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A jumping index of jumping stocks? An MCMC analysis of continuous-time models for individual stocks

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A B S T R A C T

This paper examines continuous-time models for the S&P 100 index and its constituents. We find that the jump process of the typical stock looks significantly different than that of the index. Most importantly, the average size of a jump in the returns of the typical stock is positive, while it is negative for the index. Furthermore, the estimates of the parameters for the stochastic processes exhibit pronounced heterogeneity in the cross-section of stocks. For example, we find that the jump size in returns decreases for larger companies. Finally, we find that a jump in the index is not necessarily accompanied by a large number of contemporaneous jumps in its constituent's stocks. Indeed, we find index jump days on which only one index constituent also jumps. As a consequence, we show that index jumps can be classified as induced by either synchronous price movements of individual stocks or macroeconomic events.

1. Introduction

This paper analyzes continuous-time jump-diffusion models for single stock returns. In particular, we are interested in the question of how the dynamics for index constituents differ from those of the index itself, and how a jump in the index interacts with jumps in the constituents. By answering these questions, we contribute to the understanding of return dynamics in stock markets.

The analysis of the statistical properties of stock returns is one of the main topics of interest in empirical finance research. There is a large body of literature that focuses on continuous-time models designed to capture essential features of stock price movements, including time-varying variance and jumps, i.e., sudden large movements in prices. Testing these continuous-time models has been at the center of many empirical studies. Starting with models with stochastic volatility (see, e.g. Jacquier et al., 1994, 2004) the literature has evolved to models with jump components in returns (see, e.g. Bakshi et al., 1997 and Pan, 2002) and jumps in returns and in volatility (see, among others, Eraker et al., 2003, Eraker, 2004, and Broadie et al., 2007). More recently, it has been shown that to further improve the ability of a model to consistently reproduce stylized facts in the data, it seems helpful to include non-affine terms in the variance process. The non-affine variance components in the process facilitate a faster moving variance and pick up part of what otherwise would be captured by a jump component in returns. Examples of papers from this strand of the literature are (Christoffersen et al., 2010), Chourdakis and Dotsis (2011), Mijatovic and Schneider (2014), and Ignatieva et al. (2015).

In our analysis, we employ several different model specifications. Starting from the simple stochastic volatility models (denoted by SV), we then add jumps in returns (SVJ), or, alternatively, add jumps in the return as well as in the variance process. The jumps

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in variance are either correlated (SVCJ) or independent of jumps in returns (SVIJ). In addition to affine model structures for the variance process, we also consider a non-affine setup (SVCJ-POLY) as well.

Empirical investigations of stochastic models for asset price dynamics have focused on the major equity market indices like the S&P 500 or the NASDAQ 100. From the literature, one can identify certain characteristics of these models that can be regarded 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. Fourth, non-affine specifications tend to have the best performance. Since all these findings were made exclusively for indices, it is an important question if they also remain valid for individual stocks. Answering this question represents the major motivation for our paper.

In the first step of our analysis, we compare the parameters of the aforementioned models for the S&P 100 index with those of the individual constituent stocks. The models are estimated via the Markov Chain Monte Carlo (MCMC) approach used, e.g., in Eraker et al. (2003). At the center of our study lies the analysis of index versus single stock jumps. For this reason, we take an additional step and run a simulation study on the jump models to gain insights on how to properly identify jump days for the different assets. The simulation study provides us with a posterior jump probability that allows us to, given the model, cleanly differentiate between jump and non-jump days. In the main body of our study, we analyze the relationship between index jumps and jumps in the constituent stocks.

Our first set of results shows that the jump process for the ‘typical’ (i.e., average) individual stock is significantly different from that for the S&P 100. One known stylized fact for stock indices is that jump sizes are large and negative. Contrary to this, we find that jumps in individual stock prices are in many cases on average positive. This result is found across the whole set of index constituents as well as for the typical stock across several sectors so that it is not specific to a certain subset of stocks we consider in our analysis. Although jumps are still somewhat rare, the frequency of jumps in prices is more than five times as high for the representative stock as for the index.

Furthermore, the correlation between the returns on the typical individual stocks and the associated volatility changes is estimated to be much less negative than for the index. This last result is, of course, derived under the physical probability measure, 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. Bakshi et al. (2003), Dennis and Mayhew (2002), Dennis et al. (2006) also provide evidence for structural differences in the pricing of index and individual stock options. In line with these results from empirical option pricing research, our findings support the notion that one cannot simply extend the results from the analyses of major equity indices to single stocks.

The second set of results demonstrates the considerable heterogeneity in the cross-section of index constituents. To give a first indication, we find, e.g., jump intensities that vary between 12 and 32 jumps per year and expected jump sizes that go from −0.6% to 2.8% per day. To investigate the relations between model parameters and company characteristics we regress the parameters on the four company-specific factors given in Fama and French (2015). We find large effects of, e.g., the size factor on the parameters controlling the jump process in returns. To give one example, we see that a one standard deviation increase in size decreases the jump intensity for the average firm by about 10%.

The main contribution of our empirical analysis concerns the behavior of the individual stocks on days when the index exhibits a jump. Surprisingly, we find index jump days where relatively few stocks also exhibit jumps. We find days (like February 24, 1994, or January 4, 2000) where the number of jumping stocks is even just equal to one. On the other extreme, the highest number of such contemporaneous stock jumps is 72 on October 13, 1989, and 61 observed on February 27, 2007. These findings immediately raise the question of whether the models estimated for the index and the individual stocks are compatible. The solution to this apparent ‘puzzle’ can be found via 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. The index as a diversified portfolio of stocks then naturally jumps on days when most of the component stocks exhibit large *returns* (but not necessarily jumps) in the same direction. Since the average conditional variance of the stocks in our sample is fairly stable around index jump days, at least some of these jumps must be caused by a synchronous movement of the individual stocks, generating the large and negative return in the index, which is then identified as a jump. We label these jumps as ’synchronicity jumps’. The remaining jumps, which we call ’macro-driven jumps’, are more interesting from an economic point of view. They are characterized by a large number of stocks or sectors exhibiting high jump probabilities simultaneously, and we can clearly link these jumps to important macroeconomic events.

A further surprising result of our analysis is that the models featuring jumps do not identify an unusually large number of jumps during the time of the financial crisis in 2008. This is indeed surprising since 13 of the 20 largest daily absolute returns in our sample occur during exactly that period. We show that the small number of jumps identified by the models can be explained by the fact that during the financial crisis conditional volatility is consistently high, and the large absolute returns during this period lie within the bounds given by two conditional diffusive standard deviations around the mean. This implies that these large returns can basically be generated also by a pure stochastic volatility model without jumps.

An important overall conclusion we draw from our analysis concerning the ‘right’ model for the index itself and its constituents is the following: Even if a pure stochastic volatility model could sufficiently represent the dynamics of the index constituents (single stocks), there would still be strong evidence for jumps in the index, so that here a jump model would appear to be the most appropriate choice.

A study that is related to our paper in terms of analyzing the properties of individual stock returns is Maheu and McCurdy (2004), who estimate the parameters of a discrete-time GARCH model with jumps via maximum likelihood for a rather small set of selected stocks. They attribute jumps to corporate news events and show that this hypothesis is supported by the data. In contrast to their approach, we consider a richer set of models by considering an SV, an SVJ, and an SVCJ model, and investigate these models for the large cross-section of stocks constituting the S&P 100 index. Jiang and Yao (2013) employ a methodology developed in Barndorff-Nielsen and Shephard (2004) and analyze a long time series of stock returns to decompose price changes into a continuous and a jump part. Their focus is on cross-sectional return predictability characteristics like size and book-to-market, and their results show that a large part of this predictability is due to differences in the jump part of returns. Şerban et al. (2008) propose a model where stock returns are driven by a market factor, a 'common idiosyncratic' component, and a factor which is truly idiosyncratic to the respective stock. Their findings indicate that the common factor in idiosyncratic volatility is relevant for option pricing. A more recent strand of literature examines co-jumps between stock returns. Examples can be found in Caporin et al. (2017) and Gilder et al. (2014). While these papers investigate the relationship between single stocks, our paper focuses on the relationship between the index and its constituents. Finally, Buraschi et al. (2014) come up with findings, which are similar to ours to a certain degree (although their result relates to the risk-neutral and not the physical distribution), based on an equilibrium model with differences in beliefs.

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

2. Model and estimation approach

2.1. Model

Our model specification follows (Ignatieva et al., 2015). Their approach provides a flexible model structure, which allows for affine and non-affine variance specifications as well as jumps both in prices and in the conditional volatility process. The logarithm of the stock price (Y) and the conditional variance (V) are assumed to follow the continuous-time processes

$$dY_t = \mu\, dt + \sqrt{V}_t\, dW_t^y + d\left(\sum_{j=1}^{N_t^y} \xi_j^y\right) \tag{1}$$

$$dV_t = \left(\alpha_0 + \alpha_1 \frac{1}{V_t} + \alpha_2 V_t + \alpha_3 V_t^2\right)\, dt + V_t^b\, dW_t^v + d\left(\sum_{j=1}^{N_t^v} \xi_j^v\right) \tag{2}$$

where dW_t^y and dW_t^v denote Brownian increments with correlation $E(dW_t^y dW_t^v) = \rho\, dt$. The fact that there is an (empirically mostly negative) correlation between returns and variance innovations is often called the 'leverage effect'. The term μ represents the mean diffusive return, and the terms $\sum_{j=1}^{N_t} \xi_j^y$ and $\sum_{j=1}^{N_t} \xi_j^v$ denote the jump component modeled as a compound Poisson process. The symbols ξ^y and ξ^v denote jump sizes in returns and variance, respectively. These jump sizes are allowed to be correlated. In more detail, the jump size in variance follows an exponential distribution with parameter μ_v^{-1}, i.e., $\xi_t^v \sim Exp(\mu_v^{-1})$ with expected value and standard deviation equal to μ_v. Conditional on ξ_t^v, the jump size in the log price at time t follows a normal distribution with mean $\mu_y+\rho_j\xi_t^v$ and variance σ_y^2, i.e., $\xi_t^y|\xi_t^v \sim N\left(\mu_y + \rho_j\xi_t^v, \sigma_y^2\right)$. The parameter ρ_j captures the sensitivity of the jumps in returns to the jumps in variance. The terms N_t^y and N_t^v denote Poisson processes with jump intensity λ_y and λ_v, respectively.

We use multiple restricted versions of the setup in Eq. (2) which were also used in the prior literature to model equity return dynamics. We use four affine models, analyzed, e.g. in Eraker et al. (2003), which all use the restriction $\alpha_1 = \alpha_3 = 0$ and $b = 0.5$. The additional restriction $\lambda_y = \lambda_v = 0$ results in the stochastic volatility (SV) model of Heston (1993). The stochastic volatility model with jumps in returns (SVJ) considered by Bates (1996) is obtained by setting $\lambda_v = 0$. The two versions of models with jumps in returns are given by the stochastic volatility model with correlated jumps (SVCJ) ($\lambda_y = \lambda_v$), and the stochastic volatility model with independent jumps (SVIJ) ($\rho_j = 0$). Finally, to investigate the performance of non-affine models we employ the best performing setup in Ignatieva et al. (2015) by setting $\lambda_y = \lambda_v$ and $b = 1.5$. We denote this model as "POLY-SVCJ".

We estimate each model independently for the index and its constituents. In doing so, we follow the procedure undertaken in practical applications when fitting asset returns to a model. This procedure allows us to investigate differences in the return processes between the index and its constituents without imposing structural relations. Such structural relations are, e.g., assumed in Bégin et al. (2020), Elkamhi and Ornthanalai (2010), or (Gourier, 2016). These papers assume that the constituents are linked to the index via the drift term, i.e., the risk premium. This allows the decomposition of both the risk premium into a diffusive and a jump component and total risk into a systematic and an idiosyncratic part.

We do not consider this type of specification in our analysis, since an investigation of the different components of the risk premium is beyond the scope of our paper. Our modeling choice can be seen as an unrestricted version of the above models, and as such, we are unable to identify the components of the risk premium in the stock returns, but we can uncover the relation between index and stock jumps we are interested in. In addition to this, the identification of the different components of the risk premium would make it necessary to combine options and stock return data, which would make the estimation problem substantially more complex. Furthermore, we would like to point out that the notion of a jump that we adhere to in our paper is one of jumps as large and infrequent events, in contrast to a more microstructure-oriented interpretation of jumps, with jumps typically being much more frequent and smaller in magnitude. These types of phenomena which would then more appropriately modeled via Lévy processes.

To estimate the models we consider in this paper, we use an Euler discretization scheme and set the time interval to $\Delta = 1$ (day). In our empirical analysis we will assume that one year has 252 (trading) days. Denoting the log return of the asset $Y_t - Y_{t-1}$ by R_t, we can write the discretized version of the system in (1) and (2) as

$$\begin{aligned} R_t &= \mu + \sqrt{V_{t-1}}\varepsilon_t^y + \xi_t^y J_t^y \\ V_t &= V_{t-1} + \alpha_0 + \alpha_1 \frac{1}{V_{t-1}} + \alpha_2 V_{t-1} + \alpha_3 V_{t-1}^2 + \sigma_v V_{t-1}^b \varepsilon_t^v + \xi_t^v J_t^v, \end{aligned} \tag{3}$$

where shocks to returns and volatility, $\varepsilon_t^y = W_t^y - W_{t-1}^y$ and $\varepsilon_t^v = W_t^v - W_{t-1}^v$, follow a bivariate normal distribution with zero expectation, unit variance, and correlation ρ. In the Euler discretization scheme, we follow Eraker et al. (2003) and assume at most one jump per day. J_t^y and J_t^v thus represents an indicator equal to one in the case of a jump in returns or variance and zero otherwise. In case of a model that assumes contemporaneous jumps in returns and volatility this indicator is of course the same for R and V. The jump sizes retain the distributional assumptions described above.

For technical details concerning the above discretization schemes the reader is referred to the papers by Jones (2003b), Eraker et al. (2003), Jones (2003a), Ait-Sahalia (1996), and Conley et al. (1997).

2.2. Estimation approach

The underlying model setup includes latent variables such as volatilities, jump times, and jump sizes. Each of these latent states is treated as a parameter to be estimated in a Bayesian context. This leads to a high dimensional posterior distribution, which is not equal to a known statistical distribution. We therefore rely on Markov Chain Monte Carlo (MCMC) techniques to compute the posterior moments.

In a nutshell, MCMC allows us to draw from a high dimensional distribution by breaking it down into draws from a series of lower dimensional conditional distributions.[2] We are thus able to construct a Markov Chain that converges to the desired posterior distribution. After convergence, we draw N times from that posterior to perform Monte Carlo integration.[3] In the following, we provide a brief overview of the algorithm by for the SVCJ model, since it exhibits the most complex structure. For more details on the sampling algorithm we refer to Ignatieva et al. (2015).

According to Bayes' Theorem, the posterior distribution of the parameters and the latent states is proportional to the likelihood times the prior distribution

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

where $\boldsymbol{\Theta} = (\mu, \alpha(V_t), \gamma(V_t), \rho, \mu_y, \sigma_y, \rho_j, \mu_v, \lambda)^\top$ denotes the vector of model parameters, with $\alpha(V_t)$ and $\gamma(V_t)$ representing the parameters of the drift and the diffusion component of the variance dynamics, respectively.

The time series of state variables is collected into $\{\boldsymbol{V}, \boldsymbol{\xi}^y, \boldsymbol{\xi}^v, \boldsymbol{J}\}$, and $\boldsymbol{R}$ denotes the time series of observed returns. Note that our model specifications allow us to give the prior a hierarchical structure. Therefore,

$$p(\boldsymbol{V}, \boldsymbol{\xi}^y, \boldsymbol{\xi}^v, \boldsymbol{J}, \boldsymbol{\Theta}) = p(\boldsymbol{V} | \boldsymbol{\xi}^v, \boldsymbol{J}, \boldsymbol{\Theta}) p(\boldsymbol{\xi}^y | \boldsymbol{\xi}^v, \boldsymbol{\Theta}) p(\boldsymbol{\xi}^v | \boldsymbol{\Theta}) p(\boldsymbol{J} | \boldsymbol{\Theta}) p(\boldsymbol{\Theta}).$$

Given our model framework, the only component of this prior distribution not determined by the model is $p(\boldsymbol{\Theta})$. We use the same set of independent conjugate priors as described in Ignatieva et al. (2015). Given the Markov property of the model, we can rewrite the remaining components of the posterior distribution as follows:

$$\begin{aligned} p(\boldsymbol{R} | \boldsymbol{V}, \boldsymbol{\xi}^y, \boldsymbol{\xi}^v, \boldsymbol{J}, \boldsymbol{\Theta}) &= \prod_{t=1}^{T} p(R_t | V_t, V_{t-1}, \xi_t^y, \xi_t^v, \boldsymbol{\Theta}) \\ p(\boldsymbol{V} | \boldsymbol{\xi}^v, \boldsymbol{J}, \boldsymbol{\Theta}) &\propto \prod_{t=1}^{T} p(V_t | V_{t-1}, \xi_t^v J_t, \boldsymbol{\Theta}) \\ p(\boldsymbol{\xi}^y | \boldsymbol{\xi}^v, \boldsymbol{\Theta}) &= \prod_{t=1}^{T} p(\xi_t^y | \xi_t^v, \boldsymbol{\Theta}) \\ p(\boldsymbol{\xi}^v | \boldsymbol{\Theta}) &= \prod_{t=1}^{T} p(\xi_t^v | \boldsymbol{\Theta}) \\ p(\boldsymbol{J} | \boldsymbol{\Theta}) &= \prod_{t=1}^{T} p(J_t | \boldsymbol{\Theta}) \end{aligned}$$

[2] For a detailed discussion of this algorithm in a financial econometrics context, see Johannes and Polson (2006).

[3] In our analysis we use a burn-in period of 600,000 and then draw 1.4 million times from the posterior distribution. This large number of draws is necessary to ensure convergence in the estimation of the models with a non-affine specification of the variance process. For the standard affine models convergence is obtained already after a much smaller number of draws.

The MCMC sampler then samples iteratively through the following complete conditional distributions:

$$\begin{aligned}
\text{Parameters}: &\quad p(\boldsymbol{\Theta}_i|\boldsymbol{\Theta}_{-i}, \boldsymbol{J}, \xi^y, \xi^v, \boldsymbol{V}, \boldsymbol{R}),\ i = 1, \dots, K\\
\text{Jump times}: &\quad p(J_t|\boldsymbol{\Theta}, \boldsymbol{J}_{-t}, \xi^y, \xi^v, \boldsymbol{V}, \boldsymbol{R}),\ t = 1, \dots, T\\
\text{Jump sizes}: &\quad p(\xi_t^y|\boldsymbol{\Theta}, \boldsymbol{J}, \xi_{-t}^y, \xi^v, \boldsymbol{V}, \boldsymbol{R}),\ t = 1, \dots, T\\
&\quad p(\xi_t^v|\boldsymbol{\Theta}, \boldsymbol{J}, \xi_{-t}^v, \xi^y, \boldsymbol{V}, \boldsymbol{R}),\ t = 1, \dots, T\\
\text{Volatility}: &\quad p(V_t|\boldsymbol{\Theta}, V_{t+1}, V_{t-1}, \boldsymbol{J}, \xi^v, \xi^y, R_{t+1}, R_t),\ t = 1, \dots, T.
\end{aligned}$$

Here, we denote the ith element of a vector by a subscript i, e.g., $\boldsymbol{\Theta}_i$. The vector consisting of all elements except the ith one is denoted by a subscript $-i$, i.e., $\boldsymbol{\Theta}_{-i}$ is a vector containing all elements of $\boldsymbol{\Theta}$ except for element i.

By relying on conjugate priors for the model parameters, we are able to use a Gibbs step for updating all parameters, jump times, and jump sizes. The only parameters not having a recognizably complete conditional distribution are the variances, denoted by V_t above. The complete conditional distribution for V_t is given by

$$\begin{aligned}
&p(V_t|\boldsymbol{\Theta}, V_{t+1}, V_{t-1}, \boldsymbol{J}, \xi^v, \xi^y, R_{t+1}, R_t)\\
&\quad = p(R_{t+1}, V_{t+1}|\boldsymbol{\Theta}, V_t, \boldsymbol{J}, \xi^y, \xi^v) p(V_t|\boldsymbol{\Theta}, R_t, V_{t-1}, \boldsymbol{J}, \xi^y, \xi^v),
\end{aligned}$$

where the two factors of the product on the right-hand side denote a bivariate and a univariate normal distribution, respectively. The Metropolis–Hastings step proposes a new variance $V_t^{(g)}$ in iteration g by drawing from $p(V_t|\boldsymbol{\Theta}, R_t, V_{t-1}, \boldsymbol{J}, \xi^y, \xi^v)$ and accepting that draw with probability

$$\min\left\{\frac{p(R_{t+1}, V_{t+1}|\boldsymbol{\Theta}, V_t^{(g)}, \boldsymbol{J}, \xi^y, \xi^v)}{p(R_{t+1}, V_{t+1}|\boldsymbol{\Theta}, V_t^{(g-1)}, \boldsymbol{J}, \xi^y, \xi^v)}, 1\right\}. \tag{4}$$

Since the proposal distribution is conditioned on R_t we use information in the data for the draw of the candidate. This is an important difference to the algorithm proposed in Eraker et al. (2003), who use a random walk Metropolis step. Expression (4) shows that the acceptance probability takes information from R_{t+1} and V_{t+1} into account.

3. Empirical analysis

3.1. Data

Our stock return data for the period from 1980 to 2014 are obtained from the Center for Research in Security Prices (CRSP) database. We use the index constituents file from Compustat to identify the companies included in the S&P 100 index on any given day in the sample. Although the launch date for the S&P 100 index is June 15, 1983, Compustat only provides information on index constituents beginning in September 1989. Therefore, we begin our analysis of index jump days from that date.

We find a total of 205 companies included in the S&P 100 index at least one point in time. We match these company names with the return information provided by CRSP via the cusip identifier. Using this identifier we are able to unambiguously match 201 out of the 205 companies, and it is these 201 companies that we ultimately use in our analysis. On a daily basis, we can match between 92 to 99 stocks with the 94 to 100 stocks listed in the index by Compustat. This indicates that we are able to almost perfectly replicate the index constituents with our sample. Table A.1 in the appendix shows the list of companies included in our analysis, together with descriptive statistics on their returns as well as information on the estimation period and the period they were included in the index.

3.2. Model choice

The first question of interest is which model best describes the return dynamics of the index and its constituents. There are three issues of importance in this context. First, are jump components as important for single stocks as for the index? Second, if the answer is yes, how do jump distributions for index constituents look like in comparison to the index? Third, which is the preferred variance specification? To answer these questions we need to rank the models with respect to their performance.

Since we use a Bayesian estimation method, the natural metric to use would be Bayes' factor. However, for high-dimensional problems like ours, this is computationally prohibitive.[4] We, therefore, use the Deviance Information Criterion (DIC) proposed in Spiegelhalter et al. (2002). The main idea is, as in all information criteria, to reward model fit and penalize complexity. It is particularly suited for our purpose, since it takes the hierarchical structure into account, i.e., the fact that not all model parameters can be chosen freely. This method for model comparison has been used in the finance literature by, e.g., Berg et al. (2004) and Ignatieva et al. (2015).

The estimation results can be found in Tables 1 and 2. The numbers in the panel labeled "DIC Ranking" show the frequency with which the given model ranks first, second, and so on up to fifth across the index and its constituents. For example, the SVIJ model is ranked first, second, and third 114, 78, and 10 times, respectively.

A clear pattern emerges from the results in the table. First, the SV model is performing worst by far. Its highest ranking is fourth (out of five models), and even this only happens on five occasions. This results in an average model ranking of 4.975. We, therefore,

[4] Eraker et al. (2003) show how to compute the statistic for nested affine models. However, we also include a non-affine model in our analysis and are therefore not able to use the procedure proposed in their paper.

Table 1
Parameter estimates (Affine models).

	A: SV Model					**B: SVJ Model**				
	Index		**Individual Stocks**			**Index**		**Individual Stocks**		
	Mean	Std. Err.	Avg.	2.5%	97.5%	Mean	Std. Err.	Avg.	2.5%	97.5%
μ	0.0305	0.0087	0.0281	−0.0365	0.0930	0.0325	0.0087	0.0175	−0.0803	0.0829
α_0	0.0264	0.0027	0.1376	0.0367	0.3759	0.0219	0.0025	0.0657	0.0097	0.1699
α_1	−0.0216	0.0026	−0.0299	−0.0941	−0.006	−0.0181	0.0023	−0.0180	−0.0500	−0.0016
σ_v	0.1791	0.0082	0.3722	0.2043	0.6507	0.1625	0.0081	0.2322	0.1322	0.3577
ρ	−0.5899	0.0322	−0.2673	−0.5127	−0.0574	−0.6418	0.0297	−0.3476	−0.6194	−0.0650
μ_Y	–	–	–	–	–	−2.3672	0.8727	0.7901	−1.1148	3.3742
σ_Y	–	–	–	–	–	2.7602	0.6041	5.3834	1.7476	14.3364
λ	–	–	–	–	–	0.0051	0.0021	0.0360	0.0057	0.1026
	DIC Ranking					**DIC Ranking**				
	1: 0	2: 0	3: 0	4: 5	5: 197	1: 3	2: 14	3: 94	4: 91	5: 0
	C: SVCJ Model					**D: SVIJ Model**				
	Index		**Individual Stocks**			**Index**		**Individual Stocks**		
	Mean	Std. Err.	Avg.	2.5%	97.5%	Mean	Std. Err.	Avg.	2.5%	97.5%
μ	0.0365	0.0087	0.0238	−0.0736	0.0837	0.0391	0.0090	0.0221	−0.0983	0.0931
α_0	0.0215	0.0025	0.0605	0.0059	0.2540	0.0212	0.0023	0.0346	0.0028	0.1320
α_1	−0.0266	0.0030	−0.0259	−0.1321	−0.0043	−0.0257	0.0030	−0.0236	−0.0934	−0.0035
σ_v	0.1450	0.0084	0.2113	0.1228	0.3432	0.1448	0.0086	0.1753	0.1039	0.2845
ρ	−0.6597	0.0333	−0.3763	−0.6310	−0.0878	−0.6852	0.0329	−0.4023	−0.6669	−0.0454
μ_Y	−2.4269	0.5475	0.6106	−1.4616	2.9216	−0.9278	0.3851	0.7480	−0.6010	2.7665
σ_Y	2.1621	0.4693	5.7855	2.1613	12.7180	1.6617	0.2690	4.7770	1.6917	11.6893
λ	0.0057	0.0015	0.0267	0.0045	0.0753	0.0140	0.0063	0.0476	0.0086	0.1293
λ_V	–	–	–	–	–	0.0038	0.0016	0.0246	0.0042	0.0711
μ_V	1.8524	0.4195	1.8190	0.5047	9.0287	2.4146	0.5457	2.8703	0.6702	11.9699
ρ_J	−0.0010	0.0164	−0.0005	−0.0134	0.0239	–	–	–	–	–
	DIC Ranking					**DIC Ranking**				
	1: 13	2: 75	3: 65	4: 49	5: 0	1: 114	2: 78	3: 10	4: 0	5: 0

NOTE: The table shows parameter estimates and the Deviance Information Criterion (DIC) developed in Spiegelhalter et al. (2002) for the SV, SVJ, SVCJ, and SVIJ model. For the index, we show the posterior mean and standard error. For the individual stocks, we present the cross-sectional average and the 2.5% and 97.5% quantile. For the DIC we show the number of times that the model was ranked 1–5 for the index and each constituent. Descriptive statistics for the stocks in our sample are shown in Table A.1 of the appendix.

obtain strong evidence that the results of the prior literature, namely that jump models outperform pure volatility models, also hold for single stocks.

The second conclusion is that non-affine model specifications do not result in a considerably better model fit. We see that the POLY-SVCJ model ranks second in terms of average model ranking. However, we see that it also ranks fifth five times, i.e., it is even beaten by the SV model in these cases. On the other hand, none of the affine jump models are beaten by the SV model.

The third and final conclusion from the results is that jumps in volatility play an important role in describing the return dynamics. Turning to the performance of the SVJ model, we see that it mainly ranks third or fourth, resulting in an average ranking of 3.351. Models including jumps in variance clearly outperform the SVJ model. In particular, the SVIJ model exhibits the best overall performance with an average model ranking of 1.485 and never being ranked below third. Given these results, we are going to focus on the SVIJ model as the best-performing specification in the following discussion.

3.3. Model parameters

The parameter estimates for all models considered can be found in Tables 1 and 2. However, in the following, we will restrict the discussion to the SVIJ model for the reasons given above.

The first observation is that basically all empirical studies show, the correlation between diffusive price changes and diffusive volatility changes is strongly negative for the index with a value of roughly −0.69. For the typical stock, however, ρ is much less negative with a cross-sectional average of the estimates of around −0.4 and 95% percent of the estimates ranging between −0.67 and −0.05. 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 parameter estimates for the individual stocks vary widely. The parameter α_0 has a mean of 0.0212 for the index, whereas the central 95% of the estimates for the single stocks range between 0.0346 to 0.132. For α_1, this interval ranges from −0.0934 to −0.0035, with the value for the index being −0.0257. These parameter values imply large differences in the long-run mean and the speed of mean reversion between the index and the single stocks. For the long-run mean of volatility

Table 2
Parameter estimates and priors (POLY-SVCJ model).

	A: Parameter Estimates					B: Priors
	Index		Individual Stocks			
	Mean	Std. Err.	Avg.	2.5%	97.5%	
μ	0.0507	0.0093	0.0136	−0.1221	0.0986	N(0,1)
α_0	0.0080	0.0024	−0.0613	−0.3741	0.0484	N(0,1)
α_1	−0.0012	0.0003	0.0685	−0.0221	0.5374	N(0,1)
α_2	−0.0130	0.0053	0.0268	−0.0314	0.1319	N(0,1)
α_3	0.0041	0.0016	−0.0022	−0.0193	0.0028	N(0,1)
σ_v	0.1241	0.0064	0.0824	0.0541	0.1460	$\omega^2 \sim$ IG(2,200)
ρ	−0.7450	0.0359	−0.3330	−0.5124	−0.1131	$\psi\|\omega^2 \sim N(1, 1/2\omega^2)$
μ_Y	−0.8747	0.2321	0.5873	−0.6883	2.2823	N(0,100)
σ_Y	1.5740	0.1577	3.3410	1.5896	8.8201	IG(α, β)
λ	0.0223	0.0051	0.0685	0.0178	0.1686	U(0,0.5)
λ_V	–	–	–	–	–	U(0,0.5)
μ_V	0.3912	0.0682	0.2862	0.0112	0.8195	G(10,0.1)
ρ_j	−0.0030	0.0539	−0.0057	−0.0977	0.0423	N(0,4)
	DIC Ranking					
	1: 72	2: 35	3: 33	4: 57	5: 5	

NOTE: Panel A of the table shows parameter estimates and the Deviance Information Criterion (DIC) developed in Spiegelhalter et al. (2002) for the POLY-SVCJ model. For the index, we show the posterior mean and standard error. For the individual stocks, we present the cross-sectional average and the 2.5% and 97.5% quantile. For the DIC we show the number of times that the model was ranked 1-5 for the index and each constituent. Panel B of the table shows the prior distributions for the parameters. $N(\mu, \sigma^2)$ denotes a normal distribution, $IG(\alpha, \beta)$ denotes an inverse gamma distribution, $G(\alpha, \beta)$ denotes a gamma distribution, and U(l,u) denotes a uniform distribution. We follow Jacquier et al. (2004) and parameterize the priors for ρ and σ_v by defining $\psi = \rho\sigma_v$ and $\omega = \sigma_v^2(1-\rho^2)$ and setting a prior for ψ and ω^2. Descriptive statistics for the stocks in our sample are shown in Table A.1 of the appendix.

we have an approximate average value of 35% annually for the single stocks versus 17.5% for the index. Finally, since even the maximum estimate for an individual α_1 is negative (not shown in the table), we have mean reverting variance processes for all assets.

The more interesting part of the model relates to the jump component. The first of the key parameters here is the mean jump size in returns. A stylized fact from empirical research is that this quantity is negative and large in absolute value for the major equity indices around the world. This is confirmed in our analysis since μ_y for the S&P 100 is estimated at −0.9278 with a standard error of 0.385, i.e., it is strongly significantly different from zero. In contrast to this, the typical stock exhibits a positive expected jump size (0.748) with a very large cross-sectional variation, as indicated by 2.5%- and 97.5%-quantiles equal to −0.601 and 2.77, respectively.

Looking deeper into the results for the single stocks, we find examples of both significantly positive and significantly negative jump sizes, which is 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 the index cannot be generalized to individual stocks and that there is no 'law' that jump sizes can only be negative in the context of the SVIJ model. As one might expect, the estimated standard deviation of the jump size σ_y is much smaller for the index (1.67) than for the average stock (4.78), but also the cross-sectional dispersion is substantial, with 95% of the estimates between rough 1.7 and 11.7.

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). Since the SVIJ model features independent jump processes for returns and variance, we have two intensities. Again, the differences between the stocks and the index are striking. For the S&P 100, the intensity for jumps in returns is estimated at 0.014 corresponding to an expected number of roughly $0.014 \cdot 252 \approx 3.5$ jumps per year. For the average stock, this intensity is estimated to be about 3.5 times higher (0.0476). Again there is pronounced cross-sectional variation across the individual stocks with a 2.5%-quantile of 2.17 jumps per year, while the stock representing the 97.5%-quantile would, on average, exhibit 32.6 jumps annually. For the jumps in variance, we observe a similar pattern, albeit with lower intensity levels. For the index, we estimate about 0.95 jumps per year, whereas the typical stock variance jumps about 6.2 times per year with the quantile variation ranging from 1.05 to 17.9 annual jumps.

Finally, we find that the jump sizes in variance are slightly larger for the typical stock than for the index with a value of 2.87 and 2.41, respectively. Also here we observe a large cross-sectional variation for the index constituents with values ranging from 0.67 to 11.97.

Another way of visualizing structural differences in the parameter estimates for index and single stocks is to use box plots as shown in Fig. 1. The plots show the estimated jump parameters. We see in that all jump parameters exhibit a huge variation across stocks. In particular, however, we observe that the estimated parameters for the index are always located outside the inter-quartile range for the constituent stocks, indicating that the index cannot simply be regarded as just the typical stock.

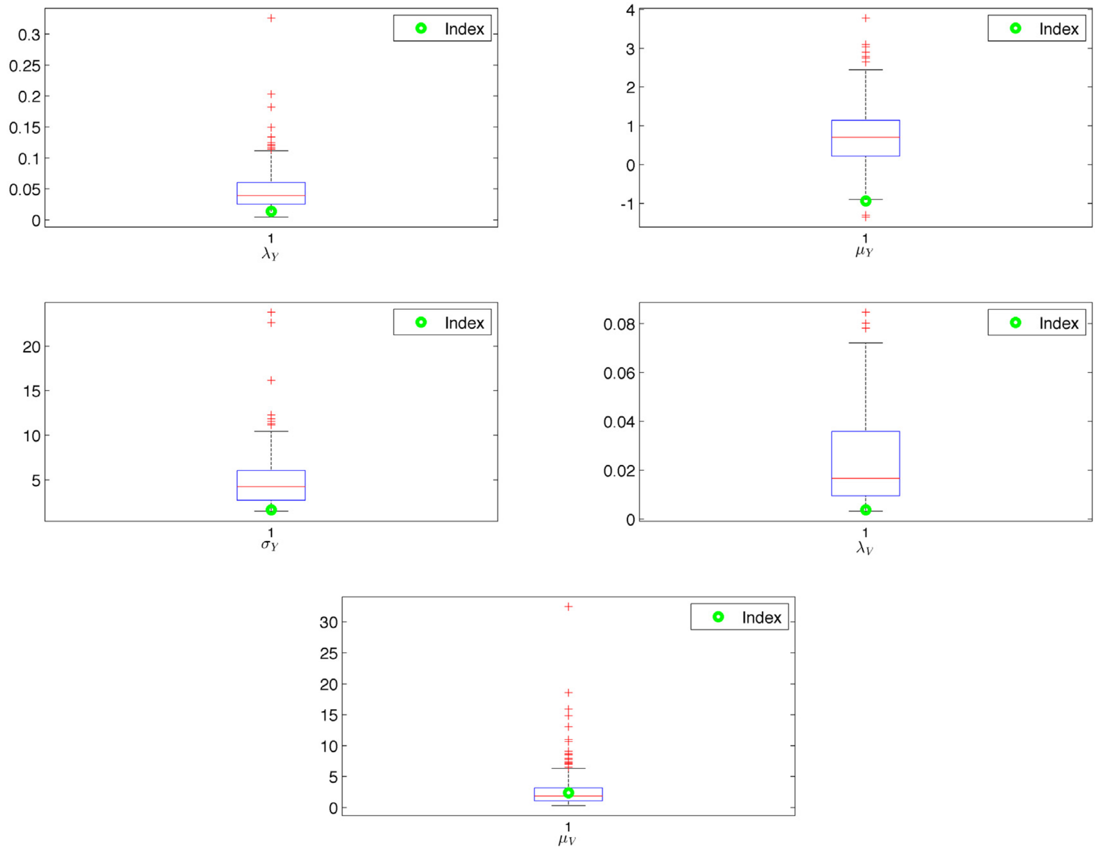

Fig. 1. Parameter Box Plots (SVIJ Model).
The figure shows the box plots for the parameters of the SVIJ model. From top to bottom, the plots show the estimates for the jump intensity λ, the expected jump size in return μ_Y, the standard deviation of the jump size in return σ_Y, and the expected jump size in variance μ_V for the individual stocks. The green dots indicate the corresponding estimates for the index.

3.4. Relation between parameters and firm characteristics

To gain further insight into the sources of the cross-sectional variation of the model parameters, we investigate their relation to firm characteristics.[5] The most natural selection of characteristics for our analysis is those which are commonly used as the basis for sorts to create risk factors.

We, therefore, focus on the four firm-specific characteristics suggested by Fama and French (2015), i.e, the market value of equity (MV), the market to book ratio (MB), profitability represented by annual revenues minus costs (PR), and investment expressed via the growth rate of total assets (INV). All data are taken from Compustat.

We take the time-series average of the characteristics for each firm and then cross-sectionally standardize each characteristic to have zero mean and unit variance. We then estimate the following regression for each parameter via OLS:

$$\theta_{k,i} = \beta_{k,0} + \beta_{k,1} MV_i + \beta_{k,2} MB_i + \beta_{k,3} PR_i + \beta_{k,4} IN_i + \varepsilon_i, \tag{5}$$

where $\theta_{k,i}$ is the estimate of parameter k for firm i and the right-hand side variables are defined above.

The estimation results are presented in Table 3. The results which are most interesting for our purpose relate to the impact of firm characteristics on the jump components of the model.

Starting with the average jump size in returns μ_y, we find that size, profitability, and investment have a significant impact. Given the strongly significantly negative coefficient of around −0.2, we see that a one standard deviation increase in firm size reduces the average jump size by around 30% relative to the cross-sectional average of around 0.75 shown in Table 1 for the SVIJ model. At the same time, more profitable firms tend to have larger average jump sizes, with a positive and significant coefficient estimate of around 0.07. This translates into roughly a 10% increase relative to the unconditional average from Table 1. Finally, the more investment-intensive a firm, the lower the average jump size, and also this coefficient is strongly significant.

[5] We thank an anonymous referee for suggesting this analysis.

Table 3
Regression of parameters on firm characteristics.

	Constant	MV	MB	PR	INV
μ	0.022	0.011	0.010	0.004	−0.003
	(0.000)	(0.000)	(0.002)	(0.247)	(0.253)
α_0	0.035	−0.000	−0.001	−0.006	0.001
	(0.000)	(0.898)	(0.910)	(0.001)	(0.426)
α_1	−0.024	−0.001	0.000	0.004	−0.001
	(0.000)	(0.738)	(0.923)	(0.002)	(0.394)
σ_V	0.175	−0.012	−0.004	0.019	−0.005
	(0.000)	(0.002)	(0.498)	(0.097)	(0.455)
ρ	−0.402	−0.010	0.001	−0.044	0.010
	(0.000)	(0.307)	(0.953)	(0.000)	(0.261)
μ_y	0.748	−0.222	0.073	0.335	−0.111
	(0.000)	(0.000)	(0.238)	(0.000)	(0.017)
σ_y	4.777	−0.671	0.117	0.816	−0.019
	(0.000)	(0.000)	(0.483)	(0.000)	(0.901)
λ	0.048	−0.003	−0.003	−0.001	0.001
	(0.000)	(0.021)	(0.139)	(0.701)	(0.747)
λ_v	0.025	−0.005	0.002	0.003	−0.001
	(0.000)	(0.000)	(0.316)	(0.021)	(0.443)
μ_v	2.870	0.050	−0.497	−0.290	0.038
	(0.000)	(0.756)	(0.001)	(0.008)	(0.740)

NOTE: The table shows parameter estimates for the regression of model parameters on firm characteristics. The firm characteristics are those which are used in Fama and French (2015) as the basis for sorts to generate risk factors. We compute the average value for the characteristic over time for each index constituent and normalize the factor by deducting the mean and dividing by the standard deviation. Estimation is performed using OLS with standard errors robustified for heteroskedasticity. The numbers in parentheses are p-values.

Analogous to the average jump size, we also find opposing impacts for size and profitability when it comes to the standard deviation σ_y of the jump size in returns. While the coefficients for the other two characteristics are not significant, size again comes up with a negative estimate, i.e., larger firms tend to have lower standard deviations in return jumps, while for profitability we find the opposite.

Concerning the intensity λ of jumps in returns, we observe that larger companies exhibit statistically significantly lower values for this parameter. The coefficient of −0.0003 implies that an increase in one standard deviation of firm size by one standard deviation decreases the intensity by about -6%, given a cross-sectional average jump intensity for the SVIJ model of around 0.048, as shown in Table 1. This result makes sense economically since we think of larger firms as being better protected against sudden economic shocks, be it, e.g., due to their more diversified business activities or their better access to funding also in bad times. In both cases, we would expect there to be on average fewer jumps for larger firms, and this is what we find in the data. Interestingly, size is the only significant variable here, we do not find a significant impact of either book to market, profitability, or investment.

For the jump intensity in variance λ_v we find that larger companies have lower intensities, while for more profitable firms, this parameter tends to be larger. The regression coefficients imply that a one standard deviation in size increase lowers λ_v by about 20% relative to its unconditional cross-sectional average ($-0.005/0.0246 \approx 0.2$), while a one standard deviation increase in profitability leads to an increase in λ_v of about 12% ($-0.003/0.0246 \approx 0.12$). Also here, book to market and investment do not exhibit a significant impact.

Concerning the parameter μ_v of the exponential distribution for the size of variance jumps, we find that here, in contrast to the other jump-related parameters, size does not play an important role. It is rather book to market and profitability, which help to explain the cross-sectional variation in this parameter. Both characteristics feature a negative sign, i.e., with a one standard deviation increase in either book to market or profitability, μ_v decreases. This in turn means that both the average size of variance jumps and their dispersion decrease.

Overall, we can see that the jump-related parameters are often systematically related to firm characteristics. Despite the lack of significance in the case of μ_v, size seems to be the most important driver of the cross-sectional variation.

3.5. When (and why) does the index jump?

3.5.1. Simulation results

We conduct a simulation study to demonstrate that our estimation method is able to correctly identify jump days in the data and to determine the appropriate threshold for the posterior jump probability used to separate jump from non-jump days.

We simulate 1,000 paths based on the SVIJ model. We generate two simulation results for each model, one based on the estimated parameters for the index and on the average parameter estimates from the single stock estimation, respectively (see Table 1). This ensures that we understand how sensitive the estimation procedure of posterior jump probabilities is with respect to different parameter values. We apply the Euler discretization scheme presented above in Eq. (3) to simulate 4,000 days per path.

Table 4
Posterior jump probabilities on jump vs. non-jump days (SVIJ model).

	Index		Single Stocks	
	Non-jump days	Jump days	Non-jump days	Jump days
Mean	0.0145	0.1630	0.0416	0.2984
Median	0.0094	0.0224	0.0278	0.0913
Q_{99}	0.1002	1.0000	0.2952	1.0000
Q_{95}	0.0365	0.9691	0.1112	0.9980
Q_{05}	0.0035	0.0051	0.0119	0.0174
Q_{01}	0.0023	0.0033	0.0079	0.0115

NOTE: The table shows descriptive statistics for the posterior jump probabilities estimated by the MCMC algorithm for the SVIJ model for non-jump and jump days. We simulate 1,000 price paths based on the estimated parameters for the S&P 100 index and based on the cross-sectional average of the parameter estimates for the single stocks. A day is labeled a jump day in the simulation when the draw from the uniform distribution over the interval $[0, 1]$ is less than or equal to $\lambda\Delta t$, where λ is the estimated intensity for the Poisson process driving jumps (see Tables 1 and 2), and Δt is 1 day.

The setup of our simulation study is chosen on the basis of two important results documented in the literature. First, Eraker et al. (2003) show that the MCMC estimation method is able to correctly recover the model parameters. Second, Jones (2003a) shows that the Euler discretization at a daily frequency is a good approximation for the continuous time setup. A very interesting and novel result (to the best of our knowledge) is that we show how well the estimation setup is able to identify jump days given the underlying model.

The results of our simulation study can be found in Table 4. We see a clear difference in the results for the posterior jump probabilities on jump and non-jump days for both the index and the typical constituent stock. The most important lesson we learn from these results is that the posterior jump probabilities for a jump day range from 0 to 100%, whereas on non-jump days we observe an upper bound for the probability of around 10% for the index and 28% for the typical single stock. Based on these results we set the threshold for the posterior jump probabilities to 10% for the index and at 30% for the typical stock.

3.5.2. Jump day analysis

The issue at the core of our analysis is to study index jumps in detail. In this section, we will discuss three main results. First, jumps are identified relative to the level of return variance. Second, we identify two distinct types of index jumps that we label 'synchronicity jumps' and 'macro jumps'. Third, we show that the two types of jumps differ with respect to the economic environment in which they occur. As stated above, all analyses refer to the SVIJ model.

The first step in this exercise is to identify the days when the index jumps. Given our simulation results, we select those days as jump days where the posterior probability for a jump is greater than 15%. Note that this threshold is rather conservative in the sense that the probability of identifying false jump days is low, given the underlying model. This will become important later on when we identify two different types of index jumps.

In our sample, we observe 53 jump days (see Table 5). Not surprisingly, on jump days, the index return is mostly negative and large in absolute terms. We observe only three jump days with a positive return.

One surprising result from Table 5 is that we do not observe an increase in the frequency of jump events during the financial crisis, since there is only one index return jump day in 2008, and these values are absolutely comparable to other years. At the same time, 13 of the 20 largest absolute index returns shown in Table 6 occurred during the year 2008. Intuitively, we would of course expect these large daily returns to contain a jump component, but Table 6 provides intuition on why this is not the case. As can be seen, most days with large absolute returns and a low posterior jump probability also feature a high conditional volatility. For example, the returns of about -6% on October 7 and November 19 of 2008 are within the bounds of two conditional standard deviations around the mean. This means that also a pure stochastic volatility model would be able to generate these movements with a sufficiently high probability.

This explanation, however, is not applicable to all observations in Table 6. For example, we observe large positive returns on October 13 and 28 of 2008. On both days, the index gained more than 10%, a return that is outside the bounds induced by the diffusive volatility component, but no jump was identified. This is an example of a situation where we are not able to rule out false negatives when identifying jump days, as discussed above.

The main takeaway from Table 6 is that, given our model framework, jump days are not identified only by large index returns, but that the index return has to be rather seen relative to the value of the conditional variance process. When the variance is small, even a relatively modest index return is potentially identified as a jump.

The next question arising naturally is how individual stocks behave on index jump days. A prior would certainly be that many individual stocks also exhibit jumps on those days. We identify jump events for single stocks by setting the posterior jump probability to 30%, as indicated by our simulation study. Unexpectedly, our results show that we find days when the index jumps, but only a very small number of stocks also jump. For example, in Table 5 we see that on January 4, 2000, only one stock jumps where the index exhibits a posterior jump probability of over 28%, which constitutes a very high value as indicated by our simulation exercise. On the other hand, we observe 72 stocks jumping on October 13, 1989, where the posterior jump probability for the index is 1.

To understand why there are such different jump patterns, Table 7 presents the five index jump days with the largest and smallest number of stocks jumping, respectively. For those days with only a few stocks jumping, we see that is even possible that only one stock out of roughly 100 features a discontinuous price movement.

Table 5
Index jump days (SVIJ model).

Date	Return	Jump Prob.	# Jum.	Prim.	Man.	Transp.	Trade	Fin.	Serv.	PA
13/10/1989	−6.53	99.99	72.00	79.60	73.04	65.45	53.86	60.44	66.70	92.03
16/10/1989	3.20	29.92	26.00	68.39	21.47	29.20	37.19	21.30	4.54	54.20
18/12/1989	−1.85	15.54	6.00	25.47	5.05	5.27	4.31	20.99	15.97	23.24
12/01/1990	−2.53	18.12	4.00	7.22	7.19	8.51	8.92	4.82	18.43	12.47
22/01/1990	−3.00	41.22	9.00	18.54	10.57	11.81	6.27	10.66	5.24	32.10
10/05/1991	−2.22	17.29	3.00	8.09	5.28	7.72	8.34	5.95	4.21	30.17
15/11/1991	−4.32	99.70	27.00	13.57	26.60	24.16	30.38	23.93	31.25	39.90
20/04/1992	−1.49	17.09	1.00	5.98	3.81	4.22	16.22	3.50	5.08	2.49
16/02/1993	−2.29	61.01	8.00	9.75	10.98	8.98	16.75	9.72	8.88	20.26
08/03/1993	2.20	18.07	6.00	7.23	8.32	9.95	10.45	17.53	6.00	16.68
21/05/1993	−1.62	23.03	1.00	7.19	3.38	3.48	5.99	5.07	2.92	3.50
18/06/1993	−1.39	17.67	4.00	5.35	7.39	3.32	6.31	5.08	3.36	2.06
04/02/1994	−2.36	99.05	10.00	11.18	11.42	12.60	4.66	9.37	23.61	48.37
24/02/1994	−1.38	39.14	1.00	12.09	3.95	4.72	5.41	4.96	1.39	16.14
22/11/1994	−1.89	26.01	9.00	12.33	11.99	4.06	5.46	12.33	20.46	4.34
18/05/1995	−1.65	27.06	4.00	11.23	7.69	5.31	5.34	2.87	7.16	5.20
08/03/1996	−3.17	86.21	11.00	10.47	11.64	10.71	6.12	31.90	4.17	42.56
08/04/1996	−1.82	32.04	4.00	18.70	4.16	19.43	5.14	11.74	2.04	2.90
02/05/1996	−1.62	17.79	2.00	15.44	3.32	5.75	5.71	20.70	4.11	2.45
05/07/1996	−2.32	21.25	7.00	11.39	4.49	25.10	4.32	19.73	2.92	5.07
15/07/1996	−2.83	21.34	10.00	21.37	9.78	10.43	18.67	5.08	10.87	13.30
27/10/1997	−7.09	43.76	56.00	55.68	48.01	48.32	50.22	36.87	46.88	12.45
04/08/1998	−3.76	15.05	4.00	11.11	6.75	12.04	5.68	6.68	21.68	22.33
31/08/1998	−7.52	16.08	15.00	12.00	15.29	15.10	20.70	8.72	27.42	7.47
20/07/1999	−2.50	22.97	1.00	11.52	4.35	3.51	5.00	5.49	12.43	4.50
04/01/2000	−3.85	28.57	1.00	7.14	4.66	6.27	5.10	6.98	3.76	7.02
14/04/2000	−6.01	18.66	6.00	17.92	8.48	8.41	7.67	11.99	14.37	4.67
17/09/2001	−5.42	27.84	27.00	8.66	27.73	22.77	25.08	20.90	16.01	12.52
24/03/2003	−3.73	18.70	5.00	7.75	10.66	8.70	12.35	11.46	12.02	15.16
20/01/2006	−1.91	56.07	9.00	28.87	7.04	6.13	4.02	20.69	15.91	98.71
27/11/2006	−1.25	26.09	6.00	5.68	7.44	2.27	7.02	19.04	18.34	2.82
25/01/2007	−1.29	60.78	4.00	8.33	4.83	4.81	23.37	9.37	6.74	4.05
27/02/2007	−3.63	99.60	61.00	27.96	41.31	49.32	46.93	46.91	25.02	18.23
13/03/2007	−2.04	26.13	8.00	4.84	8.74	4.84	19.58	31.06	3.43	3.87
10/05/2007	−1.41	22.14	5.00	8.27	6.88	3.29	1.89	14.36	1.00	6.95
09/08/2007	−3.22	15.61	10.00	7.59	13.63	8.75	5.91	14.77	5.32	16.21
19/10/2007	−2.54	17.89	5.00	43.97	9.74	5.74	4.32	6.28	2.26	6.65
06/06/2008	−3.16	25.74	6.00	5.24	12.09	11.41	6.48	7.06	4.63	11.57
30/10/2009	−2.81	15.12	5.00	14.40	6.13	5.91	3.29	15.40	5.82	8.12
04/02/2010	−3.04	43.87	15.00	22.32	15.40	14.27	14.47	21.07	7.25	31.18
11/08/2010	−2.69	31.90	7.00	10.47	14.49	11.46	4.86	14.22	2.17	11.67
19/10/2010	−1.55	25.91	1.00	7.18	5.29	3.63	3.39	5.14	27.83	4.84
04/11/2010	1.94	18.79	13.00	35.47	12.23	3.96	11.64	22.79	3.62	27.78
28/01/2011	−1.74	16.62	7.00	5.86	7.01	18.02	31.95	6.28	28.19	4.68
22/02/2011	−1.86	20.67	8.00	7.03	5.27	10.25	2.90	26.50	15.70	11.08
16/03/2011	−2.23	17.22	4.00	7.98	5.68	8.69	10.62	7.55	23.14	9.15
01/06/2011	−2.21	22.66	11.00	9.23	14.16	11.74	4.18	19.50	4.39	11.60
07/11/2012	−2.63	43.30	18.00	24.77	10.75	19.19	2.81	46.22	8.25	8.76
25/02/2013	−1.75	17.64	9.00	16.42	9.22	6.28	15.14	21.74	2.13	21.55
20/06/2013	−2.46	34.38	16.00	15.53	15.69	20.47	19.88	7.68	11.53	21.07
03/02/2014	−2.23	15.22	11.00	9.79	11.12	19.06	7.16	10.51	17.32	14.96
10/04/2014	−2.04	41.61	12.00	14.45	11.29	10.03	8.36	26.00	9.14	5.74
31/07/2014	−2.07	62.25	18.00	7.71	18.44	24.91	8.19	26.48	6.05	8.28

NOTE: The table reports the return and the jump probability for the S&P 100 index for the days when the SVIJ model identifies an index jump. "# Jum." denotes the number of stocks exhibiting a jump probability of more than 30 on those days. The following columns present the average posterior jump probabilities for the stocks belonging to the respective sector based on 2-digit SIC codes (see siccode.com). *Prim.* denotes the primary sector, containing firms from the SIC industries "Agriculture, Forestry, Fishing" as well as "Mining". *Man.* denotes that manufacturing sector, containing the firms from "Construction" and "Manufacturing". *Transp.* is short for the SIC sector "Transport and Public Utilities". *Trade* aggregates the SIC industries "Wholesale Trade" and "Retail Trade". *Fin.* is short for "Finance, Insurance and Real Estate", *Serv.* is the service industry (with the same name in the SIC classification scheme), and *PA* is short for the SIC industry "Public Administration".

What do these findings imply in terms of how we should interpret the occurrence of an index jump on these days? Obviously, given the small number of stocks jumping simultaneously, there is no additivity in the 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 hypothesis, therefore, is that, to a very large extent, index jumps are generated by diffusive price movements in the individual stocks, which happen to occur in the same direction to a very large degree.

Table 6
Posterior jump probabilities and return bounds implied by diffusive volatility (SVIJ model).

Date	Return	Jump Prob.	UB	LB
13/10/1989	−6.5273	0.9999	1.7388	−1.6606
27/10/1997	−7.0927	0.4376	3.8312	−3.7530
31/08/1998	−7.5165	0.1608	4.6915	−4.6133
14/04/2000	−6.0088	0.1866	3.9368	−3.8586
29/09/2008	−9.1862	0.0281	8.0448	−7.9666
07/10/2008	−5.9769	0.0182	8.1067	−8.0285
09/10/2008	−7.9154	0.0219	8.3175	−8.2393
13/10/2008	10.6551	0.0137	8.6374	−8.5592
15/10/2008	−8.7550	0.0238	8.2877	−8.2095
22/10/2008	−5.9697	0.0187	7.9616	−7.8834
28/10/2008	10.2961	0.0137	7.9055	−7.8273
13/11/2008	6.3306	0.0118	7.2032	−7.1250
19/11/2008	−6.0350	0.0210	6.9160	−6.8378
20/11/2008	−6.6214	0.0239	7.0423	−6.9641
21/11/2008	6.0205	0.0118	7.1527	−7.0745
24/11/2008	5.8915	0.0118	6.8991	−6.8209
01/12/2008	−8.9448	0.0575	6.2871	−6.2089
10/03/2009	6.0499	0.0174	5.3066	−5.2284
23/03/2009	6.7381	0.0324	4.5939	−4.5157
08/08/2011	−6.4430	0.0506	5.2347	−5.1565

NOTE: This table shows the 20 largest daily absolute returns for the S&P 100 index in our sample period. We show the return, the posterior jump probability ("Prob."), and the upper and lower bound of the interval around μ generated by the diffusive volatility, UB and LB using the results of the SVIJ model. The bounds are computed as $UB = \mu + 2\sqrt{V_{t-1}}$ and $LB = \mu - 2\sqrt{V_{t-1}}$, where V_t is the conditional return variance on day t and μ denotes the expected return.

Table 7
Index jump days with largest and smallest number of stocks jumping (SVIJ model).

Date	Return	Jump Prob.	# Jump. Stocks	Prim.	Man.	Transp.	Trade	Fin.	Serv.	PA
Panel A: Jump days with lowest number of stocks jumping										
21/05/1993	−1.62	23.03	1	7.19	3.38	3.48	5.99	5.07	2.92	3.50
24/02/1994	−1.38	39.14	1	12.09	3.95	4.72	5.41	4.96	1.39	16.14
20/07/1999	−2.50	22.97	1	11.52	4.35	3.51	5.00	5.49	12.43	4.50
04/01/2000	−3.85	28.57	1	7.14	4.66	6.27	5.10	6.98	3.76	7.02
19/10/2010	−1.55	25.91	1	7.18	5.29	3.63	3.39	5.14	27.83	4.84
Panel B: Jump days with largest number of stocks jumping										
13/10/1989	−6.53	99.99	72	79.60	73.04	65.45	53.86	60.44	66.70	92.03
27/02/2007	−3.63	99.60	61	27.96	41.31	49.32	46.93	46.91	25.02	18.23
27/10/1997	−7.09	43.76	56	55.68	48.01	48.32	50.22	36.87	46.88	12.45
15/11/1991	−4.32	99.70	27	13.57	26.60	24.16	30.38	23.93	31.25	39.90
17/09/2001	−5.42	27.84	27	8.66	27.73	22.77	25.08	20.90	16.01	12.52

NOTE: The table reports the return and the jump probability for the S&P 100 index for the five index jump days in the SVIJ model with the largest and the smallest number of single stocks jumping, respectively. "# Jump. Stocks" denotes the number of stocks exhibiting a jump probability of more than 30% on those days. The following columns present the average posterior jump probabilities for the stocks belonging to the respective sector based on 2-digit SIC codes (see siccode.com). *Prim.* denotes the primary sector, containing firms from the SIC industries "Agriculture, Forestry, Fishing" as well as "Mining". *Man.* denotes that manufacturing sector, containing the firms from "Construction" and "Manufacturing". *Transp.* is short for the SIC sector "Transport and Public Utilities". *Trade* aggregates the SIC industries "Wholesale Trade" and "Retail Trade". *Fin.* is short for "Finance, Insurance and Real Estate", *Serv.* is the service industry (with the same name in the SIC classification scheme), and *PA* is short for the SIC industry "Public Administration".

This reasoning can be verified by the results in Table 8, which show that in all of the five days in Panel A the overwhelming majority of stocks exhibit returns with the same signs on index jump days. 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 on and one day before the index jump days in Table 9 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.

Since the index basically represents a portfolio, the index return is given by the weighted average of the returns of the single stocks. On 'normal' days diversification would result in an index return small enough in absolute value not to be considered a jump. Put differently, due to diversification the volatility of the index is in general lower than the weighted average of the volatilities of the single stocks. However, in case the vast majority of individual stocks move in the same direction there will hardly be any diversification. Hence, a resulting large negative return of the index 'has to be' identified by the model as a jump.

However, synchronous movements do not give the full picture. To find out if *all* the index jumps in our sample are likely to be the result of index constituents moving in the same direction, we analyze the jump probabilities of the different industries our

Table 8
Signs of individual stock returns on index jump days (SVIJ model).

Date	$\#R > 0$	$\% \ R > 0$	$\#R < 0$	$\%R < 0$
Panel A: Lowest number of stocks jumping				
21/05/1993	6.00	0.07	84.00	0.93
24/02/1994	13.00	0.14	77.00	0.86
20/07/1999	19.00	0.20	75.00	0.80
04/01/2000	12.00	0.13	83.00	0.87
19/10/2010	9.00	0.10	82.00	0.90
Panel B: Largest number of stocks jumping				
13/10/1989	0.00	0.00	92.00	1.00
27/02/2007	0.00	0.00	93.00	1.00
27/10/1997	0.00	0.00	96.00	1.00
15/11/1991	2.00	0.02	90.00	0.98
17/09/2001	14.00	0.14	85.00	0.86

NOTE: The table shows the five days in our sample where an index jump (as identified by the SVIJ model) is accompanied by the smallest and the largest number of single stock jumps, respectively. $\#(R > 0)$ ($\#(R < 0)$) denotes the absolute number of stocks with positive (negative) returns on the given days, while $\%(R > 0)$ ($\%(R < 0)$) denotes the corresponding percentage.

Table 9
Index and single stock volatilities on index jump days (SVIJ model)

Date	Jump Day					Day Before Jump Day	
	Return	$\sqrt{V_t}$ index	Avg $\sqrt{V_t}$	Min. $\sqrt{V_t}$	Max. $\sqrt{V_t}$	$\sqrt{V_{t-1}}$ index	Avg. $\sqrt{V_{t-1}}$
13/10/1989	−6.53	0.94	1.55	0.69	3.34	0.85	1.51
27/02/2007	−3.63	0.68	1.23	0.43	2.43	0.63	1.18
27/10/1997	−7.09	2.01	2.15	0.82	4.02	1.90	2.10
15/11/1991	−4.32	0.77	1.81	0.87	3.76	0.70	1.77
17/09/2001	−5.42	1.77	2.85	0.60	10.20	1.65	2.78
16/10/1989	3.20	0.81	1.52	0.70	3.22	0.94	1.55
07/11/2012	−2.63	0.96	1.30	0.53	2.28	0.89	1.26
31/07/2014	−2.07	0.70	1.05	0.63	1.59	0.64	1.01
20/06/2013	−2.46	0.97	1.35	0.85	2.13	0.90	1.30
31/08/1998	−7.52	2.45	3.01	1.15	4.90	2.33	2.97

NOTE: For index jump days as identified by the SVIJ model the table shows the index return, the conditional index return volatility, as well as the cross-sectional average, minimum, and maximum of the conditional return volatilities of the index constituents. For the day before the index jump day, the table shows the conditional index return volatility and the cross-sectional average of the conditional return volatilities of the index constituents.

sample firms belong to.[6] For the sake of brevity we concentrate our following analysis on the results found for the SVJ model. The threshold for the jumps in the single stocks is set to 25% posterior jump probability. Table 7, showing the five respective index jump days with the smallest and largest number of jumping stocks also contains information on the average posterior jump probabilities across industries. Here we see a clear difference between the index jump days listed in both panels. For the days with the largest number of stocks jumping we observe significantly higher average jump probability across all sectors than for index jump days with the fewest stock jumping, where we find significant average jump probabilities for at most one sector.

The important conclusion we draw from this difference is that the index jumps on days with few stocks jumping are generated from diffusive movements in the stocks which go largely in the same direction. We call these jumps ‘synchronicity jumps’. In contrast to this, the index jumps on days with a large number of stocks are actually generated by jumps in stocks across all sectors. We, therefore, call these index jumps ‘macro-driven’.

At this point, it is instructive to briefly come back to our discussion concerning the identification of jump days. Since our estimation method rules out false positives with a probability close to one, we are very confident that the ’synchronicity jumps’ we identify are indeed index jumps that are properly identified by the models. This is important, since one of the central contributions of our analysis is exactly the characterization of two economically distinct types of jump events so that we have to make sure that the identification of either type of jump is not due to a false rejection of a hypothesis.

It is of interest to investigate which events took place on the days we classify as index jump days. Table 10 shows the results of Google searches for news stories on these particular days. For the days with a large number of stocks jumping one usually gets back stories of stock market crashes as a first or second hit. For example, the jumps on October 13, 1989, and on October 27, 1997, can be clearly linked to crucial market-wide events. The first event was termed a “mini-crash” relating to a drop in prices in the junk bond markets, whereas the second relates to an economic crisis in Asia (sometimes called the ’Asian flu’). These two days also

[6] The companies are assigned to industries according to the first two digits of the SIC codes (see siccode.com). Our sector *Primary* contains the firms from the SIC industries “Agriculture, Forestry, Fishing” as well as “Mining”, while *Manufacturing* contains the firms from “Construction” and “Manufacturing”. *Transport* is short for the SIC sector “Transport and Public Utilities”. *Trade* aggregates the SIC industries “Wholesale Trade” and “Retail Trade”. *Finance* is short for “Finance, Insurance and Real Estate”, *Services* is the industry with the same name in the SIC classification scheme, and *PA* is short for the SIC industry “Public Administration”.

Table 10
News on index jump days (SVIJ model)

Date	Google result	Event
Panel A: Lowest number of stocks jumping		
21/05/1993	Nothing	
24/02/1994	Nothing	
20/07/1999	Share prices a bit lower - NYT	
04/01/2000	Tech stock crash - CNN	
19/10/2010	Wall St drops as mortgage worries hit banks - Reuters	
Panel B: Largest number of stocks jumping		
13/10/1989	Friday the 13th mini-crash - Wikipedia	Junk bond market collapse
15/11/1991	S.E.C.'s Analysis Of Nov. 15 Plunge - NYT	Algorithmic trading
27/10/1997	October 27, 1997, mini-crash - Wikipedia	Asian economic crisis
17/09/2001	First trading day after the September 11 attacks	September 11
27/02/2007	Market gets crushed on global fears - Feb. 27, 2007	Fears of a global economic slowdown

NOTE: This table shows the results of Google news searches for the five index jump days in the SVIJ model with the largest and the smallest number of single stocks jumping, respectively. The search was performed for either just the date or the combination of the date and the word "stocks". For these searches, the table shows the respective first hit related to capital markets.

Table 11
Index jump days with largest and smallest number of stocks jumping (SVIJ model for sector returns).

Date	Return	Jump Prob.	# Jump. Stocks	Prim.	Man.	Tran.	Trade	Fin.	Serv.
Panel A: Jump days with lowest number of stocks jumping									
21/05/1993	−1.62	23.03	1	1.48	13.33	2.30	3.62	2.64	4.89
24/02/1994	−1.38	39.14	1	4.89	36.00	1.02	12.42	5.90	2.98
20/07/1999	−2.50	22.97	1	4.58	16.29	1.22	5.84	2.38	15.41
04/01/2000	−3.85	28.57	1	2.51	26.09	17.78	2.40	5.81	5.85
19/10/2010	−1.55	25.91	1	23.72	29.34	3.12	1.92	2.23	35.01
Panel B: Jump days with largest number of stocks jumping									
13/10/1989	−6.53	99.98	74	51.27	98.35	99.03	98.45	99.71	98.71
27/02/2007	−3.63	99.99	63	57.01	99.70	97.58	94.59	85.74	90.37
27/10/1997	−7.09	38.69	45	53.42	37.98	58.93	72.81	53.54	16.30
15/11/1991	−4.32	99.70	27	16.14	97.22	90.84	91.04	90.37	65.44
17/09/2001	−5.42	27.84	27	3.88	7.43	4.08	10.88	23.64	15.26

NOTE: The table reports the return and the jump probability for the S&P 100 index for the five index jump days in the SVIJ model with the largest and the smallest number of single stocks jumping, respectively. "# Jump. Stocks" denotes the number of stocks exhibiting a jump probability of more than 30% on those days. The following columns present the posterior jump probabilities for the different sectors according to 2-digit SIC codes (see siccode.com). The jump probabilities are based on value weighted sector returns. *Prim.* denotes the primary sector, containing firms from the SIC industries "Agriculture, Forestry, Fishing" as well as "Mining". *Man.* denotes that manufacturing sector, containing the firms from "Construction" and "Manufacturing". *Transp.* is short for the SIC sector "Transport and Public Utilities". *Trade* aggregates the SIC industries "Wholesale Trade" and "Retail Trade". *Fin.* is short for "Finance, Insurance and Real Estate", and *Serv.* is the service industry (with the same name in the SIC classification scheme).

represent the two largest negative index returns in our sample. Also, the news for February 27, 2007, frequently mentions a large price 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 above. In summary, the reason why we refer to these jumps as 'macro-driven jumps' is that a large number of stocks experience a jump on these days, and the reasons can be traced back to macroeconomic events.

3.5.3. Sector analysis

To investigate if the separation of jump days into synchronicity and macro-driven jumps carries over when using directly a sector index instead of average jump probabilities of single stocks within the index we relate the sector jumps to the index jumps. To do that, we construct sector returns by taking the average of the daily stock returns weighted by the market value of equity within the sector. Second, we estimate the SVIJ model for each sector and compute the posterior jump probability for each day. We show the posterior jump probabilities for the different sectors on the index jump days with the largest and smallest numbers of stocks jumping in Table 11.

The results reveal that the categorization between jumps induced by synchronous movements and macroeconomic events also holds when looking at sector portfolio returns. We see a clear difference in posterior jump probabilities between Panels A and B of the table. Taking a posterior jump probability of 10% as threshold to identify a jump day we see that in Panel A between 1–3 sectors jump whereas in Panel B 3–5 sectors jump. In addition to counting the instances where the posterior jump probability crosses the threshold, we also observe that the probabilities reaching 99% in Panel B of the table are much larger than the magnitudes in Panel A, reaching 36%.

Table 12
Jump parameters across sectors (SVIJ model).

		Prim.	Man.	Transp.	Trade	Fin.	Serv.	PA
μ_Y	Sector averages	0.614	0.707	0.605	0.992	0.666	1.179	0.821
	Prim.	0.000	0.586	0.964	0.082	0.798	0.028	0.353
	Man.		0.000	0.536	0.114	0.800	0.037	0.542
	Transp.			0.000	0.069	0.757	0.023	0.322
	Trade				0.000	0.122	0.476	0.456
	Fin.					0.000	0.041	0.474
	Serv.						0.000	0.180
	PA							0.005
σ_Y	Sector averages	3.214	4.754	4.266	4.810	5.521	5.778	1.721
	Prim.	0.000	0.000	0.036	0.006	0.016	0.000	0.000
	Man.		0.000	0.362	0.927	0.429	0.132	0.000
	Transp.			0.000	0.449	0.228	0.052	0.000
	Trade				0.000	0.510	0.244	0.000
	Fin.					0.000	0.818	0.000
	Serv.						0.000	0.000
	PA							0.000
λ	Sector averages	0.075	0.040	0.050	0.049	0.056	0.044	0.050
	Prim.	0.000	0.005	0.070	0.043	0.237	0.019	0.037
	Man.		0.000	0.160	0.147	0.194	0.533	0.002
	Transp.			0.000	0.841	0.687	0.471	0.931
	Trade				0.000	0.577	0.547	0.840
	Fin.					0.000	0.365	0.610
	Serv.						0.000	0.330
	PA							0.000
λ_V	Sector averages	0.022	0.023	0.025	0.025	0.022	0.035	0.012
	Prim.	0.000	0.819	0.665	0.680	0.950	0.075	0.183
	Man.		0.000	0.709	0.742	0.804	0.026	0.025
	Transp.			0.000	0.996	0.606	0.081	0.027
	Trade				0.000	0.639	0.103	0.040
	Fin.					0.000	0.030	0.071
	Serv.						0.000	0.000
	PA							0.005
μ_V	Sector averages	3.280	2.213	2.849	3.763	4.675	1.878	3.453
	Prim.	0.000	0.080	0.594	0.795	0.146	0.07	0.795
	Man.		0.000	0.276	0.384	0.001	0.541	0.000
	Transp.			0.000	0.623	0.054	0.204	0.349
	Trade				0.034	0.636	0.308	0.863
	Fin.					0.000	0.002	0.139
	Serv.						0.000	0.010
	PA							0.000

NOTE: The table reports the results from a regression of model parameters on a set of sector dummies. The respective sectors are based on 2-digit SIC codes (see siccode.com). *Prim.* denotes the primary sector, containing firms from the SIC industries "Agriculture, Forestry, Fishing" as well as "Mining". *Man.* denotes that manufacturing sector, containing the firms from "Construction" and "Manufacturing". *Transp.* is short for the SIC sector "Transport and Public Utilities". *Trade* aggregates the SIC industries "Wholesale Trade" and "Retail Trade". *Fin.* is short for "Finance, Insurance and Real Estate", *Serv.* is the service industry (with the same name in the SIC classification scheme), and *PA* is short for the SIC industry "Public Administration". Within each block we report the parameter averages in the first row, followed by p-values of t-tests in the remaining rows of the block. In case the sectors in the column and row are equal, the value shown is the p-value for the test that the corresponding parameter is equal to zero on average. In case the sectors in the column and row are not equal, the value shown is the p-value for the test that the corresponding parameter is on average the same in the two sectors.

3.6. Jump distributions across sectors

To gain some more insights into the jump components of the average stock across sectors, we look in more detail at the model parameters controlling the jump component.[7] To do this we modify the setup used in Eq. (5) as follows

$$\theta_{ki} = \sum_{s=1}^{7} \beta_{k,s} D_{i,s} + \varepsilon_i \tag{6}$$

with $D_{i,s}$ denoting a dummy that is one if company i belongs to sector s. Given the setup, the regression coefficients represent the average parameter values of the constituents within the sector.

The result of this exercise can be found in Table 12. The table contains five blocks, one for each parameter relating to the jump part of the SVIJ model. The first row within each block shows the parameter estimates, i.e., the sector averages, while the remaining

[7] We thank an anonymous referee and the associate editor for this suggestion.

rows show p-values for hypothesis tests. When the sectors in the row and in the column are the same, the number is the p-values for the test that the average of a certain parameter in the given sector is equal to zero. When row and column are labeled differently, the number shown is the p-value for the test that the given parameter is on average the same for the two sectors.

The first interesting observation is that the average μ_y is positive for all sectors. This shows that the result of a positive unconditional average for μ_y shown in Table 1 is not caused by specific effects which we observe only for a small subset of sectors. This gives further evidence that the jump distribution of returns of single stocks is considerably different from that of the index. Finally, the result that the average number of jumps per year is larger for single stocks is also not sector-specific but obtained across most of the industries.

4. Conclusion

This paper analyzes stochastic models for the dynamics of the S&P 100 index and its constituent stocks. The models allow for a jump component in the price as well as in the conditional variance process and are estimated Bayesian methods building on an MCMC algorithm to obtain the posterior distribution.

Our results indicate a pronounced heterogeneity across the different assets with respect to the parameters governing the stochastic processes. Unsurprisingly, the long-run level of volatility is much higher for individual stocks than for the index. Furthermore, we find a less pronounced leverage effect in the individual stocks than for the index. Considering the distribution of the price jumps we show that the stylized fact of negative average jump sizes does not in general carry over from the index to individual stocks. A novel result of our study is that we show via simulation that our estimation is able to cleanly identify a day as a jump day when a jump has actually taken place.

A key result of our analysis is that there are actually two types of index jump days, characterized by either very few (in the case of the Poly-SVCJ model even zero) or very many stocks jumping together with the index on the given day. The first type of index jump occurs when many stocks exhibit a diffusive (i.e, not jump-induced) movement in the same direction, which is why we call these jumps 'synchronicity jumps'. In contrast to this, the second type of index jump is generated by jumps in a large number of stocks across all sectors of the economy. These jumps are consequently labeled 'macro-driven jumps'.

Surprisingly, we find that the models under consideration do not identify an unusually large number of jumps during the 2008 financial crisis. Intuitively, this can be explained by the prolonged period of high levels of conditional volatility during that time, which makes it possible that large absolute index returns can even be generated by a pure stochastic volatility model without a jump component.

CRediT authorship contribution statement

Alessandro Pollastri: Computation of results, Preparation of tables and graphs. **Paulo Rodrigues:** Programming of code used in the estimation, Preparation of data, Writing. **Christian Schlag:** Developing idea for the project, Supervision of project, Writing – review & editing. **Norman J. Seeger:** Programming of code used in the estimation, Preparation of data, Writing.

Acknowledgments

We appreciate helpful comments and discussions from the Editor, Rossen I. Valkanov, an associate editor, and three anonymous referees.

Appendix A

See Table A.1.

Table A.1
Descriptive statistics of the returns data.

Name	Mean	Vol	Skew	Kurt	Sample Period	Included in Index
S&P 100 INDEX	0.0343	1.1728	−1.1766	27.6996	1982-08-02/2014-12-31	–
ABBOTT LABORATORIES	0.0719	1.6257	−0.1041	7.2728	1980-01-02/2014-12-31	2005-08-30/2014-12-31
ABBVIE INC	0.1501	1.5597	−0.2305	3.7572	2013-01-03/2014-12-31	2013-01-02/2014-12-31
ACCENTURE LTD BERMUDA	0.0790	2.0663	0.1605	9.9740	2001-07-20/2014-12-31	2012-03-19/2014-12-31
AES CORP	0.0826	3.3378	0.0392	32.3182	1991-06-27/2014-12-31	2000-12-18/2008-12-21
ALLIED CHEMICAL CORP	0.0615	1.9843	0.2593	25.2694	1980-01-02/2014-12-31	1999-12-02/2014-12-31
ALLSTATE CORP	0.0594	2.0515	−0.0218	19.5724	1993-06-04/2014-12-31	2003-04-16/2014-12-31
ALUMINUM COMPANY AMER	0.0533	2.2701	0.1412	12.2234	1980-01-02/2014-12-31	1989-09-11/2012-03-18
AMAZON COM INC	0.1977	4.1282	0.9847	11.5115	1997-05-16/2014-12-31	2009-01-02/2014-12-31
AMERICA ONLINE INC DEL	0.1538	3.1131	0.3418	9.0893	1992-03-20/2014-12-31	2000-06-19/2014-12-31
AMERICAN ELECTRIC POWER CO	0.0511	1.3461	0.1163	26.6300	1980-01-02/2014-12-31	1989-09-11/2014-03-23
AMERICAN EXPRESS CO	0.0781	2.2427	0.1368	12.2596	1980-01-02/2014-12-31	1989-09-11/2014-12-31
AMERICAN GENERAL INS CO	0.0792	1.7044	0.6678	20.5178	1980-01-02/2001-08-28	1991-09-20/2001-08-29

(continued on next page)

Table A.1 (*continued*).

Name	Mean	Vol	Skew	Kurt	Sample Period	Included in Index
AMERICAN HOME PRODUCTS CORP	0.0654	1.7628	−0.4139	16.8989	1980-01-02/2009-10-15	2008-11-19/2009-10-15
AMERICAN INFORMATION TECHS	0.0930	1.4258	−0.0882	12.3473	1984-02-17/1999-10-08	1989-09-11/1999-10-11
AMERICAN INTERNATIONAL GRP	0.0569	2.9631	1.7055	109.1684	1980-01-02/2014-12-31	1989-09-11/2008-12-21
AMERICAN TELEPHONE & TELEG	0.0458	1.8846	0.2003	15.7507	1980-01-02/2005-11-18	1989-09-11/2005-11-20
AMGEN INC	0.1108	2.5679	0.2829	8.9464	1983-06-20/2014-12-31	1999-11-08/2014-12-31
AMP INC	0.0702	1.9227	3.2582	90.9085	1980-01-02/1999-04-01	1989-09-11/1999-04-01
ANADARKO PETROLEUM CORP	0.0689	2.3675	0.0064	9.5869	1986-10-03/2014-12-31	2012-03-19/2014-12-31
ANHEUSER BUSCH COS INC	0.0797	1.5206	0.1727	12.0377	1980-01-02/2008-11-17	2001-11-30/2008-11-18
APACHE CORP	0.0595	2.4167	0.3459	6.9580	1980-01-02/2014-12-31	2011-03-21/2015-03-22
APPLE COMPUTER INC	0.1102	3.0053	−0.3784	20.0699	1980-12-15/2014-12-31	2007-06-01/2014-12-31
ATLANTIC RICHFIELD CO	0.0591	1.6313	0.5264	6.4429	1980-01-02/2000-04-17	1989-09-11/2000-04-17
AVON PRODUCTS INC	0.0450	2.0731	−0.4025	23.5689	1980-01-02/2014-12-31	1989-09-11/2012-03-18
BAKER HUGHES INC	0.0580	2.6247	−0.0569	15.5477	1987-04-27/2014-12-31	1989-09-11/2013-06-06
BANC ONE CORP	0.0788	1.8068	0.0946	12.2909	1980-01-02/2004-06-30	1998-09-16/2004-06-30
BANK NEW YORK INC	0.0760	2.1860	0.5306	17.8470	1980-01-02/2014-12-31	2007-07-02/2014-12-31
BANKAMERICA CORP	0.0688	2.1509	0.3705	16.7452	1980-01-02/1998-09-30	1989-09-11/1998-09-30
BAXTER TRAVENOL LABS INC	0.0558	1.8009	−0.8241	17.3099	1980-01-02/2014-12-31	1989-09-11/2015-06-30
BELL ATLANTIC CORP	0.0538	1.5620	0.2056	11.1753	1984-02-17/2014-12-31	1989-09-11/2014-12-31
BERKSHIRE HATHAWAY INC DEL	0.0510	1.5004	1.0250	15.0967	1996-05-10/2014-12-31	2010-02-16/2014-12-31
BETHLEHEM STEEL CORP	0.0037	3.7097	0.4113	85.6385	1980-01-02/2002-06-11	1989-09-11/2000-12-10
BLACK & DECKER MFG CO	0.0495	2.2718	0.2994	13.4094	1980-01-02/2010-03-12	1989-09-11/2007-03-22
BOEING CO	0.0649	1.9240	0.0362	8.2104	1980-01-02/2014-12-31	1989-09-11/2014-12-31
BOISE CASCADE CORP	0.0464	2.7668	0.9903	22.8418	1980-01-02/2013-11-05	1989-09-11/2006-11-30
BRISTOL MYERS CO	0.0666	1.7138	−0.3464	16.4181	1980-01-02/2014-12-31	1989-09-11/2014-12-31
BRUNSWICK CORP	0.0883	2.8465	0.6917	29.5052	1980-01-02/2014-12-31	1989-09-11/2000-12-17
BURLINGTON NORTHERN INC	0.0843	1.9329	0.2613	14.6961	1980-01-02/2010-02-12	1989-09-11/2010-02-15
BURROUGHS CORP	0.0433	3.5554	1.3325	39.7964	1980-01-02/2014-12-31	1989-09-11/2006-10-01
CAMPBELL SOUP CO	0.0606	1.5917	0.4189	9.9510	1980-01-02/2014-12-31	1998-10-01/2011-03-20
CAPITAL CITIES COMMUNICATIONS	0.0910	1.4446	0.8221	16.6306	1980-01-02/1996-02-09	1989-09-11/1996-02-11
CAPITAL ONE FINANCIAL CORP	0.1075	3.1526	−0.1844	16.8348	1994-11-17/2014-12-31	2006-12-01/2014-12-31
CATERPILLAR TRACTOR INC	0.0588	1.9891	−0.0718	9.0190	1980-01-02/2014-12-31	2005-08-19/2014-12-31
CELGENE CORP	0.1484	3.7360	0.2958	8.3539	1987-07-29/2014-12-31	2015-03-23/2014-12-31
CHAMPION INTERNATIONAL CORP	0.0492	1.9932	0.3683	12.6571	1980-01-02/2000-06-20	1989-09-11/2000-06-18
CHEMICAL NEW YORK CORP	0.0730	2.3385	0.4510	16.6208	1980-01-02/2014-12-31	2000-12-18/2014-12-31
CHRYSLER CORP	0.1192	2.6628	0.6932	8.3257	1980-01-02/1998-11-12	1994-03-18/1998-11-12
CIGNA CORP	0.0667	2.0513	−0.7635	30.3265	1982-04-21/2014-12-31	1989-09-11/2008-12-21
CISCO SYSTEMS INC	0.1335	2.7626	0.2716	9.1528	1990-02-20/2014-12-31	1996-04-01/2014-12-31
CLEAR CHANNEL COMM.CATIONS	0.1088	2.3059	0.2779	10.1534	1984-04-23/2008-07-30	2000-12-18/2008-07-30
COASTAL CORP	0.0885	2.2246	0.2402	7.7094	1980-01-02/2001-01-29	1991-04-02/2001-01-29
COCA COLA CO	0.0690	1.5382	−0.0175	18.0170	1980-01-02/2014-12-31	1989-09-11/2014-12-31
COLGATE PALMOLIVE CO	0.0737	1.6001	0.2726	13.7735	1980-01-02/2014-12-31	1989-09-11/2014-12-31
COLUMBIA HOSPITAL CORP	0.0695	2.2850	0.2226	9.1957	1990-05-18/2006-11-17	1996-01-02/2006-11-19
COMCAST CORP NEW	0.0638	1.9496	0.4501	16.4274	2002-11-20/2014-12-31	2005-03-28/2014-12-31
COMMERCIAL CREDIT CO	0.0653	2.9103	1.2585	47.7310	1986-10-30/2014-12-31	1998-10-07/2014-12-31
COMMONWEALTH EDISON CO	0.0618	1.3330	−0.2357	9.3855	1980-01-02/2000-10-20	1989-09-11/2000-10-22
COMPUTER SCIENCES CORP	0.0614	2.2768	−0.5338	20.6186	1980-01-02/2014-12-31	1989-09-11/2007-07-01
CONSOLIDATED FOODS CORP	0.0751	1.7167	0.3055	25.7033	1980-01-02/2014-08-28	1999-12-01/2011-03-20
CONTROL DATA CORP DE	0.0499	2.4132	0.2903	9.2141	1980-01-02/2007-11-08	1989-09-11/2000-12-17
COSTCO WHOLESALE CORP	0.0883	2.2817	0.0115	9.3191	1985-11-29/2014-12-31	2009-01-02/2014-12-31
COVIDIEN LTD	0.0714	1.7210	1.0893	18.0512	2007-07-03/2014-12-31	2007-07-02/2009-06-04
DELL COMPUTER CORP	0.1254	3.0933	0.0037	7.4415	1988-06-23/2013-10-29	2004-07-01/2013-01-01
DELTA AIR LINES INC	0.0012	2.7491	−0.4874	23.8109	1980-01-02/2005-10-12	1989-09-11/2005-08-18
DEVON ENERGY CORP NEW	0.0594	2.3414	0.1143	8.6114	1999-08-19/2014-12-31	2008-12-22/2014-12-31
DIGITAL EQUIPMENT CORP	0.0394	2.3889	−0.2140	12.7653	1980-01-02/1998-06-11	1989-09-11/1998-06-11
DISNEY WALT PRODUCTIONS	0.0757	1.9467	−0.2903	16.8432	1980-01-02/2014-12-31	1989-09-11/2014-12-31
DOW CHEMICAL CO	0.0574	1.9982	−0.0364	10.3790	1980-01-02/2014-12-31	1989-09-11/2014-12-31
DU PONT E I DE NEMOURS & CO	0.0575	1.7318	−0.0720	8.1014	1980-01-02/2014-12-31	1989-09-11/2014-12-31
EASTMAN KODAK CO	0.0109	2.8249	1.8525	101.2664	1980-01-02/2012-01-18	1989-09-11/2007-04-01
EBAY INC	0.1474	3.6787	1.6611	20.3824	1998-09-25/2014-12-31	2012-03-19/2015-07-19
EL PASO NATURAL GAS CO	0.0712	2.8792	−0.2316	27.7503	1992-03-16/2012-05-24	2001-01-30/2008-12-21
EMC CORP MA	0.1250	3.3334	−0.1229	11.5252	1986-04-07/2014-12-31	2000-04-18/2014-12-31
EMERSON ELECTRIC CO	0.0598	1.6415	0.0655	10.0294	1980-01-02/2014-12-31	2011-03-21/2014-12-31
EXXON CORP	0.0649	1.4931	−0.0184	19.5141	1980-01-02/2014-12-31	1989-09-11/2005-08-28
FACEBOOK INC	0.1526	3.0153	1.7286	20.0418	2012-05-21/2014-12-31	2013-12-23/2014-12-31
FEDERAL EXPRESS CORP	0.0691	2.1041	0.1931	6.7529	1980-01-02/2014-12-31	1989-09-11/2014-12-31
FIRST ALABAMA BANCSHARES INC	0.0654	2.4806	1.5101	59.2637	1980-01-02/2014-12-31	2006-11-06/2011-03-20

(*continued on next page*)

Table A.1 (*continued*).

Name	Mean	Vol	Skew	Kurt	Sample Period	Included in Index
FIRST BANK SYSTEM INC	0.0679	1.9883	0.1791	21.0219	1980-01-02/2014-12-31	2001-02-27/2014-12-31
FIRST NATIONAL ST BANC.	0.0882	1.6984	−0.0039	21.9818	1980-01-02/1995-12-29	1994-07-13/1996-01-01
FIRST UNION CORP	0.0705	2.7970	4.2971	321.7767	1980-01-02/2008-12-31	2006-10-02/2009-01-01
FLEET CALL INC	0.1363	4.3190	0.6717	9.8212	1992-01-29/2005-08-12	2000-12-18/2005-08-14
FLUOR CORP NEW	0.0772	2.6595	0.2407	9.3999	2000-12-26/2014-12-31	1989-09-11/2000-12-17
FORD MOTOR CO DEL	0.0705	2.3896	0.5249	16.7504	1980-01-02/2014-12-31	1989-09-11/2014-12-31
FREEPORT MCMORAN COP. & GLD.	0.0674	3.0267	0.0612	8.0146	1995-08-01/2014-12-31	2009-11-06/2015-03-22
GALEN HEALTH CARE INC	0.4542	3.2914	4.5166	38.4934	1993-03-09/1993-08-31	1989-09-11/1993-03-07
GENERAL DYNAMICS CORP	0.0702	1.7574	0.3222	10.0093	1980-01-02/2014-12-31	1989-09-11/2014-12-31
GENERAL ELECTRIC CO	0.0632	1.7319	0.1696	12.1074	1980-01-02/2014-12-31	1989-09-11/2014-12-31
GENERAL MOTORS CO	0.0245	1.9556	0.0730	6.3680	2010-11-19/2014-12-31	2013-06-07/2014-12-31
GILEAD SCIENCES INC	0.1436	3.3830	0.3577	7.9008	1992-01-23/2014-12-31	2008-12-22/2014-12-31
GILLETTE CO	0.0946	1.8885	−0.1493	18.2620	1980-01-02/2005-09-30	2000-12-12/2005-10-02
GLOBAL CROSSING LTD	−0.2070	8.0609	−0.1735	18.9322	1998-08-17/2002-01-30	2000-12-18/2001-10-09
GOLDMAN SACHS GROUP INC	0.0612	2.5330	0.8161	15.5364	1999-05-05/2014-12-31	2002-07-22/2014-12-31
GOOGLE INC	−0.0332	1.3342	−0.3257	3.9544	2014-04-04/2014-12-31	2014-04-03/2014-12-31
GOOGLE INC	0.1111	2.0476	0.8505	13.2077	2004-08-20/2014-12-31	2006-11-20/2014-12-31
GREAT WESTERN FINANCIAL CORP	0.0898	2.4521	0.3476	19.7749	1980-01-02/1997-07-01	1989-09-11/1997-07-01
GULF & WESTERN INDS INC	0.0879	1.7611	0.3831	10.0506	1980-01-02/1994-07-07	1989-09-11/1993-11-23
HALLIBURTON COMPANY	0.0584	2.5840	−0.2697	17.0982	1980-01-02/2014-12-31	1989-09-11/2014-12-31
HARRIS CORP	0.0573	2.0798	0.1318	10.5475	1980-01-02/2014-12-31	1989-09-11/1999-11-07
HEINZ H J CO	0.0671	1.4860	0.4932	10.8937	1980-01-02/2013-06-07	1989-09-11/2013-06-06
HEWLETT PACKARD CO	0.0698	2.3768	0.0606	9.5706	1980-01-02/2014-12-31	1989-09-11/2014-12-31
HOLIDAY INNS INC	0.1462	2.3836	−0.5722	36.6306	1980-01-02/1990-02-07	1989-09-11/1990-02-07
HOME DEPOT INC	0.1251	2.2725	−0.2434	14.2860	1981-09-23/2014-12-31	1999-10-12/2014-12-31
HOMESTAKE MINING CO	0.0443	2.8279	0.4877	7.3386	1980-01-02/2001-12-14	1989-09-11/2000-12-17
HONEYWELL INC	0.0749	1.7748	−0.0464	8.8373	1980-01-02/1999-12-01	1989-09-11/1999-12-01
IDEC PHARMACEUTICALS CORP	0.1558	3.8988	0.3487	10.9795	1991-09-18/2014-12-31	2014-03-24/2014-12-31
INTEL CORP	0.0897	2.5912	−0.0100	8.4256	1980-01-02/2014-12-31	1993-03-08/2014-12-31
INTERNATIONAL BUSINESS MACHS	0.0503	1.7118	0.0011	13.5375	1980-01-02/2014-12-31	1989-09-11/2014-12-31
INTERNATIONAL FLAVORS & FRAG	0.0564	1.6633	0.1486	9.7585	1980-01-02/2014-12-31	1989-09-11/2000-12-17
INTL MINERALS & CHEM CO	0.0553	1.9555	1.1227	43.8950	1980-01-02/2000-10-17	1989-09-11/2000-10-17
INTERNATIONAL PAPER CO	0.0545	2.0807	0.1447	14.3673	1980-01-02/2014-12-31	1989-09-11/2008-12-21
INTERNATIONAL TEL & TELEG	0.0692	1.7419	−0.4519	22.6547	1980-01-02/2014-12-31	1989-09-11/1995-12-19
ITT HARTFORD GROUP INC	0.0832	3.6644	4.8677	161.6137	1995-12-21/2014-12-31	1995-12-20/2008-12-21
JOHNSON & JOHNSON	0.0670	1.4805	−0.1422	10.4876	1980-01-02/2014-12-31	1989-09-11/2014-12-31
K MART CORP	0.0028	2.9084	−1.4132	52.1555	1980-01-02/2002-12-18	1989-09-11/2000-12-17
KINDER MORGAN INC	0.0572	1.4405	0.2657	8.7428	2011-02-14/2014-12-31	2015-03-23/2014-12-31
KRAFT FOODS INC	0.0369	1.3281	−0.3082	10.7533	2001-06-14/2014-12-31	2007-04-02/2014-12-31
LEHMAN BROTHERS HOLDINGS INC	0.0226	3.8205	−4.8513	140.0087	1994-06-01/2008-09-17	2000-12-18/2008-09-16
LILLY ELI & CO	0.0608	1.7193	−0.6146	21.6938	1980-01-02/2014-12-31	2012-03-19/2014-12-31
LIMITED STORES INC	0.1147	2.4454	0.2591	7.4929	1980-01-02/2014-12-31	1989-09-11/2007-10-24
LITTON INDUSTRIES INC	0.0635	1.9833	2.0809	111.1357	1980-01-02/2001-05-30	1989-09-11/1994-03-17
LOCKHEED CORP	0.0729	1.9107	0.2539	13.7155	1980-01-02/2014-12-31	2008-12-22/2014-12-31
LOWES COMPANIES INC	0.0956	2.2709	0.1404	7.4377	1980-01-02/2014-12-31	2008-12-22/2014-12-31
LUCENT TECHNOLOGIES INC	0.0439	3.8410	−0.0236	11.1382	1996-04-08/2006-11-30	1999-04-02/2006-11-30
MCI COMMUNICATIONS CORP	0.1309	2.7754	0.0772	11.6370	1980-01-02/1998-09-14	1989-09-11/1998-09-15
MASTERCARD INC	0.1664	2.4505	0.7597	11.3591	2006-05-26/2014-12-31	2008-07-18/2014-12-31
MAY DEPARTMENT STORES CO	0.0740	1.8467	0.1657	9.5297	1980-01-02/2005-08-29	1993-11-24/2005-08-28
MCDONALDS CORP	0.0696	1.5808	−0.0059	8.3107	1980-01-02/2014-12-31	1989-09-11/2014-12-31
MEDIMMUNE INC	0.1693	4.1281	0.2680	12.6918	1991-05-09/2007-06-18	2000-12-18/2007-05-31
MELVILLE CORP	0.0727	1.8495	−0.2962	14.1645	1980-01-02/2014-12-31	2007-03-23/2014-12-31
MERCK & CO INC	0.0645	1.6725	−0.4963	15.7386	1980-01-02/2014-12-31	1989-09-11/2014-12-31
MERRILL LYNCH & CO INC	0.0782	2.7541	0.5784	21.2506	1980-01-02/2008-12-31	1989-09-11/2009-01-01
METLIFE INC	0.0804	2.8039	0.6068	23.2407	2000-04-06/2014-12-31	2009-06-05/2014-12-31
MICROSOFT CORP	0.1143	2.2217	−0.1290	13.5677	1986-03-14/2014-12-31	1997-08-18/2014-12-31
MIDDLE SOUTH UTILITIES INC	0.0556	1.5671	−0.1894	18.4182	1980-01-02/2014-12-31	1989-10-06/2012-03-18
MINNESOTA MINING & MFG CO	0.0607	1.4817	−0.4948	17.9756	1980-01-02/2014-12-31	1989-09-11/2014-12-31
MOBIL CORP	0.0751	1.6884	0.0008	16.0957	1980-01-02/1999-11-30	1989-09-11/1999-11-30
MONSANTO CO	0.0805	1.9509	−0.3507	16.5776	1980-01-02/2003-04-15	1989-09-11/2003-04-15
MONSANTO CO NEW	0.0985	2.2486	0.1318	10.3522	2000-10-19/2014-12-31	2009-03-17/2014-12-31
MORGAN STANLEY GROUP INC	0.0822	2.9231	3.8522	122.0236	1986-03-24/2014-12-31	2000-04-03/2014-12-31
NATIONAL DETROIT CORP	0.0862	1.5419	0.1807	6.4340	1980-01-02/1998-10-01	1989-09-11/1998-10-01
NATIONAL OILWELL INC	0.1131	3.2491	0.1810	9.0072	1996-10-30/2014-12-31	2008-04-22/2015-03-22
NATIONAL SEMICONDUCTOR CORP	0.0822	3.4263	1.2795	29.2925	1980-01-02/2011-09-23	1989-09-11/2007-07-01
NCNB CORP	0.0715	2.5100	0.7587	31.7124	1980-01-02/2014-12-31	1997-07-02/2014-12-31
NEWS CORP	0.0637	2.2513	0.6366	14.4908	2004-11-15/2014-12-31	2009-10-16/2014-12-31

(*continued on next page*)

Table A.1 (*continued*).

Name	Mean	Vol	Skew	Kurt	Sample Period	Included in Index
NIKE INC	0.0950	2.2192	0.1775	8.8340	1980-12-03/2014-12-31	2008-12-22/2014-12-31
NORFOLK SOUTHERN CORP	0.0674	1.8796	0.0281	8.4887	1982-06-28/2014-12-31	1989-09-11/2014-12-31
NORTHERN NAT GAS CO	0.0438	3.2118	5.4086	441.1611	1980-01-02/2002-01-11	2000-12-11/2001-11-29
NORTHERN TELECOM LTD	0.0122	3.2614	−0.4326	26.5146	1980-01-02/2009-01-13	1989-09-11/2002-07-21
NORTHWEST BANCORPORATION	0.0829	2.2071	1.3609	30.9468	1980-01-02/2014-12-31	1999-01-04/2014-12-31
NYNEX CORP	0.0703	1.2448	0.0116	21.1318	1984-02-17/1997-08-14	1995-07-31/1997-08-17
NYSE GROUP INC	0.0331	3.1962	1.0572	17.2035	2006-03-09/2013-11-12	2007-10-25/2011-03-20
OCCIDENTAL PETROLEUM CORP	0.0606	1.9711	0.0733	11.5760	1980-01-02/2014-12-31	1989-09-11/2000-12-17
ORACLE SYSTEMS CORP	0.1424	3.2087	0.4584	15.3404	1986-03-13/2014-12-31	1996-02-12/2014-12-31
PEPSICO INC	0.0707	1.5945	0.1918	9.9154	1980-01-02/2014-12-31	1989-09-11/2014-12-31
PFIZER INC	0.0682	1.7527	−0.0580	7.1721	1980-01-02/2014-12-31	2000-12-18/2014-12-31
PHARMACIA & UPJOHN INC	0.0775	2.0571	−0.2234	7.1764	1995-11-06/2000-03-31	1989-09-11/2000-04-02
PHILADELPHIA ELECTRIC CO	0.0573	1.4983	0.1878	11.9797	1980-01-02/2014-12-31	2000-10-23/2014-12-31
PHILIP MORRIS INC	0.0890	1.6769	−0.2565	15.1802	1980-01-02/2014-12-31	2001-10-10/2014-12-31
PHILIP MORRIS INTERNATIONAL	0.0560	1.4665	0.1642	12.2630	2008-04-01/2014-12-31	2008-03-31/2014-12-31
PHILLIPS PETROLEUM CO	0.0636	1.9736	0.0286	9.4972	1980-01-02/2014-12-31	2006-12-01/2014-12-31
POLAROID CORP	−0.0219	2.7873	−0.8217	20.8630	1980-01-02/2001-10-09	1989-09-11/2000-12-11
PRICELINE COM INC	0.1343	4.6438	0.2881	16.6555	1999-03-31/2014-12-31	2015-07-01/2014-12-31
PROCTER & GAMBLE CO	0.0639	1.4724	−1.3897	48.0556	1980-01-02/2014-12-31	1998-06-12/2014-12-31
PROMUS COMPANIES INC	0.0902	2.4311	0.2926	6.9420	1990-02-27/2008-01-25	1990-02-08/2008-01-28
QUALCOMM INC	0.1419	3.3219	0.9578	11.8472	1991-12-16/2014-12-31	2008-07-31/2014-12-31
RALSTON PURINA CO	0.0848	1.6452	1.0845	20.6945	1980-01-02/2001-12-12	1989-09-11/2001-12-12
RAYTHEON CO	0.0556	1.7719	−1.5036	59.1846	1980-01-02/2014-12-31	1989-09-11/2014-12-31
ROCKWELL INTERNATIONAL CORP	0.0770	2.2723	−0.1074	9.1508	1996-12-17/2014-12-31	1989-09-11/2008-04-21
SCHERING PLOUGH CORP	0.0755	2.0287	−0.2580	13.2578	1980-01-02/2009-11-03	2008-12-22/2009-11-03
SCHLUMBERGER LTD	0.0564	2.1973	−0.0622	8.0232	1980-01-02/2014-12-31	1989-09-11/2014-12-31
SEARS ROEBUCK & CO	0.0699	2.1427	−0.0957	21.4413	1980-01-02/2005-03-24	1989-09-11/2005-03-27
SIMON PROPERTY GROUP INC	0.0826	2.0631	0.9723	25.3419	1993-12-15/2014-12-31	2012-03-19/2014-12-31
SKYLINE CORP	0.0305	2.5161	0.4262	9.5888	1980-01-02/2014-12-31	1989-09-11/1995-07-30
SOUTHERN CO	0.0644	1.2359	0.1019	14.3641	1980-01-02/2014-12-31	1989-09-11/2014-12-31
SOUTHWESTERN BELL CORP	0.0563	1.6269	0.1115	15.3978	1984-02-17/2014-12-31	2001-08-30/2014-12-31
SQUIBB CORP	0.1075	1.8673	1.2111	27.8156	1980-01-02/1989-10-03	1989-09-11/1989-10-05
STANDARD OIL CO CALIFORNIA	0.0618	1.6604	0.1778	11.3158	1980-01-02/2014-12-31	2005-10-04/2014-12-31
STANDARD OIL CO IND	0.0689	1.6268	−0.1362	12.9094	1980-01-02/1998-12-31	1989-09-11/1999-01-03
STARBUCKS CORP	0.1195	2.5889	0.2055	9.2841	1992-06-29/2014-12-31	2012-03-19/2014-12-31
TANDY CORP	0.0311	2.9874	0.0142	18.9871	1980-01-02/2014-12-31	1989-09-11/2006-11-05
TEKTRONIX INC	0.0537	2.3927	0.4827	18.2175	1980-01-02/2007-11-21	1989-09-11/2000-12-17
TELEDYNE INC	0.0638	2.7064	0.5007	10.8077	1980-01-02/2014-12-31	1989-09-11/2008-03-30
TEXAS INSTRUMENTS INC	0.0773	2.5917	0.1542	9.8111	1980-01-02/2014-12-31	1989-09-11/2014-12-31
TOYS R US INC	0.0763	2.3302	0.3190	10.2141	1980-01-02/2005-07-21	1989-09-11/2005-07-21
TYCO LABS INC	0.0874	2.3186	0.4469	40.1974	1980-01-02/2014-12-31	2000-10-18/2009-03-16
UAL INC	0.0318	3.2699	−1.3699	56.0458	1980-01-02/2003-04-02	1989-09-11/1994-07-12
UNION PACIFIC CORP	0.0670	1.7747	−0.1085	8.4833	1980-01-02/2014-12-31	2011-03-21/2014-12-31
UNITED HEALTHCARE CORP	0.1239	2.7098	−0.0004	20.7194	1984-10-18/2014-12-31	2008-01-29/2014-12-31
UNITED PARCEL SERVICE INC	0.0325	1.4728	0.3712	10.6931	1999-11-11/2014-12-31	2005-11-21/2014-12-31
UNITED TECHNOLOGIES CORP	0.0679	1.7043	−0.4090	15.5116	1980-01-02/2014-12-31	1989-09-11/2014-12-31
UNITED TELECOMMUNICATIONS	0.0568	2.5963	0.0770	20.7018	1980-01-02/2013-07-10	2005-08-15/2012-03-18
VIACOM INC	0.0621	2.5252	0.5624	13.2874	1990-06-15/2014-12-31	2000-05-05/2008-12-21
VISA INC	0.1159	2.1614	0.3222	10.3211	2008-03-20/2014-12-31	2011-03-21/2014-12-31
WAL MART STORES INC	0.0930	1.7866	0.2376	6.6456	1980-01-02/2014-12-31	1989-09-11/2005-08-28
WALGREEN CO	0.0868	1.7948	0.1262	8.2066	1980-01-02/2014-12-31	2008-12-22/2014-12-31
WESTERN BANCORPORATION	0.0814	1.9801	1.4664	28.7596	1980-01-02/1996-03-29	1989-09-11/1996-03-31
WESTINGHOUSE ELECTRIC CORP	0.0841	2.1743	0.0871	21.1441	1980-01-02/2000-05-03	1998-11-13/2000-05-04
WEYERHAEUSER CO	0.0513	2.0307	−0.1422	9.8389	1980-01-02/2014-12-31	1989-09-11/2005-08-28
WILLIAMS COS	0.0843	2.9563	1.9961	126.7370	1980-01-02/2014-12-31	1989-09-11/2013-12-22
XEROX CORP	0.0445	2.3887	0.2469	24.6742	1980-01-02/2014-12-31	1989-09-11/2005-08-28

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