not raw returns for the analysis. Moreover, since we do not annualize the returns for the estimation routine, the parameter estimates need to be annualized when the results are compared to standard results in the option pricing literature, e.g. Bates (2000) or Pan (2002). A list of the companies in our sample as well as some descriptive statistics for the returns can be found in Table 1.

3.2 Parameter estimates

We will first discuss the parameter estimates for the different models. As a general statement one can say that the estimation results for the S&P 100 index in our paper are comparable, as expected, to those shown in other papers for indices like the S&P 500. Furthermore, the SVIJ model turned out to be very hard to estimate, with very large standard errors especially for the parameters related to the jump components of the model. We thus decided not to include it in the set of models analyzed empirically.

We will only briefly describe the estimates, since the main emphasis of our analysis is on the economic interpretation of the models, especially on those with jump components, and their implications for the joint dynamic behavior of the index and the single stocks.

3.2.1 SV

As in basically all empirical studies for the Heston SV model, the correlation between diffusive price changes and diffusive volatility changes is strongly negative for the index with a value of roughly -0.7. For the typical stock, however, ρ is much less negative with a cross-sectional average estimate of -0.3 with 95% percent of the estimates ranging between -0.50 and -0.15. Although we do not analyze options data in this paper, this result for ρ provides support (under the $\mathbb{P}$-measure) for the finding that implied volatility smiles for individual stocks tend to be much flatter than those for the major equity indices around the world (see, e.g. Bollen and Whaley (2004)).

Not surprisingly, the long-run mean of volatility θ is much higher for the typical stock than for the index. The average estimate of 4.71 for the stocks represents an annualized long-run volatility of $\sqrt{4.71 \cdot 252} = 34.45\%$. Note the wide variation across stocks with a 2.5%-quantile of 22.4% and a 97.5%-quantile of 50.2%. For the index the corresponding value for long-run volatility is 17.39%. Also, the speed of mean-reversion for the typical stock is about twice as high as for index (0.028 vs. 0.013).

3.2.2 SVJ

Compared to the SV model we now introduce jumps in the price process, which constitutes the SVJ model. The estimates for κ, ρ, and θ as well as the differences between the index and the single stocks are very similar to the SV case, so we will not discuss them in detail.

One of the key parameters in the SVJ model is the mean jump size. A stylized fact from empirical research is that his quantity is negative and large in absolute value for the major equity indices. This is confirmed in our analysis, since μ_y for the S&P 100 is estimated at -3.9 with a standard error of 1.06, i.e. significantly different from zero. In contrast to this, the typical stock exhibits a weakly positive expected jump size (0.42) with a very large cross-sectional variation with 2.5%- and 97.5%-quantiles equal to -17.7 and 11.1, respectively. Looking deeper into the results for the single stocks, we find examples for both significantly positive and significantly negative jump sizes, again evidence for the wide variation in the characteristics of the stochastic processes for the stocks in our sample. These findings clearly show that the estimation results for indices cannot be generalized to individual stocks and that there is no 'law' that jump sizes can only be chosen to be negative in applications of SVJ models. As one might expect the estimated standard deviation of the jump size σ_y, is much smaller for the index (1.13) than for the average stock (4.05). Again this is evidence for the large cross-sectional variation across stocks.

Another key parameter of a jump process is the intensity or, loosely speaking, the probability of a jump over the next time interval (here one day). Again, the differences between the stocks and the index are striking. for the S&P 100 λ is estimated at 0.003, corresponding to an expected number of roughly 0.8 jumps per year. For the average stock λ is estimated to be almost eight times larger (0.023). Again there is pronounced cross-sectional variation in this estimate for individual stocks with a 2.5%-quantile of 0.25 jumps per year, while the stock representing 97.5%-quantile would on average exhibit 16.6 jumps annually.

3.2.3 SVCJ

Compared to the SVJ case the SVCJ model additionally includes jumps in the local variance process V. Again jumps are rare events for the index with an estimate for λ of 0.008, implying about two jumps per year. For the stocks we obtain a cross-sectional average for λ of 0.019, resulting in an average number of 4.8 jumps annually. As in the cases of the models analyzed above there is considerable variation in these estimates across stocks with 95% of the estimates ranging between roughly 1 and 14 jumps per year.

Similar to the other models the correlation between diffusive price changes and diffusive volatility changes is strongly negative for index (roughly -0.64) and much less negative for the typical stock with a cross-sectional average estimate of -0.28. Nevertheless, this correlations tends to be negative also for the stocks, with a cross-sectional 97.5%-quantile of -0.1.

One has to be careful when interpreting the expected jump size for the price process. Conditional on the current jump size in volatility this is given by $\mu_y + \rho_j \xi_t^V$, which yields an unconditional expectation equal to $\mu_y + \rho_j \mu_v$. For the index this expected value is equal to −2.68, while for the average stock we obtain an estimate of 1.52. Clearly there is again no such thing as *the* representative stock, with both positive and negative mean jump sizes, depending on the stock under consideration.

For the remaining parameters we obtain results that are qualitatively very similar to those shown for the other two models.

3.2.4 Model Choice

An inspection of the QQ plots for the index and the individual stocks shows that, again not surprisingly, the SV model is severely misspecified, while the SVJ and SVCJ models are hardly distinguishable in their goodness of fit to a straight line in the plot. Figures 1 and 2 show these plots for the S&P 100 index and for Disney Co., respectively. Disney Co. was chosen more or less arbitrarily as an example for the stocks in our sample, but it represents the 'typical' stock quite well. The improvement in fit from SV to SVJ and SVCJ is clearly visible, while the two models containing jumps do not seem much different.

A more sophisticated diagnostic tool is given by the Bayes factors for the models under consideration. Eraker, Johannes, and Polson (2003) showed that the odds ratio for the SV relative to the SVJ can be estimated as

$$\frac{p(\mathrm{SV}|\mathbf{R})}{p(\mathrm{SVJ}|\mathbf{R})} = \frac{B(\alpha_0, \beta_0)}{B(\alpha_0, \beta_0 + T)} \frac{1}{G} \sum_{g=1}^{G} \frac{B(\alpha_0 + \sum_{t=1}^{T} J_t^g, \beta_0 + 2T - \sum_{t=0}^{T} J_t^g)}{B(\alpha_0 + \sum_{t=1}^{T} J_t^g, \beta_0 + T - \sum_{t=0}^{T} J_t^g)}, \tag{9}$$

where G is the number of non-discarded draws in the MCMC sample. Table 5 shows that for most of the individual stocks as well as for the index, the SV model is rejected against the more flexible alternatives, and that is why we do not consider this model any more in the subsequent analysis. Somewhat surprisingly the SVCJ model does not consistently outperform SVJ. One reason may be that the SVJ model is not exactly nested in the SVCJ approach, so that one cannot obtain the SVJ model by meaningfully restricting certain parameters in the SVCJ model. The latter model is somewhat more flexible, but at the same time imposes the strong requirement that every price jump has to be accompanied by a variance jump. This may make it difficult for the SVCJ model to outperform the SVJ approach, since it is not clear that indeed price and variance jumps occur in a strictly simultaneous fashion.

3.3 Diffusive components of volatilities

Although our sample of stocks does not replicate the index composition perfectly, it should nevertheless allow us to draw meaningful conclusions about the co-movement in the diffusive variance components of the individual stocks. This is of interest, e.g., for two-factor stochastic volatility option pricing models in the spirit of Chernov (2003), who assumes one common and one idiosyncratic factor in the volatility dynamics for the individual assets.

We investigate the issue of idiosyncratic versus common volatility *innovations* from a different angle by first isolating the (diffusive) innovation in the variance process and then extracting principal components from the panel of variance innovations. A first factor which is highly correlated with market variance innovations would yield support for models which are built on the assumption of a common and an idiosyncratic volatility factor.

In a first step we compute the diffusive innovation to firm i's variance process as

$$\varepsilon_{t+1}^{v} = \frac{V_{t+1} - V_t - \kappa(\theta - V_t)}{\sigma_v \sqrt{V_t}}$$

for the SVJ model and as

$$\varepsilon_{t+1}^{v} = \frac{V_{t+1} - V_t - \kappa(\theta - V_t) - J_{t+1}\xi_{t+1}^{v}}{\sigma_v \sqrt{V_t}}$$

for the SVCJ model. All of the parameters and latent variables appearing in the computation of the variance innovations for the two models were evaluated at the sample mean of the non-discarded MCMC iterations.

After having computed these variance innovations for the 83 individual stocks we perform a principal component analysis to extract common factors from the individual time series. There is a clear 'most important' first factor which explains about 26% and 32% of the variance innovations for the SVJ and SVCJ model, respectively. For the SVJ model, the second factor explains only another 3.6% percent of the variation in the data, and only about 4% in the case of the SVCJ model.

The key issue, however, is not so much what percentage of variation in the data is explained by this first factor, but how strongly this first factor is correlated with index variance innovations. The result of this correlation analysis yields strong support for the notion that the variance innovations of the market (represented by the S&P 100 in this case) represent a meaningful common factor for the diffusive variance innovations in the individual stocks. For the SVCJ model the correlation between the first principal component and the market is an impressive 0.85, and for the SVJ model it is still very high with a value of 0.79. So, based on our results, it seems justified to follow the approach suggested by Chernov (2003), who estimates the variance process for the index first and then uses the results of this step to estimate the full-scale two-factor model for the individual assets.

3.4 When (and why) does the index jump?

The issue at the core of our analysis is to study index jumps in detail. The first step is then to identify the days when the index jumps. We chose to select those days as jump days where the posterior probability for a jump was greater than 0.5, which seems a natural choice for the critical level. This is, of course, a probabilistic statement, since we cannot directly observe whether indeed a jump took place or not. In any case our results are very robust with respect to the choice of a critical level of the posterior jump probability, i.e. we obtain very similar findings for jump days which are characterized by a posterior probability above, e.g., 0.4. In the following we therefore refer to the results generated by a critical posterior probability of 0.5.

For the SVCJ model this is the case for seven days in our sample period, whereas for the SVJ model we observe five index jump days (see Tables 6 and 7). Not surprisingly jump days exhibit large negative index returns, with a posterior jump probability which is significantly higher than on surrounding days (on which it is, as a matter of fact, always practically zero).

The interesting question now is how individual stocks behave on these index jump days. A natural prior would certainly be that many individual stocks also exhibit jumps (i.e., posterior jump probabilities above 0.5) on these selected days. However, it turns out that surprisingly few individual stocks exhibit jumps simultaneous to the index. By far the largest number of cross-sectional stock jumps is observed on October 27 1997, where 22 out of 83 (SVJ: 19) stocks also jump. To see how special even this seemingly small number is, compare it to the other index jump days shown in the tables. The next largest value is 10 (SVJ: 8) stock jumps on August 31, 1998 (during the LTCM crisis), i.e. less than half the jumps we find for October 27, 1997.

The most striking result is that there are even cases for the SVCJ model where none of the individual stocks exhibits a posterior jump probability of at least 0.5. What does this imply in terms of how we interpret the occurrence of an index jump? Obviously, given the small number of stocks jumping simultaneously with the index, there is no additivity in the strict sense that an index jump is the sum of jumps in individual stock prices. On the other hand, the index return *has to be* equal to the weighted sum of individual stock returns. The conclusion therefore is that index jumps are generated to a very large extent by diffusive price movements in the individual stocks, which happen to go mostly in one direction (here: down).

This is confirmed by the results in Table 9, which show that the overwhelming majority of stocks exhibits negative returns on index jump days, with an average of these returns which is very close to the index return. So why is it that the individual stocks do not also jump on these days? A look at the average conditional variance of stock returns around index jump days confirms the intuition that individual stock return volatility is much higher than index volatility, so that it is more likely for stocks to have large returns in absolute value generated by just the diffusive component of the stochastic process. On 'normal' days diversification would result in an index return which is small enough in absolute value not to be considered an index jump. However, when the correlation between the individual stocks goes up significantly, the large stock returns will basically all have the same sign (here: negative), destroying the diversification effect and resulting in a rather large and negative index return. This large negative return on the index can then more or less 'has to be' identified as a jump, since the conditional variance of the index is small compared to that of the typical stock, making such a large negative return as the result of a diffusive move rather unlikely.

These findings seem to imply that index jumps are more the result of correlations between individual stocks going up rather than a sudden sharp increase in *individual* conditional volatility. Support for this intuition can be drawn from Tables 6 and 7, which show that the average conditional variance of the stocks in our sample hardly changes around index jump days. The only degree of freedom left in the computation of the index return variance is then the correlation between individual stock returns, which (in a non-parametric sense) increases significantly on index jump days (see Table 9). A simple correlation measure is the ratio of stocks which exhibit returns in a given direction. As one can see from the table, the distribution of the signs of individual stocks returns is much less symmetric on index jump days than on other surrounding days.

However, correlation is not the full story. To find out if *all* the index jumps in our sample are likely to be the result of a correlation moving (or jumping) towards one, we analyze the jump probabilities of the different industries our sample firms belong to, i.e. we want to see whether, e.g., stocks from 'young' sectors like telecommunication are more likely to jump on these days than firms from other industries. To do so we compute the average jump probabilities of the stocks included in different sectors based on the Global Industry Classification System (GICS) developed by Standard & Poor's and Morgan Stanley. We use the first two digits of the classification to allocate the firms in our sample to ten different sectors, namely 'Energy', 'Materials', 'Industrials', 'Consumer Discretionary', 'Consumer Staples', 'Health Care', 'Financials', 'Information Technology', 'Telecommunications', and 'Utilities'.

Using the same threshold as for the index (50% posterior jump probability) we saw in the previous subsection that only very few stocks jump at all, so we cannot expect to see an industry effect based on this critical value. Nevertheless, a clear picture of the nature of index jumps emerges. Figure 4 shows the sector jump probabilities for the seven days for which the SVCJ model identified index jumps. We find big differences in the overall level of sector jump probabilities between days like October 27, 1997 and August 31, 1998, and (to a lesser degree) February 27, 2007, and the rest of the jump days. For these three days we find rather high jump probabilities for a large number of sector. E.g., on October 27, 1997, eight out of the ten sectors exhibit jump probabilities of more than 10%, on August 31, 1998, this is true for six out of ten. Although a critical level of 10% may seem low at first sight, one should keep in mind that the jump intensity for the typical stock roughly equals 2% (see Table 4) so that on these special days we observe *sector averages* which are five times higher than the usual *individual* probability. Put differently, with a 10% probability of a jump every day, we would see on average roughly 25 jumps per year, an enormous number. This emphasizes that the sector jump probabilities on these three special days stand out indeed, since for the other four index jump days there is at most one sector with a jump probability exceeding 10%.

Especially the jumps on October 27, 1997 and August 31, 1998 can be linked to crucial macroeconomic events. The first relates to an economic crisis in Asia (sometimes called the 'Asian flu'), whereas the second was caused by financial turmoil in both Asia and Russia. These two days also represent the two largest percentage drops in the index for our sample. Stock market reports for February 27, 2007, frequently mention a large drop in the Chinese stock market as an important reason for the big loss in the S&P 100 on that day, so the reasons for this jump are similar to the ones described before. In summary, since relatively many industries jump on these days, and since the reasons can be traced back to macroeconomic events, we refer to these jumps as 'macro-driven'.

On the other hand, the remaining four jump days are characterized by very small sector jump probabilities, so the fact that we identify an index jump at all is more due to the statistical properties of the stochastic process for stock prices, which tends to label a price move as a jump mostly when it is too large to be generated with a sufficiently high probability by the diffusive component. We therefore refer to these jumps as 'statistical jumps', driven mostly by the correlation effect described above in Subsection 3.4.

Here a significant discrepancy between the SVCJ and the SVJ model arises. As can be seen in Table 7 the SVJ model identifies only four index jump days, as compared to seven for SVCJ. The 'selection' of the subset of jump days in the SVJ model does not seem random, since it exactly identifies what we call 'macro-driven' jumps, while the SVCJ statistical jumps on January 4, 2000, April 14, 2000, and March 12, 2001, do not represent SVJ index jumps.

The fact that the SVJ model is generally less likely than the SVCJ model to identify jumps can also be explained via a comparison of the parameter estimates in Tables 3 and 4. The estimate for the long-run variance θ in the SVJ model is about 30% higher than in the SVCJ case, so that it is more likely for the latter model to regard a large negative index return as the result of a jump rather than a diffusive move of the index level.

The next item of interest is the decomposition of index returns on jump days into a diffusive and a jump part. Table 10 shows that there is no clear pattern concerning the relative share of the return that the jump is responsible for. For example, on February 27, 2007, almost the full negative return was due to a jump. the jump component (more than 85% for the SVCJ model, and basically 100% for the SVJ model). On the other hand, for March 8, 1996, the SVCJ model attributes less than half of the total S&P 100 return to a jump. The same is true for April 14, 2000, and March 12, 2001. It is also not true, although this might seem rather intuitive, that the largest negative returns are the ones that exhibit the largest relative jump part. On October 27, 1997, both models indicate that roughly 70% of the index return were due to a jump, and on August 31, 1998, this share is even lower at roughly 50%. This further shows that there are no clear and easy predictions when it comes to the role of jumps in index price dynamics.

4 Conclusion

This paper analyzed stochastic equity price models for a large cross section of individual stocks, i.e. 83 stocks included in the S&P 100 index. To the best of our knowledge, this is the first detailed study on individual stocks. Furthermore, we compared the estimation results for the individual stocks to the results for the S&P 100 index. The models under consideration allowed for a jump component in the return as well as in the variance process. The estimation method relied on Bayesian econometric methods using a MCMC algorithm in order to compute the moments of the posterior distribution.

Our results show that the parameters governing the stochastic processes for individual stocks are very heterogenous. Unsurprisingly, the volatility process for individual stocks is much higher than the volatility process for the index. Furthermore, we find a less pronounced leverage effect in the individual stocks compared to the index. Considering the distribution of the jumps in returns we can show that it is not clear if the mean jump is positive or negative for the individual stock. We find examples for both cases in our sample.

For the diffusive component of the volatilities we performed a principal component analysis with the aim of finding a common factor explaining these variance innovations. We find that this 'most important' factor explains about 30% of the variance innovations. Analyzing the correlation of this first factor withe the variance innovations for the market (here the S&P 100 index) we find a correlation of about 0.8. This indicates that the support for the notion that the variance innovations of the market represent a meaningful common factor for the diffusive variance innovations in the individual stocks, justifying the approach suggested by Chernov (2003) for the estimation of a two-factor model for individual assets.

Considering the behavior of the individual stocks from which the index is constructed on days that the index jumps we find a rather surprising result. We find that on these days a very small number of stocks also jumps, in the extreme case this number of stocks jumping simultaneously is even zero. The fact that a very large percentage number of stocks, in the extreme case all of them, have large negative returns indicates that one of the reasons for jumps in the index can be found in the correlation structure of the diffusive individual stock returns, rather than in jump components of the stocks. Besides those index jumps which seem to be generated mostly by the correlation moving towards one ('statistical jumps') without additional jumps in the stocks, we also identify 'macro-driven' jumps with relatively high jump probabilities for a large number of industries. We also find significant differences in terms of the identification of index jump days between the SVJ and the SVCJ model.

A natural next step would be to incorporate option prices into the estimation to identify the risk premia for stochastic volatility and jumps. The results of such an analysis would provide further evidence on how individual stock characteristics are aggregated up to the market level.

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Table 1: Descriptive Statistics of the Returns Data
The table reports means, standard deviation, skewness, kurtosis, minimums and maximum for the returns of the S&P 100 index and the individual stocks contained in the analysis.

Company	Mean	Volatility	Skewness	Kurtosis	Min	Max
S&P 100	0.04	1.12	-0.13	6.59	-7.52	5.69
Oracle Systems Corp	0.13	3.32	0.34	11.23	-29.15	31.09
Microsoft Corp	0.10	2.17	0.13	8.68	-15.60	19.57
Allied Signal Inc	0.07	2.16	0.19	18.19	-17.78	28.22
E M C Corp Ma	0.12	3.44	0.05	8.33	-28.07	24.86
Unisys Corp	0.04	3.25	-0.51	20.96	-37.57	32.40
Dell Computer Corp	0.16	3.02	0.12	6.60	-18.94	20.76
Coca Cola Co	0.05	1.55	0.01	7.49	-10.48	9.65
Du Pont E I De Nemours & Co	0.04	1.78	0.13	6.05	-11.04	9.87
Eastman Kodak Co	0.01	2.03	-0.87	16.99	-24.79	12.71
Exxon Corp	0.08	1.50	0.08	5.63	-8.46	11.05
General Dynamics Corp	0.09	1.65	-0.10	7.25	-12.38	9.12
General Electric Co	0.07	1.71	0.20	7.15	-10.67	12.46
General Motors Corp	0.03	2.18	0.28	7.08	-13.97	18.11
International Business Machs Cor	0.08	1.99	0.26	9.93	-15.54	13.16
Pepsico Inc	0.07	1.65	0.60	11.61	-11.16	16.14
Philip Morris Cos Inc	0.09	1.93	0.00	11.18	-13.86	16.27
Amgen Inc	0.09	2.43	0.33	6.74	-13.41	15.10
Schlumberger Ltd	0.10	2.24	0.10	4.86	-12.19	10.34
Tandy Corp	0.05	2.73	-0.26	11.54	-26.49	23.26
Texas Instruments Inc	0.11	3.19	0.43	5.83	-18.22	24.07
United Technologies Corp	0.09	1.79	-1.17	24.26	-28.25	9.83
Procter & Gamble Co	0.07	1.61	-2.36	50.32	-31.38	9.52
Southern Co	0.06	1.31	0.17	6.73	-8.47	9.18
Colgate Palmolive Co	0.07	1.66	0.30	15.35	-15.46	20.32
Bristol Myers Squibb Co	0.05	1.94	-0.49	14.74	-22.41	14.64
Boeing Co	0.07	1.99	-0.31	9.38	-17.63	11.63
Black & Decker Corp	0.06	2.04	0.36	8.34	-15.95	13.77
Dow Chemical Co	0.05	1.84	0.21	7.02	-10.58	11.39
International Paper Co	0.02	1.92	0.33	5.81	-10.46	11.89
PECO Energy Co	0.09	1.58	-0.07	7.87	-11.79	11.11
Pfizer Inc	0.06	1.87	-0.08	5.82	-11.15	9.71
Johnson & Johnson	0.07	1.46	-0.22	9.92	-15.85	8.21
Minnesota Mining & Mfg Co	0.06	1.55	0.15	7.00	-9.59	11.07
Merck & Co Inc	0.06	1.81	-0.94	21.17	-26.78	13.03
Sara Lee Corp	0.04	1.56	0.38	8.92	-9.83	14.10
Heinz H J Co	0.05	1.40	0.32	6.81	-8.25	10.87
Halliburton Company	0.10	2.83	-0.48	23.08	-42.45	24.35
Entergy Corp New	0.08	1.51	-0.52	14.48	-18.10	10.60
Clear Channel Communications Inc	0.08	2.37	0.08	7.49	-16.50	14.68
American Electric Power Co Inc	0.04	1.58	-0.03	31.49	-22.78	19.84
Aluminum Company Amer	0.07	2.19	0.34	5.73	-11.01	14.06
Raytheon Co	0.05	2.15	-2.32	71.03	-43.60	26.76
Campbell Soup Co	0.04	1.62	0.36	10.20	-13.16	14.29
Disney Walt Co	0.05	2.03	0.05	10.39	-18.36	15.26
Hewlett Packard Co	0.09	2.65	0.21	8.65	-18.70	20.91
Baxter International Inc	0.07	1.88	-1.35	22.39	-26.28	10.91

Table 1: (continued)

Company	Mean	Volatility	Skewness	Kurtosis	Min	Max
Xerox Corp	0.05	3.01	0.34	22.65	-25.75	39.06
Williams Cos	0.13	3.76	2.40	127.00	-61.05	87.74
Norwest Corp	0.07	1.64	0.25	6.19	-8.78	10.00
Weyerhaeuser Co	0.05	1.91	0.30	5.53	-11.94	11.75
Computer Sciences Corp	0.05	2.44	-1.22	28.68	-39.56	18.09
Avon Products Inc	0.08	2.07	-0.28	19.90	-27.67	19.19
Boise Cascade Corp	0.03	2.28	0.50	7.77	-15.51	15.59
Teledyne Inc	0.10	2.85	0.46	7.34	-16.47	19.64
Mcdonalds Corp	0.06	1.74	0.11	7.36	-12.82	10.86
Chemical Banking Corp	0.08	2.17	0.36	8.79	-18.11	16.04
Burlington Northern Inc	0.07	1.78	0.16	6.47	-12.56	11.43
National Semiconductor Corp	0.09	3.68	0.10	7.75	-34.35	20.94
Merrill Lynch & Co Inc	0.09	2.43	0.29	5.83	-11.57	15.08
Wal Mart Stores Inc	0.07	1.89	0.27	5.88	-9.75	9.43
American Express Co	0.08	2.05	0.10	6.25	-13.60	12.77
Anheuser Busch Cos Inc	0.06	1.45	-0.09	6.34	-8.25	7.74
Intel Corp	0.10	2.76	-0.12	8.13	-22.03	20.12
Nationsbank Corp	0.07	1.82	-0.05	6.38	-10.89	8.80
Medtronic Inc	0.08	1.95	0.09	7.66	-12.98	11.90
Federal Express Corp	0.08	2.00	0.31	6.98	-14.32	11.59
CIGNA Corp	0.09	2.03	-2.09	48.02	-38.07	18.93
Limited Inc	0.06	2.26	0.19	6.44	-13.06	14.22
Norfolk Southern Corp	0.06	2.06	0.31	6.59	-10.49	15.41
Bell Atlantic Corp	0.05	1.77	0.24	7.08	-11.85	12.26
First Bank System Inc	0.07	1.93	-0.74	22.43	-27.76	15.32
Home Depot Inc	0.06	2.18	-0.59	15.26	-28.74	12.89
American International Group Inc	0.06	1.78	0.23	6.54	-10.43	11.03
Morgan Stanley Group Inc	0.10	2.57	0.21	6.52	-13.09	16.03
Travelers Inc	0.08	2.10	0.27	8.55	-15.73	18.34
Baker Hughes Inc	0.08	2.55	0.27	6.24	-14.44	18.62
Cisco Systems Inc	0.13	2.98	0.44	8.59	-13.53	24.39
Promus Companies Inc	0.07	2.25	0.22	8.61	-17.18	15.96
A E S Corp	0.12	3.75	0.07	30.97	-49.48	41.03
America Online Inc Del	0.15	3.29	0.33	6.64	-17.14	17.95
El Paso Natural Gas Co	0.06	2.95	-0.53	31.76	-35.65	33.02
Allstate Corp	0.07	1.81	-0.15	7.95	-12.62	10.43
Lehman Brothers Holdings Inc	0.13	2.73	0.48	8.18	-18.57	19.29

Table 2: Parameter Estimates for the SV Model

The table shows the parameter estimates for the stochastic volatility (SV) model. The data sets on the S&P 100 index and the individual stocks span from January 3, 1995 to December 31, 2007. The parameter estimates correspond to continuously compounded daily percentage returns. The parametrization of the model as well as the estimation methodology are given in Section 2. We report the means, the standard deviation and the 95% credibility intervals for each parameter.

S&P 100 index

Parameter	Mean	Std. Err.	$Q_{2.5}$	$Q_{97.5}$
μ	0.0347	0.0149	0.0054	0.0639
θ	1.2196	0.2215	0.7970	1.6792
κ	0.0134	0.0040	0.0070	0.0222
σ_v	0.1216	0.0141	0.0979	0.1515
ρ	−0.7054	0.0373	−0.7805	−0.6310

Individual stocks (cross−sectional statistics)

Parameter	Mean	Std. Err.	$Q_{2.5}$	$Q_{97.5}$
μ	0.0395	0.0256	−0.0081	0.0927
θ	4.7138	2.4242	1.9926	10.0608
κ	0.0283	0.0184	0.0089	0.0744
σ_v	0.3391	0.1186	0.1919	0.6109
ρ	−0.3053	0.0966	−0.5027	−0.1513

Table 3: Parameter Estimates for the SVJ Model

The table shows the parameter estimates for the stochastic volatility containing jumps in returns (SVJ) model. The data sets on the S&P 100 index and the individual stocks span from January 3, 1995 to December 31, 2007. The parameter estimates correspond to continuously compounded daily percentage returns. The parametrization of the model as well as the estimation methodology are given in Section 2. We report the means, the standard deviation and the 95% credibility intervals for each parameter.

S&P 100 index

Parameter	Mean	Std. Err.	$Q_{2.5}$	$Q_{97.5}$
μ	0.0405	0.0150	0.0113	0.0698
θ	1.1916	0.2114	0.7863	1.6265
κ	0.0134	0.0034	0.0075	0.0207
σ_v	0.1203	0.0111	0.0994	0.1434
μ_y	−3.9371	1.0633	−6.0034	−1.5904
σ_y	1.1312	0.2918	0.7216	1.8359
ρ	−0.6873	0.0393	−0.7596	−0.6052
λ	0.0031	0.0018	0.0009	0.0078

Individual stocks (cross−sectional statistics)

Parameter	Mean	Std. Err.	$Q_{2.5}$	$Q_{97.5}$
μ	0.0319	0.0380	−0.0697	0.1003
θ	4.1658	1.9912	1.9278	8.9820
κ	0.0191	0.0123	0.0068	0.0398
σ_v	0.2476	0.0480	0.1797	0.3605
μ_y	0.4169	5.9164	−17.6792	11.1078
σ_y	4.0508	3.4964	1.0631	13.0616
ρ	−0.2682	0.1028	−0.4891	−0.1243
λ	0.0228	0.0162	0.0012	0.0656

Table 4: Parameter Estimates for the SVCJ Model

The table shows the parameter estimates for the stochastic volatility containing jumps in returns and in volatilities (SVCJ) model. The data sets on the S&P 100 index and the individual stocks span from January 3, 1995 to December 31, 2007. The parameter estimates correspond to continuously compounded daily percentage returns. The parametrization of the model as well as the estimation methodology are given in Section 2. We report the means, the standard deviation and the 95% credibility intervals for each parameter.

S&P 100 index

Parameter	Mean	Std. Err.	$Q_{2.5}$	$Q_{97.5}$
μ	0.0464	0.0152	0.0168	0.0764
θ	0.8576	0.1462	0.5887	1.1614
κ	0.0237	0.0059	0.0141	0.0364
σ_v	0.1239	0.0121	0.1026	0.1484
μ_y	-1.5662	1.0566	-3.7988	0.3786
ρ_J	-1.0901	0.7239	-2.5963	0.3374
σ_y	1.1317	0.2607	0.7272	1.7535
μ_v	1.0259	0.2224	0.6534	1.5372
ρ	-0.6394	0.0538	-0.7380	-0.5236
λ	0.0077	0.0034	0.0028	0.0159

Individual stocks (cross−sectional statistics)

Parameter	Mean	Std. Err.	$Q_{2.5}$	$Q_{97.5}$
μ	0.0314	0.0374	-0.0574	0.1009
θ	3.1959	1.5941	1.3997	7.0751
κ	0.0256	0.0164	0.0089	0.0535
σ_v	0.2507	0.0501	0.1776	0.3638
μ_y	2.7195	2.7439	-5.2559	8.6255
ρ_J	-1.1751	2.6325	-5.0014	4.2423
σ_y	2.9884	3.1204	1.0823	11.0949
μ_v	1.0180	0.0143	1.0046	1.0664
ρ	-0.2766	0.1032	-0.5025	-0.0998
λ	0.0192	0.0114	0.0044	0.0549

Table 5: Model Selection

This table summarizes the results given by the computation of the Bayes Factors. The procedure for the computation of the Bayes Factors is described in Section 3.2.4. The interpretation of the results follows Kaas and Raftery (1995) in that evidence for the model mentioned in the first place of each column is positive if the value of twice the natural logarithm of the Bayes Factor is between 2 and 6, strong if it is between 6 and 10 and very strong if it is greater than 10. For example the evidence in favor of the SVJ model in comparison to the SV model is very strong in 76 cases. The SV model is rejected in all but four cases when compared to models containing jumps. These four cases are Merck & Co. Inc., Xerox Corp., CIGNA Corp. and AES Corp.

Evidence is ...	SVJ vs. SV	SVCJ vs. SV	SVCJ vs. SVJ	SVJ vs. SVCJ
Positive	1	1	3	19
Strong	1	2	2	14
Very Strong	76	71	4	25

Table 6: Index Jump Days for the SVCJ Model

The table reports the returns, the jump probability, the variance for the S&P 100 index on the days where the SVCJ model identifies a jump. Furthermore, the table shows the number of stocks that exhibit a jump probability of more than 50% on the days the index jumps, the average variance, the minimum variance and the maximum variance for the individual stocks on these days. The jump days are given by the rows in bold.

Date	Return	Jump Prob.	V_t Index	# Stocks w/ Jumps	Avg. V_t Stocks	Min. V_t Stocks	Max. V_t Stocks
7-Mar-96	0.3249	0.0027	0.7160	0	3.7395	0.7160	16.9207
8-Mar-96	**-3.1725**	**0.5358**	**1.0296**	**2**	**3.9626**	**1.0296**	**16.8209**
11-Mar-96	1.2299	0.0005	0.8986	2	3.8298	0.8986	16.3715
12-Mar-96	-0.4061	0.0013	0.9053	1	3.7917	0.9053	16.1157
24-Oct-97	-1.3207	0.0058	1.7146	1	5.1527	1.0678	19.6711
27-Oct-97	**-7.0939**	**0.8966**	**3.7784**	**22**	**6.2440**	**1.2026**	**21.0635**
28-Oct-97	5.6062	0.0016	3.2143	7	5.9327	1.0866	19.9602
29-Oct-97	-0.4425	0.0026	3.1533	1	5.8087	0.9573	19.6473
28-Aug-98	-1.6081	0.0150	3.0067	0	8.8549	1.6887	27.3843
31-Aug-98	**-7.5165**	**0.7989**	**4.9689**	**10**	**9.7597**	**1.6912**	**29.4822**
1-Sep-98	4.1899	0.0019	4.5352	2	9.6005	1.7055	29.5368
2-Sep-98	-1.0337	0.0045	4.5323	0	9.6060	1.7802	28.8597
3-Jan-00	-0.5109	0.0070	0.5540	0	7.5026	0.5540	22.2529
4-Jan-00	**-3.8485**	**0.9331**	**1.8780**	**0**	**7.7905**	**1.8780**	**22.8810**
5-Jan-00	0.3301	0.0021	1.8337	0	7.8132	1.8337	22.9072
6-Jan-00	0.1470	0.0053	1.8169	2	7.7549	1.8169	23.0106
13-Apr-00	-1.9884	0.0273	2.6192	0	9.8440	2.6192	23.0352
14-Apr-00	**-6.0088**	**0.6374**	**3.9262**	**1**	**10.2523**	**2.9251**	**25.5452**
17-Apr-00	4.0864	0.0018	3.5179	3	10.0868	2.9792	24.9353
18-Apr-00	3.0266	0.0012	3.1950	0	9.8297	3.1950	23.4204
9-Mar-01	-2.8114	0.1210	2.7102	0	8.2683	1.4042	33.8233
12-Mar-01	**-5.1659**	**0.5347**	**3.9763**	**0**	**8.6728**	**1.6096**	**34.8554**
13-Mar-01	1.9753	0.0029	3.7742	1	8.6016	1.7306	33.4241
14-Mar-01	-2.8788	0.0243	3.9684	0	8.7825	1.9411	33.6740
26-Feb-07	-0.0949	0.0038	0.4592	1	1.9294	0.2836	6.3913
27-Feb-07	**-3.6333**	**0.9429**	**0.9516**	**9**	**2.2410**	**0.3156**	**7.2046**
28-Feb-07	0.6280	0.0010	0.8866	0	2.1503	0.2919	6.5127
1-Mar-07	-0.2629	0.0012	0.8977	0	2.1334	0.2955	6.5335

Table 7: Index Jump Days for the SVJ Model

The table reports the returns, the jump probability, the variance for the S&P 100 index on the days where the SVJ model identifies a jump. Furthermore, the table shows the number of stocks that exhibit a jump probability of more than 50% on the days the index jumps, the average variance, the minimum variance and the maximum variance for the individual stocks on these days. The jump days are given by the rows in bold.

Date	Return	Jump Prob.	V_t Index	# Stocks w/ Jumps	Avg. V_t Stocks	Min. V_t Stocks	Max. V_t Stocks
7-Mar-96	0.3249	0.0003	0.7991	0	3.6937	0.7991	20.6250
8-Mar-96	**-3.1725**	**0.5758**	**0.8932**	**3**	**3.8593**	**0.8932**	**20.6044**
11-Mar-96	1.2299	0.0003	0.7765	1	3.7386	0.7765	20.2115
12-Mar-96	-0.4061	0.0006	0.8006	1	3.7080	0.8006	20.0616
24-Oct-97	-1.3207	0.0009	1.9930	1	5.2792	0.9973	16.1961
27-Oct-97	**-7.0939**	**0.9761**	**2.1945**	**19**	**5.6487**	**1.0775**	**17.3000**
28-Oct-97	5.6062	0.0034	1.7156	12	5.3357	0.9846	16.8747
29-Oct-97	-0.4425	0.0007	1.7468	1	5.2635	0.8665	16.9677
28-Aug-98	-1.6081	0.0015	3.0694	0	8.9298	1.7875	24.5461
31-Aug-98	**-7.5165**	**0.7548**	**3.3823**	**8**	**9.4155**	**1.7962**	**26.8148**
1-Sep-98	4.1899	0.0005	3.0286	3	9.2648	1.8201	26.9718
2-Sep-98	-1.0337	0.0013	3.1120	1	9.3202	1.9175	26.3734
26-Feb-07	-0.0949	0.0002	0.5317	1	1.8736	0.2778	7.3305
27-Feb-07	**-3.6333**	**0.9615**	**0.5533**	**9**	**2.0362**	**0.3066**	**8.3732**
28-Feb-07	0.6280	0.0002	0.5197	1	1.9760	0.2876	7.6678
1-Mar-07	-0.2629	0.0002	0.5630	0	1.9768	0.2941	7.7416

Table 8: Index and Individual Stock Returns on Jump Days

The table shows the index and individual stock returns on and around index jump days. The table reports the index return on the given days in the second column. For the individual stocks the table reports the average return, the minimum return, the 5% quantile, the maximum return and the 95% quantile. The jump days are given by the rows in bold.

Date	Return Index	Avg. Ret. Stocks	Min. Ret. Stocks	$Q_{5.0}$	Max. Ret. Stocks	$Q_{95.0}$
7-Mar-96	0.3249	0.3406	-3.5896	-2.0284	6.1644	3.8294
8-Mar-96	**-3.1725**	**-2.9390**	**-8.2293**	**-6.3126**	**3.0075**	**-0.1193**
11-Mar-96	1.2299	1.2350	-4.5350	-2.1154	9.9432	5.3057
12-Mar-96	-0.4061	-0.1738	-4.2552	-2.5472	14.7287	2.5416
24-Oct-97	-1.3207	-1.0936	-7.4456	-3.9364	10.2804	1.9468
27-Oct-97	**-7.0939**	**-7.0768**	**-15.9291**	**-12.3253**	**-0.7253**	**-2.8637**
28-Oct-97	5.6062	4.6042	-3.3556	-1.4822	14.7368	11.2899
29-Oct-97	-0.4425	0.0858	-8.2417	-3.7091	7.0833	3.3910
28-Aug-98	-1.6081	-1.9684	-9.4175	-6.1615	4.6310	1.9399
31-Aug-98	**-7.5165**	**-6.6220**	**-16.4739**	**-13.6595**	**2.4226**	**0.3396**
1-Sep-98	4.1899	3.7127	-2.4054	-1.6413	16.1435	10.5855
2-Sep-98	-1.0337	-0.0485	-5.8823	-4.2800	6.3091	3.8267
3-Jan-00	-0.5109	-1.2626	-6.9904	-6.1283	10.1652	6.2396
4-Jan-00	**-3.8485**	**-2.7877**	**-8.8359**	**-7.5839**	**6.2762**	**1.1271**
5-Jan-00	0.3301	0.7090	-7.0174	-5.3153	7.1046	6.1991
6-Jan-00	0.1470	1.4276	-8.7679	-5.8453	11.4286	7.4468
13-Apr-00	-1.9884	-1.3035	-6.2427	-5.2757	5.6022	3.7951
14-Apr-00	**-6.0088**	**-5.5150**	**-18.5733**	**-10.4653**	**8.2474**	**-0.4362**
17-Apr-00	4.0864	2.0008	-6.1124	-2.7722	19.7000	12.0997
18-Apr-00	3.0266	1.7834	-5.4166	-3.8918	11.0632	9.5220
9-Mar-01	-2.8114	-2.0609	-11.4661	-7.5689	2.6198	1.4278
12-Mar-01	**-5.1659**	**-3.9527**	**-11.9358**	**-8.6468**	**0.8411**	**0.0527**
13-Mar-01	1.9753	0.7785	-8.4278	-4.7905	13.6213	7.6716
14-Mar-01	-2.8788	-2.4138	-7.7003	-5.5093	3.5398	0.7970
26-Feb-07	-0.0949	-0.1609	-3.2900	-2.6455	4.5836	2.3808
27-Feb-07	**-3.6333**	**-3.1651**	**-7.8538**	**-5.5985**	**11.9376**	**-1.5314**
28-Feb-07	0.6280	0.4664	-2.7490	-1.1430	3.6992	2.7248
1-Mar-07	-0.2629	-0.2901	-3.9837	-1.5123	2.0694	1.2101

Table 9: Number of Positive and Negative Returns on Index Jump Days

The table shows the number of positive and negative returns for the individual stocks on the index jump days and around these days. The jump days are given by the rows in bold.

Returns

Date	# $R > 0$	Fraction $R > 0$	# $R < 0$	Fraction $R < 0$
7-Mar-96	42	0.5060	33	0.3976
8-Mar-96	**4**	**0.0482**	**79**	**0.9518**
11-Mar-96	55	0.6627	24	0.2892
12-Mar-96	31	0.3735	48	0.5783
24-Oct-97	19	0.2289	63	0.7590
27-Oct-97	**0**	**0.0000**	**83**	**1.0000**
28-Oct-97	74	0.8916	7	0.0843
29-Oct-97	46	0.5542	35	0.4217
28-Aug-98	18	0.2169	62	0.7470
31-Aug-98	**7**	**0.0843**	**76**	**0.9157**
1-Sep-98	66	0.7952	17	0.2048
2-Sep-98	42	0.5060	39	0.4699
3-Jan-00	20	0.2410	63	0.7590
4-Jan-00	**11**	**0.1325**	**69**	**0.8313**
5-Jan-00	44	0.5301	38	0.4578
6-Jan-00	59	0.7108	24	0.2892
13-Apr-00	25	0.3012	58	0.6988
14-Apr-00	**1**	**0.0120**	**81**	**0.9759**
17-Apr-00	55	0.6627	27	0.3253
18-Apr-00	54	0.6506	27	0.3253
9-Mar-01	17	0.2048	66	0.7952
12-Mar-01	**5**	**0.0602**	**78**	**0.9398**
13-Mar-01	38	0.4578	44	0.5301
14-Mar-01	7	0.0843	75	0.9036
26-Feb-07	32	0.3855	49	0.5904
27-Feb-07	**1**	**0.0120**	**82**	**0.9880**
28-Feb-07	57	0.6867	24	0.2892
1-Mar-07	29	0.3494	54	0.6506

Table 10: Index Return Decomposition on Jump Days for the SVCJ and SVJ Model

The table shows the return decomposition of the index on and around the jump days. The first column reports the return of the index. The second and third column shows the decomposition of the return into a jump and a diffusive part for the SVJ model. The fourth and fifth column shows the same decomposition in the case of the SVCJ column. Return jump days are given by the rows in bold.

		SVJ		SVCJ	
Date	Index Return	Jump Component	Diffusive Component	Jump Component	Diffusive Component
7-Mar-96	0.3249	-0.0001	0.2845	-0.0010	0.2795
8-Mar-96	**-3.1725**	**-1.9699**	**-1.2432**	**-1.5437**	**-1.6752**
11-Mar-96	1.2299	0.0002	1.1892	0.0001	1.1834
12-Mar-96	-0.4061	-0.0007	-0.4460	-0.0011	-0.4514
24-Oct-97	-1.3207	-0.0020	-1.3592	-0.0090	-1.3581
27-Oct-97	**-7.0939**	**-5.0867**	**-2.0476**	**-4.9807**	**-2.1596**
28-Oct-97	5.6062	0.0101	5.5555	0.0014	5.5584
29-Oct-97	-0.4425	-0.0013	-0.4817	-0.0030	-0.4858
28-Aug-98	-1.6081	-0.0037	-1.6450	-0.0325	-1.6220
31-Aug-98	**-7.5165**	**-3.8721**	**-3.6848**	**-4.3547**	**-3.2081**
1-Sep-98	4.1899	0.0003	4.1492	-0.0001	4.1437
2-Sep-98	-1.0337	-0.0029	-1.0713	-0.0072	-1.0729
3-Jan-00	-0.5109	-	-	-0.0079	-0.5493
4-Jan-00	**-3.8485**	**-**	**-**	**-3.4145**	**-0.4804**
5-Jan-00	0.3301	-	-	-0.0018	0.2856
6-Jan-00	0.1470	-	-	-0.0057	0.1062
13-Apr-00	-1.9884	-	-	-0.0599	-1.9749
14-Apr-00	**-6.0088**	**-**	**-**	**-2.9170**	**-3.1381**
17-Apr-00	4.0864	-	-	0.0001	4.0399
18-Apr-00	3.0266	-	-	0.0000	2.9802
9-Mar-01	-2.8114	-	-	-0.3440	-2.5138
12-Mar-01	**-5.1659**	**-**	**-**	**-2.2492**	**-2.9631**
13-Mar-01	1.9753	-	-	-0.0017	1.9307
14-Mar-01	-2.8788	-	-	-0.0585	-2.8667
26-Feb-07	-0.0949	-0.0001	-0.1354	-0.0015	-0.1398
27-Feb-07	**-3.6333**	**-3.6290**	**-0.0448**	**-3.1048**	**-0.5748**
28-Feb-07	0.6280	0.0000	0.5874	-0.0002	0.5818
1-Mar-07	-0.2629	-0.0001	-0.3033	-0.0007	-0.3085

Figure 1: QQ plots for the Index

This figure shows the normality plots for the residuals in the returns equation for each model, where the underlying time series is the S& P 100 index. The first figure shows the QQ plot for the SV model the second figure shows the QQ plot for the SVJ model and the third figure gives the QQ plot for the SVCJ model.

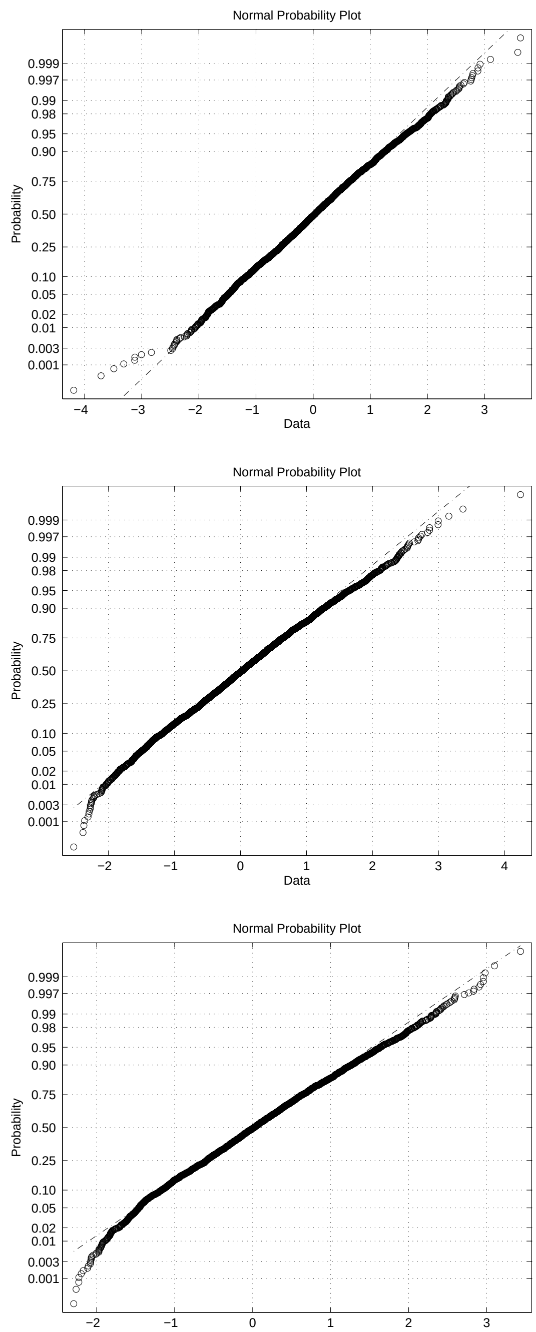
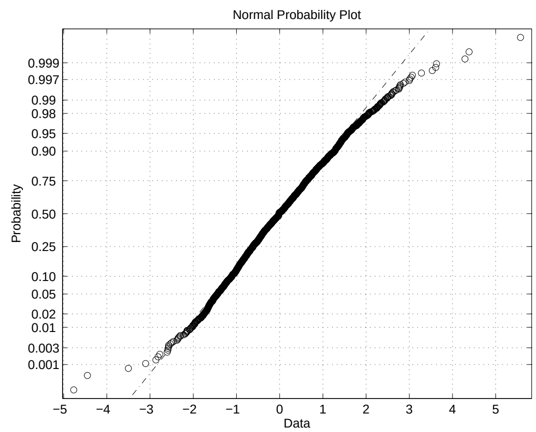
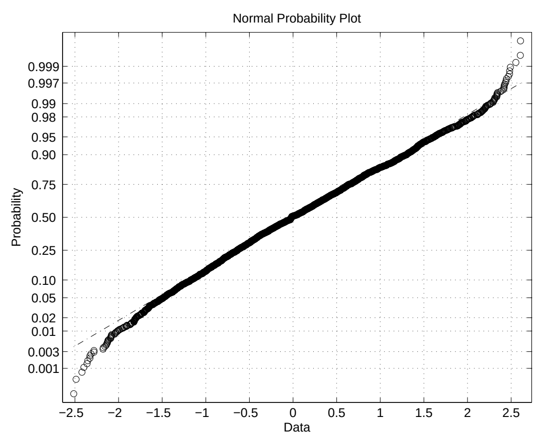


Figure 2: QQ plots for Disney Co.

This figure shows the normality plots for the residuals in the returns equation for each model, where the underlying time series is the Disney Co. The first figure shows the QQ plot for the SV model the second figure shows the QQ plot for the SVJ model and the third figure gives the QQ plot for the SVCJ model.





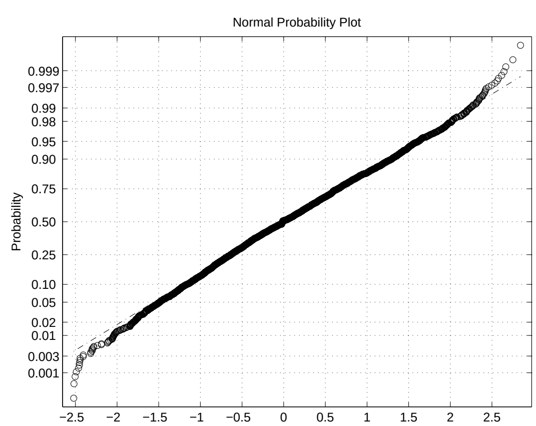


Figure 3: Industry Jump Probabilities on Index Jump Days for the SVJ Model

The figure shows the mean of the jump probabilities of the stocks in each of the industries. The industries are (from left to right): Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Telecommunications and Utilities.

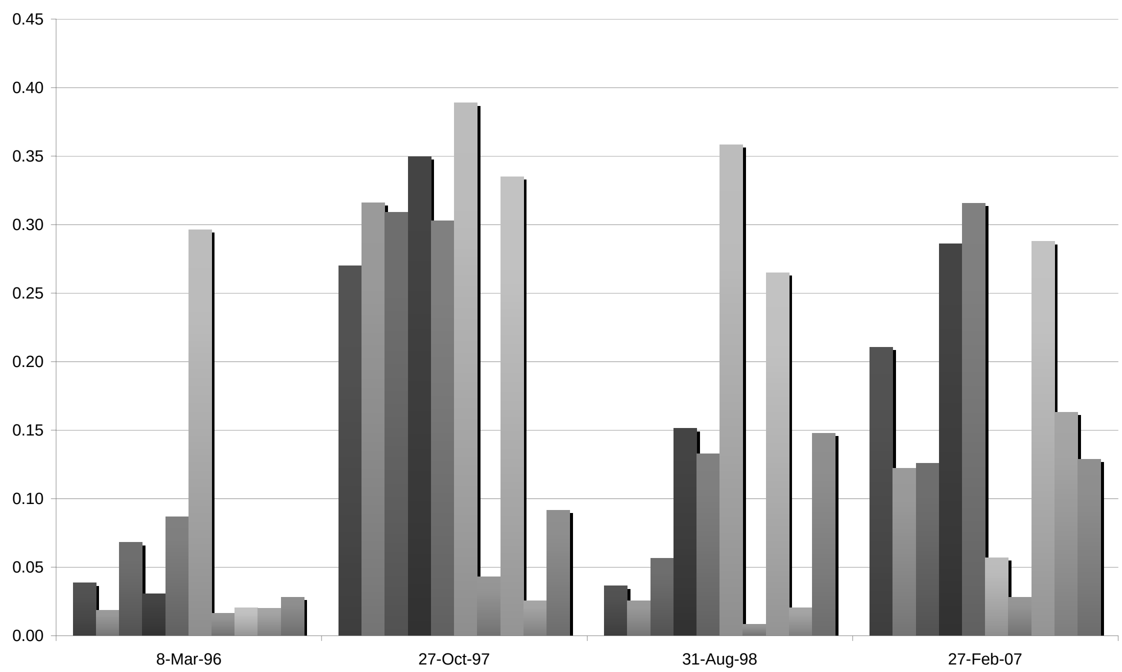


Figure 4: Industry Jump Probabilities on Index Jump Days for the SVCJ Model

The figure shows the mean of the jump probabilities of the stocks in each of the industries. The industries are (from left to right): Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Telecommunications and Utilities.