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GARCH Models, Tail Indexes and Error Distributions: An Empirical Investigation

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Abstract:
We perform a large simulation study to examine the extent to which various generalized autoregressive conditional heteroskedasticity (GARCH) models capture extreme events in stock market returns. We estimate Hill's tail indexes for individual S&P 500 stock market returns ranging from 1995-2014 and compare these to the tail indexes produced by simulating GARCH models. Our results suggest that actual and simulated values differ greatly for GARCH models with normal conditional distributions, which underestimate the tail risk. By contrast, the GARCH models with Student's t conditional distributions capture the tail shape more accurately, with GARCH and GJR-GARCH being the top performers.

Keywords: GARCH, extreme events, S&P 500 study, tail index
JEL: C15, C58, G17

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1 Introduction

The financial crisis has reminded us that the quality of statistical models for risk management is often lower than expected (Daníelsson, 2008). While the models typically work well for small shocks, they often fail in crisis times characterized by extreme events. Therefore, the adoption of the appropriate risk management model to assess the expected financial losses in stock markets remains a challenge (Rossignolo et al., 2012).

Generalized autoregressive conditional heteroskedasticity (GARCH) models have become the most popular models (Engle, 2001) of the conditional variance of stock returns for many purposes, ranging from portfolio optimization and day-to-day risk management to regulatory reporting under the Basel framework. Despite many variations, the application of simple Gaussian GARCH models is most common (Hansen and Lunde, 1997). These models are established to successfully capture key stylized facts about stock returns: volatility clustering and fat-tailed return distributions.

The aim of this paper is to examine precisely how different GARCH models are able to capture/model the tail behavior of various equity stock prices using extreme value theory (EVT) as a basis for our simulation study. Correct modeling of tail behavior is key to properly managing risks (e.g., calculating capital requirements), optimizing portfolios, designing stress testing scenarios and generally improving understandings of stock market dynamics. A related discussion on the assessment of the unconditional distributions of financial time series using EVT is available in Daníelsson and de Vries (1997b, 2000), Daníelsson et al. (1998), Embrechts et al. (1998) and Longin (2000).

We analyze whether there is a particular GARCH model that outperforms other GARCH models in terms of correctly assessing the shape of the tail distributions. Underestimation of fat tails in the loss distribution leads to systematic undervaluation of the risk hidden in stock returns. In fact, the increased Value at Risk (VaR)[1] buffers imposed by Basel III are the result of undervaluation of the fatness of the tails of the loss distributions (Basel II, 2007; Basel III, 2011). The importance of tail fatness for capital reporting and Value at Risk calculations is emphasized in Huisman et al. (1998) and, more recently, for VaR estimation using EVT in Karmakar (2013).

In this study, we quantify the magnitude with which various GARCH models capture and reproduce the tail fatness of the unconditional loss distribution based on a large data set. The analysis starts by assessing the tail behavior of all series by calculating the tail indexes using the Hill method (Hill, 1975) modified by Huisman et al. (2001). The tail

[1] VaR is a quantile based measure used for regulatory reporting purposes, day-to-day risk management, trading desk limit setting etc.

index is a characteristic of the tail behavior of a given distribution. For example, in case of the Student's t distribution, its reciprocal coincides with the degrees of freedom; intuitively, the smaller the value, the lighter tails of the distribution. Specifically, depending on the value of the tail index, the distribution has one of the following characteristics: a short tail with a finite terminal value, a light tail with no terminal value, or a fat tail with no terminal value that slowly approaches infinity. Needless to say, asymmetric distributions may have different tail indexes for each tail. We focus on the minima of the returns or, in other words, on the maxima of the loss distributions.

We estimate 8 different GARCH-family models (with various distributional assumptions and lag structures) for stocks currently listed on the S&P 500 stock market index with data ranging from 1995–2014 and estimate tail indexes for the individual series of this stock market index. Thus, we perform Monte Carlo simulations of all the models to replicate the return series. For each simulated series, we calculate the tail index, and thus, we assess the model-implied tail index. Consequently, we are able to compare the tail behavior of the actual time series to the tail behavior implied by the model. We motivate our analysis by the fact that there is a non-trivial analytical expression to calculate the model-implied tail index for a simple GARCH(1,1) model (Groenendij et al., 1995), but an analytical solution does not exist for more complicated specifications of GARCH models. Hence, we perform a Monte Carlo simulation study of tail indexes. A similar analysis has been conducted by Mikosch and Stărică (2000), who find that, although GARCH-family models generally reproduce fat-tailed return series, the tails captured by some models are lighter then the data show. By contrast, our paper employs different methods to evaluate the tail shape, and we use a large data set accompanied by an extensive simulation study.

We find that, although the GARCH models that assume a conditional normal distribution imply fat-tailed unconditional distributions, the left tails of the actual stock return distributions are much fatter than these models can capture. Our results suggest that using such models to calculate regulatory capital leads to an underestimation of over 12%. Moreover, models based on the normal assumption fail to capture the correct tail shape for up to two-thirds of examined stock returns series. The models assuming a Student's t distribution better capture tail shape, failing to capture the tail shape for approximately 15% of stock return series. Therefore, according to our results, models with a Student's t distribution are preferable for modeling tail risk more accurately.

The paper is organized as follows: Section 2 introduces some GARCH-family models and the EVT methodology; Section 3 presents the empirical results; and Section 4 concludes.

2 GARCH models

To examine tail risk, we estimate simple GARCH as well as more complex EGARCH and GJR-GARCH models. We choose these models because they are all commonly used to model financial time series data. To overcome the shortcomings of the simplest GARCH specifications, such as not allowing for negative correlations between returns of stocks and volatility non-negativity constraints on estimated parameters, we also employ the more complex models. This section briefly summarizes all the models and presents the motivation for the more complex models.

2.1 GARCH

The GARCH model was introduced by Bollerslev (1986) as a direct extension of the ARCH model developed by Engle (1982). The extension allows for past conditional variance in the current conditional variance equation:

$$r_t = \mu + \epsilon_t = \mu + \sigma_t z_t \tag{1}$$

$$\epsilon_t|\Omega_{t-1} \sim N(0, \sigma_t^2) \quad or \quad t(0, \sigma_t^2, \nu) \tag{2}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{3}$$

where $\epsilon_t = r_t - \mu$ is the mean-corrected strictly stationary time series, z_t is an independent identically distributed random variable, Ω_{t-1} is an information set (σ-field) of all information through time *t–1*, parameters p, q determine the lag structure of the model, $\omega > 0$ is a constant and $\alpha_i \geqq 0$ is a coefficient measuring the short-term impact of ϵ_t on conditional variance, while $\beta_j \geqq 0$ is a coefficient measuring the long-term impact on conditional variance.

2.1.1 EGARCH

Nelson (1991) proposed the exponential GARCH to overcome some simplifications of GARCH models. We use the EGARCH(p,q) formulation in which equation (3) is replaced by:

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \beta_i \ln(\sigma_{t-i}^2) + \sum_{j=1}^{q} \alpha_j \left[\frac{|\epsilon_{t-j}|}{\sigma_{t-j}} - \mathrm{E}\left\{ \frac{|\epsilon_{t-j}|}{\sigma_{t-j}} \right\} \right] + \sum_{j=1}^{q} \gamma_j \left(\frac{\epsilon_{t-j}}{\sigma_{t-j}} \right), \tag{4}$$

where ω is a constant parameter, α_j represents a symmetric effect, β_i measures the persistence in conditional volatility, parameter γ_j allows for asymmetries, which is known as a leverage effect, and $\gamma < 0$ indicates that negative innovation create more volatility than does positive and *vice versa*. As the variance is in logarithmic form, coefficients $\omega, \alpha_j, \beta_i$ or γ_j may reach negative values and not affect σ_t^2, which will be positive.

2.1.2 GJR-GARCH

Glosten et. al (1993) proposed another extension of the GARCH model, which is a simplification of the EGARCH model that still allows the estimation of the asymmetry effect. The conditional variance in Glosten-Jagannathan-Runkle GARCH(p,q) (GJR-GARCH) is defined as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{i=1}^{q} \gamma_i \epsilon_{t-i}^2 I_{t-i}, \tag{5}$$

$$\text{where} \quad I_{t-i} = \begin{cases} 1 & \epsilon_{t-i} < 0 \\ 0 & \epsilon_{t-i} \geq 0 \end{cases} \text{ is an indicator function} \tag{6}$$

and the coefficients α_j, β_i and ϵ_t are interpreted as in the GARCH model. However, coefficient γ_j denotes the asymmetric effect. The GRJ-GARCH model constraints are:

$$\omega \geq 0, \sum_{i=1}^{q} \alpha_i \geq 0, \sum_{j=1}^{p} \beta_j \geq 0 \text{ and } \sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{q} \gamma_i \geq 0.$$

An asymmetric effect is present whenever γ_i is positive, whereas γ_i equals zero indicates a symmetric reaction of volatility change to the returns.

2.2 Model selection

This sub-section presents the models and their respective specifications, which are further used in the analysis below. We selected a few models from each of the presented categories—GARCH, E-GARCH, and GJR-GARCH—and for each, we consider both normal and Student's t distributions for the unconditional distribution of ϵ_t. Moreover, a lag structure has been selected based on the Akaike information criterion (AIC) for each model and distributional assumption.

Denoting the respective lag as p, q, we estimate the model parameters and calculate the AIC for all combinations of p and $q \in [1, 5]$, yielding 25 combinations for each return series. For each model and returns series, the optimal lag structure was chosen based on the AIC. We also include an analysis of the standard GARCH(1,1) specification with both normal and Student's t distributions. Table 1 summarizes our models.

Table 1: Model specifications

Normal GARCH(1,1)	Student's t GARCH(1,1)
Normal GARCH(p,q)	Student's t GARCH(p,q)
Normal E-GARCH(p,q)	Student's t E-GARCH(p,q)
Normal GJR-GARCH(p,q)	Student's t GJR-GARCH(p,q)

Although one may argue that we could use more models and various specifications, we settle on the above models predominantly to be able to analyze all individual return series underlying the S&P 500 and retain a manageable number of models.

2.3 Extreme value theory

To assess the degree to which a GARCH model captures tail behavior, we employ EVT methods. There are two approaches: the block maxima method (BMM) and peak over threshold (POT) approach (McNeil et al., 2005). The former discards a larger amount of data, as it works only with extreme observations over different periods, whereas the latter uses all the data in tail of the distribution. The tractability and easy application of the latter method has made it common practice (Wagner and Marsh (2005), Huisman et al. (2001) or McNeil and Frey (2000)). The POT approach essentially sets a threshold high enough in the tail of the distribution (McNeil et al. (2005) suggest using less than 5% of the dataset), but it still uses all the data above the threshold. The aim is to estimate the parameters of a generalized Pareto distribution (GPD). These parameters then describe the nature of the tail. Maximum likelihood or similar methods are typically used for estimation.

The distribution function of the generalized Pareto distribution is given by:

$$G_{\xi,\beta}(x) = \begin{cases} 1-(1+\xi x/\beta)^{-1/\xi}), & \xi \neq 0, \\ 1-\exp(1-x/\beta), & \xi = 0, \end{cases}$$

where $\beta > 0$ and $x \geqslant 0$ when $\xi \geqslant 0$, and $0 \leqslant x \leqslant -\beta/\xi$ when $\xi \leqslant 0$. The parameters ξ and β are referred to as shape and scale parameters, respectively.

The aim of our analysis is to work with ξ, which is generally referred to as the tail index, which characterizes the tail shape of the distribution. For $\xi < 0$, we have short-tailed distributions with finite right end points, such as uniform or beta distributions; for $\xi = 0$, we have light-tailed distributions, such as normal, exponential, gamma or lognormal distributions; and for $\xi > 0$, we obtain heavy-tailed distributions, such as Pareto, Student's t, Cauchy, Burr, loggamma and Fréchet distributions (McNeil and Frey, 2000).

We focus on estimating ξ with a method based on Hill (1975), which estimates as reciprocal value of $\xi = (\alpha^H)^{-1}$, as modified by Huisman et al. (2001). Note that Hill (1975) denotes his estimator as α, which is usually referred to as Hill α^H, and it is completely unrelated to the α that we use to denote the coefficients of GARCH models. We choose this method because it is widely used, straightforward and asymptotically unbiased (Hill (1975), Resnick and Stărică (1997)). A side effect is that the Hill α^H also shows the number of finite moments of a given distribution.

The original approach of Hill (1975) provides the estimate, which is sensitive to the threshold selection, and there is no straightforward way to select the appropriate threshold. For practical application, it is sufficient and generally accepted to use the Hill plot[2], observe the stable region and select the estimate from that region. Due to the high volatility of the Hill estimate for a given threshold k, there is the obvious disadvantage that different researchers may, and usually will, arrive at different estimates, which may mar the conclusions. Hence, the Hill method is not suitable for our purposes for two reasons: it is heavily subjective, and it will not be feasible to estimate for all stocks on the S&P 500 automatically. Therefore, we use a more stable modification of the Hill method, which minimizes estimate bias and allows us to unify our approach across all S&P 500 returns series. We use the modified Hill method introduced by Huisman et al. (2001), which makes the calculation robust to threshold selection. The modified Hill method essentially *averages* over the Hill estimates for all thresholds k for $k \in [1, k_{max}]$ using weighted least squares regression with weights set to $\frac{1}{\sqrt{k}}$, i.e., by assigning higher weights to estimates higher in the tail. The estimate of the tail index $\hat{\xi}$ is given as the intercept of the regression. For other methods of estimation see Barunik and Vacha (2010).

To apply the Hill method, we must assume that the underlying distribution of interest is heavy-tailed; therefore, it is in the maximum domain of attraction of the Fréchet distribution (McNeil and Frey, 2000), which can be characterized by slowly or regularly

[2] Hill plot $\{(k, \hat{\alpha}_k^H)$:2,..., k$\}$ plots various Hill α_k^H's for various thresholds k.

varying functions. Hill (1975) originally suggests applying the method for independent observations, yet Resnick and Stărică (1997) argue that this assumption may be relaxed and that, even for financial time series, Hill estimates are consistent.

3 Results

We conduct the empirical study using the S&P 500, which includes 502 stocks.[3] Due to our focus on tail behavior and extreme losses, we consider stocks listed more than 5 years. As a result, we include 477 stocks[4]. The maximum span of the data is 1995–2014. The complete list of studied stocks is available in the Appendix along with the descriptive statistics and respective stock sectors. For clarity, we outline the computation steps in detail:

1. Log-return series calculation as $r_t = \log(\frac{p_t}{p_{t-1}})$
2. Estimation of all GARCH models (including lag structure selection, where applicable)
3. Simulation of 500 replications for each model with the selected lag structure
4. Calculation of tail indexes using the modified Hill method for all return series—setting the threshold $k = 200$
5. Calculation of tail index by the modified Hill method for each of 500 replication—setting the threshold $k = 200$
6. Comparison of tail indices from the steps 4 and 5

3.1 Case Study – Exxon Mobile

To clarify our approach, we perform a step-by-step analysis of a selected stock. We consider the stock with largest composite weight—Exxon Mobile. The return series is slightly skewed to the right (skewness is 0.029) and has very high kurtosis of 11.76. The tail index $\hat{\xi} = 0.2869$ and reciprocal $\hat{\alpha}^H = 3.4858$ suggest that the unconditional distribution of the returns has no more than 3 finite moments. This result is consistent with various studies. Among others, Huisman et al. (2001) find similar tail indexes for exchange rates, Sun and Zhou (2014) arrive at similar results for both simulated data

[3]The data were retrieved on October 13, 2014 from http://finance.yahoo.com.

[4]Several return series were shortened due to data issues in early years of the sample, such as days without trading

using GARCH(1,1) model and, more importantly, actual stock return series data from the S&P 500 and 12 various US stock indices. Finally, Ibragimov et al. (2013) analyze exchange rates and report Hill $\hat{\alpha}^H$ in range of 2.88 to 4.28 for threshold $k = 170$.

Table 2: GARCH Estimations – Exxon Mobile

	Fixed lag (1,1)		Estimated lag (p,q)					
	Normal GARCH	Student GARCH	Normal GARCH	Student GARCH	Normal E-GARCH	Student E-GARCH	Normal GJR-GARCH	Student GJR-GARCH
LL	-7871.4	-7816.6	-7866.2	-7816.6	-7833.2	-7781.1	-7844.7	-7805.4
ω	0.0296	0.0259	0.0668	0.0259	0.0018	0.0009	0.0817	0.0328
	(0.0188)	(0.0180)	(0.0188)	(0.0180)	(0.0186)	(0.0179)	(0.0191)	(0.0183)
α_1	0.0737	0.0736	0.0733	0.0736	0.1313	0.1462	0.0491	0.0414
	(0.0049)	(0.0066)	(0.0128)	(0.0066)	(0.0008)	(0.0007)	(0.0139)	(0.0072)
α_2			0.1038		0.0417	0.0357	0.0399	
			(0.1333)		(0.0675)	(0.0346)	(0.1077)	
α_3					-0.1494	-0.0011		
					(0.1189)	(0.0046)		
α_4						-0.1420		
						(0.0050)		
α_5						-0.0138		
						(0.0342)		
β_1	0.9146	0.9169	0.0000	0.9169	0.9849	0.9070	0.0000	0.9117
	(0.0059)	(0.0086)	(0.1066)	(0.0086)	(0.0657)	(0.0367)	(0.0912)	(0.0092)
β_2			0.4416		0.8073	0.0008	0.3884	
			(0.1336)		(0.0195)	(0.0378)	(0.1043)	
β_3			0.0000		-0.7941	0.9910	0.0000	
			(0.1069)		(0.0219)	(0.0087)	(0.0880)	
β_4			0.3546			-0.9004	0.3988	
			(0.0124)			(0.0370)	(0.0126)	
df		8.76		8.76		9.64		9.14

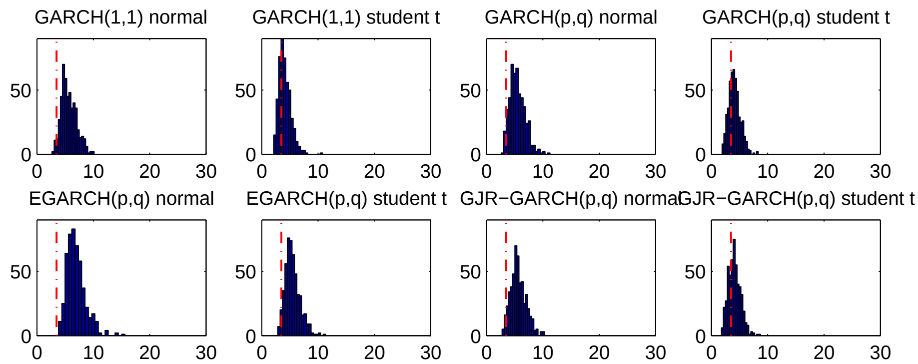
Table 2 presents the estimates of the GARCH models with different types of innovations. The coefficients of the models are consistent with expectations, i.e., high (over 0.9) coefficients β_1 on lagged conditional variance, which suggest a high degree of persistence in volatility. The only exceptions are two models—Normal GARCH(p,q) and GJR-GARCH(p,q)—whose coefficients β_1 are not significantly different from 0. None of the models needed 5 lags for its lagged condition variance, so we do display the results for β_5. Interestingly, the parsimonious GARCH(1,1) with the Student's t assumption for the conditional distribution outperformed possibly longer lag structures (p,q) of the same model. For comparison, Table A1 in the Appendix shows the average lag structure across all time series.

According to Table 2, the GARCH models with Student's t conditional distributions seem to outperform those with normal assumption in terms of parsimony. An exception is an E-GARCH model, which apparently requires the longest lag structure, despite the Akaike selection criterion penalty for extra parameters.

Table 3 shows the tail index estimates and Hill's $\hat{\alpha}^H$ for the Exxon Mobile return series. We present the tail index estimated from actual Exxon Mobile return series with relevant standard errors, but then we proceed to work with reciprocal Hill's $\hat{\alpha}^H$, which can be directly linked to the maximum number of existing moments.

In addition, we examine whether the Hill $\hat{\alpha}^H$ calculated on the replicated data by

Figure 1: Simulated Hill's α^H histograms – Exxon Mobil



The red dotted line indicates the actual data $\hat{\alpha}^H$. The histograms of simulated α^H are based on 500 replications of the Exxon return series using 25 bins.

various models is significantly different from that estimated based on the actual data series. The results are available in Figure 1. The GARCH models that assume a Student's t conditional distribution seem to perform better, i.e., the actual Hill $\hat{\alpha}^H$ is more consistent with the simulated Hill $\hat{\alpha}^H$ values.

Table 3: Exxon Mobile tail index and Hill α^H results

		Fixed lag (1,1)		Estimated lag (p,q)					
$\hat{\xi}$	$\hat{\alpha}^H$	Normal GARCH	Student GARCH	Normal GARCH	Student GARCH	Normal E-GARCH	Student E-GARCH	Normal GJR-GARCH	Student GJR-GARCH
0.2869	3.4858	5.6758	4.0884	5.4977	4.1098	6.9469*	5.4803	5.6497	4.0947
(0.00125)		(1.3366)	(1.0557)	(1.3355)	(1.0433)	(1.6636)	(1.3007)	(1.3693)	(1.0995)

** denotes the t-test result for whether the model-implied Hill $\hat{\alpha}^H$ is significantly different at the 95% confidence level from the $\hat{\alpha}^H = 3.4858$. Note that the standard errors presented for the simulated results are simulation SE.*

3.2 Results for the S&P 500

In this subsection, we present the estimated tail indexes using the modified Hill method for individual series underlying the S&P 500 index. The average estimated $\hat{\alpha}^H$ of the whole sample is 3.62, which suggests very heavy tailed unconditional loss distributions of returns and implies that, on average, no more than 3 moments exist. Table 4 presents the results by sectors.

The results are consistent with common sense, the sectors generally perceived as more stable produce larger estimates of $\hat{\alpha}^H$ and thus lighter tails: the materials, energy, industrials sectors. The healthcare sector had the lowest average estimate of $\hat{\alpha}^H$ and thus the fattest tail. In addition, the financial sector has the second lowest estimate, confirming its heavy fat tails, which is also consistent with expectations.

Table 4: Estimated Hill's $\hat{\alpha}^H$ for Different Sectors

		Fixed lag (1,1)		Estimated lag (p,q)					
Stock sector	Average $\hat{\alpha}^H$	Normal GARCH	Student GARCH	Normal GARCH	Student GARCH	Normal E-GARCH	Student E-GARCH	Normal GJR-GARCH	Student GJR-GARCH
Consumer Dics.	3.75	6.01	2.99	5.79	3.01	6.38	4.15	4.88	2.79
Cons. Staples	3.60	6.23	3.21	6.24	3.19	6.59	4.01	5.65	3.15
Energy	3.83	5.41	3.89	5.42	3.99	6.74	5.26	5.44	4.03
Financial	3.32	3.89	2.67	3.91	2.69	5.65	4.10	3.71	2.72
Healthcare	3.02	5.29	3.05	4.93	3.09	6.07	3.88	4.32	2.97
Industrial	3.89	5.39	3.18	5.31	3.16	6.35	4.29	4.83	3.12
IT	3.85	5.72	2.67	5.40	2.65	6.26	3.98	4.43	2.61
Materials	3.97	5.67	3.23	5.58	3.28	6.51	4.40	5.12	3.27
Telco Services	3.75	5.75	3.08	5.88	3.08	6.67	4.35	5.15	3.06
Utilities	3.50	4.51	3.91	4.52	3.94	6.22	4.86	4.72	4.01
Overall	3.62	5.29	3.09	5.16	3.11	6.25	4.25	4.67	3.06

The table presents the average estimates of $\hat{\alpha}^H$ for actual time series in the first column. The other columns present the average estimates of the simulated model-implied $\hat{\alpha}^H$ from various GARCH specifications.

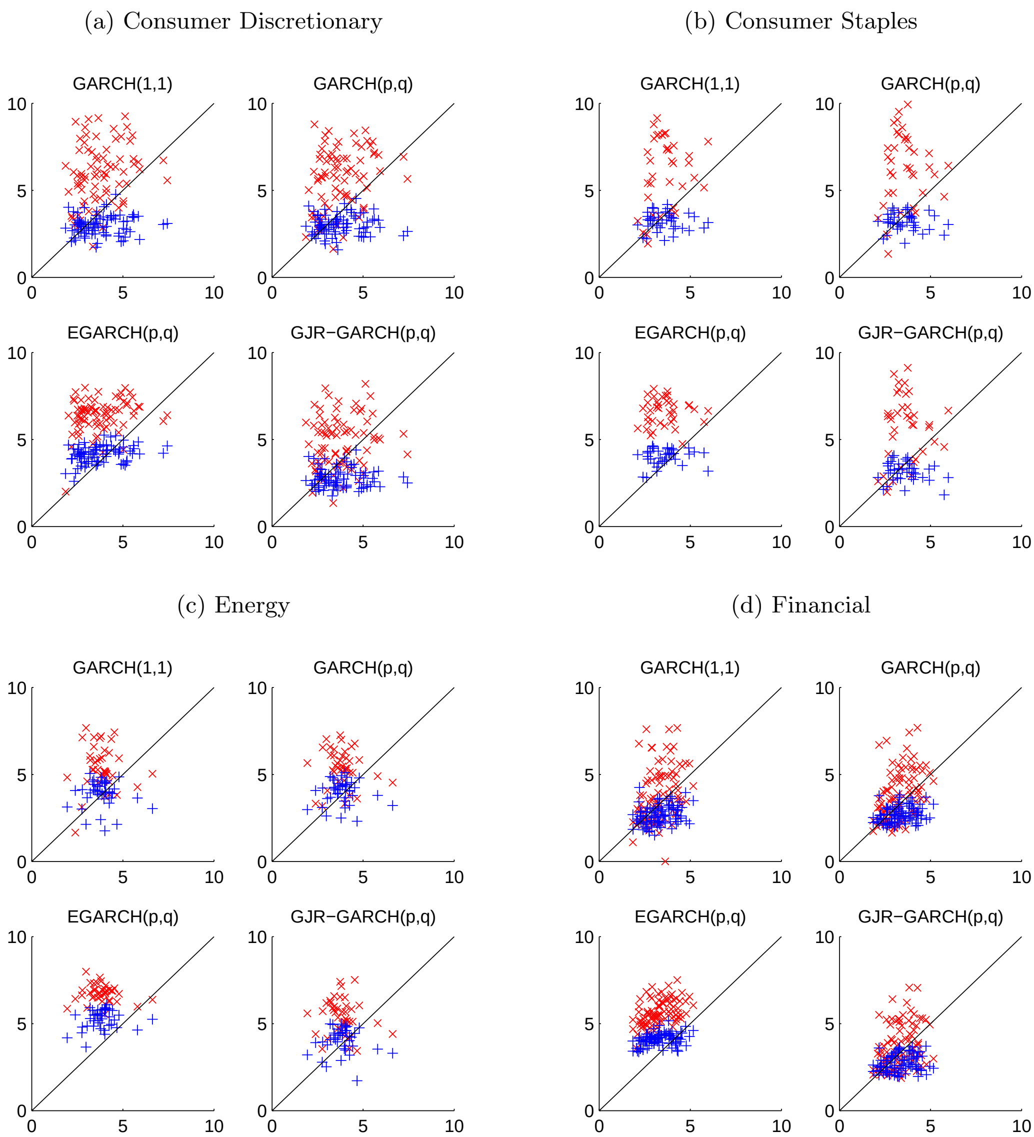
Turning to the analysis of the whole sample of 477 stock returns, we estimate 8 GARCH-family models for each stock return series, simulate all models and calculate the tail indexes for the simulated paths. We simulate 500 replications of 5000 observation long paths for all 8 models and 477 stocks.

The scatter plots in Figures 2, 3 and 4 show the estimates of $\hat{\alpha}^H$ based on actual data on the x-axis and the GARCH-family model simulation-implied $\hat{\alpha}^H$ on the y-axis. Ideally, the data should be on or near the $x = y$ line. The area above the $x = y$ line suggests underestimation of the tail index by the respective model, i.e., the model produces lighter tails than it should. As we can see in the Figure, this is common to the models with a normal distribution assumption. By contrast, the area below the $x = y$ line shows the opposite, i.e., the simulated time series have fatter tails than the original data. Although, generally, this is also an inaccurate outcome, for risk management purposes, we are at least on the "safe side".

We denote models with normal distributions by red $\times$ and models with Student's t distributions by blue $+$. As shown in Table 4, the models with the normal distribution assumption generally fail to reproduce sufficiently fat tails and have the estimate of $\hat{\alpha}^H$ substantially higher than those with the Student's t assumption. Similarly to Figures 2, 3 and 4, we can see this graphically in Figure 5; the majority of the observations fall above the $x = y$ line. By contrast, the models assuming Student's t distribution are closer to the x=y line and outperform their normal counterparts.

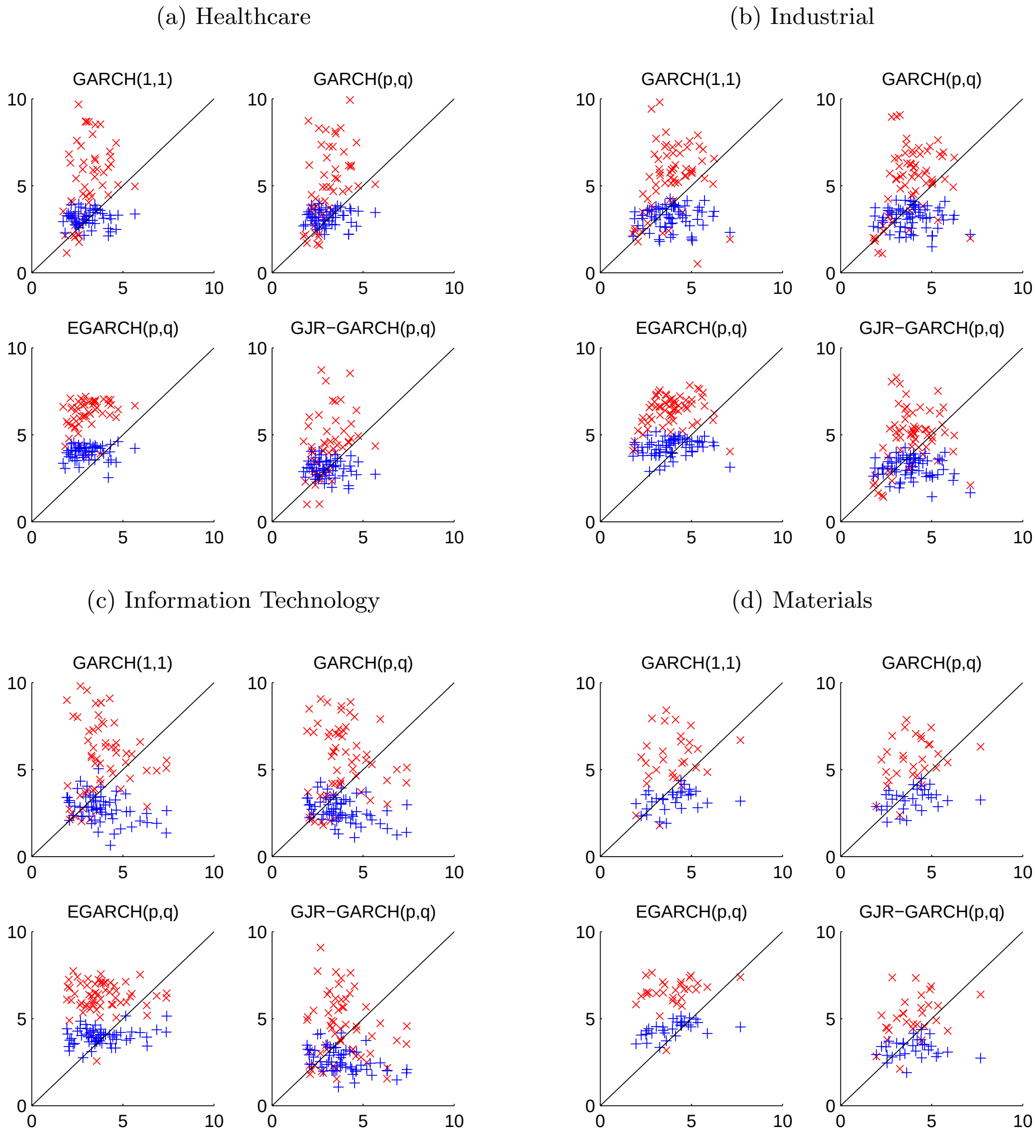
To illustrate the economic significance of our results, we compare VaR calculations (McNeil et al., 2005). Assume that the unconditional loss distribution follows a Student's t distribution (not scaled and with 0 mean), the percentile for 95% VaR is 2.198 with 3.62 degrees of freedom and only 1.929 with 6.25 degrees of freedom. The degrees of freedom are based on Table 4 and represent the average values of $\hat{\alpha}^H$ of the overall estimate and the lightest tail model—Normal E-GARCH. The relative difference is large: 12.2%.

Figure 2: Scatter plots of implied vs. simulated $\hat{\alpha}^H$ – part I



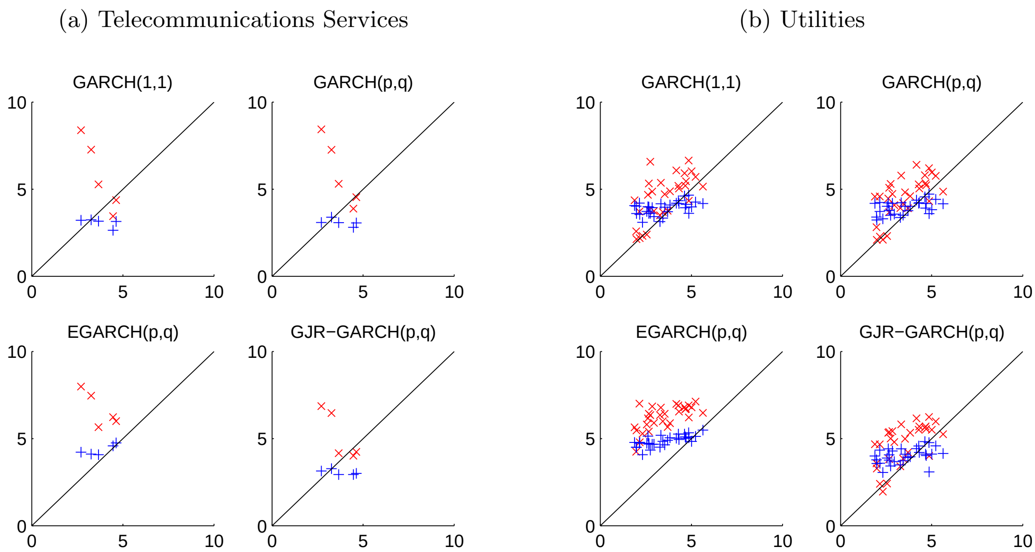
The x-axis shows the actual time series estimates of tail indexes $\hat{\alpha}^H$; the y-axis shows GARCH model simulation-based estimates of the tail indexes $\hat{\xi}$. Red $\times$ denotes GARCH models with normal conditional distributions; blue $+$ denotes GARCH models with Student's t conditional distributions.

Figure 3: Scatter plots of implied vs. simulated $\hat{\alpha}^H$ – part II



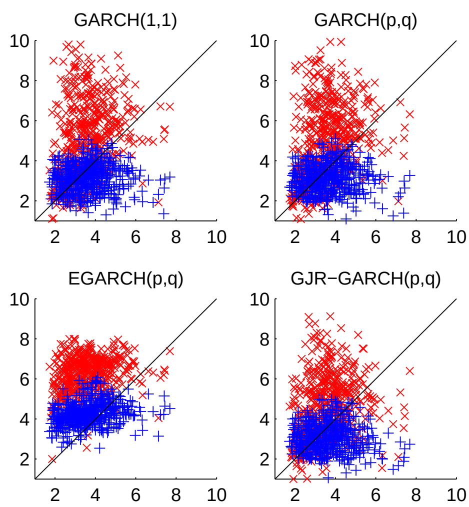
The x-axis shows the actual time series estimates of tail indexes $\hat{\alpha}^H$; the y-axis shows the GARCH model simulation-based estimates of tail indexes $\hat{\xi}$. Red $\times$ denotes GARCH models with normal conditional distributions; blue $+$ denotes GARCH models with Student's t conditional distributions.

Figure 4: Scatter plots of implied vs. simulated $\hat{\alpha}^H$ – part III



The x-axis shows the actual time series estimates of tail indexes $\hat{\alpha}^H$; the y-axis shows GARCH model simulation based estimates of tail indexes $\hat{\xi}$. Red $\times$ denotes GARCH models with normal conditional distributions; blue $+$ denotes GARCH models with Student's t conditional distributions.

Figure 5: Scatter plots of implied vs. simulated $\hat{\alpha}^H$ – all stocks



The x-axis shows the actual time series estimates of tail indexes $\hat{\alpha}^H$; the y-axis shows the GARCH model simulation based estimates of tail indexes $\hat{\xi}$. Red $\times$ denotes GARCH models with normal conditional distributions; blue $+$ denotes GARCH models with Student's t conditional distributions.

In case of the widely used normal GARCH(1,1) model, the percentile for 95% VaR with 5.29 degrees of freedom is 1.991 and the relative difference is 9.4%, which is still quite large. These relative differences multiplied by the portfolio value directly yield the relevant capital requirement impact. However, taking the model replicating the fattest tail, we arrive at a percentile of 2.335, which leads to relative difference of -6.2%, i.e., effectively overestimating the VaR capital requirement by over 6%. Hence, by using these models, one remain on the "safe side" in terms of risk management. This is again a strong argument supporting the usage of models that assume Student's t conditional distributions.

To quantify performance in a more rigorous way, we perform t-tests to consider the accuracy of the simulated $\hat{\alpha}^H$. Formally, we test $H_0 : \hat{\alpha}^H = \alpha^H_{actualdata}$ against two sides alternative. Table 5 presents the percentages of H_0 rejections by sector for all models. We call this the "fail percentage".

Table 5: Fail percentage summary

	Fixed lag (1,1)		Estimated lag (p,q)					
Stock sector	Normal GARCH	Student GARCH	Normal GARCH	Student GARCH	Normal E-GARCH	Student E-GARCH	Normal GJR-GARCH	Student GJR-GARCH
Consumer Dics.	42.17%	7.23%	38.55%	9.64%	54.22%	12.05%	24.10%	14.46%
Cons. Staples	50.00%	2.50%	57.50%	2.50%	67.50%	7.50%	37.50%	5.00%
Energy	20.45%	11.36%	25.00%	9.09%	77.27%	13.64%	34.09%	9.09%
Financial	22.09%	18.60%	24.42%	18.60%	74.42%	23.26%	15.12%	18.60%
Healthcare	47.27%	9.09%	36.36%	7.27%	76.36%	21.82%	21.82%	10.91%
Industrial	31.82%	18.18%	31.82%	16.67%	60.61%	16.67%	21.21%	16.67%
IT	41.27%	23.81%	49.21%	25.40%	52.38%	20.63%	34.92%	25.40%
Materials	33.33%	13.33%	23.33%	13.33%	53.33%	10.00%	13.33%	10.00%
Telco Services	40.00%	20.00%	40.00%	20.00%	60.00%	0.00%	40.00%	20.00%
Utilities	13.33%	23.33%	13.33%	23.33%	73.33%	33.33%	30.00%	23.33%
Total	34.26%	14.34%	34.26%	14.34%	64.94%	17.53%	25.10%	15.54%

The table shows percentages of significant results for each model. The null hypothesis is that the mean of the simulated data is significantly not different from the actual data estimated $\hat{\alpha}^H$. We use ordinary t-test. The lower the percentage, the better the model captures tail shape of various stock returns.

Clearly, the Student's t models fail to reproduce less often than those with normal conditional distributions. Somewhat surprisingly, the ordinary GARCH(1,1) with a Student's t assumption provides the lowest fail percentages, which is closely followed by the GJR-GARCH specification.

The results across sectors follow those of the whole sample. There are some variations, which are usually caused by the lower number of stocks in a given sector, i.e., the Student E-GARCH model has a fail percentage of 0, which means that it did not fail to reproduce a single tail shape, yet there are only 5 stocks in the telecommunication services sector. In case of the two most populated sectors (Consumer Discretionary with 77 and Financial with 85 stocks), we see the Student GARCH(1,1) outperforming others with only a 7.23% fail percentage for the former and, surprisingly, the Normal GJR-GARCH with 15.12% for the latter.

4 Conclusions

We analyze the extent to which the extensively used GARCH models capture the tail behavior of financial time series. We perform a large scale simulation study comparing actual and model-implied tail behavior using individual S&P 500 stock return series for the period 1995–2014. For each of the series, we estimate a reciprocal of the tail index Hill α^H using a modified Hill method (Huisman et al., 2001). Next, we estimate 8 different GARCH models (such as GARCH, EGARCH and GJR-GARCH) with both normal and Student's t assumptions for the conditional distributions. We simulate all the models to replicate 500 paths of individual S&P 500 stock return series. We estimate the tail indexes for all stocks and all considered models to obtain implied tail indexes. Finally, we compare the simulated $\hat{\alpha}^H$ with those originally estimated on the actual S&P 500 stock return series. Having simulated each model 500 times, we obtain a simulation distribution of the $\hat{\alpha}^H$. Thus, we are able to see how the originally estimated $\hat{\alpha}^H$ using actual data correspond to the simulation. Formally, we use t-tests, and models that are not statistically close were considered fails. We use these fail percentages to compare the actual and simulated values formally.

Our results are as follows. First, we confirm that models that assume a Student's t unconditional distribution outperform those that assume normal distributions. The extent to which models with innovations that are normally distributed underestimate the fatness of the tails is rather large, suggesting that its applications for practical purposes is risky. We show that in the worst case scenario, regulatory capital can be undervalued by over 12%. Second, we find that a GARCH(1,1) model with Student's t innovations captures the fatness of tail of the unconditional distribution relatively well. Generally speaking, models assuming a Student's t conditional distribution have much lower fail percentages of 14–15% compared to 25–65% using a normal distribution assumption.

In addition, this paper provides a large scale analysis of S&P 500 stocks and indicates the Hill α^H values that we can expect in further analyses. The Hill $\hat{\alpha}^H$ values suggest that the unconditional distribution of the analyzed stock returns has very fat left tails and that no more than 3 moments exist.

In terms of future research, we believe it would be worthwhile to examine less liquid stock markets to investigate the extent to which our results hold. We expect that the results from less liquid markets would provide even stronger support for the use of Student's t models. The results might lean towards GJR-GARCH models allowing for asymmetrical tails.

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Appendix

(*does not have to be published*)

Table A1: Average lag structure

Model	q	p
Normal GARCH	4.01	2.28
Student GARCH	3.13	1.26
Normal E-GARCH	4.40	4.41
Student E-GARCH	4.00	3.93
Normal GJR-GARCH	4.10	2.68
Student GJR-GARCH	3.14	1.33

Ticker symbol	Security	Obs.	Mean	Standard deviation	Skewness	Kurtosis
ABT	Abbott Laboratories	4500	0.038	1.612	-0.142	10.588
ABBV	AbbVie	0				
ACE	ACE Limited	4500	0.045	2.247	0.217	13.182
ACN	Accenture plc	3277	0.058	2.063	-0.120	10.136
ACT	Actavis plc	4500	0.056	2.284	-2.636	60.723
ADBE	Adobe Systems Inc	4500	0.057	3.058	-0.385	12.472
ADT	ADT Corp	0				
AES	AES Corp	4500	0.002	3.601	-1.669	47.859
AET	Aetna Inc	4500	0.051	2.376	-0.478	15.938
AFL	AFLAC Inc	4500	0.043	2.540	-1.106	38.681
AMG	Affiliated Managers Group Inc	4197	0.052	2.807	-0.080	11.304
A	Agilent Technologies Inc	3696	-0.005	3.003	0.252	19.814
GAS	AGL Resources Inc.	4500	0.039	1.341	-0.148	8.468
APD	Air Products & Chemicals Inc	4500	0.037	1.901	-0.082	7.823
ARG	Airgas Inc	4500	0.034	2.556	-0.045	20.726
AKAM	Akamai Technologies Inc	3710	-0.043	4.752	0.553	11.704
AA	Alcoa Inc	4500	0.006	2.629	-0.079	10.029
ALXN	Alexion Pharmaceuticals	4500	0.096	3.874	0.324	15.203
ATI	Allegheny Technologies Inc	3690	0.024	3.389	-0.129	6.761
ALLE	Allegion	4500	0.073	1.976	-0.191	9.925
AGN	Allergan Inc	4500	0.073	1.976	-0.191	9.925
ADS	Alliance Data Systems	3300	0.084	2.505	-1.175	38.892
ALL	Allstate Corp	4500	0.026	2.151	-0.640	21.237
ALTR	Altera Corp	4500	0.031	3.454	-0.042	8.161
MO	Altria Group Inc	4500	0.061	1.770	-0.138	13.553

AMZN	Amazon.com Inc	4329	0.112	4.061	0.419	10.284
AEE	Ameren Corp	4170	0.022	1.341	-0.572	21.638
AEP	American Electric Power	4500	0.025	1.590	-0.485	29.433
AXP	American Express Co	4500	0.044	2.425	0.015	10.764
AIG	American International Group. Inc.	4500	-0.046	3.973	-3.185	109.387
AMT	American Tower Corp A	4132	0.036	3.413	-0.324	20.703
AMP	Ameriprise Financial	2233	0.051	2.961	0.108	14.771
ABC	AmerisourceBergen Corp	4500	0.065	2.191	-0.959	25.695
AME	Ametek	4500	0.064	1.923	-0.384	11.968
AMGN	Amgen Inc	4500	0.051	2.228	0.242	7.809
APH	Amphenol Corp A	4500	0.079	2.431	0.195	11.601
APC	Anadarko Petroleum Corp	4500	0.040	2.545	-0.413	10.691
ADI	Analog Devices. Inc.	4500	0.037	3.055	0.238	7.468
AON	Aon plc	4500	0.032	2.062	-2.278	52.164
APA	Apache Corporation	4500	0.039	2.387	-0.053	7.772
AIV	Apartment Investment & Mgmt	4500	0.035	2.433	-0.680	26.055
AAPL	Apple Inc.	4500	0.107	3.105	-2.750	75.187
AMAT	Applied Materials Inc	4500	0.040	3.084	0.281	6.342
ADM	Archer-Daniels-Midland Co	4500	0.029	2.064	-0.175	12.027
AIZ	Assurant Inc	2639	0.039	2.297	-0.770	25.800
T	AT&T Inc	4500	0.024	1.791	0.072	8.285
ADSK	Autodesk Inc	4500	0.050	2.977	-0.401	9.354
ADP	Automatic Data Processing	4500	0.040	1.657	-0.913	22.309
AN	AutoNation Inc	4500	0.012	2.638	0.164	10.088
AZO	AutoZone Inc	4500	0.067	1.963	0.031	11.863
AVGO	Avago Technologies	1254	0.122	2.212	-0.032	5.889
AVB	AvalonBay Communities. Inc.	4500	0.050	1.954	-0.053	16.203
AVY	Avery Dennison Corp	4500	0.014	1.958	-0.617	10.629
AVP	Avon Products	4500	0.004	2.304	-0.876	22.415
BHI	Baker Hughes Inc	4500	0.014	2.719	-0.192	9.043
BLL	Ball Corp	4500	0.072	1.811	0.219	7.825
BAC	Bank of America Corp	4500	0.002	3.064	-0.313	26.549
BK	The Bank of New York Mellon Corp.	4500	0.025	2.540	-0.057	17.873
BCR	Bard (C.R.) Inc.	4500	0.058	1.597	0.342	13.919
BAX	Baxter International Inc.	4500	0.037	1.790	-2.008	32.791
BBT	BB&T Corporation	4500	0.029	2.197	0.110	19.881
BDX	Becton Dickinson	4500	0.048	1.754	-0.527	21.180
BBBY	Bed Bath & Beyond	4500	0.050	2.641	0.516	10.776
BMS	Bemis Company	4500	0.028	1.669	-0.422	11.885
BRK.B	Berkshire Hathaway	4500	0.041	1.501	0.744	13.322

BBY	Best Buy Co. Inc.	4500	0.072	3.317	-1.482	27.232
BIIB	BIOGEN IDEC Inc.	4500	0.099	3.384	-1.124	26.268
BLK	BlackRock	3730	0.083	2.353	0.103	9.651
HRB	Block H&R	4500	0.042	2.125	-0.416	11.183
BA	Boeing Company	4500	0.028	2.046	-0.381	9.741
BWA	BorgWarner	4500	0.056	2.305	0.145	9.854
BXP	Boston Properties	4307	0.052	2.075	-0.040	19.118
BSX	Boston Scientific	4500	-0.005	2.707	-0.785	16.765
BMY	Bristol-Myers Squibb	4500	0.029	1.886	-0.682	15.453
BRCM	Broadcom Corporation	4098	0.029	3.941	0.067	8.129
BF.B	Brown-Forman Corporation	4500	0.052	1.478	0.205	7.450
CHRW	C. H. Robinson Worldwide	4223	0.065	2.221	0.139	10.143
CA	CA. Inc.	4500	-0.008	2.906	-2.129	43.687
CVC	Cablevision Systems Corp.	4500	0.048	2.880	-0.055	14.889
COG	Cabot Oil & Gas	4500	0.069	2.706	-0.024	8.010
CAM	Cameron International Corp.	4500	0.042	2.947	-0.077	6.533
CPB	Campbell Soup	4500	0.012	1.520	0.015	10.738
COF	Capital One Financial	4500	0.046	3.295	-1.116	24.114
CAH	Cardinal Health Inc.	4500	0.039	2.132	1.057	85.555
CFN	Carefusion	1243	0.076	1.617	1.652	27.043
KMX	Carmax Inc	4400	0.041	3.421	0.597	14.132
CCL	Carnival Corp.	4500	0.027	2.448	-0.904	21.286
CAT	Caterpillar Inc.	4500	0.045	2.156	-0.108	7.140
CBG	CBRE Group	2552	0.058	4.107	0.725	23.735
CBS	CBS Corp.	2177	0.042	2.856	-0.117	16.041
CELG	Celgene Corp.	4500	0.121	3.568	-0.022	9.212
CNP	CenterPoint Energy	4500	0.022	2.339	-2.198	135.759
CTL	CenturyLink Inc	4500	0.035	1.847	-0.818	20.076
CERN	Cerner	4500	0.082	3.176	-1.135	41.920
CF	CF Industries Holdings Inc	2257	0.137	3.177	-1.365	21.060
SCHW	Charles Schwab Corporation	4500	0.045	3.109	0.425	7.509
CHK	Chesapeake Energy	4500	-0.007	3.632	-0.156	11.423
CVX	Chevron Corp.	4500	0.040	1.655	0.086	12.726
CMG	Chipotle Mexican Grill	2142	0.116	2.659	-0.503	14.543
CB	Chubb Corp.	4500	0.037	1.800	0.393	11.052
CI	CIGNA Corp.	4500	0.043	2.455	-2.748	65.848
XEC	Cimarex Energy	2982	0.066	2.476	-0.189	9.154
CINF	Cincinnati Financial	4500	0.034	1.945	-0.198	19.388
CTAS	Cintas Corporation	4500	0.031	2.130	0.198	11.218
CSCO	Cisco Systems	4799	0.039	2.705	0.057	9.158

C	Citigroup Inc.	4500	-0.016	3.286	-0.442	37.653
CTXS	Citrix Systems	4500	0.050	4.078	-2.880	78.273
CLX	The Clorox Company	4500	0.039	1.635	-0.349	13.691
CME	CME Group Inc.	2931	0.084	2.510	-0.304	12.468
CMS	CMS Energy	4500	0.011	1.981	-2.190	38.162
COH	Coach Inc.	3473	0.077	2.741	-0.243	10.569
KO	The Coca Cola Company	4500	0.021	1.495	0.018	9.705
CCE	Coca-Cola Enterprises	4500	0.034	2.147	-0.589	27.044
CTSH	Cognizant Technology Solutions	4054	0.127	3.454	0.029	13.035
CL	Colgate-Palmolive	4500	0.045	1.568	-0.003	14.661
CMCSA	Comcast Corp.	4500	0.053	2.375	0.165	9.123
CMA	Comerica Inc.	4500	0.016	2.449	-0.193	14.525
CSC	Computer Sciences Corp.	4500	0.010	2.495	-2.022	45.758
CAG	ConAgra Foods Inc.	4500	0.019	1.523	-0.814	17.427
COP	ConocoPhillips	4500	0.045	1.825	-0.348	9.087
CNX	CONSOL Energy Inc.	3700	0.057	3.324	-0.799	13.088
ED	Consolidated Edison	4500	0.035	1.185	0.150	7.786
STZ	Constellation Brands	4500	0.072	2.122	0.556	21.682
GLW	Corning Inc.	4500	0.014	3.373	-0.589	14.485
COST	Costco Co.	4500	0.059	2.044	-0.488	13.140
COV	Covidien plc	1729	0.064	1.725	0.783	15.072
CCI	Crown Castle International Corp.	4029	0.056	3.482	-0.166	19.710
CSX	CSX Corp.	4500	0.038	2.144	-0.137	7.556
CMI	Cummins Inc.	4500	0.061	2.670	-0.080	9.249
CVS	CVS Caremark Corp.	0				
DHI	D. R. Horton	4500	0.050	3.186	0.143	8.824
DHR	Danaher Corp.	4500	0.058	1.741	0.055	7.491
DRI	Darden Restaurants	4500	0.054	2.272	-0.241	12.010
DVA	DaVita Inc.	4500	0.052	2.998	-5.883	189.587
DE	Deere & Co.	4500	0.037	2.226	-0.142	7.605
DLPH	Delphi Automotive	0				
DAL	Delta Air Lines	1824	0.025	4.045	-0.078	8.455
DNR	Denbury Resources Inc.	4500	0.027	3.127	0.109	12.474
XRAY	Dentsply International	4500	0.043	1.743	-1.031	21.478
DVN	Devon Energy Corp.	4500	0.030	2.317	-0.094	8.012
DO	Diamond Offshore Drilling	4500	0.017	2.690	-0.033	6.716
DTV	DirecTV	2668	0.062	1.781	0.277	13.121
DFS	Discover Financial Services	1795	0.058	3.200	0.132	10.077
DISCA	Discovery Communications-A	2281	0.067	2.209	-0.357	25.115
DISCK	Discovery Communications-C	1476	0.103	1.867	-0.097	8.460

DG	Dollar General	0				
DLTR	Dollar Tree	4500	0.059	2.832	-1.910	46.659
D	Dominion Resources	4500	0.046	1.342	-0.576	13.004
DOV	Dover Corp.	4500	0.034	1.914	-0.153	8.157
DOW	Dow Chemical	4500	0.027	2.238	-0.240	9.505
DPS	Dr Pepper Snapple Group	1400	0.114	1.437	0.857	13.244
DTE	DTE Energy Co.	4500	0.039	1.346	0.027	10.717
DD	Du Pont (E.I.)	4500	0.021	1.902	-0.143	7.124
DUK	Duke Energy	4500	0.031	1.576	-0.186	14.109
DNB	Dun & Bradstreet	4500	0.058	1.725	-0.537	13.599
ETFC	E-Trade	4500	-0.008	4.803	-0.875	35.597
EMN	Eastman Chemical	4500	0.035	2.070	-0.071	11.181
ETN	Eaton Corporation	4500	0.045	1.925	0.180	11.243
EBAY	eBay Inc.	3987	0.048	3.443	0.419	12.034
ECL	Ecolab Inc.	4500	0.059	1.556	0.034	9.115
EIX	Edison Int'l	4500	0.035	2.233	-1.567	68.480
EW	Edwards Lifesciences	3608	0.067	2.190	-4.573	114.864
EA	Electronic Arts	4500	0.033	3.060	0.013	9.136
EMC	EMC Corp.	5300	0.048	3.052	-0.288	10.562
EMR	Emerson Electric	4500	0.030	1.834	-0.058	9.157
ESV	Ensco plc	4500	0.015	3.028	-0.094	6.360
ETR	Entergy Corp.	4500	0.038	1.551	-0.417	15.414
EOG	EOG Resources	4500	0.060	2.508	0.016	7.769
EQT	EQT Corporation	4500	0.062	1.888	-0.130	13.708
EFX	Equifax Inc.	4500	0.036	1.911	-0.512	13.806
EQR	Equity Residential	4500	0.047	2.150	0.081	25.188
ESS	Essex Property Trust Inc	4500	0.060	1.817	-0.420	17.221
EL	Estee Lauder Cos.	4500	0.043	1.960	0.418	10.541
EXC	Exelon Corp.	4500	0.037	1.681	-0.019	10.974
EXPE	Expedia Inc.	2272	0.047	3.036	-1.597	34.053
EXPD	Expeditors Int'l	4500	0.061	2.499	0.118	7.797
ESRX	Express Scripts	0				
XOM	Exxon Mobil Corp.	4500	0.040	1.606	0.029	11.760
FFIV	F5 Networks	3813	0.034	4.359	0.153	9.830
FB	Facebook	0				
FDO	Family Dollar Stores	4500	0.062	2.335	0.387	10.310
FAST	Fastenal Co	4500	0.050	2.415	-0.205	9.298
FDX	FedEx Corporation	4500	0.046	2.083	-0.062	7.051
FIS	Fidelity National Information Services	3297	0.039	1.986	-1.616	63.182
FITB	Fifth Third Bancorp	4500	0.008	3.345	-0.329	58.310

FSLR	First Solar Inc	1936	0.028	4.462	0.471	11.654
FE	FirstEnergy Corp	4206	0.024	1.587	0.114	13.573
FISV	Fiserv Inc	4300	0.051	2.259	0.010	9.489
FLIR	FLIR Systems	4500	0.064	3.238	-0.812	28.175
FLS	Flowserve Corporation	4500	0.047	2.748	-2.427	48.958
FLR	Fluor Corp.	3434	0.039	2.669	-0.084	9.176
FMC	FMC Corporation	4500	0.039	2.186	-0.811	22.255
FTI	FMC Technologies Inc.	3300	0.078	2.552	-0.276	8.531
F	Ford Motor	4500	0.013	2.755	-0.023	16.402
FOSL	Fossil. Inc.	4500	0.079	3.240	-0.904	21.626
BEN	Franklin Resources	5700	0.056	2.303	0.045	8.188
FCX	Freeport-McMoran Cp & Gld	4500	0.024	3.112	-0.253	7.787
FTR	Frontier Communications	4500	0.012	2.151	0.221	12.623
GME	GameStop Corp.	3137	0.047	2.875	-0.680	15.467
GCI	Gannett Co.	4500	0.002	2.480	0.462	26.624
GPS	Gap (The)	4500	0.035	2.640	-0.256	11.352
GRMN	Garmin Ltd.	3429	0.058	2.687	-0.584	11.868
GD	General Dynamics	4500	0.050	1.705	-0.197	7.218
GE	General Electric	4500	0.019	1.983	0.018	10.304
GGP	General Growth Properties Inc.	4500	0.042	4.709	-2.024	125.838
GIS	General Mills	4500	0.038	1.168	-0.436	11.500
GM	General Motors	0				
GPC	Genuine Parts	4500	0.037	1.425	0.150	7.257
GNW	Genworth Financial Inc.	2563	-0.018	5.232	-0.064	59.232
GILD	Gilead Sciences	4500	0.111	3.076	0.082	8.829
GS	Goldman Sachs Group	3835	0.029	2.528	0.313	13.823
GT	Goodyear Tire & Rubber	4500	-0.015	3.111	-0.350	8.297
GOOGL	Google Inc Class A	2504	0.070	2.005	0.383	11.470
GOOG	Google Inc Class C	0				
GWW	Grainger (W.W.) Inc.	4500	0.047	1.816	0.155	9.144
HAL	Halliburton Co.	4500	0.034	2.963	-1.445	34.224
HOG	Harley-Davidson	4500	0.041	2.450	0.030	10.068
HAR	Harman Int'l Industries	4500	0.045	2.869	-1.398	31.242
HRS	Harris Corporation	4500	0.040	2.211	0.113	10.045
HIG	Hartford Financial Svc.Gp.	4500	0.010	3.667	-0.413	86.382
HAS	Hasbro Inc.	4500	0.031	2.124	-0.792	16.169
HCP	HCP Inc.	4500	0.046	2.083	0.420	18.914
HCN	Health Care REIT. Inc.	4500	0.051	1.733	-0.236	12.051
HP	Helmerich & Payne	4500	0.051	2.795	-0.277	7.735
HES	Hess Corporation	4500	0.037	2.362	-0.771	12.505

HPQ	Hewlett-Packard	4500	0.016	2.545	-0.231	9.945
HD	Home Depot	4500	0.053	2.131	-0.801	20.743
HON	Honeywell Int'l Inc.	4500	0.028	2.140	-0.260	13.911
HRL	Hormel Foods Corp.	4500	0.054	1.516	-0.105	10.214
HSP	Hospira Inc.	2579	0.025	1.827	-1.668	25.049
HST	Host Hotels & Resorts	4500	0.020	2.780	-0.248	18.581
HCBK	Hudson City Bancorp	3787	0.051	1.821	-0.155	13.250
HUM	Humana Inc.	4500	0.044	2.822	-1.108	16.478
HBAN	Huntington Bancshares	4500	0.000	3.446	0.416	31.511
ITW	Illinois Tool Works	4500	0.038	1.773	0.112	7.041
IR	Ingersoll-Rand PLC	4500	0.040	2.310	-0.100	7.453
TEG	Integrys Energy Group Inc.	4500	0.041	1.388	-2.418	65.773
INTC	Intel Corp.	4500	0.024	2.555	-0.370	9.848
ICE	IntercontinentalExchange Inc.	2189	0.064	3.215	0.232	15.191
IBM	International Bus. Machines	4500	0.040	1.819	-0.097	10.459
IP	International Paper	4500	0.013	2.397	0.044	10.364
IPG	Interpublic Group	4500	0.004	2.679	-0.338	22.625
IFF	Intl Flavors & Fragrances	4500	0.026	1.674	-1.266	31.762
INTU	Intuit Inc.	4500	0.057	3.153	-0.082	14.720
ISRG	Intuitive Surgical Inc.	3551	0.079	3.534	0.456	12.313
IVZ	Invesco Ltd.	4500	0.040	2.982	0.128	9.936
IRM	Iron Mountain Incorporated	4050	0.044	2.053	-0.028	13.773
JBL	Jabil Circuit	4500	0.042	3.753	-0.110	9.593
JEC	Jacobs Engineering Group	4500	0.046	2.353	-0.273	10.906
JNJ	Johnson & Johnson	4500	0.039	1.347	-0.270	13.604
JCI	Johnson Controls	4500	0.050	2.102	-0.012	7.639
JOY	Joy Global Inc.	3314	0.060	3.141	-0.337	8.818
JPM	JPMorgan Chase & Co.	4500	0.026	2.649	0.244	13.948
JNPR	Juniper Networks	3798	-0.014	3.958	0.295	9.646
KSU	Kansas City Southern	4500	0.105	2.737	0.019	7.926
K	Kellogg Co.	4500	0.024	1.485	0.116	9.061
KEY	KeyCorp	4500	-0.001	2.949	-0.408	38.053
GMCR	Keurig Green Mountain	4500	0.140	3.948	-0.992	32.997
KMB	Kimberly-Clark	4500	0.029	1.466	-0.262	10.337
KIM	Kimco Realty	3500	0.035	2.604	0.141	23.951
KMI	Kinder Morgan	0				
KLAC	KLA-Tencor Corp.	4500	0.036	3.392	0.223	6.487
KSS	Kohl's Corp.	4500	0.041	2.246	0.110	5.845
KRFT	Kraft Foods Group	0				
KR	Kroger Co.	4500	0.037	1.930	-1.031	19.277

LB	L Brands Inc.	4500	0.062	2.411	-0.051	8.327
LLL	L-3 Communications Holdings	4076	0.051	1.917	1.088	25.673
LH	Laboratory Corp. of America Holding	4500	0.057	2.630	-1.207	33.557
LRCX	Lam Research	4500	0.042	3.722	0.252	7.047
LM	Legg Mason	4500	0.041	2.857	-0.310	13.553
LEG	Leggett & Platt	4500	0.031	1.994	-0.387	12.619
LEN	Lennar Corp.	4500	0.051	3.268	-0.050	11.434
LUK	Leucadia National Corp.	4500	0.035	2.209	-0.401	17.375
LLY	Lilly (Eli) & Co.	4500	0.024	1.838	-1.376	34.987
LNC	Lincoln National	4500	0.023	3.373	-1.199	47.695
LLTC	Linear Technology Corp.	4500	0.037	2.921	0.276	6.325
LMT	Lockheed Martin Corp.	4500	0.039	1.775	-0.246	10.089
L	Loews Corp.	4500	0.026	1.878	-0.416	19.645
LO	Lorillard Inc.	1546	0.081	1.686	0.310	11.200
LOW	Lowe's Cos.	4500	0.057	2.244	0.222	6.742
LYB	LyondellBasell	0				
MTB	M&T Bank Corp.	4500	0.042	1.959	0.196	14.588
MAC	Macerich	4083	0.044	2.689	-0.573	28.552
M	Macy's Inc.	4500	0.032	2.613	-0.065	7.825
MMM	3M Company	4500	0.035	1.566	-0.008	7.338
MNK	Mallinckrodt plc	0				
MRO	Marathon Oil Corp.	4500	0.047	2.256	-0.293	11.191
MPC	Marathon Petroleum	0				
MAR	Marriott Int'l.	4500	0.041	2.183	-0.211	9.956
MMC	Marsh & McLennan	4500	0.032	1.917	-0.653	20.056
MAS	Masco Corp.	4500	0.015	2.518	-0.169	8.401
MA	Mastercard Inc.	2059	0.129	2.450	0.376	10.128
MAT	Mattel Inc.	4500	0.011	2.222	-1.255	31.074
MKC	McCormick & Co.	4500	0.049	1.437	0.176	10.864
MCD	McDonald's Corp.	4500	0.038	1.601	-0.062	8.540
MHFI	McGraw Hill Financial	4500	0.051	1.987	0.132	12.794
MCK	McKesson Corp.	4500	0.047	2.274	-5.289	152.252
MJN	Mead Johnson	1376	0.100	1.606	-0.103	9.082
MWV	MeadWestvaco Corporation	5000	0.025	2.054	-0.559	10.684
MDT	Medtronic Inc.	4500	0.035	1.817	-0.261	8.943
MRK	Merck & Co.	4500	0.022	1.857	-1.296	26.317
MET	MetLife Inc.	3601	0.031	2.815	-0.322	23.564
MCHP	Microchip Technology	4500	0.042	3.152	0.119	8.975
MU	Micron Technology	4500	0.013	3.927	-0.091	6.080
MSFT	Microsoft Corp.	4500	0.042	2.079	-0.050	10.226

MHK	Mohawk Industries	4800	0.048	2.481	0.432	8.489
TAP	Molson Coors Brewing Company	4500	0.053	1.921	-0.403	13.491
MDLZ	Mondelez International	3302	0.024	1.336	-0.540	11.928
MON	Monsanto Co.	3465	0.066	2.251	-0.200	10.192
MNST	Monster Beverage	2800	0.198	3.325	0.104	13.352
MCO	Moody's Corp	3900	0.054	2.327	-0.267	10.382
MS	Morgan Stanley	4500	0.026	3.320	1.132	41.563
MOS	The Mosaic Company	4500	0.008	3.010	-1.566	29.211
MSI	Motorola Solutions Inc.	4500	0.002	2.853	-0.427	11.267
MUR	Murphy Oil	4500	0.048	2.134	-0.223	9.749
MYL	Mylan Inc.	4500	0.046	2.471	-0.760	18.916
NBR	Nabors Industries Ltd.	4500	0.014	3.130	-0.176	6.219
NDAQ	NASDAQ OMX Group	3042	0.048	2.851	0.309	9.807
NOV	National Oilwell Varco Inc.	4467	0.052	3.263	-0.208	8.998
NAVI	Navient Corp	0				
NTAP	NetApp	0				
NFLX	Netflix Inc.	3068	0.144	4.004	-0.974	25.967
NWL	Newell Rubbermaid Co.	4500	0.013	2.173	-1.019	23.556
NFX	Newfield Exploration Co	4500	0.019	2.757	-0.389	8.120
NEM	Newmont Mining Corp. (Hldg. Co.)	4500	-0.014	2.782	0.416	8.132
NWSA	News Corporation	0				
NEE	NextEra Energy	4500	0.046	1.431	0.191	12.287
NLSN	Nielsen Holdings	0				
NKE	NIKE Inc.	4500	0.046	2.132	-0.158	12.116
NI	NiSource Inc.	4500	0.034	1.517	-0.558	13.460
NE	Noble Corp	4500	0.020	2.987	-0.114	6.802
NBL	Noble Energy Inc	4500	0.039	2.414	-0.049	9.439
JWN	Nordstrom	4500	0.049	2.750	0.130	8.231
NSC	Norfolk Southern Corp.	4500	0.037	2.140	-0.032	6.463
NTRS	Northern Trust Corp.	4500	0.035	2.294	0.375	14.883
NOC	Northrop Grumman Corp.	4500	0.036	1.713	0.107	15.390
NU	Northeast Utilities	4500	0.039	1.503	-0.124	12.316
NRG	NRG Energy	2683	0.042	2.272	0.630	19.015
NUE	Nucor Corp.	4500	0.039	2.561	-0.285	10.650
NVDA	Nvidia Corporation	3905	0.061	4.169	-0.213	14.943
KORS	Michael Kors	0				
ORLY	O'Reilly Automotive	4500	0.079	2.328	0.303	10.404
OXY	Occidental Petroleum	4500	0.056	2.094	-0.205	11.835
OMC	Omnicom Group	4500	0.043	1.956	-0.273	10.971
OKE	ONEOK	4500	0.066	1.806	0.960	23.173

ORCL	Oracle Corp.	4500	0.045	2.949	-0.202	14.406
OI	Owens-Illinois Inc	4500	0.007	3.179	-1.142	29.344
PCG	P G & E Corp.	4500	0.027	2.254	-3.886	124.276
PCAR	PACCAR Inc.	4500	0.061	2.470	0.012	6.412
PLL	Pall Corp.	4500	0.033	1.999	-0.649	16.903
PH	Parker-Hannifin	4500	0.046	2.105	-0.057	6.752
PDCO	Patterson Companies	4500	0.051	2.112	-0.886	16.343
PAYX	Paychex Inc.	4500	0.040	2.224	0.066	7.554
PNR	Pentair Ltd.	4500	0.041	2.137	-0.741	12.748
PBCT	People's United Bank	4500	0.044	1.849	-0.044	12.859
POM	Pepco Holdings Inc.	4500	0.022	1.488	0.080	15.089
PEP	PepsiCo Inc.	4500	0.035	1.513	0.286	12.751
PKI	PerkinElmer	4500	0.039	2.598	-1.134	24.502
PRGO	Perrigo	4500	0.063	2.331	-0.358	10.245
PETM	PetSmart. Inc.	4500	0.025	3.065	-0.412	12.665
PFE	Pfizer Inc.	4500	0.026	1.794	-0.188	6.914
PM	Philip Morris International	1605	0.048	1.486	-0.087	11.778
PSX	Phillips 66	0				
PNW	Pinnacle West Capital	4500	0.031	1.401	-0.138	9.059
PXD	Pioneer Natural Resources	4271	0.035	2.857	-0.308	8.246
PBI	Pitney-Bowes	4500	0.012	1.947	-1.357	32.064
PCL	Plum Creek Timber Co.	4500	0.032	1.925	0.383	15.805
PNC	PNC Financial Services	4500	0.029	2.471	-1.353	65.643
RL	Polo Ralph Lauren Corp.	4311	0.045	2.495	0.258	7.398
PPG	PPG Industries	4500	0.036	1.831	0.130	7.668
PPL	PPL Corp.	4500	0.042	1.591	-0.483	11.727
PX	Praxair Inc.	4550	0.045	1.880	0.118	8.579
PCP	Precision Castparts	4500	0.067	2.240	-0.329	18.507
PCLN	Priceline.com Inc	3858	0.016	4.592	-1.070	23.256
PFG	Principal Financial Group	3214	0.030	3.212	-0.386	27.969
PG	Procter & Gamble	4500	0.034	1.532	-3.068	74.970
PGR	Progressive Corp.	4500	0.040	2.021	-0.056	19.381
PLD	Prologis	4197	0.028	2.627	-0.948	33.050
PRU	Prudential Financial	3178	0.039	3.090	-0.033	26.125
PEG	Public Serv. Enterprise Inc.	4500	0.041	1.580	0.058	11.492
PSA	Public Storage	4500	0.057	1.927	0.180	18.056
PHM	Pulte Homes Inc.	4500	0.037	3.106	0.131	6.922
PVH	PVH Corp.	4500	0.051	2.692	0.280	7.457
QEP	QEP Resources	0				
PWR	Quanta Services Inc.	4142	0.029	3.908	-6.168	184.357

QCOM	QUALCOMM Inc.	4500	0.078	3.103	0.458	10.963
DGX	Quest Diagnostics	4427	0.063	2.069	-0.471	15.710
RRC	Range Resources Corp.	4500	0.040	3.379	0.497	13.174
RTN	Raytheon Co.	4500	0.024	2.092	-4.831	142.297
RHT	Red Hat Inc.	3766	0.010	3.859	0.461	10.843
REGN	Regeneron	4500	0.065	4.533	-0.702	44.826
RF	Regions Financial Corp.	4500	-0.005	3.194	-0.543	42.557
RSG	Republic Services Inc	4046	0.040	2.137	-1.059	42.535
RAI	Reynolds American Inc.	3816	0.083	1.790	-0.740	16.579
RHI	Robert Half International	4500	0.034	2.612	0.056	18.100
ROK	Rockwell Automation Inc.	4500	0.048	2.283	-0.394	9.928
COL	Rockwell Collins	3300	0.047	1.824	-0.483	11.608
ROP	Roper Industries	4500	0.060	2.148	-0.119	13.359
ROST	Ross Stores	4500	0.076	2.361	0.328	9.348
R	Ryder System	4500	0.030	2.237	-0.401	8.806
SWY	Safeway Inc.	4500	0.017	2.066	-0.495	9.947
CRM	Salesforce.com	2544	0.108	2.929	0.323	8.109
SNDK	SanDisk Corporation	3800	0.038	4.373	-0.164	13.193
SCG	SCANA Corp	4500	0.032	1.259	0.222	9.761
SLB	Schlumberger Ltd.	4500	0.036	2.426	-0.287	7.636
SNI	Scripps Networks Interactive Inc.	1544	0.040	2.061	0.344	13.583
STX	Seagate Technology	2928	0.068	3.089	-0.541	13.792
SEE	Sealed Air Corp.(New)	4500	0.014	2.495	-2.106	97.491
SRE	Sempra Energy	4048	0.051	1.617	-0.392	13.869
SHW	Sherwin-Williams	4500	0.052	1.900	-0.376	14.791
SIAL	Sigma-Aldrich	4500	0.052	1.989	0.409	20.303
SPG	Simon Property Group Inc	4500	0.061	2.179	0.269	21.433
SJM	Smucker (J.M.)	4500	0.048	1.597	0.836	15.189
SNA	Snap-On Inc.	4500	0.037	1.888	0.032	10.904
SO	Southern Co.	4500	0.046	1.256	0.288	8.677
LUV	Southwest Airlines	4500	0.041	2.360	-0.396	10.606
SWN	Southwestern Energy	4300	0.073	3.077	-0.411	17.097
SE	Spectra Energy Corp.	1907	0.039	1.780	0.163	14.496
STJ	St Jude Medical	4500	0.043	2.118	0.030	9.741
SWK	Stanley Black & Decker	4500	0.033	2.054	0.082	8.289
SPLS	Staples Inc.	4500	0.021	2.690	-0.002	8.596
SBUX	Starbucks Corp.	4500	0.064	2.533	-0.294	13.837
HOT	Starwood Hotels & Resorts	4500	0.034	2.624	-0.427	13.932
STT	State Street Corp.	4500	0.036	2.968	-5.796	194.581
SRCL	Stericycle Inc	4500	0.091	2.475	0.475	10.567

SYK	Stryker Corp.	4500	0.057	1.911	0.167	17.769
STI	SunTrust Banks	4500	0.003	2.759	-0.374	23.304
SYMC	Symantec Corp.	0				
SYY	Sysco Corp.	4500	0.042	1.555	0.202	8.386
TROW	T. Rowe Price Group	4500	0.053	2.652	0.136	8.676
TGT	Target Corp.	4500	0.046	2.199	0.021	8.731
TEL	TE Connectivity Ltd.	1795	0.029	2.337	0.111	9.243
TE	TECO Energy	4500	0.014	1.727	-0.999	30.381
THC	Tenet Healthcare Corp.	4500	-0.002	3.294	-1.751	58.170
TDC	Teradata Corp.	1720	0.026	2.378	-0.516	8.488
TSO	Tesoro Petroleum Co.	4500	0.050	3.511	-0.406	12.904
TXN	Texas Instruments	4500	0.045	2.802	0.124	6.697
TXT	Textron Inc.	4500	0.015	2.719	-0.741	32.909
HSY	The Hershey Company	4300	0.037	1.509	0.755	21.109
TRV	The Travelers Companies Inc.	4400	0.034	1.976	0.347	16.010
TMO	Thermo Fisher Scientific	4500	0.029	2.031	0.186	9.479
TIF	Tiffany & Co.	4000	0.060	2.678	0.155	9.272
TWX	Time Warner Inc.	4500	0.068	2.809	-0.032	9.923
TWC	Time Warner Cable Inc.	1902	0.062	1.982	-0.115	9.283
TJX	TJX Companies Inc.	4500	0.074	2.175	0.086	8.550
TMK	Torchmark Corp.	4500	0.041	2.004	-0.097	15.446
TSS	Total System Services	4500	0.016	2.093	-0.670	12.955
TSCO	Tractor Supply Company	4500	0.085	2.728	-0.083	13.304
RIG	Transocean	4500	-0.004	2.866	-0.131	6.278
TRIP	TripAdvisor	0				
FOXA	Twenty-First Century Fox	4500	0.035	2.262	0.286	10.375
TSN	Tyson Foods	4500	0.018	2.403	-0.561	12.665
TYC	Tyco International	4500	0.018	2.871	-4.870	139.626
USB	U.S. Bancorp	4500	0.030	2.370	-0.573	21.019
UA	Under Armour	2187	0.085	3.234	-0.201	11.151
UNP	Union Pacific	4500	0.051	1.841	-0.232	6.856
UNH	United Health Group Inc.	4500	0.064	2.326	-0.756	26.574
UPS	United Parcel Service	3702	0.019	1.463	0.076	10.617
MLM	Martin Marietta Materials	4500	0.041	2.111	0.161	7.882
URI	United Rentals. Inc.	4179	0.030	3.553	-0.709	12.933
UTX	United Technologies	4500	0.047	1.811	-1.022	23.729
UHS	Universal Health Services. Inc.	4500	0.064	2.066	-0.481	9.872
UNM	Unum Group	4500	0.006	2.911	-2.959	54.296
URBN	Urban Outfitters	4500	0.066	3.262	-0.761	18.928
VFC	V.F. Corp.	4500	0.055	1.893	0.176	8.122

VLO	Valero Energy	4500	0.060	2.639	-0.345	8.053
VAR	Varian Medical Systems	3700	0.062	2.064	0.408	11.382
VTR	Ventas Inc	4338	0.048	2.726	-0.568	22.561
VRSN	Verisign Inc.	4151	0.042	4.116	-0.672	20.286
VZ	Verizon Communications	4500	0.029	1.721	0.149	8.071
VRTX	Vertex Pharmaceuticals Inc	4500	0.041	3.905	0.563	20.234
VIAB	Viacom Inc.	2177	0.026	2.125	0.047	17.927
V	Visa Inc.	1603	0.057	2.123	-0.138	10.022
VNO	Vornado Realty Trust	4500	0.053	2.192	0.177	19.152
VMC	Vulcan Materials	4500	0.030	2.136	0.329	7.785
WMT	Wal-Mart Stores	4300	0.038	1.678	0.111	7.330
WAG	Walgreen Co.	4500	0.044	1.882	-0.128	9.667
DIS	The Walt Disney Company	4500	0.033	2.054	-0.059	10.533
WM	Waste Management Inc.	4500	0.016	2.004	-2.576	73.298
WAT	Waters Corporation	3700	0.028	2.561	-1.254	22.563
WLP	WellPoint Inc.	3209	0.049	2.012	-1.639	30.750
WFC	Wells Fargo	4500	0.044	2.527	0.798	26.370
WDC	Western Digital	4500	0.028	4.168	0.348	11.916
WU	Western Union Co	1970	-0.014	2.310	-1.907	35.247
WY	Weyerhaeuser Corp.	4500	0.025	2.164	-0.139	7.430
WHR	Whirlpool Corp.	4500	0.034	2.432	0.146	7.570
WFM	Whole Foods Market	4500	0.058	2.702	-0.111	18.807
WMB	Williams Cos.	4500	0.039	3.704	-3.087	143.440
WIN	Windstream Communications	2384	0.026	1.748	0.130	12.958
WEC	Wisconsin Energy Corporation	4500	0.041	1.209	-0.106	7.501
WYN	Wyndham Worldwide	2022	0.056	3.407	-0.574	25.232
WYNN	Wynn Resorts Ltd	2960	0.103	3.123	0.356	10.625
XEL	Xcel Energy Inc	4500	0.026	1.784	-4.614	136.020
XRX	Xerox Corp.	4500	-0.009	2.989	-0.568	20.214
XLNX	Xilinx Inc	4500	0.033	3.246	-0.092	7.023
XL	XL Capital	4500	0.007	3.343	-1.927	99.881
XYL	Xylem Inc.	0	0.000	0.000	0.000	0.000
YHOO	Yahoo Inc.	4500	0.089	3.735	0.231	10.546
YUM	Yum! Brands Inc	4244	0.054	2.025	-0.131	11.213
ZMH	Zimmer Holdings	2990	0.033	1.745	-0.528	12.697
ZION	Zions Bancorp	4500	0.009	2.972	-0.119	18.772
ZTS	Zoetis	0				

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