Equity portfolio diversification with high frequency data.

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Abstract

Investors wishing to achieve a particular level of diversification may be misled on how many stocks to hold in a portfolio by assessing the portfolio risk at different data frequencies. High frequency intradaily data provide better estimates of volatility, which translate to more accurate assessment of portfolio risk. Using 5-minute, daily and weekly data on S&P500 constituents for the period from 2003 to 2011 we find that for an average investor wishing to diversify away 85% (90%) of the risk, equally weighted portfolios of 7 (10) stocks will suffice, irrespective of the data frequency used or the time period considered. However, to assure investors of a desired level of diversification 90% of the time, instead of on average, using low frequency data results in an exaggerated number of stocks in a portfolio when compared with the recommendation based on 5-minute data. This difference is magnified during periods when financial markets are in distress, as much as doubling during the 2007-2009 financial crisis.

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Given the advantages of diversification, many experts recommend maximum diversification, also known as "buying the market portfolio." For an individual, constructing such a portfolio is difficult to say the least. Index funds that track market portfolios provide a good and less costly alternative. However, for actively managed funds, the large number of assets can result in elevated fund fees. If portfolio diversification can be achieved with a relatively small number of stocks, the need for funds comprising large numbers of assets might not be justified.

We trace the dynamics of the number of portfolio holdings, hereafter portfolio size, required to achieve a fixed level of diversification using 5-minute, daily and weekly data for the US equity market through the 2003-2011 period. Additionally, instead of assuming a fixed level of diversification, we fix the portfolio sizes at 5, 10, 20, 30 and 40 stocks and trace

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the dynamics of diversification level through time. Early literature based on (semi-) annual and quarterly data and using standard deviation as a risk metric suggested that portfolios of 8 to 16 stocks are sufficient to achieve most of the available diversification benefits (Evans and Archer, 1968; Fisher and Lorie, 1970; Jennings, 1971; Fielitz, 1974; Johnson and Shannon, 1974). Subsequent work using monthly data supports a range of between 10 and 20 stocks (Klemkosky and Martin, 1975; Bloomfield, Leftwich, and Long, 1977; Bird and Tippett, 1986; Statman, 1987; Beck, Perfect, and Peterson, 1996; Brands and Gallagher, 2005). Solnik (1974) used weekly data for 8 international markets and found similar results. We are only aware of one study utilizing daily data to examine diversification; Domian, Louton, and Racine (2007). However, they estimate terminal wealth and terminal wealth standard deviation: measures independent of the data frequency. Although many studies investigate asset correlations using high frequency data and discuss its implications for portfolio diversification, e.g. Silvapulle and Granger (2001), we found no references to works directly exploring the benefits of using high frequency data for portfolio diversification.

High frequency data demonstrably improves estimation of risk. A range of efficient estimators has been developed offering a more accurate estimation of financial risk (see McAleer and Medeiros (2008) for an excellent survey on realized estimators), and in many applications high frequency data offers considerable gains to decision making. For example, realized volatility constructed from intraday data outperforms daily measures in forecasting future volatility (Blair, Poon, and Taylor, 2001; Andersen, Bollerslev, Christoffersen, and Diebold, 2006; Patton and Sheppard, 2009) and may improve hedging outcomes (Lai and Sheu, 2010). It has led to a considerable improvement in our understanding of how the data generating process of financial prices may be characterized (see particularly Aït-Sahalia and Jacod, 2012) and begun to improve our understanding of how price disruptions may be correlated across different assets and asset classes (see for example Dungey, McKenzie, and Smith, 2009; Todorov and Bollerslev, 2010). This approach is not without difficulties, however. Higher frequency sampling comes with the cost of microstructure noise, which can result in biased estimates. Although optimal sampling frequencies are the subject of ongoing research building from Bandi and Russell, 2006, currently a commonly accepted compromise in using high frequency data is to sample at 5 minute intervals (for example Wasserfallen and Zimmermann, 1985; Andersen and Bollerslev, 1997; Dacorogna, 2001; Hansen and Lunde, 2006; Lahaye, Laurent, and Neely, 2011).

This paper examines how the use of higher frequency data may affect recommendations for the number of stocks required to reduce risk to some pre-specified level. We compare results calculated using weekly, daily and 5 minute observations for equally weighted portfolios drawn from the S&P500 constituent list over 2003 to 2011 for investors who wish to diversify 85% (90%) of risk. As a sample average it turns out that portfolios of 7(10) stocks will suffice irrespective of the frequency of price observation. However, tightening the risk reduction criteria so that the investor achieves the desired (85% or 90%) reduction in diversifiable risk in 90% of the time during the sample leads to quite different results. In this instance, examining higher frequency data allows us to dramatically reduce the number of stocks required to achieve the required risk reduction. Lower frequency sampling overstates the number of stocks required, and this is particularly evident during periods of market stress. Evidence from fixing the portfolio size vividly demonstrates that although during quiescent periods the difference in diversifiable risk assessed at different data frequencies is minimal, during periods of high volatility, when estimation of risk is key, the difference in diversifiable risk is quite pronounced. Using lower frequency data exaggerates estimates of diversifiable risk during periods of financial distress.

The paper proceeds as follows. Section I presents data and methodology, and Section II, presents the empirical results, followed by a conclusion in Section III.

I. Data and Methodology

Our data are obtained from Thomson Reuters Tick-History via SIRCA and consist of 5 minute intraday prices on constituents of the S&P500 index from 2003 to 2011 during the trading day of 9:30 to 16:00 EST. Following convention, the intraday data are drawn as the last trade conducted during the 5 minute interval. The original data set consists of over 900 stocks from the constituent list of S&P500 (RIC code #0.SPX in the database). Only the stocks traded on NYSE and Nasdaq are retained; for details see Dungey, Luciani, and Veredas (2012). The choice of 5 minute data is consistent with the existing literature across a range of assets. The data do not consist of all stocks in the S&P500 during the sample period, the data were selected to allow for a balanced panel in estimation subperiods, as discussed below, thus we do not totally account for survivorship bias. However, each of the measures we calculate, at differing frequency, face the same draw of companies. The sample contains 502 stocks over the sample period, and these are listed in a web appendix (attached to this submission for convenience).

Days in the sample are indexed by $t = 1, ..., T$. Each day is divided into 5-minute intervals indexed by $i = 0, ..., I$. The current price of an asset is then denoted by $S_{t,i}$, and the continuously compounded return $r_{t,i}$ is calculated as

$$r_{t,i} = \begin{cases} ln\left(\frac{S_{t,i}}{S_{t,i-1}}\right) & \text{for } i \geq 1 \\ ln\left(\frac{S_{t,i}}{S_{t-1,I}}\right) & \text{for } i = 0 \end{cases} \tag{1}$$

The second term in equation (1) represents the overnight return, and is deleted from the sample[1], leading to a total number of return observations of $T \times I$. In order to match the volatility measures, daily observations are obtained based on the transaction price at the last grid-point time in day t. Similarly, weekly observations are obtained using the last grid-point time in each week. This ensures that identical transaction data are used for each frequency, and the only thing that we are changing is the length of the grid blocks. We use the same data set to get daily, $r_t^{(d)}$, and weekly, $r_t^{(w)}$, returns and define these below as

$$r_t^{(d)} = ln\left(\frac{S_{t,I}}{S_{t-1,I}}\right) \tag{2}$$

$$r_t^{(w)} = ln\left(\frac{S_{t,I}}{S_{t-5,I}}\right) \tag{3}$$

Daily realized variance (RV) is constructed as the sum of squared intraday returns

$$RV_{(r),t} = \sum_{i=1}^{I} r_{t,i}^2 \tag{4}$$

and the average RV for a period from $t = 1$ to T is found as

$$\overline{RV}_{(r)} = \frac{1}{T}\sum_{t=1}^{T} RV_{(r),t} = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{I} r_{t,i}^2 \tag{5}$$

Figure 1 provides some descriptive statistic on each of the S&P500 constituents ranked by the magnitude of the average RV. Securities with high average RV have lower average returns. Similar to Andersen, Bollerslev, Diebold, and Ebens (2001) we find that the unconditional distributions of realized variances are strongly right-skewed.

The corresponding measure of realized covariance, $RCov$, is expressed as

$$RCov_{(r_1 r_2),t} = \sum_{i=1}^{I} r_{1,t,i}^2 r_{2,t,i}^2 \tag{6}$$

and the average $RCov$

$$\overline{RCov}_{(r_1 r_2)} = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{I} r_{1,t,i}^2 r_{2,t,i}^2. \tag{7}$$

Realized correlation on day t is computed as

[1] We performed estimations inclusive of overnight returns and observed only slight change in our results with our main conclusion intact. Thus we omit these results from the paper for brevity but they are available upon request.

$$\rho_{(r_1 r_2),t} = \frac{\sum_{i=1}^{I} r_{1,t,i}^2 r_{2,t,i}^2}{\sqrt{\sum_{i=1}^{I} r_{1,t,i}^2 \sum_{i=1}^{I} y_{t,i}^2}} = \frac{RCov_{(r_1 r_2),t}}{\sqrt{RV_{(r_1),t} RV_{(r_2),t}}}. \tag{8}$$

The average realized correlation, $\overline{\rho}_{(r_1 r_2)}$, for a period from $t = 1$ to T is found as

$$\overline{\rho}_{(r_1 r_2)} = \frac{1}{T} \sum_{t=1}^{T} \frac{\sum_{i=1}^{I} r_{1,t,i}^2 r_{2,t,i}^2}{\sqrt{\sum_{i=1}^{I} r_{1,t,i}^2 \sum_{i=1}^{I} r_{2,t,i}^2}} \neq \frac{\sum_{t=1}^{T} \sum_{i=1}^{I} r_{1,t,i}^2 r_{2,t,i}^2}{\sqrt{\sum_{t=1}^{T} \sum_{i=1}^{I} r_{1,t,i}^2 \sum_{t=1}^{T} \sum_{i=1}^{I} r_{2,t,i}^2}} = \frac{\overline{RCov}_{(r_1 r_2)}}{\sqrt{\overline{RV}_{(r_1)} \overline{RV}_{(r_2)}}}. \tag{9}$$

Note that the left-hand side and right-hand side of (9) are not equivalent when $T \neq 1$, and as t increases the measures become more differentiated. Our methodology does not rely on the correlation estimates. Instead, we calculate unconditional correlations in Table 1 for comparison and illustrative purposes. This paper adopts the right hand side measure because we find it more appropriate to capture the average of daily measures for comparison with other metrics.

We construct portfolios by randomly drawing n stocks without replacement from the entire sample in a particular time period. We use the same draw of stocks in estimation of risk metrics for each data frequency to avoid sample selection bias. Our portfolios are equally weighted to give a portfolio P_m^n, where $n = 1..N$ indicates the number of stocks in the portfolio, N is the total number of stocks available in the dataset during the subperiod analyzed, and $m = 1..M$ represents the draw number. Given that our sample includes non-surviving stocks, if a stock that is part of the chosen portfolio does not survive an initial period it is replaced with another randomly selected stock not already in the portfolio in the subsequent period.

We construct $M = 5,000$ n-stock portfolios for each $n = 1..N$, unless the number of combinations of n stocks out of N available is lower than M. For example, when $n = 1$, the number of unique single security portfolios equals N and when $n = N$ only one equally weighted portfolio can be constructed - we define it as the market portfolio. We find that 5,000 replications are sufficient to give a robust measure of central tendency of our risk measures.

For $n = 1..N$ the return of the n-stock equally weighted random portfolio m is defined as

$$P_{m,\tau}^n = \sum_{j=1}^{n} \frac{\{r_{j,\tau}\}_m}{n} \tag{10}$$

where τ is an equidistant time index defined as $\tau = 1..T \times I$ for intraday returns, $\tau = 1..T$

for daily and $\tau = 1..\lfloor T/5 \rfloor$ for weekly.[2]

The average time series return over time of portfolio m can be expressed as

$$\bar{P}_m^n = \sum_{\tau} \frac{P_{m,\tau}^n}{sup(\tau)} \tag{11}$$

where $sup(\tau)$ in the denominator of (11) allows us to refer to either the 5 minute, daily of weekly samples as appropriate. Let Ω_m^n represent a risk measure of an n-stock portfolio m. We define the average risk metric of M portfolios, each of size n, as follows:

$$\overline{\Omega^n} = \sum_{m=1}^{M} \frac{\Omega_m^n}{M} \tag{12}$$

When equally weighted, the market portfolio consisting of all available securities is a unique portfolio, and $\overline{\Omega^N} = \Omega^N$. If $\overline{\Omega^1}$ and Ω^N are risk metrics for the average single-stock and market portfolios, we can define a scaled and standardized measure of diversification for an n-stock portfolio that adjusts for the average security risk and for the level of market risk. To derive the required number of securities for portfolios with a given level of diversifiable risk, we find it convenient to define a measure exclusively focused on diversifiable risk that is bounded from 0 to 1 as follows:

$$\eta\left(n\right) = \frac{\overline{\Omega^n} - \Omega^N}{\overline{\Omega^1} - \Omega^N} \tag{13}$$

We show the graphical representation of this measure in Figure 2 with a solid curve. Of course, the simplest way to express diversification is to plot the total risk against the portfolio size ($\overline{\Omega^n}$ vs. n). Often, it is convenient to look at diversifiable risk only ($\overline{\Omega^n} - \Omega^N$ vs. n). However, when comparing multiple periods with different levels of total risk and non-diversifiable risk, it is best to standardize the diversification measure (as in equation 13 and as shown in Figure 2).

In addition, for a series of random draws of n-stock portfolios, let Ω_q^n be a qth percentile of a risk measure Ω^n. Similar to (13) we define:

$$\eta\left(n, q\right) = \frac{\Omega_q^n - \Omega^N}{\overline{\Omega^1} - \Omega^N} \tag{14}$$

and depict (14) in Figure 2 with a dashed curve.

Despite its drawbacks, standard deviation is most commonly used in the finance literature

[2]We recognize that aggregating log returns cross-sectionally is not the same as the log of aggregated simple returns, however the difference is small especially for 5 minute returns, and does not qualitatively affect our relative diversification measure in equation (13).

as a measure of risk. The standard deviation of a portfolio is defined as follows:

$$\Omega_m^n \equiv \sigma_m^n = \sqrt{\sum_\tau \frac{\left(P_{m,\tau}^n - \bar{P}_m^n\right)^2}{\sup(\tau) - 1}} \tag{15}$$

and the average standard deviation of M random portfolios, each of size n is

$$\overline{\sigma^n} = \sum_{m=1}^{M} \frac{\sigma_m^n}{M} \tag{16}$$

We derive the standard deviations based on daily data and weekly data. Average realized variance for the period is defined analogously to equation (5) as

$$\Omega_m^n \equiv \overline{RV^n} = \sum_{m=1}^{M} \frac{RV_m^n}{M} \tag{17}$$

Finally we require a choice of the target risk reduction via diversification. Our methodology assumes that portfolio total risk is comprised of systematic risk and specific or non-systematic risk. As the number of securities included in a portfolio approaches the number of securities in the market, the portfolio risk approaches the overall level of systematic risk - that is, market risk, suggesting a relationship which behaves as a decreasing asymptotic function. Reduction in portfolio risk can then be achieved up to the point where the incremental decrease in non-systematic risk brings insignificant benefits. Larger portfolios, however, are associated with higher transaction costs. We follow the existing literature which finds that an 85 to 95% reduction in risk via diversification is optimal (see Fisher and Lorie, 1970; Copp and Cleary, 1999; Kryzanowski and Singh, 2010 for empirical applications and discussions in Elton and Gruber, 1977; Tang, 2004 based on theoretical results). The next section presents results based on 85 and 90 percent risk reductions.

II. Results

Figures 3 and 4 depict the portfolio size needed to achieve desired level of risk reduction for an average investor and for investors requiring a particular level of diversification 90% of the time. For example, investors wishing to reduce the level of diversifiable risk in their portfolios by 85% (see Figure 3), require 7 stocks on average irrespective of the frequency of the data or the time period analysed (Figure 3, solid lines). This is consistent with previous literature. Fisher and Lorie (1970) suggest portfolios of 8 to 16 stocks to achieve 85% reduction, while Evans and Archer, 1968; Johnson and Shannon, 1974; Klemkosky and Martin, 1975 suggest portfolios comprising of as little as 3 to 10 stocks to achieve optimal diversification without specifying the exact percentage reduction in diversifiable risk.

However, in the first part of our sample period (prior to financial crisis) to assure investors of the desired level of diversification 90% of the time instead of on average, the portfolio requirements suggest portfolios of 13-16 stocks when using daily data and 14-19 stocks when using weekly data (Figure 3, dashed lines). This is compared to portfolios of size 11-15 when using realized volatility as a risk measure with 5-minute data.

Figure 3 shows that there is considerable departure in the estimated numbers of stocks with different frequencies through time. In the earlier part of the sample, up until the second quarter of 2007, the disparities are not large. However, the advent of a period of financial stress, from the second half of 2007, and most particularly from third quarter of 2008 to first quarter 2009 associated with the collapse of Lehman Bros, rescue of AIG, the TARP program and complex negotiations concerning Bear-Stearns amongst other crisis events, changes this conclusion. While using realized variance as a risk measure, investors holding anywhere from 20 to 29 stocks can achieve 85% reduction in diversifiable risk 90% of the time, while the results using daily and weekly data suggest portfolios that at times are twice as large.

Figure 4 shows similar results for a 90% reduction of diversifiable risk. An average investor achieves 90% reduction in diversifiable risk with only 10-11 stocks. This result is consistent across the risk measures and time periods and conforms to previous findings in the literature. Portfolio sizes required to achieve 90% reduction in diversifiable risk 90% of the times differ across measures and these difference is substantial during periods of market distress with larger recommended portfolio sizes when assessed with lower frequency data.[3]

Our results indicate that if the investor is concerned with reducing the diversifiable risk on average, then the choice among weekly, daily or 5-minute data will not have any impact on that decision. However, to assure the investor of the desired risk reduction level 90% of the time, using 5-minute data significantly lowers the number of stocks required in the portfolio. When the microstructure noise is removed, we argue that data with higher frequency provides a more accurate estimation of portfolio risk resulting in a lower confidence band around the average estimated portfolio size requirement. Using daily or weekly data frequency to arrive at the portfolio size recommendation may exaggerate and mislead investors wanting a particular degree of assurance (85% or 90% of the time instead of achieving the set level of diversifiable risk reduction on average).

We admit that this reduction in portfolio size requirement might be subject to a number of important omissions, such as overnight trade and microstructure noise present in high frequency data. We have attempted to minimise these problems by avoiding the thin

[3]We conducted the same exercise but using median as our central tendency measure and the results are qualitatively similar and only marginally quantitatively different. The results are available upon request.

overnight markets and concentrating on the constituents of S&P500 only, which are heavily traded, instead of all securities listed on US national markets. Asymptotically, our derived diversification measure in equation 13 is quite appealing. It is unaffected by the inclusion or exclusion of overnight returns which makes it useful in a high frequency data setting. It is also unaffected by the scaling of the standard deviation or realized variance - which enables us to compare equivalently the sum of squared returns (typically used in realized variance measures) or the sum of squared demeaned returns (e.g., standard deviation). Although our results hold asymptotically, we also confirm empirically that this holds in our sample. These additional results are available upon request.

In Figure 5 instead of assuming a fixed level of diversification, we fix the portfolio at several size levels (i.e., 5, 10, 20, 30 and 40 stock portfolios). The left hand panel shows the percentage of diversifiable risk remaining in a portfolio of these fixed sizes calculated using daily data. The right hand panel gives the same measure but estimated using the 5-minute data. As expected, the diversifiable risk remaining in a portfolio reduces with the number of stocks. The levels of diversification are broadly consistent in both panels during the quiescent period (2003-early 2007). The crisis period (late 2007 - 2009), is characterised by a dramatic increase in the estimated diversifiable risk suggesting the need for larger portfolios, consistent with Figures 3 and 4. However, the diversification results from the 5-minute data provide more reliable estimates since the underlining volatility measures are known to be more accurate when estimated using high frequency data (see Blair, Poon, and Taylor, 2001; Andersen, Bollerslev, Christoffersen, and Diebold, 2006; Patton and Sheppard, 2009). The heightened level of diversifiable risk indicated with the daily data suggest excessively large portfolios, sometimes more than doubling the number of stocks held suggested by the 5-minute estimates. Working with an even lower frequency data, such as monthly, is only likely to exacerbate this problem.

The availability of a large number of observations, as in the case of high frequency data, enables us to estimate extreme tail risk measures without the need for model-based bootstrap techniques, which may suffer from model estimation biases. Thus relying on historical observations only, we are able to estimate expected shortfall measures at 95%, 99% and 99.9 % levels and reconstruct in Figure 6 the recommended portfolio sizes to achieve 90% reduction in diversifiable risk along with the confidence bands needed to assure this reduction 90% of the time. These results are largely consistent with those obtained from Figures 3 and 4. An interesting feature is that as the risk measure becomes more extreme, the recommended portfolio size decreases independently of market conditions. This aspect is worthy of a future separate investigation.

The results in Figures 3 and 4 strongly indicate the difference in portfolio size recommendations during tranquil vs distressed markets. To explore this further we implement the conditional correlation analysis of Silvapulle and Granger (2001) who consider the differences between bear and bull markets. We estimate conditional correlations for portfolios for the period from 2003 to 2011 using one month rolling window with a 12 month estimation period at each estimation point. As we have 502 assets in the data sample, this involves drawing a possible 125,751 combinations of stocks. As in Silvapulle and Granger (2001) we conduct quantile analysis, and concentrate on the upper and lower 5% tails, while presenting also the results for the 'middle' quantile between them. Thus, we anticipate that there may well be fewer than 125,751 combinations in the upper and lower quantiles when particular stocks do not have tail events.

Table 1 shows the average unconditional correlations for each of the full sample and the pre-crisis period prior to July 2007 and the period thereafter, and conditional correlation coefficients for the three quantiles for the same subsamples. The unconditional results show that during the pre-crisis subsample correlation is lower than in the second half of the sample. This increase in unconditional correlation coefficients between a period of tranquility and a period of stress is well recognised in the literature as a sign of stress, for example Butler and Joaquin (2002), although it is necessary to account for the possibility that the observed result may be a simple consequence of increased volatility rather than a sign of distressed conditions; see Forbes and Rigobon (2002). It is clear that the increases in conditional correlation for the middle quantile is less dramatic. However, the increases in correlation for the tail returns is much more pronounced, particularly in the case of the upper tail.

We now examine these characteristics in more detail. The results for the three quantiles are presented in Figure 7 for a 12 month estimation window. The solid line represents the average conditional correlation for the medium quantile with the solid shaded area representing the interquantile range around it. Each point on the graph represents the average conditional correlation calculated from stock returns for the previous and following 6 months, that is the point is the centre of the rolling sample. It is quite clear that the average of the conditional correlations for this medium quantile shows an upward move from values of 0.15 or below prior to the crisis period in mid-2007 and rises steadily to peak in early 2009, consistent with a period of calculation which encompasses the volatile second half of 2008 and the first half of 2009 before the presumed end of the US recession according to NBER dating.

The second rise in the average conditional correlation relates to increased international financial volatility associated with the burgeoning European debt crisis - visible first in Greece in early 2010 (and thus represented in the figure from mid-2009 onwards due to the data centering) and the further escalation of this crisis in 2011. The figure is completely consistent with an analysis of generally rising volatility conditions in financial markets during the crisis period, which will result in rising correlation even without changes in the interrelationships between assets. The pronounced rise in correlation of the stocks in the bear market associated with the crisis originating in the US is consistent with many papers on the poor performance of diversification during periods of stress; for an example in non-equity markets see Knight, Lizieri, and Satchell (2005).

The upper and lower quantiles present interesting variations on the middle quantile result. Up until the crisis period the tail quantiles were not particularly different in profile to the middle quantile. As we would expect their interquantile range is larger, but the point estimates are sometimes below and sometimes above that for the middle quantile. However, in periods of stress the tail quantiles experience a much more notable rise in correlation than the middle quantile - thus the rise in volatility across different assets is demonstrably not the same, lending credence to this measure as representing a change in market interactions not associated with generally increased market volatility. The marked increase in correlations of tail returns during periods of stress was also noted for the lower tail by Silvapulle and Granger (2001).

The difference in lower and higher quantiles in Figure 7 shows two major periods of increase in correlation. These are the period around the US financial crisis, beginning in mid-2008 (and thus visible in the 12 month centred data for the observation around March 2008), when the average correlation in the upper tail rose more than the average correlation in the lower tail. This is consistent with a domestically sourced crisis which corresponded to a domestic recession associated with both flight out of stocks generally, and flight towards relatively higher performing (blue-chip) stocks within the market.

During the rise in correlation associated with the European sovereign debt problems the tail correlations rose more than in the US based crisis period, and the correlation in the lower tail rose more than in the upper tail. In this period the US economy is recovering, albeit slowly, and the outlook for US equity markets is more positive. The finding that the lower tail quantiles are generally more correlated than the middle quantiles is consistent with the existing findings on the behavior of poorly performing stocks; Butler and Joaquin (2002), Silvapulle and Granger (2001). The higher correlation amongst the lower performing stocks may well represent the sluggish nature of the economy in some sectors, particularly if sectors of the economy exhibit differing behaviours.

To investigate the behavior of the lower tails more carefully we conduct the same analysis using the 12 month estimation windows for 9 sectors of the economy; materials, congolmerates, consumer goods, finance, health care, industrials, technology, services and utilities. The results shown in Figure 8 are striking. In almost all cases, during the period associated with the US based crisis and US recession the correlation of the higher performing stocks is greater than the correlation of the lowest performing stocks, but for the materials, conglomerates and technology sectors the lower tail correlations are below those of the middle quantile - they are reacting less than the market to the stressful conditions. The one exception is for consumer goods, where the two tails have an approximately equal rise in correlation, potentially reflecting the sluggish return of consumption in the US recovery. The largest gap between the correlations of the upper and lower tails during the 2010-11 period is for the health care sector.

In the financial sector results, correlations amongst both the highest performing stocks and the lowest performing stocks are below those of the middle quantile stocks. Although this may at first appear counterintuitive the results are consistent with the events. The highest performing stocks in this sector were very diverse as the sector was in complete dissarray - and insurance and banking sector stocks often provided completely different pictures as different support packages and bailouts were announced. Dungey, Luciani, and Veredas (2012) provide a detailed analysis. In the period from 2010, when the European crisis became the dominant concern of international financial markets all sectors of the US market experienced higher correlation amongst the lowest performing stocks than the highest performing tail. This aligns with the usual findings for bear markets, that the lowest performing stocks in the sector are most vulnerable to loss of investor confidence.

III. Conclusion

We find that for investors wishing to diversify away 85% (90%) of the risk, equally weighted portfolios of 7 (10) stocks will suffice irrespective of the data frequency used or the time period considered. However, to assure the investors of the desired level of diversification 90% of the time, the portfolio requirements based on lower frequency data are exaggerated when compared with the results based on the 5-minute data. We find that this difference is greater during the periods when financial markets are in distress. Assuming risk measures based on higher frequency data are superior to their lower frequency based counterparts, investors may not need to hold portfolios as large as otherwise suggested by lower frequency risk measures, especially during financial crisis episodes.

The high frequency data allow us to assess conditional correlations between stocks for moving windows during the sample period. We ascertain that the changes in the correlation between stocks occur during periods of stress, generally increases, but that this is particularly the case for upper and lower tail performing stocks. During the US based crisis period, associated with a domestic recession, correlation amongst the best performing stocks increased more than that between the worst performing stocks. However, during the later period in 2010-11 where the US was recovering and international financial markets were stressed by international events originating in Europe, correlation between the lowest performing stocks exceeded that of the worst performing stocks, consistent with existing literature that domestic stocks behave differently when highly correlated with an international bear market.

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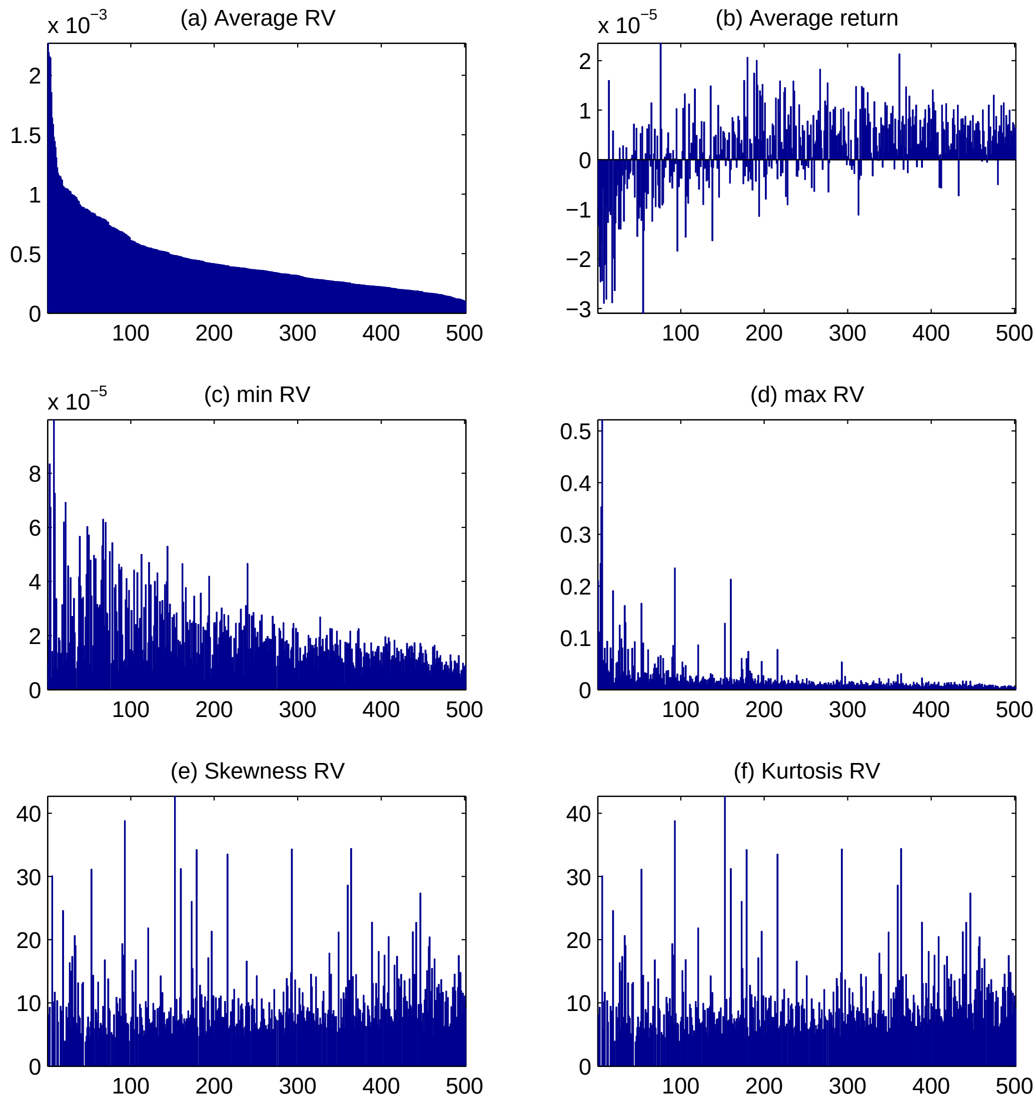


Figure 1: Descriptive statistic. The horizontal axis represents the index for each of the S&P 500 constituents ranked by the magnitude of the average RV. Similar to Andersen, Bollerslev, Diebold, and Ebens (2001) we find that the unconditional distributions of realized variances are highly right-skewed.

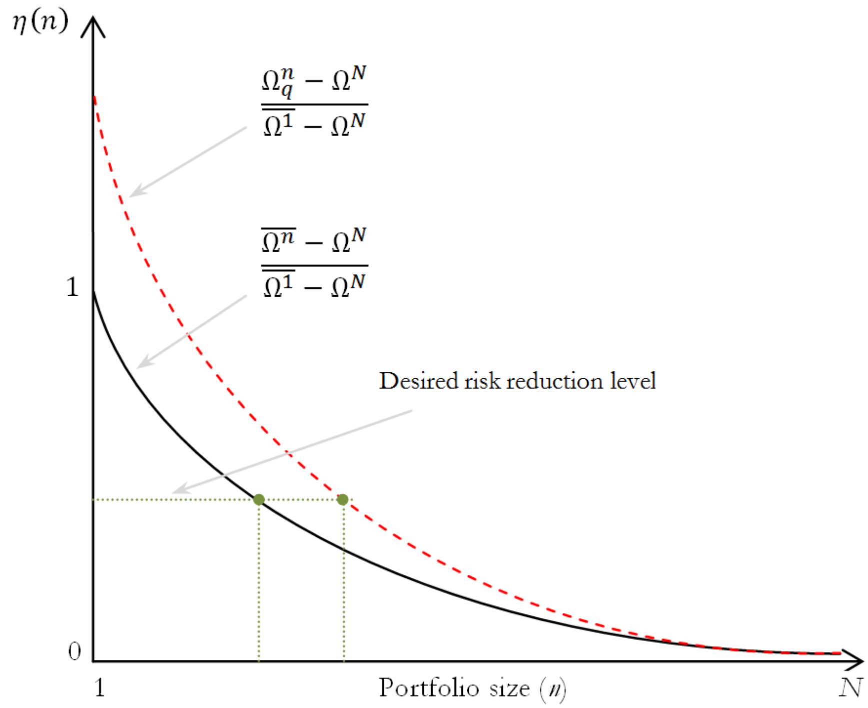


Figure 2: Standardized risk as a function of portfolio size. The solid black curve represents the average standardized risk measure as defined in (12). The dashed red curve represents the qth percentile of the standardized risk measure and is defined in (13).

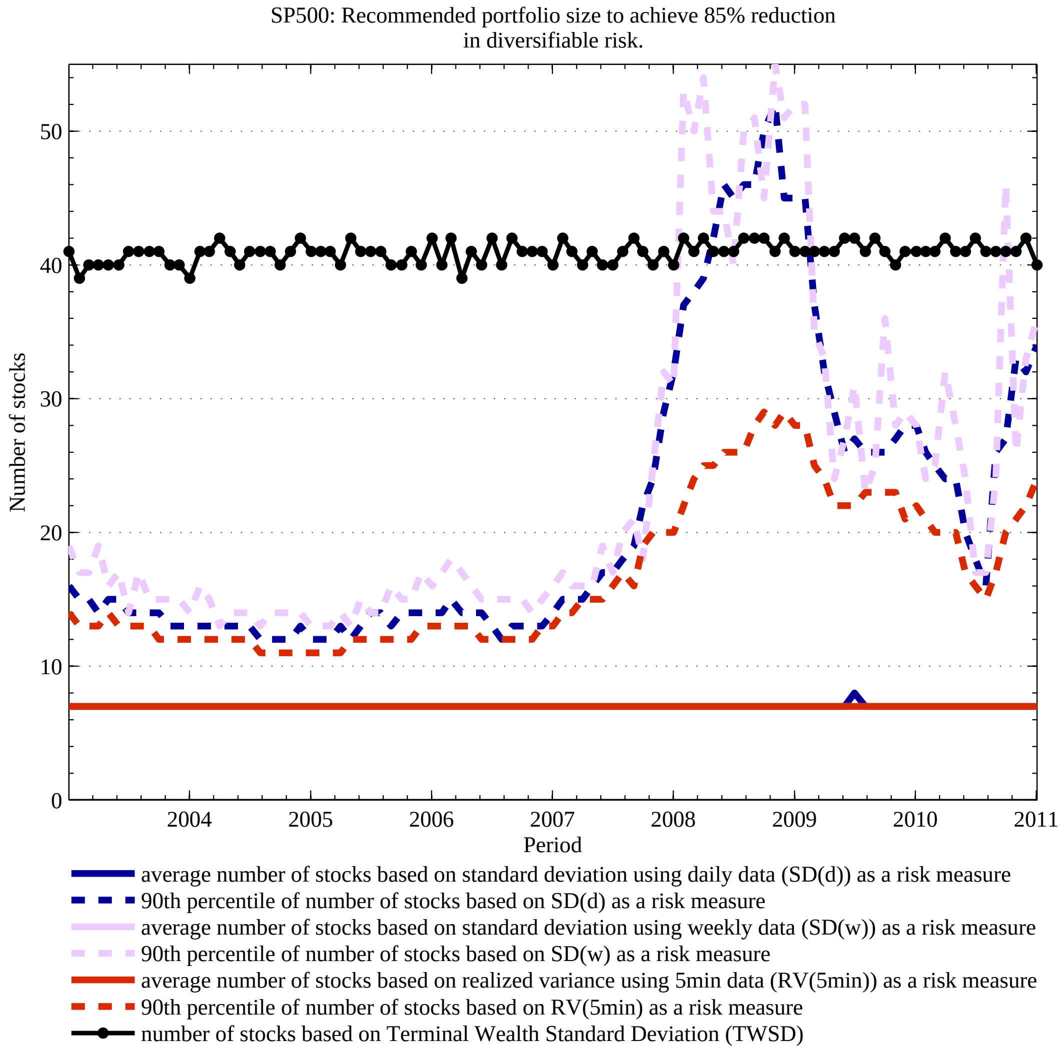


Figure 3: Portfolio size requirement for 85% reduction in diversifiable risk. The figure depicts portfolio size recommendations through time and across three different risk measure based on 5-minute, daily and weekly frequencies. We use realized variance as a measure of risk using 5-minute data, standard deviation with daily and weekly data. We have also derived recommendations based on sum of squared returns using daily and weekly data to make it equivalent to realized volatility. Our results were identical to the ones obtained from standard deviation for both weekly and daily. Portfolio size recommendations based on risk measure with higher frequency data are generally smaller. The difference is minimal during the normal market conditions and exacerbated during the periods of market distress. To obtain the results we repeat the analysis every month using one year of past data.

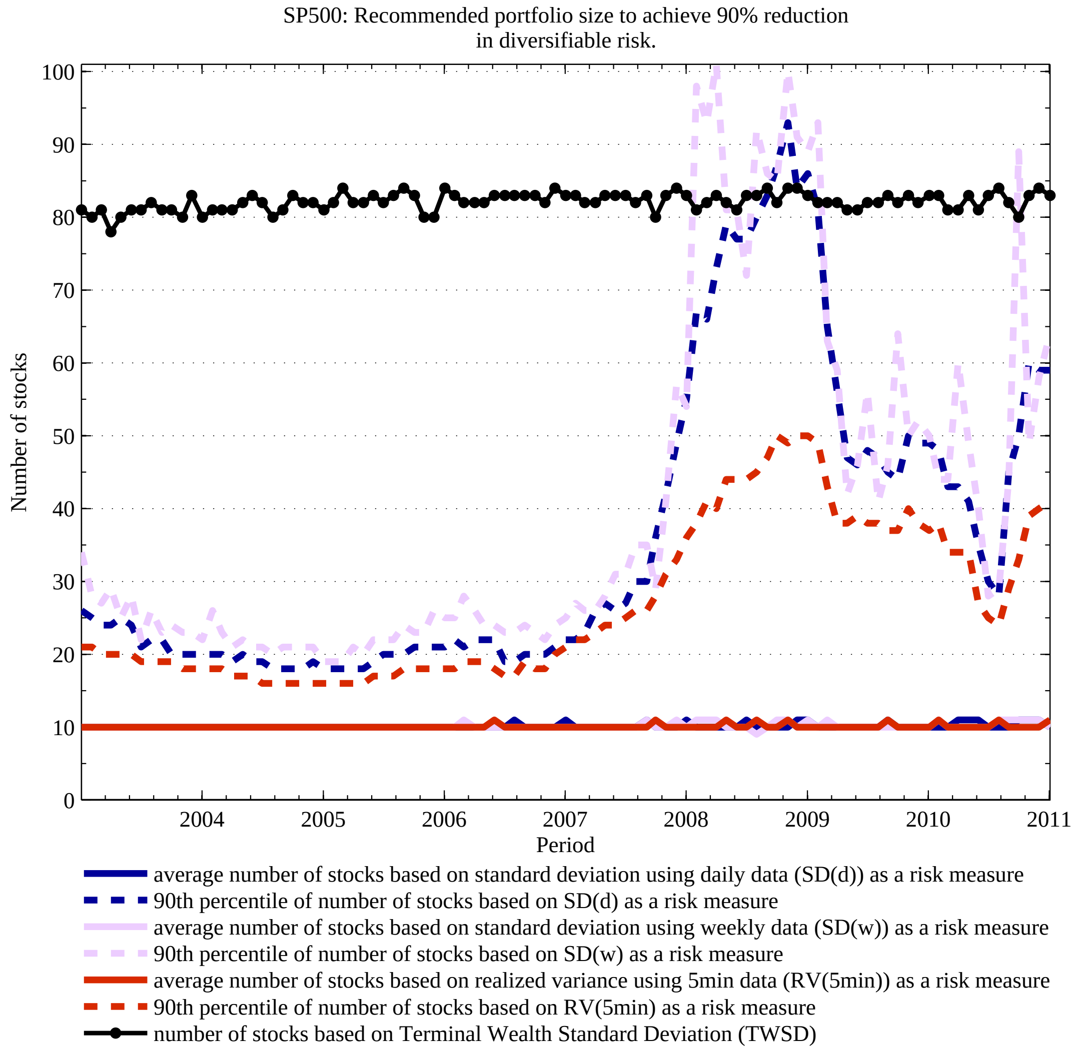


Figure 4: Portfolio size requirement for 90% reduction in diversifiable risk. The figure depicts portfolio size recommendations through time and across three different risk measure based on 5-minute, daily and weekly frequencies. We use realized variance as a measure of risk using 5-minute data, standard deviation with daily and weekly data. We have also derived recommendations based on sum of squared returns using daily and weekly data to make it equivalent to realized volatility. Our results were identical to the ones obtained from standard deviation for both weekly and daily. Portfolio size recommendations based on risk measure with higher frequency data are generally smaller. The difference is minimal during the normal market conditions and exacerbated during the periods of market distress. To obtain the results we repeat the analysis every month using one year of past data.

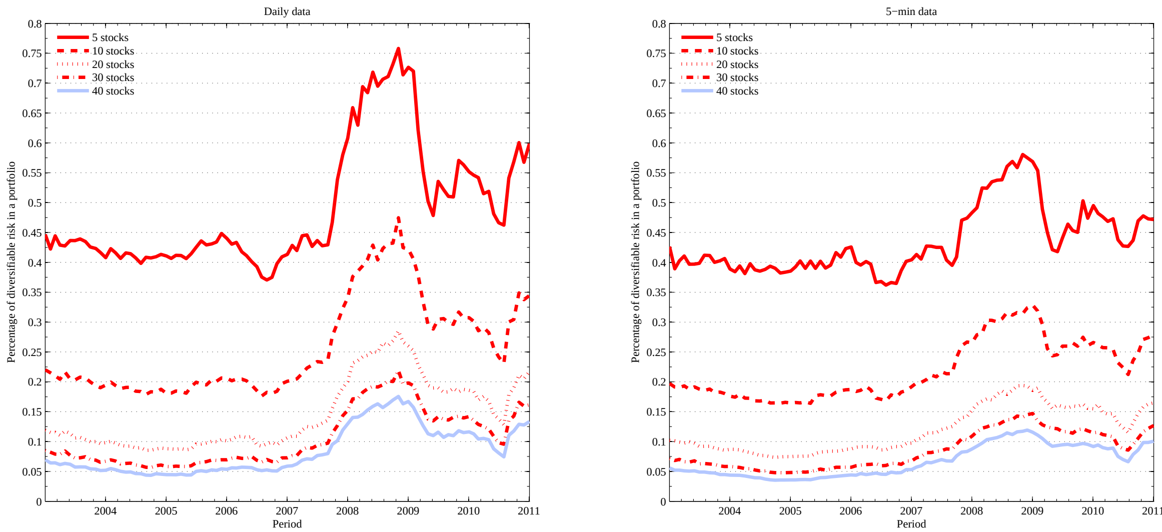


Figure 5: Diversifiable risk remaining for portfolios of various sizes. As the number of stocks in portfolios increases the percentage of diversifiable risk decrease changes over the years. The panels above show the dynamics of diversifiable risk remaining for portfolios of various sizes. Results are obtained for an investor seeking to diversify with assurance 90% of the time. The left panel is based on standard deviations with daily data; the panel on the right uses 5-minute data and is based on the realized volatility.

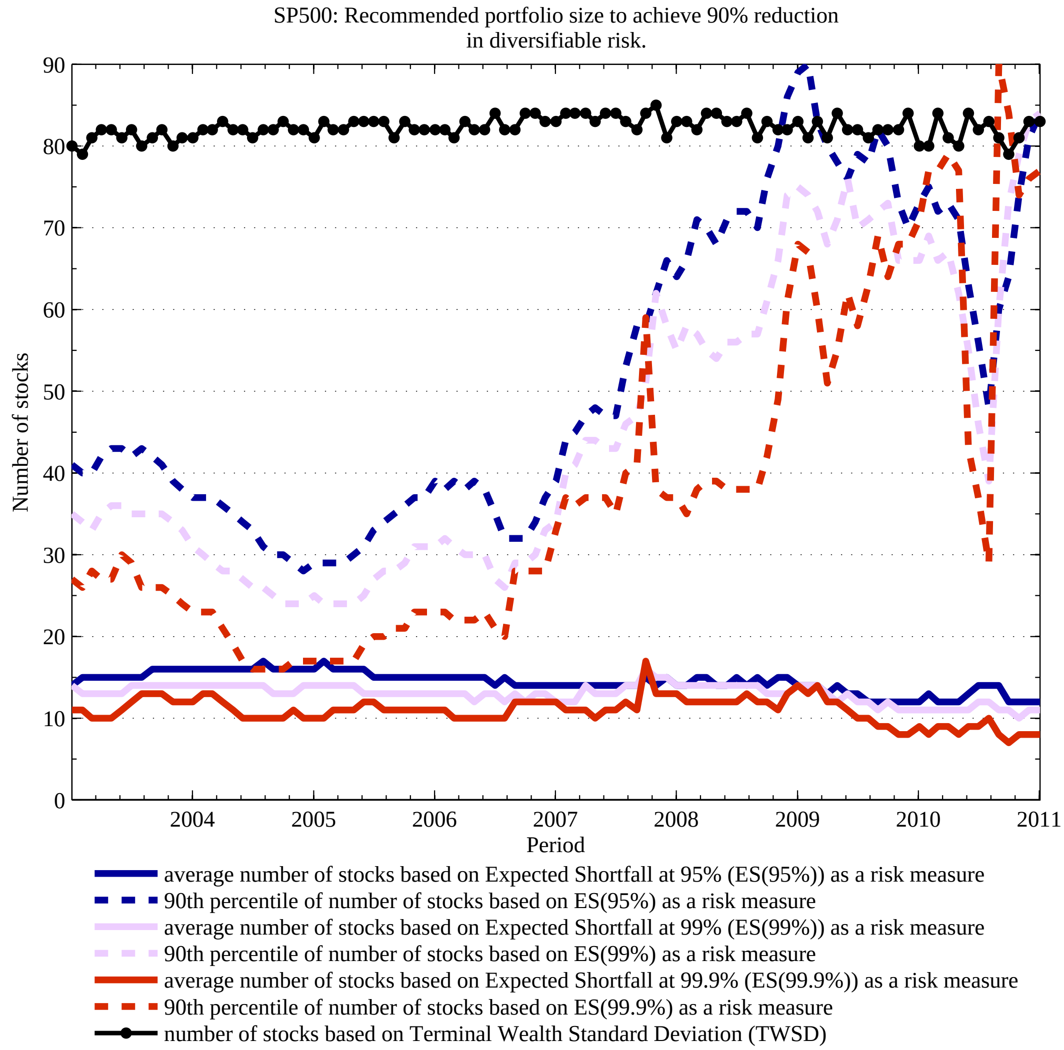


Figure 6: Portfolio size requirement for 90% reduction in diversifiable risk. The figure depicts portfolio size recommendations through time and across three different risk measure based on 5-minute. We use expected shortfall as a measure of risk using 5-minute data, and calculate expected shortfall values at 95%, 99% and 99.9% levels. Portfolio size recommendations based on expected shortfall with extreme losses are generally smaller. To obtain the results we repeat the analysis every month using one year of past data.

Table 1: CONDITIONAL CORRELATION COEFFICIENTS. The table shows average unconditional correlations for each of; the full sample and the pre-crisis period prior to July 2007 and the period thereafter, and conditional correlation coefficients for the three quantiles for the same subsamples.

Correlation	**Full period**	**01.2003-06.2007**	**07.2007-12.2011**
	Unconditional correlation, ρ_i		
Average	0.3278	0.1899	0.3945
[min; max]	[0.0716; 0.7718]	[0.0111; 0.7041]	[0.0752; 0.8195]
IQR	[0.2784; 0.3725]	[0.1346; 0.2354]	[0.3417; 0.4428]
	Conditional correlation (middle), ρ_{Mi}		
Average	0.2034	0.1393	0.2717
[min; max]	[0.0767; 0.5890]	[0.0249; 0.5459]	[0.1154;0.6760]
IQR	[0.1703; 0.2292]	[0.1038; 0.1688]	[0.2298; 0.3067]
	Conditional correlation (5% lower tail), ρ_{Li}		
Average	0.3623	0.1364	0.3617
[min; max]	[0.0131; 0.7269]	[-0.1079; 0.5786]	[-0.0129; 0.7452]
IQR	[0.3042; 0.4224]	[0.0875; 0.1804]	[0.2983; 0.4290]
	Conditional correlation (5% upper tail), ρ_{Ui}		
Average	0.4017	0.1481	0.4056
[min; max]	[-0.0299; 0.7656]	[-0.0984; 0.6005]	[0.0193; 0.7695]
IQR	[0.3426; 0.4648]	[0.0913; 0.1986]	[0.3418; 0.4735]

Estimated using the 5-minute return data of S&P500 constituents and their interquartile range. Overnight returns have been removed prior to correlation estimation. For assets 1 and 2 with returns r_1 and r_2, suppose Q_{L1} and Q_{L2} are the p per cent quantiles and Q_{U1} and Q_{U2} are the $1-p$ per cent quantiles, defining the lower and upper tails of the bivariate distribution of r_1 and r_2. Following Silvapulle and Granger (2001), for any given t, we define the conditional returns as
$(r_{L1t}, r_{L2t}) = \{(r_{1t}, r_{2t})\,|r_{1t} < Q_{L1} \,\text{and}\, r_{2t} < Q_{L2}\}$,
$(r_{M1t}, r_{M2t}) = \{(r_{1t}, r_{2t})\,|Q_{L1} \leq r_{1t} \leq Q_{U1} \,\text{and}\, Q_{L2} \leq r_{2t} \leq Q_{U2}\}$ and
$(r_{U1t}, r_{U2t}) = \{(r_{1t}, r_{2t})\,|r_{1t} > Q_{U1} \,\text{and}\, r_{2t} > Q_{U2}\}$ and the conditional correlations of these returns are ρ_{Li}, ρ_{Mi} and ρ_{Ui} respectively.

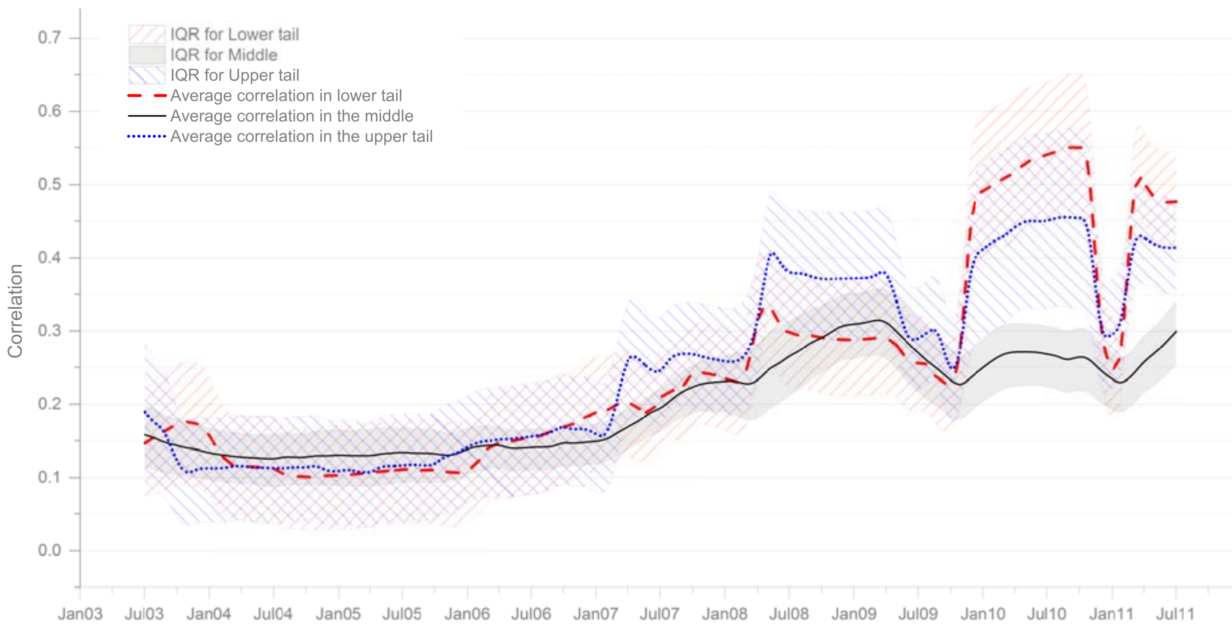


Figure 7: Conditional correlation dynamics ($p = 5\%$). The graph depicts average conditional correlations for the 5-minute return data of S&P500 constituents and their interquartile range. Overnight returns have been removed prior to correlation estimation. For assets 1 and 2 with returns r_1 and r_2, suppose Q_{L1} and Q_{L2} are the p per cent quantiles and Q_{U1} and Q_{U2} are the $1-p$ per cent quantiles, defining the lower and upper tails of the bivariate distribution of r_1 and r_2. Following Silvapulle and Granger (2001), for any given t, we define the conditional returns as $(r_{L1t}, r_{L2t}) = \{(r_{1t}, r_{2t})\,|r_{1t} < Q_{L1}\,\text{and}\,r_{2t} < Q_{L2}\}$, $(r_{M1t}, r_{M2t}) = \{(r_{1t}, r_{2t})\,|Q_{L1} \leq r_{1t} \leq Q_{U1}\,\text{and}\,Q_{L2} \leq r_{2t} \leq Q_{U2}\}$ and $(r_{U1t}, r_{U2t}) = \{(r_{1t}, r_{2t})\,|r_{1t} > Q_{U1}\,\text{and}\,r_{2t} > Q_{U2}\}$ and the conditional correlations of these returns are ρ_{Li}, ρ_{Mi} and ρ_{Ui} respectively. The figure plots the averages and the interquartile ranges of ρ_{Li} (dashed red line representing the average and right-slanted red pattern area representing the IQR), ρ_{Mi} (solid black line and shaded region) and ρ_{Ui} (dotted blue line representing and left-slanted blue pattern area).

Figure 8: CONDITIONAL CORRELATION DYNAMICS BY INDUSTRIES.

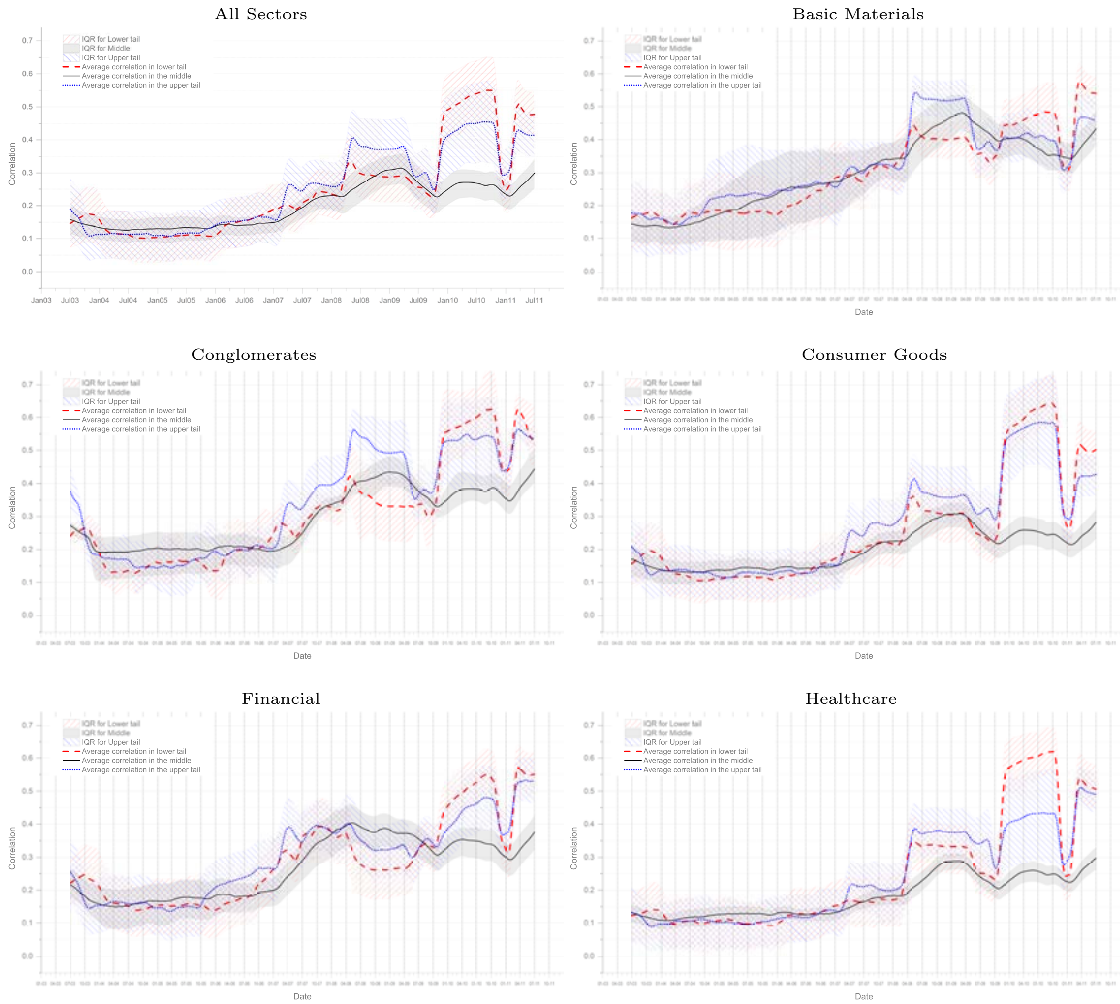
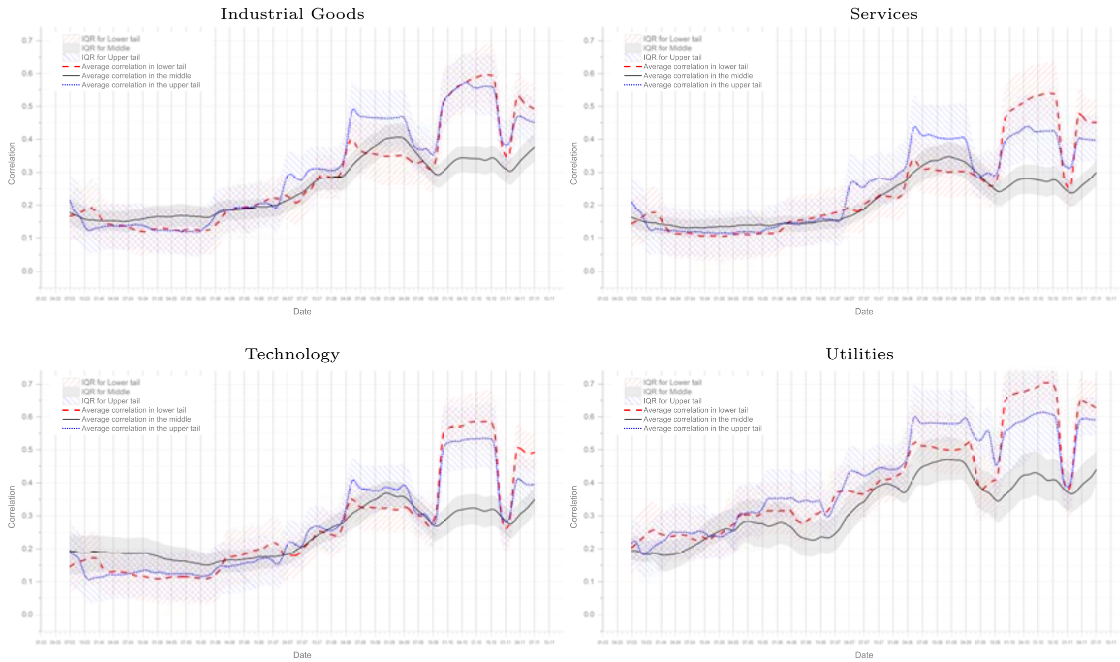


Figure 8: continued...



Additional information for web appendix only

RIC Code	Company Name	RIC Code	Company Name
A.N	Agilent Technologies Inc	AA.N	Alcoa Inc
AAPL.OQ	Apple Inc	ABC.N	AmerisourceBergen Corporation
ABT.N	Abbott Laboratories	ACAS.OQ	American Capital Ltd
ACE.N	ACE Limited	ACN.N	Accenture plc
ADBE.OQ	Adobe Systems Inc	ADI.N	Analog Devices Inc
ADM.N	Archer Daniels Midland Company	ADP.OQ	Automatic Data Processing Inc
ADSK.OQ	Autodesk Inc	AEE.N	Ameren Corporation
AEP.N	American Electric Power Co Inc	AES.N	The AES Corporation
AET.N	Aetna Inc	AFL.N	AFLAC Inc
AGN.N	Allergan Inc	AIG.N	American International Group Inc
AIV.N	Apartment Investment & Management Co	AIZ.N	Assurant Inc
AKAM.Oq	Akamai Technologies Inc	AKS.N	AK Steel Holding Corporation
ALL. N	The Allstate Corporation	ALTR.OQ	Altera Corp
AM.N	American Greetings Corp	AMAT.OQ	Applied Materials Inc
AMCC.OQ	Applied Micro Circuits Corp	AMD.N	Advanced Micro Devices Inc
AMGN.OQ	Amgen Inc	AMT.N	American Tower Corporation
AMZN.OQ	Amazoncom Inc	AN.N	AutoNation Inc
ANF.N	Abercrombie & Fitch Co	APA.N	Apache Corp
APC.N	Anadarko Petroleum Corporation	APD.N	Air Products & Chemicals Inc
APH.N	Amphenol Corporation	APOL.OQ	Apollo Group Inc
ARG.N	Airgas Inc	ASH.N	Ashland Inc
ATI.N	Allegheny Technologies Inc	AVB.N	Avalonbay Communities Inc
AVP.N	Avon Products Inc	AVY.N	Avery Dennison Corporation
AXP.N	American Express Company	AZO.N	AutoZone Inc
BA.N	Boeing Co	BAC.N	Bank of America Corporation
BAX.N	Baxter International Inc	BBBY.OQ	Bed Bath & Beyond Inc
BBT.N	BB&T Corporation	BBY.N	Best Buy Co Inc
BC.N	Brunswick Corporation	BCR.N	CR Bard Inc
BDX.N	Becton Dickinson and Company	BEN.N	Franklin Resources Inc
BHI.N	Baker Hughes Incorporated	BIIB.OQ	Biogen Idec Inc
BK.N	The Bank of New York Mellon Corporation	BLK.N	BlackRock Inc
BLL.N	Ball Corporation	BMC.OQ	BMC Software Inc
BMS.N	Bemis Company Inc	BMY.N	Bristol-Myers Squibb Company
BRCM.OQ	Broadcom Corp	BSX.N	Boston Scientific Corporation
BUT.N	Peabody Energy Corp	BWA.N	BorgWarner Inc
BXP.N	Boston Properties Inc	C.N	Citigroup Inc
CA.OQ	CA Technologies	CAG.N	ConAgra Foods Inc
CAH.N	Cardinal Health Inc	CAM.N	Cameron International Corporation
CAT.N	Caterpillar Inc	CB.N	The Chubb Corporation
CBE.N	Cooper Industries plc	CBG.N	CBRE Group Inc
CCE.N	Coca-Cola Enterprises Inc	CCL.N	Carnival Corporation
CEG.N	Constellation Energy Group Inc	CELG.OQ	Celgene Corporation
CERN.OQ	Cerner Corporation	CHK.N	Chesapeake Energy Corporation
CHRQ.OQ	CH Robinson Worldwide Inc	CI.N	Cigna Corp
CIEN.OQ	CIENA Corp	CINF.OQ	Cincinnati Financial Corp
CL.N	Colgate-Palmolive Co	CLF.N	Cliffs Natural Resources Inc
CLX.N	The Clorox Company	CMA.N	Comerica Incorporated
CME.OQ	Comcast Corporation	CMI.N	CME Group Inc
CMS.N	Cummins Inc	CMSCSA.OQ	CMS Energy Corp
CNP.N	CenterPoint Energy Inc	CNX.N	CONSOL Energy Inc
COF.N	Capital One Financial Corp	COG.N	Cabot Oil & Gas Corporation
COH.N	Coach Inc	COL.N	Rockwell Collins Inc
COP.N	ConocoPhillips	COST.OQ	Costco Wholesale Corporation
CPB.N	Campbell Soup Co	CPWR.OQ	Compuware Corporation
CR.N	Crane Co	CRM.N	Salesforcecom
CSC.N	Computer Sciences Corporation	CSCO.OQ	Cisco Systems Inc
CSX.N	CSX Corp	CTAS.OQ	Cintas Corporation
CTB.N	Cooper Tire & Rubber Co	CTL.N	CenturyLink Inc
CTSH.OQ	Cognizant Technology Solutions Corporation	CTXS.OQ	Citrix Systems Inc
CVC.N	Cablevision Systems Corporation	CVG.N	Convergys Corporation
CVH.N	Coventry Health Care Inc	CVS.N	CVS Caremark Corporation
CVX.N	Chevron Corporation	D.N	Dominion Resources Inc
DD.N	E I du Pont de Nemours and Company	DDR.N	DDR Corp
DDS.N	Dillards Inc	DE.N	Deere & Company

RIC Code	Company Name	RIC Code	Company Name
DELL.OQ	Dell Inc	DF.N	Dean Foods Company
DGX.N	Quest Diagnostics Inc	DHI.N	DR Horton Inc
DHR.N	Danaher Corp	DIS.N	Walt Disney Co
DLTR.OQ	Dollar Tree Inc	DLX.N	Deluxe Corp
DNB.N	Dun & Bradstreet Corp	DNR.N	Denbury Resources Inc
DO.N	Diamond Offshore Drilling Inc	DOV.N	Dover Corp
DOW.N	The Dow Chemical Company	DRI.N	Darden Restaurants Inc
DTE.N	DTE Energy Co	DTV.OQ	DIRECTV Inc
DUK.N	Duke Energy Corporation	DV.N	DeVry Inc
DVA.N	DaVita Inc	DVN.N	Devon Energy Corporation
DYN.N	Dynegy Inc	EA.OQ	Electronic Arts Inc
EBAY.OQ	eBay Inc	ECL.N	Ecolab Inc
ED.N	Consolidated Edison Inc	EFX.N	Equifax Inc
EIX.N	Edison International	EL.N	Estee Lauder Companies Inc
EMC.N	EMC Corporation	EMN.N	Eastman Chemical Co
EMR.N	Emerson Electric Co	EOG.N	EOG Resources Inc
EP.N	El Paso Corp	EQR.N	Equity Residential
EQT.N	EQT Corporation	ESRX.OQ	Express Scripts Inc
ESV.N	Ensco plc	ETFC.OQ	E_TRADE Financial Corporation
ETN.N	Eaton Corporation	ETR.N	Entergy Corporation
EW.N	Edwards Lifesciences Corp	EXC.N	Exelon Corporation
EXPD.OQ	Expeditors International of Washington Inc	EXPE.OQ	Expedia Inc
F.N	Ford Motor Co	FAST.OQ	Fastenal Company
FCX.N	Freeport-McMoRan Copper & Gold Inc	FDO.n	Family Dollar Stores Inc
FDX.N	FedEx Corporation	FE.N	FirstEnergy Corp
FFIV.OQ	F5 Networks Inc	FHN.N	First Horizon National Corporation
FII.N	Federated Investors Inc	FISV.OQ	Fiserv Inc
FITB.OQ	Fifth Third Bancorp	FLIR.OQ	FLIR Systems Inc
FLR.N	Fluor Corporation	FLS.N	Flowserve Corp
FMC.N	FMC Corp	FMCC.OB	Federal Home Loan Mtg
FNMA.OB	Fannie Mae	FRX.N	Forest Laboratories Inc
FTI.N	FMC Technologies Inc	GAS.N	AGL Resources Inc
GCI.N	Gannett Co Inc	GD.N	General Dynamics Corp
GE.N	General Electric Company	GGP.N	Gilead Sciences Inc
GILD.OQ	General Mills Inc	GIS.N	Corning Inc
GLW.N	GameStop Corp	GME.N	Genworth Financial Inc
GNW.N	Google Inc	GPC.N	Genuine Parts Company
GPS.N	Gap Inc	GR.N	Goodrich Corp
GS.N	The Goldman Sachs Group Inc	GT.N	Goodyear Tire & Rubber Co
GWW.N	WW Grainger Inc	HAL.N	Halliburton Company
HAR.N	Harman International Industries Inc	HAS.O	Hasbro Inc
HBAN.OQ	Huntington Bancshares Incorporated	HCBK.OQ	Hudson City Bancorp Inc
HCN.N	Health Care REIT Inc	HCP.N	HCP Inc
HD.N	The Home Depot Inc	HIG.N	Hartford Financial Services Group Inc
HMA.N	Health Management Associates Inc	HNZ.N	H J Heinz Company
HON.N	Honeywell International Inc	HOT.N	Starwood Hotels & Resorts Worldwide Inc
HP.N	Helmerich & Payne Inc	HPQ.N	Hewlett-Packard Company
HRB.N	H&R Block Inc	HRL.N	Hormel Foods Corp
HRS.N	Harris Corp	HSP.N	Hospira Inc
HSY.N	Hershey Co	HUM.N	Humana Inc
IACI.O	IAC_InterActiveCorp	IBM.N	International Business Machines Corp
IFF.N	International Flavors & Fragrances Inc	IGT.N	International Game Technology
INTC.OQ	Intel Corporation	INTU.OQ	Intuit Inc
IP.N	International Paper Co	IPG.N	The Interpublic Group of Companies Inc
IR.N	Ingersoll-Rand Plc	IRM.N	Iron Mountain Inc
ISRG.OQ	Intuitive Surgical Inc	ITT.N	ITT Corporation
ITW.N	Illinois Tool Works Inc	JBL.N	Jabil Circuit Inc
JCI.N	Johnson Controls Inc	JCP.N	J C Penney Company Inc
JDSU.OQ	JDS Uniphase Corporation	JEC.N	Jacobs Engineering Group Inc
JNJ.N	Johnson & Johnson	JNPR.K	Juniper Networks Inc
JNS.N	Janus Capital Group Inc	JNY.N	The Jones Group Inc
JOY	Joy Global Inc	JPM.N	JPMorgan Chase & Co
JWN.N	Nordstrom Inc	K.N	Kellogg Company
KBH.N	KB Home	KEY.N	KeyCorp
KFT.N	Kraft Foods Inc	KIM.N	Kimco Realty Corporation
KLAC.OQ	KLA-Tencor Corporation	KMB.N	Kimberly-Clark Corporation
KMX.N	CarMax Inc	KO.N	The Coca-Cola Company

RIC Code	Company Name	RIC Code	Company Name
KR.N	The Kroger Co	KSS.N	Kohls Corp
L.N	Loews Corporation	LEG.N	Leggett & Platt Incorporated
LEH.N	Lehman Brothers	LEN.N	Lennar Corp
LH.N	Laboratory Corp of America Holdings	LIFE.OQ	Life Technologies Corporation
LIZ.N	Liz Claiborne Inc	LLL.N	L-3 Communications Holdings Inc
LLTC.OQ	Linear Technology Corp	LLY.N	Eli Lilly & Co
LM.N	Legg Mason Inc	LMT.N	Lockheed Martin Corporation
LNC.N	Lincoln National Corp	LOW.N	Lowes Companies Inc
LPX.N	Louisiana-Pacific Corp	LSI.N	LSI Corporation
LTD.N	Limited Brands Inc	LUK.N	Leucadia National Corp
LUV.N	Southwest Airlines Co	LXK.N	Lexmark International Inc
MAR.N	Marriott International Inc	MAS.N	Masco Corporation
MAT.O	Mattel Inc	MBI.N	MBIA Inc
MCD.N	McDonalds Corp	MCHP.OQ	Microchip Technology Inc
MCK.N	McKesson Corporation	MCO.N	Moodys Corp
MDP.N	Meredith Corp	MDT.N	Medtronic Inc
MET.N	MetLife Inc	MHP.N	The McGraw-Hill Companies Inc
MHS.N	Medco Health Solutions Inc	MKC.N	McCormick & Co Inc
MMC.N	Marsh & McLennan Companies Inc	MMM.N	3M Co
MO.N	Altria Group Inc	MOLX.OQ	Molex Inc
MON.N	Monsanto Co	MOS.N	The Mosaic Company
MRK.N	Merck & Co Inc	MRO.N	Marathon Oil Corporation
MS.N	Morgan Stanley	MSFT.OQ	Microsoft Corporation
MTB.N	M&T Bank Corporation	MTG.N	MGIC Investment Corp
MTW.N	Manitowoc Co Inc	MU.OQ	Micron Technology Inc
MUR.N	Murphy Oil Corporation	MWV.N	MeadWestvaco Corporation
MWW	Monster Worldwide Inc	MYL.OQ	Mylan Inc
NBL.N	Noble Energy Inc	NBR.N	Nabors Industries Ltd
NCR.N	NCR Corp	NDAQ.OQ	Nasdaq OMX Group Inc
NE.N	Noble Corp	NEM.N	Newmont Mining Corp
NFLX.OQ	Netflix Inc	NFX.N	Newfield Exploration Co
NI.N	NiSource Inc	NKE.N	Nike Inc
NOC.N	Northrop Grumman Corporation	NOV.N	National Oilwell Varco Inc
NRG.N	NRG Energy Inc	NSC.N	Norfolk Southern Corp
NTAP.OQ	NetApp Inc	NTRS.OQ	Northern Trust Corporation
NU.N	Northeast Utilities	NUE.N	Nucor Corporation
NVDA.OQ	NVIDIA Corporation	NVLS.OQ	Novellus Systems Inc
NWL.N	Newell Rubbermaid Inc	NWSA.O	News Corp
NYT.N	The New York Times Company	ODP.N	Office Depot Inc
OI.N	Owens-Illinois Inc	OKE.N	ONEOK Inc
OMC.N	Omnicom Group Inc	OMX.N	OfficeMax Incorporated
ORCL.OQ	Oracle Corporation	ORLY.OQ	OReilly Automotive Inc
OXY.N	Occidental Petroleum Corporation	PAYX.OQ	Paychex Inc
PBCT.OQ	Peoples United Financial Inc	PBI.N	Pitney Bowes Inc
PCAR.OQ	PACCAR Inc	PCG.N	PG&E Corp
PCL.N	Plum Creek Timber Co Inc	PCLN.OQ	pricelinecom Incorporated
PCP.N	Precision Castparts Corp	PDCO.OQ	Patterson Companies Inc
PEG.N	Public Service Enterprise Group Inc	PEP.N	Pepsico Inc
PFE.N	Pfizer Inc	PFG.N	Principal Financial Group Inc
PG.N	Procter & Gamble Co	PGN.N	Progress Energy Inc
PGR.N	Progressive Corp	PH.N	Parker Hannifin Corporation
PHM.N	PulteGroup Inc	PKI.N	PerkinElmer Inc
PLD.N	Prologis Inc	PLL.N	Pall Corp
PMCS.OQ	PMC-Sierra Inc	PMTC.OQ	Parametric Technology Corporation
PNC.N	PNC Financial Services Group Inc	PNW.N	Pinnacle West Capital Corporation
POM.N	Pepco Holdings Inc	PPG.N	PPG Industries Inc
PPL.N	PPL Corporation	PRGO.OQ	Perrigo Co
PRU.N	Prudential Financial Inc	PSA.N	Public Storage
PWER.OQ	Power-One Inc	PWR.N	Quanta Services Inc
PX.N	Praxair Inc	PXD.N	Pioneer Natural Resources Co
QCOM.OQ	QUALCOMM Incorporated	QLGC.OQ	QLogic Corp
R.N	Ryder System Inc	RAI.N	Reynolds American Inc
RDC.N	Rowan Companies Inc	RF.N	Regions Financial Corp
RHI.N	Robert Half International Inc	RIG.N	Transocean Ltd
RL.N	Ralph Lauren Corporation	ROK.N	Rockwell Automation Inc
ROP.N	Roper Industries Inc	ROST.OQ	Ross Stores Inc
RRC.N	Range Resources Corporation	RRD.OQ	RR Donnelley & Sons Company

RIC Code	Company Name	RIC Code	Company Name
RSG.N	Republic Services Inc	RSH.N	RadioShack Corp
RTN.N	Raytheon Co	S.N	Sprint Nextel Corp
SANM.OQ	Sanmina-SCI Corp	SBUX.OQ	Starbucks Corporation
SCG.N	SCANA Corp	SE.N	Spectra Energy Corp
SEE.N	Sealed Air Corporation	SHLD.OQ	Sears Holdings Corporation
SHW.N	The Sherwin-Williams Company	SIAL.OQ	Sigma-Aldrich Corporation
SJM.N	The J M Smucker Company	SLB.N	Schlumberger Limited
SLE.N	Sara Lee Corp	SLM.O	SLM Corporation
SNA.N	Snap-on Inc	SNDK.OQ	SanDisk Corp
SNV.N	Synovus Financial Corp	SO.N	Southern Company
SPG.N	Simon Property Group Inc	SPLS.OQ	Staples Inc
SRCL.OQ	Stericycle Inc	SRE.N	Sempra Energy
SSP.N	The E W Scripps Company	STI.N	SunTrust Banks Inc
STJ.N	St Jude Medical Inc	STR.N	Questar Corporation
STT.N	State Street Corp	STZ.N	Constellation Brands Inc
SUN.N	Sunoco Inc	SVU.N	SUPERVALU Inc
SWK.N	Stanley Black & Decker Inc	SWN.N	Southwestern Energy Co
SWY.N	Safeway Inc	SYK.N	Stryker Corp
SYMC.OQ	Symantec Corporation	SYY.N	Sysco Corp
T.N	AT&T Inc	TAP.N	Molson Coors Brewing Company
TE.N	TECO Energy Inc	TER.N	Teradyne Inc
TEX.N	Terex Corp	TGT.N	Target Corp
THC.N	Tenet Healthcare Corp	TIE.N	Titanium Metals Corporation
TIF.N	Tiffany & Co	TIN.N	Temple-Inland Inc
TJX.N	The TJX Companies Inc	TLAB.OQ	Tellabs Inc
TMK.N	Torchmark Corp	TMO.N	Thermo Fisher Scientific Inc
TNB.N	Thomas & Betts Corp	TROW.OQ	T Rowe Price Group Inc
TSN.N	Tyson Foods Inc	TSO.N	Tesoro Corporation
TSS.N	Total System Services Inc	TUP.N	Tupperware Brands Corporation
TWX.N	Time Warner Inc	TXN.N	Texas Instruments Inc
TXT.N	Textron Inc	TYC.N	Tyco International Ltd
UIS.N	Unisys Corporation	UNH.N	Unitedhealth Group Inc
UNM.N	Unum Group	UNP.N	Union Pacific Corporation
UPS.N	United Parcel Service Inc	URBN.OQ	Urban Outfitters Inc
USB.N	US Bancorp	UTX.N	United Technologies Corp
VAR.N	Varian Medical Systems Inc	VFC.N	VF Corporation
VLO.N	Valero Energy Corporation	VMC.N	Vulcan Materials Company
VNO.N	Vornado Realty Trust	VRSN.OQ	VeriSign Inc
VTR.N	Ventas Inc	VZ.N	Verizon Communications Inc
WAG.N	Walgreen Co	WAT.N	Waters Corp
WDC.N	Western Digital Corp	WEC.N	Wisconsin Energy Corp
WFC.N	Wells Fargo & Company	WFR.N	MEMC Electronic Materials Inc
WFT.N	Weatherford International Ltd	WHR.N	Whirlpool Corp
WLP.N	WellPoint Inc	WM.N	Waste Management Inc
WMB.N	Williams Companies Inc	WMT.N	Wal-Mart Stores Inc
WOR.N	Worthington Industries Inc	WPI.N	Watson Pharmaceuticals Inc
WPO.N	The Washington Post Company	WY.N	Weyerhaeuser Co
WYNN.OQ	Wynn Resorts Ltd	X.N	United States Steel Corp
XEL.N	Xcel Energy Inc	XL.N	XL Group plc
XLNX.OQ	Xilinx Inc	XOM.N	Exxon Mobil Corporation
XRAY.OQ	DENTSPLY International Inc	XRX.N	Xerox Corp
YHOO.OQ	Yahoo! Inc	YUM.N	Yum! Brands Inc
ZION.OQ	Zions Bancorp	ZMH.N	Zimmer Holdings Inc