Continuous and Jump Betas: Firm and Industry Level Evidence*

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Abstract

This paper examines the behavior of industry-level betas and its implications for industry-based portfolio diversification. With the recent advances in disentangling continuous and jump price movements using high frequency data, we are able to estimate the time-varying betas towards both the continuous and jump systematic risk for firms from different industries. Our results show that both beta estimates vary considerably over the sample period of 2003 to 2011. There is strong evidence of structural change in the continuous betas for most sectors during the global financial crisis. In general the continuous betas are usually much smaller than the jump betas. Distinct behaviors in both the continuous and jump betas between sectors suggest a certain degree of clustering of firms in the same sector. These findings provide new insights in cross-industry risk diversification.

Keywords: jumps, industry portfolios.

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1 Introduction

Industry based portfolio selection is a common diversification recommendation. As firms in the same industry are assumed to face similar conditions, investors can reduce the information costs associated with monitoring individual firms while retaining diversification benefits (Bekaert et al., 2011; Hoberg and Phillips, 2010). Evidence suggests that even equity analysts specialise along industry lines (Menzly and Ozbas, 2010), and there has been considerable recent debate about whether global portfolios should be more concerned about industry or country diversification – Bekaert et al. (2009), Bekaert et al. (2011) and Bekaert et al. (2013) find country risk dominates, while Ehling and Ramos (2006) finds that industry risk is lower than country risk only due to the presence of shortsales constraints.

In every case the issue of time-varying beta for individual firms and industries is of significant interest to investors. Internationally this may reflect changing global integration of markets (Bekaert et al., 2011), but it may also reflect industry boom and bust cycles associated with competitive behaviours and the availability of financial capital (Hoberg and Phillips, 2010). Recently Patton and Verardo (2012) establish that daily beta, calculated from high frequency data, may move by a significant amount. They establish a relationship between these movements, firm-specific news announcements and the spread of information. While they use high frequency data on S&P500 firms, Patton and Verardo (2012) present only the market average results, and do not explore industry groupings.

This paper takes advantage of the new methodology of Todorov and Bollerslev (2010) to construct estimates of beta for S&P500 firms from high frequency data. The unique aspect of this approach is to decompose the betas into a continuous and discontinuous component, following the asset pricing literature which suggests the evolution of prices follows a continuous process such as Brownian motion augmented with discrete jump events. Confirmation that this process describes the characteristics of stocks has been demonstrated in Aït-Sahalia and Jacod (2010), while the existence and prevalence of jumps in many assets, including stocks, and the relationship of those jumps to news events, is now well-documented in papers such as Andersen et al. (2007), Dungey et al. (2009), Jacod and Todorov (2009) and Lahaye et al. (2011). Accounting for jumps has been shown to improve both the estimation of the yield curve (Lahaye et al., 2005), estimates and forecasts of daily volatility (Andersen et al., 2003; Blair et al., 2001) and to complicate optimal hedging strategies – Lai and Sheu (2010) show that optimal hedging can be improved with high frequency data, but Dungey et al. (2011) show that asynchronous jumping may cause problems.

Understanding how individual firms, and industry clusters, are influenced by systematic risk, and jumps in this risk, is therefore of considerable interest. We produce estimates of the extent to which individual firms follow the continuous component of the market – continuous beta; and the extent to which they follow disruptions – discontinuous beta. A number of key firms analysed in prior research are individually examined, but to keep the information tractable we allocate the firms to 9 industry sectors (basic materials, conglomerates, consumer goods, financial, healthcare, industrial goods, services, technology and utilities) and analyse the results by sector. This provides us with both a median point estimate of the continuous and discrete beta for each industry grouping, and a confidence range around those estimates. Additionally, we produce time varying estimates of the betas for each industry – while these can be produced at a range of frequencies, we focus on monthly results to conserve space.

For all 501 stocks examined, the continuous component beta is lower than the jump component beta. Overall jump betas are 38 percent higher than continuous component betas on average, and only rarely do the confidence bands for the two betas overlap. As jumps are an indicator of new information arrival, and Patton and Verardo (2012) find that earnings announcements are used as a learning mechanism to update expectations about the economy, the finding that the jumps beta is higher than that for the continuous time component may imply faster updating for unexpected information arrival than previously estimated. In addition, the continuous and jump betas vary considerably between industry groupings and over time. Over the sample period of 2003 to 2011, the continuous component beta approximately tripled for the basic materials and financial sectors, doubled for industrial goods and services and increased to a lesser extent for consumer goods and healthcare. Only in the technology and utilities sectors were the betas less obviously altered – a finding somewhat consistent with the lower expectations for boom bust cycles in concentrated industries found in Hoberg and Phillips (2010). Formal break tests on these beta estimates clearly reveal that a number of key industries experienced a significant change in their relationship to the continuous component of the systematic market risk during September-October 2008, the time of the Lehman Brothers collapse, rescue of AIG and subsequent TARP (Troubled Asset Relief Program). Of the 9 industry categories, only technology and industrial goods do not indicate a significant break at this point of time.

Interestingly, the estimates of jump betas do not show an obvious trend during the sample. They remain consistently above the continuous component estimates, with a few exceptions around the periods of extreme market stress in September 2008, when, for a number of industries the response to systematic risk outweighed the beta to discontinuous movements. This occurs at only one other jointure in the sample, in March/April 2010 for the basic materials and financial sectors, and can presumably be associated with the extreme market stress also experienced at this time in the early stages of the Greek debt crisis.

For investors, the knowledge that individual stocks respond differently to the continuous and jump components of systematic risk, and that this can be converted to differential responses by industry classification and through time, is likely to provide a valuable tool in managing portfolio diversification. Across different industry categories the response to the continuous component of systematic risk varies considerably, from the lowest sustained level in our sample in the healthcare sector, and the highest in the financial sector. Given our sample period, this latter result is not surprising. However, we also present an examination of the evolution of the beta estimates across the sample, and the structural break for the financial sector is particularly evident – prior to mid-2007 the beta estimate for the financial sector was lower than that for technology, industrial goods and conglomerates, and on par with consumer goods. While there is evidence for significant structural breaks in these continuous component betas, they largely follow a relative slowly evolving AR structure suggesting a reasonably high degree of certainty in their response to systematic risks.

The responses of individual stocks and industry sectors to new information, as evidenced by the jump betas, are far higher than those same sectors response to the continuous component. News is important and has higher weight; although, for most sectors the estimates are highly variable. In the financial sector there seems to be a consistent margin between the continuous and jump betas. During periods of financial stress the increase in continuous beta is sometimes sufficient to outweigh the impact of the beta on new information, but this is highly unusual.

The paper proceeds as follows. Section 2 introduces the modelling framework, and Section 3 describes the data set and parameter choices used in estimation. The empirical results are presented and discussed in Section 4 along with robustness analysis. Section 5 concludes.

2 Modeling Framework

A standard factor model CAPM representation relating returns of an individual stock, r_i, to a benchmark (or market) return, r_0, takes the form,

$$r_i = \alpha_i + \beta_i r_0 + \epsilon_i, \quad i = 1, \ldots, N. \tag{1}$$

The β_i coefficient in equation (1) is the usually estimated sensitivity of the expected return on the i-th asset to the return on the market (or systematic) factor with a long history in the literature add references. Todorov and Bollerslev (2010) show how, using high frequency data, the return can be decomposed into two components: one associated with continuous price movements and the other associated with jumps. Hence in the presence of jumps, equation (1) becomes

$$r_i = \alpha_i + \beta_i^c r_0^c + \beta_i^d r_0^d + \epsilon_i, \quad i = 1, \ldots, N, \tag{2}$$

where $r_0 = r_0^c + r_0^d$. Using equation (2) we can effectively attribute the overall systematic risk to either the continuous component r_0^c, or the discontinuous component r_0^d. Recognition of this is important as the implication that $\beta_0^c = \beta_0^d = 1$ is critical in the identification of the β_i^c and β_i^d coefficients. Importantly, the sensitivity of an asset return to the two components of systematic risk can be different, represented by β_i^c and β_i^d respectively.

2.1 Continuous Time Case

In a continuous time model, under the assumption that the log-price series p_i, $i = 0, \ldots, N$ are generated by semimartingale processes, we have

$$\begin{aligned} \mathrm{d}p_{i,t} =& \alpha_{i,t}\,\mathrm{d}t + \beta_i^c \sigma_{0,t}\,\mathrm{d}W_{0,t} + \beta_0^d \left(\int_{E^0} \kappa \circ \delta_0(t,x)\tilde{\mu}_0(\mathrm{d}t, \mathrm{d}\mathbf{x}) + \int_{E^0} \kappa' \circ \delta_0(t,x)\mu_0(\mathrm{d}t, \mathrm{d}\mathbf{x}) \right) \\ &+ \sigma_{i,t}\,\mathrm{d}W_{i,t} + \int_{E^i} \kappa \circ \delta_i(t,x)\tilde{\mu}_i(\mathrm{d}t, \mathrm{d}\mathbf{x}) + \int_{E^i} \kappa' \circ \delta_i(t,x)\mu_i(\mathrm{d}t, \mathrm{d}\mathbf{x}) \end{aligned} \tag{3}$$

for the i-th asset $i = 1, \ldots, N$; and for the market,

$$\mathrm{d}p_{0,t} = \alpha_{0,t}\,\mathrm{d}t + \sigma_{0,t}\,\mathrm{d}W_{0,t} + \int_{E^0} \kappa \circ \delta_0(t,x)\tilde{\mu}_0(\mathrm{d}t, \mathrm{d}\mathbf{x}) + \int_{E^0} \kappa' \circ \delta_0(t,x)\mu_0(\mathrm{d}t, \mathrm{d}\mathbf{x}). \tag{4}$$

In equations (3)-(4), $t \in [0, T]$, W_i, $i = 0 \ldots, N$ are standard Brownian motions, μ_i is a Poisson random measure on $[0, \infty) \times E^i$ with $(E^i, \mathcal{E}^i)$ an auxiliary measurable space, $i = 0 \ldots, N$. The measurable compensator of μ_i is ν_i, hence $\tilde{\mu}_i := \mu_i - \nu_i$ is the compensated jump measure; and $\delta_i(\cdot, \cdot)$ is the jump size function, $i = 0 \ldots, N$. $\kappa(\cdot)$ is a continuous function on $\mathbb{R}$ into itself with compact support, and satisfies that $\kappa \circ x = x$ on a neighbourhood of 0, and $\kappa' \circ x = x - \kappa \circ x$.

Equations (3)-(4) facilitate non-parametric representations of the β_i^c and β_i^d, which make use of the power covariations between the continuous or discontinuous part of p_i and p_0 for any asset i, $i = 0, \ldots, N$. It follows from equations (3) that

$$[p_i^c, p_0^c]_{(0,T]} = \beta_i^c \int_0^T \sigma_{0,s}^2 \mathrm{d}s, \qquad \text{and} \quad [p_0^c, p_0^c]_{(0,T]} = \int_0^T \sigma_{0,s}^2 \mathrm{d}s, \tag{5}$$

and hence

$$\beta_i^c = \frac{[p_i^c, p_0^c]_{(0,T]}}{[p_0^c, p_0^c]_{(0,T]}} \quad, i = 1, \ldots, N. \tag{6}$$

For the discontinuous price movement, we have

$$\sum_{s\le T} |\Delta p_{i,s}\Delta p_{0,s}|^{\tau} = |\beta_i^d|^{\tau} \int_0^T \int_{E^0} |\delta_0(t,x)|^{2\tau} \mu_0(\mathrm{d}t, \mathrm{d}x), \tag{7}$$

$$\sum_{s\le T} |\Delta p_{0,s}|^{2\tau} = \int_0^T \int_{E^0} |\delta_0(t,x)|^{2\tau} \mu_0(\mathrm{d}t, \mathrm{d}x), \tag{8}$$

where $\Delta p_{i,s} = p_{i,s} - p_{i,s-}$ with $p_{i,s-}$ denotes the left limit; τ is some positive number such that the integral in equation (7) is meaningful, $i = 1 \ldots, N$.[1] Equations (7)-(8) lead to the result that for $i = 1, \ldots, N$,

$$\beta_i^d = \text{sign}\left\{ \sum_{s\le T} \text{sign}\{\Delta p_{i,s}\Delta p_{0,s}\} |\Delta p_{i,s}\Delta p_{0,s}|^{\tau} \right\} \times \left(\frac{\left|\sum_{s\le T} \text{sign}\{\Delta p_{i,s}\Delta p_{0,s}\} |\Delta p_{i,s}\Delta p_{0,s}|^{\tau}\right|}{\sum_{s\le T} |\Delta p_{0,s}|^{2\tau}} \right)^{\frac{1}{\tau}}. \tag{9}$$

The difficulty that we face in practice is that we often do not have access to continuous records of price series, and hence the β_i^c and β_i^d in (6) and (9) cannot be directly calculated. Assume that the prices are observed every Δ_n time interval, from $0, \Delta_n, 2\Delta_n, \ldots,$ to $[T/\Delta_n]$. Todorov and Bollerslev (2010) show that under very general regularity conditions, the discrete time equivalence of (6) and (9) converge in probability to the continuous time β_i^c and β_i^d as $\Delta_n \to 0$.

2.2 The Estimators in Discrete Time

Let the $(N+1)\times 1$ vector of the observed log-price series be $\mathbf{p} = (p_0,\ p_1,\ \ldots,\ p_N)'$, and denote the discrete time price increment by

$$\Delta_j^n \mathbf{p} = \mathbf{p}_{j\Delta_n} - \mathbf{p}_{(j-1)\Delta_n}, \qquad \text{for} \quad j = 1, \ldots, [T/\Delta_n]. \tag{10}$$

The truncation threshold is set to be an $(N+1)\times 1$ vector

$$\mathbf{u}_n = (\alpha_0\Delta_n^{\varpi},\ \alpha_1\Delta_n^{\varpi},\ \ldots,\ \alpha_N\Delta_n^{\varpi})', \quad \text{where} \quad \varpi \in (0, \frac{1}{2}),\ \text{and}\ \alpha_i \ge 0,\ i = 0, \ldots, N. \tag{11}$$

Equation (11) implies that we allow for different truncation thresholds across different assets by controlling α_i. In fact this is exactly the case in our empirical analysis later. The continuous price movement corresponds to those observations that satisfy $|\Delta_j^n \mathbf{p}| \le \mathbf{u}_n$. Hence the discrete time equivalent to the estimated sensitivity to continuous systematic

[1] To put it differently, 2τ needs to be above the generalized Blumenthal-Getoor index (see Aït-Sahalia and Jacod, 2010) of the process p_0 on $[0, T]$.

risk factor, $\hat{\beta}_i^c$, has the following form

$$\hat{\beta}_i^c = \frac{\sum_{j=1}^{[T/\Delta_n]} \Delta_j^n p_i \, \Delta_j^n p_0 \, \mathbb{1}_{\{|\Delta_j^n \mathbf{p}| \leq \mathbf{u}_n\}}}{\sum_{j=1}^{[T/\Delta_n]} (\Delta_j^n p_0)^2 \, \mathbb{1}_{\{|\Delta_j^n \mathbf{p}| \leq \mathbf{u}_n\}}}, \quad \text{for} \quad i = 1, \ldots, N, \tag{12}$$

where $\mathbb{1}$ is the indicator function.

The discrete time estimator of β_i^d is

$$\hat{\beta}_i^d = \operatorname{sign}\left\{ \sum_{j=1}^{[T/\Delta_n]} \operatorname{sign}\{\Delta_j^n p_i \, \Delta_j^n p_0\} |\Delta_j^n p_i \, \Delta_j^n p_0|^\tau \right\} \times \left(\frac{\sum_{j=1}^{[T/\Delta_n]} \operatorname{sign}\{\Delta_j^n p_i \, \Delta_j^n p_0\} |\Delta_j^n p_i \, \Delta_j^n p_0|^\tau}{\sum_{j=1}^{[T/\Delta_n]} (\Delta_j^n p_0)^{2\tau}} \right)^{\frac{1}{\tau}}, \tag{13}$$

where $i = 1, \ldots, N$, and the power τ is restricted to be $\tau \geq 2$ so that the continuous price movements do not matter asymptotically.

Todorov and Bollerslev (2010) show that $\hat{\beta}_i^d \xrightarrow{\mathbb{P}} \beta_i^d$ on $\Omega^{(0)}$, and $\hat{\beta}_i^c \xrightarrow{\mathbb{P}} \beta_i^c$ as $\Delta_n \to 0$, where $\Omega^{(0)}$ is the set where there is at least one systematic jump on $[0, T]$. Further, the Central Limit Theorems for these two discrete time estimators are also given (see Todorov and Bollerslev, 2010, Theorem 1 and Theorem 2). They show that $\frac{1}{\sqrt{\Delta_n}}\left(\hat{\beta}_i^d - \beta_i^d\right)$ and $\frac{1}{\sqrt{\Delta_n}}\left(\hat{\beta}_i^c - \beta_i^c\right)$ converge stable in law to some normal distributions with mean 0, and the estimates of the asymptotic variances are as follows:

$$\widehat{Avar}_i^d = \frac{\sum_{j=k_n+2}^{[T/\Delta_n]-k_n-1} |\Delta_j^n p_0|^{4\tau-2} (\hat{c}(n,-)_j + \hat{c}(n,+)_j) \, \mathbb{1}_{\{|\Delta_j^n p_0| \geq \alpha_0 \Delta_n^{\varpi}\}}}{2\left(\sum_{j=2}^{[T/\Delta_n]} |\Delta_j^n p_0|^{2\tau} \, \mathbb{1}_{\{|\Delta_j^n p_0| \geq \alpha_0 \Delta_n^{\varpi}\}}\right)^2}, \tag{14}$$

$$\hat{c}(n, \pm)_j = \frac{\pi}{2k_n \Delta_n} \sum_{j \in I_{n,\pm}(j)} |\Delta_j^n \hat{e}_i^c||\Delta_{j-1}^n \hat{e}_i^c|, \quad \text{where} \quad \hat{e}_i^c := p_i - \hat{\beta}_i^c p_0,$$

and $I_{n,-}(j) = \{j - k_n, j - k_n + 1, \ldots, j - 1\}$ for $j > k_n + 1$, and $I_{n,+}(j) = \{j+2, \ldots, j + k_n\}$ for $j < [T/\Delta_n] - k_n$; $k_n \to \infty$ and $k_n \Delta_n \to 0$ as $\Delta_n \to 0$; and $\hat{\beta}_i^c$ denotes some consistent estimate of β_i^c. Then

$$\widehat{Avar}_i^c = \frac{\left(\frac{1}{\Delta n} \sum_{j=1}^{[T/\Delta_n]-3} |\Delta_j^n p_0 \cdot \Delta_{j+1}^n \hat{e}_i^c \cdot \Delta_{j+2}^n p_0 \cdot \Delta_{j+3}^n \hat{e}_i^c|\right)^{\frac{1}{2}}}{\sum_{j=1}^{[T/\Delta_n]-1} |\Delta_j^n p_0 \cdot \Delta_{j+1}^n p_0|} \tag{15}$$

provides a consistent estimate of the true asymptotic variance of $\hat{\beta}_i^c$, $i = 1 \ldots, N$. The feasible estimates of the asymptotic variances (14) and (15) will be used to construct confidence intervals, and conduct statistical tests on $\hat{\beta}_i^d$ and $\hat{\beta}_i^c$.

2.3 Testing for Jumps

Todorov and Bollerslev (2010) point out that the convergence of $\hat{\beta}^d$ only holds when there is at least one systematic jump on $[0, T]$ (Andersen et al., 2007). Thus we need to test for the existence of jumps on the log-price series p_0 of the market portfolio. We use the adjusted ratio test statistic by Barndorff-Nielsen and Shephard (2006), which utilizes the difference between realized quadratic variation and bipower variation. Define the discrete time power variations of p_0 as follows:

$$\begin{aligned} \text{realized quadratic variation:} \quad QV_0^{[0,T]} &= \sum_{j=1}^{[T/\Delta_n]} \Delta_j^n p_0^2, \\ \text{realized bipower variation:} \quad BV_0^{[0,T]} &= \sum_{j=1}^{[T/\Delta_n - 1]} |\Delta_j^n p_0|\,|\Delta_{j+1}^n p_0|, \\ \text{realized quadpower variation:} \quad DV_0^{[0,T]} &= \sum_{j=1}^{[T/\Delta_n - 3]} |\Delta_j^n p_0|\,|\Delta_{j+1}^n p_0|\,|\Delta_{j+2}^n p_0|\,|\Delta_{j+3}^n p_0|. \end{aligned}$$

The feasible test statistic is given by

$$\hat{\mathcal{J}} = \frac{1}{\sqrt{\Delta_n}} \cdot \frac{1}{\sqrt{\theta \cdot \max\left(1/T,\, DV_0^{[0,T]}/(BV_0^{[0,T]})^2\right)}} \left(\frac{\mu_1^{-2} \cdot BV_0^{[0,T]}}{QV_0^{[0,T]}} - 1 \right), \tag{16}$$

where $\mu_1 = \mathbb{E}(|\mathbf{U}|) = \sqrt{2/\pi}$, $\mathbf{U} \sim \mathcal{N}(0,1)$, and $\theta = \pi^2/4 + \pi - 5$. Barndorff-Nielsen and Shephard (2006) show that under the null of no jumps,

$$\hat{\mathcal{J}} \xrightarrow{L} \mathcal{N}(0,1) \quad \text{as} \quad \Delta_n \to 0. \tag{17}$$

Under the alternative hypothesis of jumps, equation (16) implies that

$$\left(\frac{\mu_1^{-2} \cdot BV_0^{[0,T]}}{QV_0^{[0,T]}} - 1 \right) \xrightarrow{\mathbb{P}} - \frac{\sum_{s \le T} |\Delta p_{0,s}|^2}{\int_0^T \sigma_{0,s}^2 \mathrm{d}s + \sum_{s \le T} |\Delta p_{0,s}|^2} \le 0, \tag{18}$$

where the terms in the limit are given in equation (5) and (8). Clearly this jump test is one-sided.

The $\hat{\mathcal{J}}$ statistic and other test statistics proposed by Barndorff-Nielsen and Shephard (2006) are known to over reject the null of no jump (see, for example, Barndorff-Nielsen and Shephard, 2006; Andersen et al., 2007), thus we use a very conservative critical value of -3.09, which corresponds to the one-sided significance level of 0.1%.

3 Data and Parameter Choices

We investigate the behavior of the β_i^c and β_i^d estimates over a 9 year sample period from January 2, 2003 to December 30, 2011, which includes the period of the financial crisis associated with the bankruptcy of Lehman Brothers in September 2008 and the subsequent period of turmoil in US and international financial markets. The underlying data are 5 minute observations on prices for 501 stocks drawn from the constituent stocks of the S&P500 index during the sample period obtained from SIRCA Thomson Reuters Tick History. This data set was constructed by Dungey et al. (2012) and does not purport to be all the stocks listed on the S&P500 index, but has drawn from that population of stocks to select those with sufficient coverage and data availability for high frequency time series analysis of this type.

The original dataset consisted of over 900 stocks taken from the 0#.SPX mneumonic provided by SIRCA. This included a number of stocks which trade OTC and on alternative exchanges, as well as some which altered currency of trade during the period; these stocks were excluded. We adjusted the dataset for changes in RIC code during the period through mergers and acquisitions, stock splits and trading halts. We also removed some stocks with insufficient observations during the sample period. The data handling process is fully documented in the web-appendix to Dungey et al. (2012) and C++ code is available on request. In the dataset for this paper we force the inclusion of Lehman Brothers until their bankruptcy in September 2008, but drop Fannie Mae and Freddie Mac from the analysis. The final data set contains 501 individual stocks, hence $N = 501$. The S&P500 index is used as the benchmark portfolio asset 0.

3.1 Data Processing

The intra-day returns and prices data start from 9:30 am, and end at 4:00 pm, observations with time stamps outside this window and overnight returns are removed. Missing 5 minute price observations are filled with the previous observation, corresponding to zero inter-interval returns. In the case where the first observations of the day are missing, we use the first non-zero price observation on that day to fill backwards. Approximately 20 price observations which are orders of magnitude away from their neighbouring observations are also removed. Thus we have 78 intra-day observations for 2262 active trading days and 108 calendar months.

The 5 minute sampling frequency is chosen as relatively conventional in the high frequency literature, especially for univariate estimation, see for example Andersen et al. (2007), Lahaye et al. (2011) and for some sensitivity to alternatives Dungey et al. (2009). Optimal sampling frequency is an area of ongoing research, and despite the univariate work by Bandi and Russell (2006), this issue is outstanding for analysing multiple series with varying degrees of liquidity. The 5 minute frequency is much finer than those employed in either Patton and Verardo (2012) who use 25 minute sampling, and Todorov and Bollerslev (2010) and Bollerslev et al. (2008) who use 22.5 minute data. Most of the multivariate estimations employ lower sampling frequencies most likely because of the Epps effect (Epps, 1979). However as the quality of high frequency data and market liquidity have improved in many ways, finer sampling does not pose a threat to the robustness of our results. Further discussions on sampling frequency is presented later.

3.2 Choices of Parameter Values

Although most of the parameters involved in the calculation of $\hat{\beta}$'s in Section 2.2 are nuisance parameters asymptotically, they do play important roles in any finite sample applications. We start the analysis by setting most of the parameter values to be the same as in Todorov and Bollerslev (2010), and then conduct robustness test on the results obtained using different parameter settings.

Estimates of $\hat{\beta}^c$ and $\hat{\beta}^d$ are computed for both daily and monthly windows. We set $T = 1$ to be one day or one month, according to the sample period that is used. Since there are $[T/\Delta_n]$ observations in $[0, T]$, it is legitimate to set Δ_n to be the reciprocal of the number of observations in each day (or month). Thus $\Delta_n = 1/78$ for the daily $\hat{\beta}$'s, but for the montly estimates, Δ_n varies from one month to another. Notice however, in the estimated variances of $\hat{\beta}$'s, equations (14) and (15), Δ_n enter as a scaling factor. For the monthly $\hat{\beta}$'s we use different values of Δ_n corresponding to each month in the calculation of the variance estimates. We also investigate the case where an average value of Δ_n is chosen for all monthly estimates, the results are qualitatively similar.

The truncation threshold $\mathbf{u}_n$ in equation (11), is chosen to follow Todorov and Bollerslev (2010) who set $\varpi = 0.49$, and let α_i vary not only amongst individual stocks, but also between $\hat{\beta}_i^d$ and $\hat{\beta}_i^c$. Denote the bipower variation of the i-th stock over the time interval $[0, T]$ by $BV_i^{[0,T]}$, $i = 0, 1, \ldots, N$. Then for $\hat{\beta}_i^d$ we set $\alpha_i^d = \sqrt{BV_i^{[0,T]}}$, and for $\hat{\beta}_i^c$ we set $\alpha_i^c = 3\sqrt{BV_i^{[0,T]}}$, $i = 0, 1, \ldots, N$.[2] A relatively low value of α_i^d is set for technical reasons which will be investigated in detail in the next section. Recall that when calculating $\hat{\beta}_i^c$ in equation (12), only those observations that satisfy $|\Delta_j^n \mathbf{p}| \leq \mathbf{u}_n$ are used. As the number of stocks N increases, this condition can be rather restrictive for all N stocks returns to be bounded below the threshold. We conduct sensitivity analysis to using different truncation thresholds to examine whether the estimated β_i^c and β_i^d are robust to less (or more) restrictive truncation levels in Section 4.6.

The value of τ in equation (13) is set to be $\tau = 2$. Finally, we need to choose a functional form for k_n in equation (14). There are many forms of function for k_n that

[2]Note that α_i^d does not enter the point estimates of $\hat{\beta}_i^d$, but only affects the estimated asymptotic variances and hence the interval estimates of $\hat{\beta}_i^d$.

satisfy the criteria for consistency:

$$k_n \to \infty \quad \text{and} \quad k_n\Delta_n \to 0 \quad \text{as} \quad \Delta_n \to 0. \tag{19}$$

For simplicity we set $k_n = \mathbf{C}/\sqrt{\Delta_n}$ where $\mathbf{C}$ is a positive constant. Asymptotically the value of $\mathbf{C}$ does not have any impact on the consistency of the variance estimates (14). The role of $\mathbf{C}$ is to keep k_n at a relative low value in finite sample. Notice that in the calculation of the estimated variance for $\hat{\beta}^d$ in equation (14), there are $k_n + 1$ observations eliminated at each end of the day (or month). If k_n goes to infinity too fast, it is possible that there are insufficient observations which satisfy $|\Delta_j^n p_0| \geq \alpha_0 \Delta_n^{\varpi}$, in which case we cannot obtain valid estimates for the variance. We set $\mathbf{C} = 0.1$ in our empirical application in order to obtain variance estimates for all monthly $\hat{\beta}^d$.

4 Empirical Analysis

We use the parameter values chosen in Section 3.2 to compute $\hat{\beta}_i^d$ and $\hat{\beta}_i^c$ given by equations (12) and (13) over the sample period 2003–2011 for each of the 501 stocks. Initially we examine the $\hat{\beta}_i^d$ and $\hat{\beta}_i^c$ for several stocks analyzed by Todorov and Bollerslev (2010), before considering clustering at industry level and the time series of these estimates. We are able to focus on the role of the 2008-2009 financial crisis and test whether there are any structural changes in the firm-specific and industry $\hat{\beta}$'s before and after the crisis.

We detect jumps on 87 out of 2262 trading days using the statistic $\hat{\mathcal{J}}$ given in equation (16), which is below the proportion reported in Todorov and Bollerslev (2010). One possible reason is that Todorov and Bollerslev (2010) use the test statistic based on the difference of bipower variation and quadratic variation rather than the ratio. Andersen et al. (2007), however, use the same ratio test statistic as applied here on the S&P500 index from December 1986 through June 1999, and report 244 significant jump days (*i.e.* 7.6%) out of 3045 trading days, at 0.1% significant level. We would expect to obtain lower proportion of jump days by using the adjusted ratio test, as Barndorff-Nielsen and Shephard (2006) show that the difference test statistic has more severe size distortion compared to the adjusted ratio test statistic. Patton and Verardo (2012) test the S&P500 index between January 1996 and December 2006, a total of 2770 trading days, and find a significant jump on 4.04% of the days, which is more consistent with our findings.

Consistent with the existing literature, jumps are primarily detected on days of major macroeconomic news announcements in the US. Of the 87 days detected in the sample, 52 occur on days of pre-scheduled macroeconomic US news announcements, and 14 of these are associated with the release of non-farm payrolls data. It is well documented

Table 1: Association of jumps with news

news category	no. of jumps	news category	no. of jumps
US macro announcement[a]	52	Gulf War	3
non-farm payrolls	14	oil/energy prices	12
US monetary policy[b]	10	international monetary policy	3
Bernanke	2	Hurricane Katrina/storms	3
Financial crisis events	11	company announcements	8

[a] Including: non-farm payrolls, retail sales, GDP, CPI, PPI, consumer confidence, home sales, durable goods, manufacturing production.
[b] Includes changes in discount rate and release of FOMC minutes.

elsewhere that US employment data is the most influential news announcements across a number of assets; for example Andersen et al. (2007) and Dungey et al. (2009). The next most prevalent news effects relate to developments in oil markets (12 instances), which is unsurprising given the overlap of the sample period with both the War in Iraq and the impact of Hurricane Katrina on US oil supplies. Monetary policy or FOMC announcements were precipitating factors in 11 instances, with a further two prompted by remarks by Ben Bernanke, including the his testimony to Congress regarding the subprime crisis in February 2008. In the latter part of the sample, events associated with financial crisis in the US (such as policy intervention announcements) and in Europe (such as concerns over Greece) became a common association with jumps. In fact these events were associated with 7 of the last 11 jumps observed in our dataset. Even the instances when individual company news, such as earnings reports, were the cause of the jumps (which occurred 8 times in the sample) became more associated with reassessments of economic conditions related to the crisis in the latter part of the sample, an example being rumours and announcements about earnings data for Goldman Sachs in July 2009. International events were rarely the cause of jumps, except in instances associated with the Gulf war, oil prices, crisis developments or coordinated central bank actions to combat the crisis. Table 1 provides a summary classification of the jumps in the sample by reason.

At the monthly level the detected jump days are assigned into the calender months to which they belong, thus 77 out of 108 months contain at least one jump day. All 36 quarters have at least one jump day. As Todorov and Bollerslev (2010) also find, the daily $\hat{\beta}$'s have huge outliers occasionally, and are much noisier than the monthly and quarterly estimates. On the other hand, although quarterly estimates show long-run dynamic dependencies, they fail to pick up subtle variations in the $\hat{\beta}$'s through time. Hence we will concentrate our analysis on the monthly $\hat{\beta}_i^c$ and $\hat{\beta}_i^d$ in our subsequent analysis.

Table 2: Average monthly betas for selected stocks

stock	industry	$\hat{\beta}_i^c$		$\hat{\beta}_i^d$	
XOM[a]	basic materials	1.0615	[1.0015,1.1216][b]	1.1286	[1.1091,1.1481]
MMM	conglomerates	0.8849	[0.8261,0.9437]	1.0282	[1.0084,1.0481]
KO	consumer goods	0.6655	[0.6106,0.7205]	0.8314	[0.8128,0.8500]
GS	financial	1.1865	[1.1169,1.2561]	1.4945	[1.4653,1.5237]
JPM	financial	1.2262	[1.1589,1.2935]	1.4592	[1.4354,1.4831]
LEH[c]	financial	1.4585	[1.3810,1.5360]	1.6798	[1.6480,1.7115]
JNJ	healthcare	0.6067	[0.5530,0.6604]	0.7862	[0.7720,0.8003]
GE	industrial goods	1.0828	[1.0221,1.1436]	1.2448	[1.2252,1.2643]
MCD	services	0.7304	[0.6726,0.7954]	0.9947	[0.9721,1.0174]
IBM	technology	0.8707	[0.8144,0.9270]	1.0064	[0.9891,1.0237]
GAS	utilities	0.8139	[0.7531,0.8747]	1.0738	[1.0515,1.0961]

[a] The stocks include: Exxon Mobil (XOM), 3M (MMM), Coca-Cola (KO), Goldman Sachs (GS), JP-Morgan Chace (JPM), Lehman Brother (LEH), Johnson & Johnson (JNJ), General Electric (GE), McDonald's (MCD), IBM and AGL Resources (GAS).
[b] Confidence bands of the corresponding $\hat{\beta}_i$'s are in the square brackets.
[c] The average of $\hat{\beta}^c$ for Lehman Brothers are calculated based on 69 months of estimates before it went bankrupt, and the average of $\hat{\beta}^d$ are calculated based on 53 jump months until September 2008.

4.1 Estimating Betas for Representative Stocks in Each Industry

Our sample period has an overlap of three years with that considered by Todorov and Bollerslev (2010), from January 2003 to December 2005. Although we use finer frequency, it is expected that the $\hat{\beta}^c$ and $\hat{\beta}^d$ should be roughly the same given the consistency of these estimates. Thus we first examine the estimated β's for several representative stocks in each industry, most of which are also investigated in Todorov and Bollerslev (2010). We tabulate the mean of the individual stock's monthly $\hat{\beta}_i^c$ and $\hat{\beta}_i^d$ in Table 2, as well as the respective 95% confidence intervals.[3] Most of the point and interval estimates are very close to those that are reported in Todorov and Bollerslev (2010).

Table 2 shows that the jump $\hat{\beta}^d$ is higher than the continuous $\hat{\beta}^c$ for all stocks considered in Table 2. The two β estimates do not have overlapping interval estimates for any stock with the exception of Exxon Mobil. Across all 501 stocks in the dataset, the monthly $\hat{\beta}^d$ is on average 38% higher than $\hat{\beta}^c$. Financial stocks tend to have highest average values of both $\hat{\beta}^c$ and $\hat{\beta}^d$, whereas stocks in the consumer goods, healthcare and services sectors usually have much lower values for both $\hat{\beta}$'s, and hence much lower exposure to both the systematic risk and sudden arrival of news announcements. This is partly due to the nature of the recent crisis. Financial stocks were at the heart of the turmoil in equity markets and are thus likely to have exhibited high betas during

[3] The estimated variance of the average monthly β_i's for each firm in Table 2 is constructed by taking the mean of the monthly variance estimates, because the $\hat{\beta}_i$ from one month is uncorrelated with the $\hat{\beta}_i$ from another.

this period. The average values shown in Table 2 do not provide much insight on this aspect, but in the following sections we will consider the distinct time variation in $\hat{\beta}_i^c$ and $\hat{\beta}_i^d$ by industrial sector.

As our sample period includes the financial crisis of 2008, we consider a number of banking stocks in closer detail. We plot the monthly continuous and jump $\hat{\beta}$'s of three financial stocks – Goldman Sachs (GS), JPMorgan Chace (JPM) and Lehman Brothers (LEH) – in Figure 1. The vertical line is drawn in July 2007, which signals the initial credit crunch originating with problems in the mortgage backed securities markets. Results for Lehman Brothers record its average $\hat{\beta}^c$ and $\hat{\beta}^d$ and their confidence bands calculated using the estimates up to September 2008 when it went bankrupt in Table 2. On average Lehman Brother has significantly higher sensitivities than other financial firms to both continuous and jump systematic risk. The monthly $\hat{\beta}^c$ and $\hat{\beta}^d$ for these three stocks build up gradually from early 2005. Their continuous $\hat{\beta}^c$'s maintain a high level from late 2007, and peak in mid 2008. The jump $\hat{\beta}^d$ for Lehman Brother is much more volatile than the other firms in 2008, achieving its peak value of almost 5 in March 2008. The jump $\hat{\beta}^d$ for Goldman Sachs and JPMorgan Chace both reach their peak values in April 2010 during the European sovereign debt crisis.

4.2 Average Betas

In Patton and Verardo (2012) the authors compile results for estimated betas on event days across all stocks in the S&P500 - that is a market wide estimate. In a related vein Figure 2 presents the average of the estimated continuous and jump betas across the markets. It is immediately apparent that the continuous beta seems to have trended upwards over the sample period, consistent with the hypothesis of greater market integration, although as we shall see below this finding can be considerably refined once sector results are considered. The results indicate that prior to mid-2007, the average beta to systematic events was below unity, so individual stocks were reacting on average less than the signal received from the market, whilst from 2008 onwards the continuous beta indicates that on average firms are at least as sensitive to the market risk as the signal received (that is $\hat{\beta}^c$ is approximately one). In the period most consistently identified as a period of crisis in the existing literature from the last quarter of 2008 until mid 2009, the average sensitivity to systematic risk signals exceeds the signal itself – that is stocks are hypersensitive to systematic signals.[4]

It is also obvious that the jump betas are consistently higher than the continuous betas on average, although again it is evident that during periods of financial stress – late 2008 and first quarter of 2010 – the gap between the impact of systematic and news events becomes much reduced; there is more attention paid to systematic risk informa-

[4] Examples of identification of crisis period dates include Anand et al. (2013), Beber and Pagano (2013).

Figure 1: Monthly $\hat{\beta}^c$ and $\hat{\beta}^d$ for GS, JPM and LEH

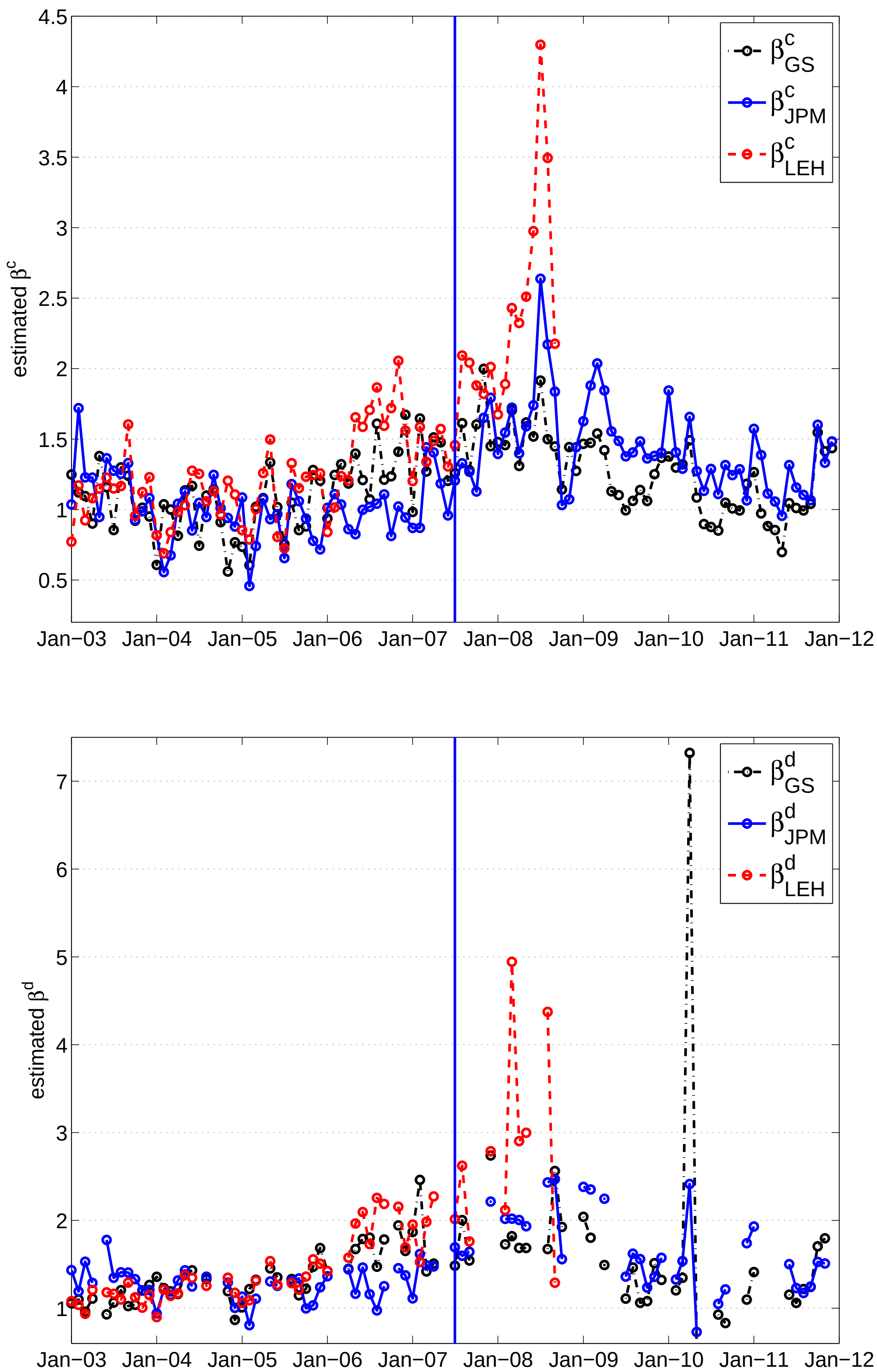
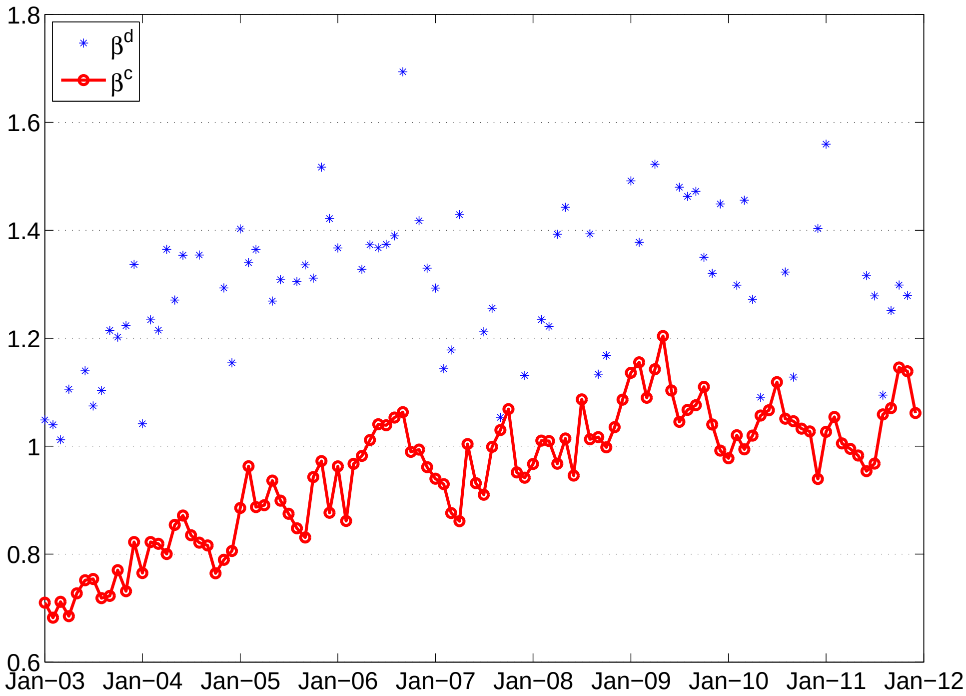


Figure 2: The average monthly $\hat{\beta}^c$ and $\hat{\beta}^d$ for all S&P500 stocks



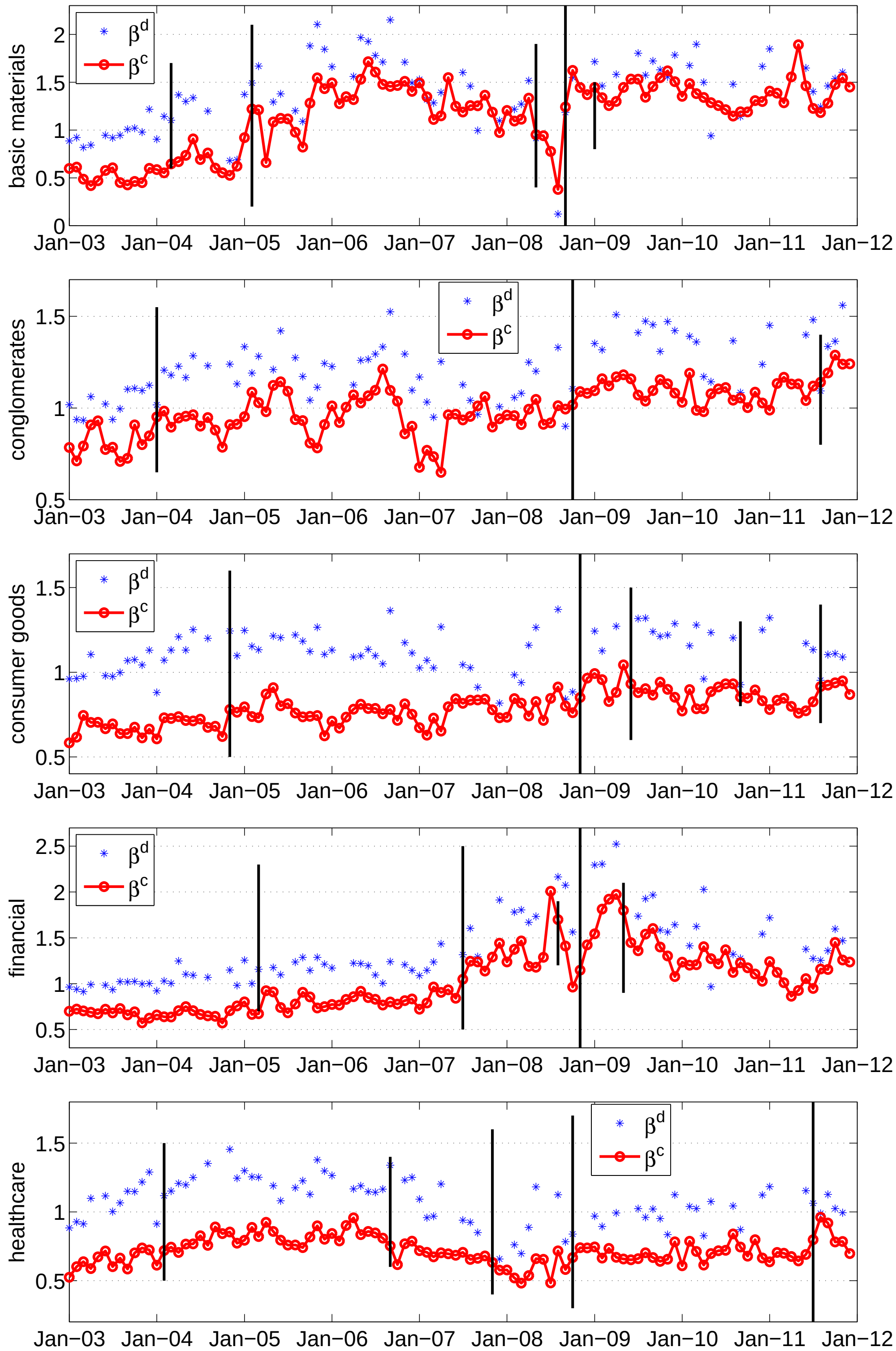
tion in the market than to individual news items. Unlike the continuous betas, however, the jump betas do not display a discernible trend during the sample. The impact of the individual news which is sufficient to cause discontinuities is largely contained in the range 1.0-1.6 (and even more concentrated in the 1.2-1.4 range). As a consequence, the average gap between the discontinuous an continuous beta estimates has fallen over the sample.

4.3 Industry Betas

In this section we investigate whether there is any difference across different industries in the time variation of $\hat{\beta}^c$ and $\hat{\beta}^d$. Figures 3 and 4 plot the intra-industry averages of monthly $\hat{\beta}^c$ and $\hat{\beta}^d$ throughout the entire sample period. It is evident that the $\hat{\beta}$'s have very different scales among different industries. Consistent with the evidence given for the representative stocks in Table 2, stocks in consumer goods, healthcare and services have relatively low and less volatile $\hat{\beta}^c$ in particular. The continuous $\hat{\beta}^c$ for these three sectors are usually bounded below 1, which means that they are less exposed to the continuous component of the systematic risk in the market portfolio than other sectors.

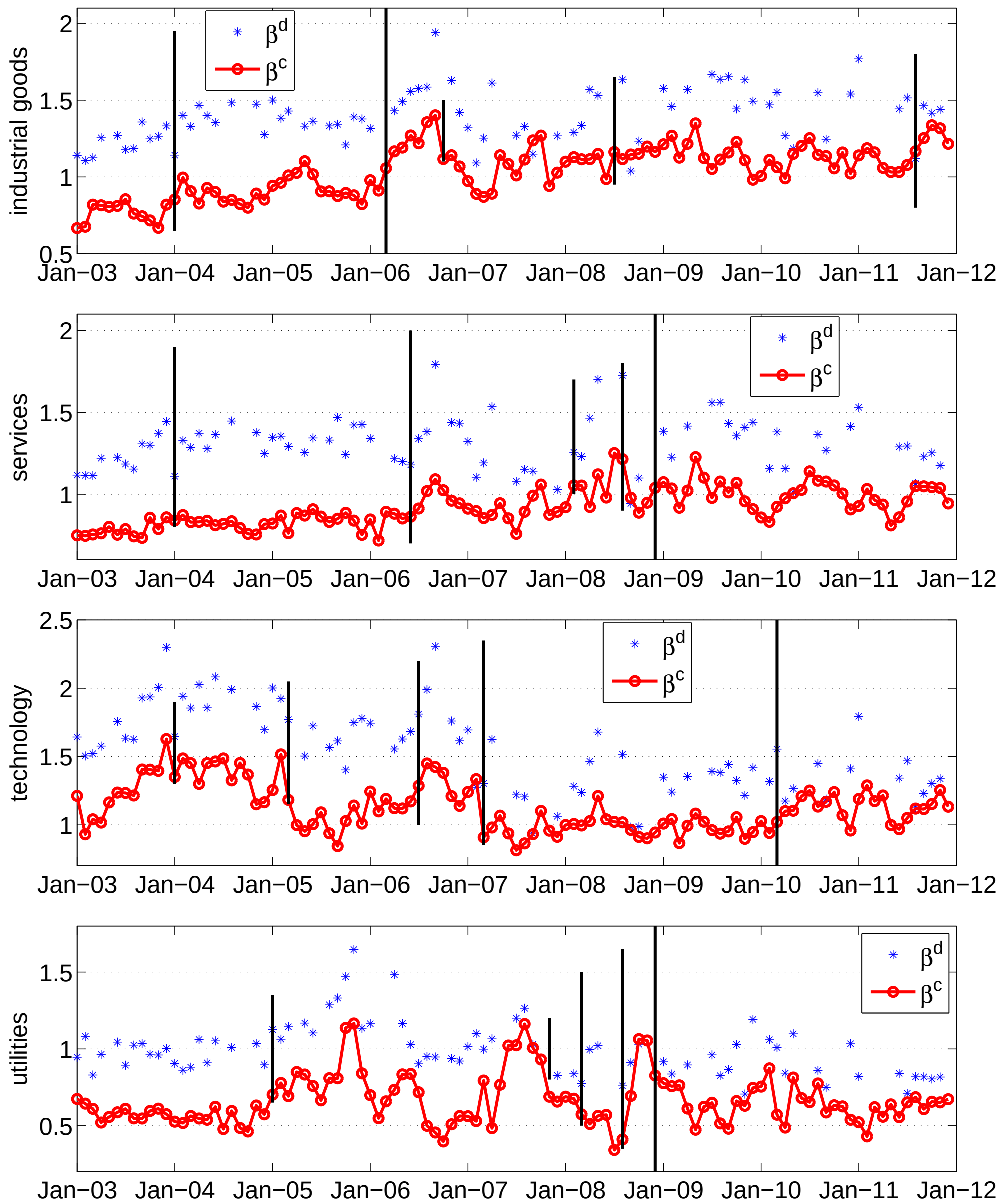
Not surprisingly, both the continuous and jump $\hat{\beta}$'s for the financial sector exhibit a sharp upward trend and large fluctuations during the period of financial crisis, beginning in mid-2007 with the onset of tight credit conditions, evident particularly in the

Figure 3: Average monthly $\hat{\beta}^c$ and $\hat{\beta}^d$ for each industry



The four panels plot the average monthly estimates of the continuous and jump betas for basic materials, conglomerates, consumer goods, financial and healthcare sectors. The red circles denote average monthly $\hat{\beta}^c$ for all stocks in each sector. The blue asterisks denote the average monthly estimates of the jump beta for all stocks in each sector, which are only calculated in jump months. The black vertical lines denote the time points of structural breaks in the industrial average $\hat{\beta}^c$, while the length of the line represents the importance of the break – the longer the more important.

Figure 4: Average monthly $\hat{\beta}^c$ and $\hat{\beta}^d$ for each industry



The four panels plot the average monthly estimates of the continuous and jump betas for industrial goods, services, technology and utilities sectors. Symbols used here are the same as those in Figure 3.

UK, but becoming even more pronounced in the following year in the difficult conditions leading up to September 2008. The continuous $\hat{\beta}$ for the financial sector reaches a peak in July 2008 at $\hat{\beta}^c = 2.0081$, and drops quickly to slightly less than 1 after the bankruptcy of Lehman Brothers, the rescue of AIG and the announcement of TARP. This abrupt drop in response to systematic risk in the financial sector is consistent with the reduction in systematic risk measured via interconnectedness between the real and financial sectors in Dungey et al. (2012). On the other hand, the discontinuous $\hat{\beta}^d$ achieves the highest value of $\hat{\beta}^d = 2.5225$ in June 2009, a date generally associated with the end of the crisis, and the NBER dating of the end of the associated recession. The differences in the timing and also in the magnitude of the $\hat{\beta}$'s shed some lights on the importance of decomposing continuous and jump price movements. These results strongly suggest that during the period of extreme financial stress this sector had very high systematic risk, but that as the real economy became more resilient, and signs of recovery began to emerge, individual news information events returned to the centre stage in understanding the evolution of information transfer through the stock market.

The monthly $\hat{\beta}$'s for the basic materials and the utilities sectors display interesting patterns. As the $\hat{\beta}$'s for financial sector spiking up during the GFC, the $\hat{\beta}^c$ for the basic materials and the utilities sectors hit the lowest values of less than 0.4 in July and August 2007. As for the discontinuous systematic risk, $\hat{\beta}^d$ for the basic materials sector drops down to 0.1221 in August 2007. This discrepancy in the sensitivities across different sectors provide a means of risk diversification.

The continuous $\hat{\beta}$'s for most industries show a general upward trend, with the exception of the technology sector. Its monthly $\hat{\beta}^c$ is higher in the first half of our sample period, and seems to fall back and stabilise after the financial crisis. The burst of dot-com bubble in early 2000 contributes to the high risk exposure of technology stocks to some degree. Starting from 2007, the market stress originated from the financial sector starts to build up. Thus the technology sector becomes less sensitive to the continuous systematic risk in the market portfolio, reflecting its relative independence from other sectors in the economy – potentially indicative of the industry boom and bust cycles evident in specific competitive industries in Hoberg and Phillips (2010). At the same time, its sensitivity to discontinuous systematic risk also falls by a considerable amount compared to the pre-2007 estimates.

The movements shown in Figures 3 and 4 suggest that the monthly $\hat{\beta}^c$'s for each industry cover a relatively wide ranges during the sample period. Thus we conduct the sequential test of multiple structural changes developed by Bai (1997); Bai and Perron (1998, 2003*a*) on each industry-based average of monthly $\hat{\beta}^c$. This test is a generalization of the sup-F statistic outlined in Andrews (1993); Andrews and Ploberger (1994).

Starting from $l = 0$ we sequentially test that

$$\mathbf{H}_0: \text{ there are } l \text{ breaks,} \quad \text{against} \quad \mathbf{H}_1: \text{ there are } l+1 \text{ breaks.}$$

If $\mathbf{H}_0$ is rejected, we proceed to test for $l+1$ breaks against $l+2$ breaks, until $l_{max} = 9$. The test statistic and critical values are provided by Bai and Perron (2003*b*). We drop approximately one year of observations at each end, and examine the possible break points between January 2004 and September 2011. The Newey-West heteroskedasticity and auto-correlation robust standard errors are used to construct the test statistic due to the presence of possible time-varying volatility in the data. We also allow for different distributions of the errors across breaks.

At 5% significance level, we find more than 5 break points in all sectors except the conglomerates, for which only 3 break points are detected. The vertical lines in Figures 3 and 4 denote the estimated dates of possible structural changes in $\hat{\beta}^c$. The top 5 most important break points are shown for each industry, where the length of the vertical lines represent the ranking of importance. Late 2008 is flagged as an important structural change date most often, the $\hat{\beta}^c$ for 6 industries have the most drastic shift during September to December 2008. In addition, the healthcare sector has the second important structural change in its $\hat{\beta}^c$ in October 2008, and fourth important change for the industrial goods sector occurs in July 2008. Thus it is evident that the systematic risk of many stocks has shifted during the GFC period.

4.4 Exploring Firm Homogeneity within Each Industry

Investment strategies based on industry sector are based on the presumption that since individual firms in a particular industrial sector will have relatively similar opportunities, they should have relatively similar reaction to common news. Thus, their reaction to systematic information should be broadly similar. To explore this presumption, Figures 5 and 6 plot the interquartile range and average monthly $\hat{\beta}^c$ for all the firms in each industry. However, the firms removed from the first and fourth quartile in each period are not consistently the same. In fact, for each of the industries around half of the stocks in any industry are included in the interquartile range only half of the time. Specifically, the proportion of firms in each industry which spend half of the sample time in the upper or lower quartile is as follows: basic materials (48 percent), conglomerates (57 percent), consumer goods (57 percent), finance (49 percent), healthcare (51 percent), industrial goods (57 percent), services (44 percent), technology (55 percent) and utilities (58 percent). The number of firms in each industry also varies considerably; with 61 firms in the basic materials sector, 7 in conglomerates, 56 in consumer goods, 77 in financial, 45 in healthcare, 49 in industrial goods, 95 in services, 78 in technology and 33

Figure 5: The interquartile range and average of the monthly $\hat{\beta}^c$ for each industry

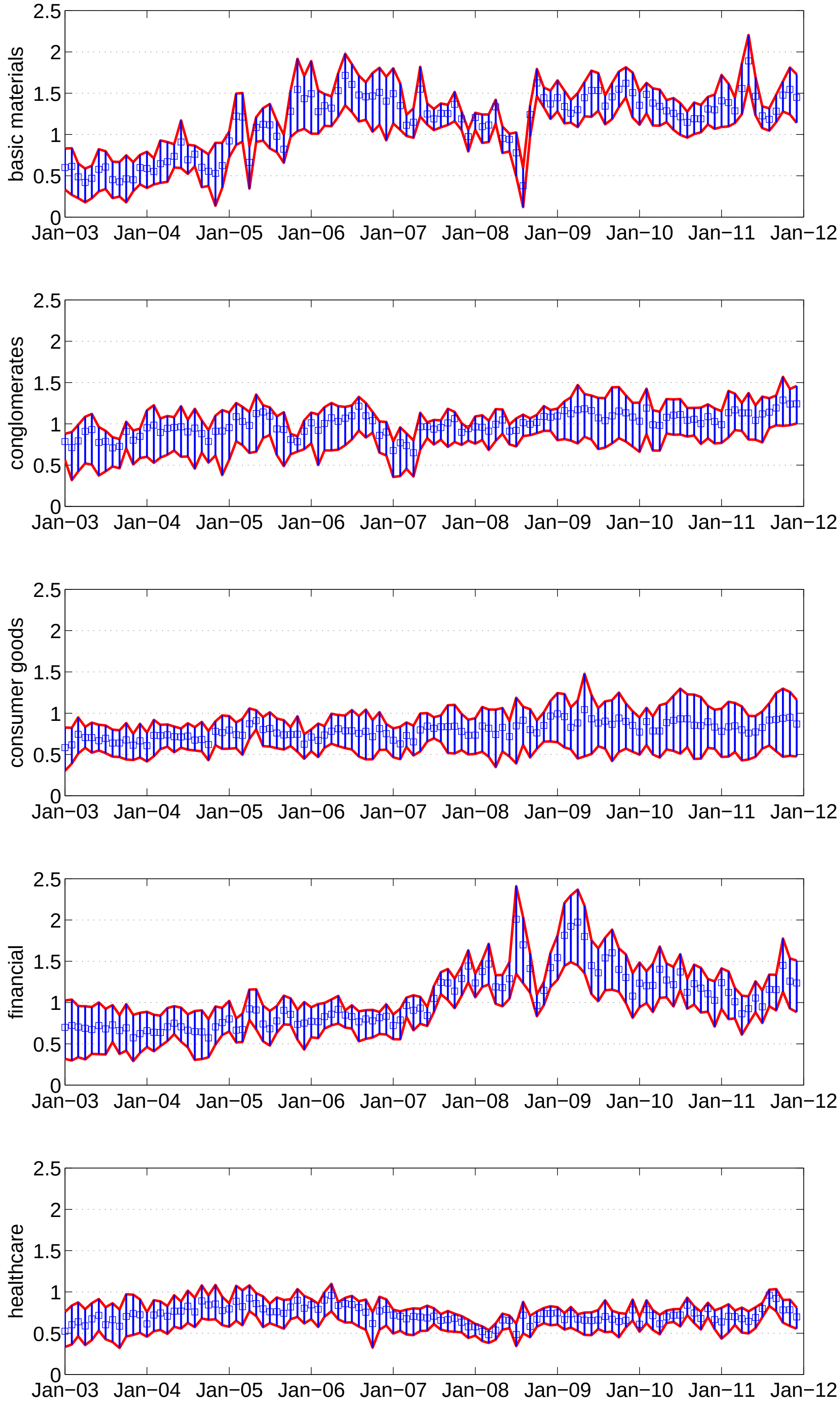
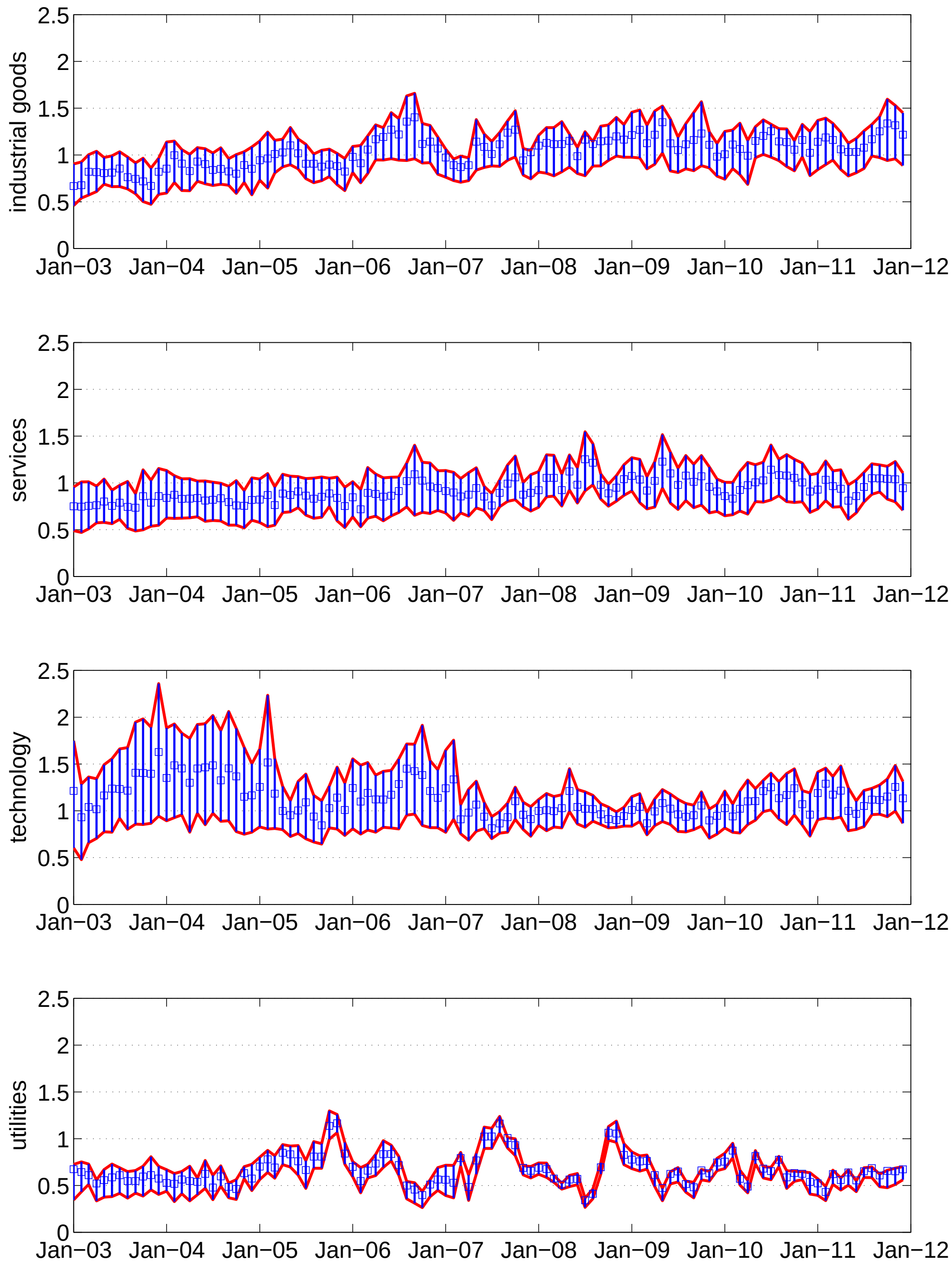


Figure 6: The interquartile range and average of the monthly $\hat{\beta}^c$ for each industry



in the utilities sector. It is immediately apparent that the consistently tightest interquartile range of $\hat{\beta}^c$ estimated for any sector are found in the conglomerates, healthcare and utilities sectors. These sectors contain relatively few, but large firms. In the utilities sector in particular, the goods they produce are relatively uniform and well-understood. Thus, although there is some variation evident in the interquartile range and the average estimate, they tend to remain positive and bounded above by 2.

The estimates of continuous beta for the 501 firms strongly suggest the utilities, healthcare and conglomerates firms are more aligned with the assumption of a homogeneous response than other sectors, while the evidence from both the technology and finance sectors strongly suggest that the degree of responsiveness within a sector can change. In these examples the responsiveness changed in opposite directions. With much market movement emanating from the financial sector itself, the responsiveness of that sector to the market portfolio moves naturally increased over the sample, but the turmoil has also engendered a rise in the range of the responses to common shocks from firms in that sector. In the technology sector the opposite has occurred. Technology firms display a relatively wide interquartile range for the early part of the sample, but narrows considerably by the second half, presumably reflecting that this sector is behaving more homogenously in respect to the systematic risks it faces during the period of stress and subsequent recession in the market than experienced in other sectors, such as finance.

Services and consumer goods display considerably and consistently moderate ranges. Neither the range nor the average vary as much as the more volatile results for basic materials, industrials and financial markets. In these cases the ranges for the continuous betas are moving quite considerably – in the financial sector this is particularly evident, with a spike in values to the highest betas recorded in the sample over 4 during the September 2008 crisis, and a subsequently wider range than prior to the crisis events. This result may well be consistent with the many papers recording structural changes in the financial sector as a result of differential regulatory support actions following the crisis events, which have helped to differentiate deposit-taking and non-deposit taking financial institutions, insurance companies and property investment firms from each other more clearly than prior to the crisis; see for example discussions in King (2011) on the effects of TARP on banks, and discussions on "too big to fail" policies for non-bank financial firms under Dodd-Franks.

When we couple these results with the estimated outcomes on jump betas, which show no systematic change to news events across the sample (with the exception of periods of extreme market stress when this information is downplayed), our results show the importance of understanding the clustering of firms into the industry groupings. Some industry sectors have a more diverse set of responses to market information than others, and some have more volatility in that response over time. Incorporating this information into portfolio management can help to obtain better outcomes for tracking performance and hedging, and assist in understanding how the market absorbs information. Thus the results are complementary to those provided in Patton and Verardo (2012). Additionally, the estimated jump betas emphasise both the higher impact by news associated with discontinuities in the price process, compared with the continuous component, and the relatively high volatility and lack of time-varying structure in these estimates. These features suggest that all industry sectors are subject to a relatively high response to information that is important enough to cause discontinuities. But as there is no systematic evidence that reactions to this type of information over time, there is no evidence of learning about these events, nor opportunity to better hedge against them. The means by which individual sectors (and firms) react to incorporate information of this nature is not easily taken advantage of in a portfolio strategy.

4.5 Firm Characteristics

Firm characteristics usually have strong impacts on firm's sensitivity to systematic risk. For example, we would expect that larger firms are less vulnerable to market risks, and hence have lower beta compared to small firms. To explore the roles of firm characteristics in understanding the estimates of $\hat{\beta}^c$ and $\hat{\beta}^d$, we conduct regression analysis using firm's size, leverage and liquidity level. We measure firm size by market capitalization rescaled by a factor of 10^{-6}, and measure leverage as the book value of assets minus the book value of equity plus the market value of equity. They are both available at daily measures on Thomson Reuters Datastream. Correspondingly, we use daily beta estimates to increase the sample size and ideally obtain more reliable interpretation of the relationship between the betas and the firm characteristics. Liquidity is measured by the sum of cash and short term investments, divided by the book value of assets, which is only observed on a quarterly basis. We estimate the following regression model

$$\beta_i = year_i + \gamma_1\, Leverage_i + \gamma_2\, Liquidity_i + \gamma_3\, Size_i + u_i \tag{20}$$

for both $\hat{\beta}_i^c$ and $\hat{\beta}_i^d$. $year_i$ is a time dummy variable that accounts for the year fixed effects (FE). Any observations with missing values are left out from model (20), and the original beta estimates are taken as the "filtered" ones in such situation. We also estimate model (20) using simple OLS regression without year fixed effects, the estimation results are reported in Table 3. All of the coefficients are statistically significant at 1% level. The "filtered" estimates $\tilde{\beta}_i^c$ and $\tilde{\beta}_i^d$ are constructed by taking the sum of the residuals $\hat{u}_i$ and the corresponding intercept term in the regression, where the influences of firm-specific characteristics have been partialed out. OLS and fixed effects regressions

Table 3: OLS and FE regression estimates

	LHS variable: $\hat{\beta}_i^c$		LHS variable: $\hat{\beta}_i^d$	
	OLS	FE	OLS	FE
γ_1	0.0080 (37.001)	0.0074 (117.40)	0.0095 (18.390)	0.0092 (17.851)
γ_2	0.4426 (46.328)	0.4419 (34.321)	0.5608 (27.721)	0.5589 (27.665)
γ_3	-0.4327 (9.2215)	-0.3805 (46.152)	-1.0957 (10.758)	-1.1309 (11.133)
R^2	0.0029	0.0054	0.0253	0.0347
F-stat	1058.9	548.9	372.0	140.5
nobs	1107773	1107773	42971	42971

The t-statistic for each estimated coefficient is reported in the brackets underneath.

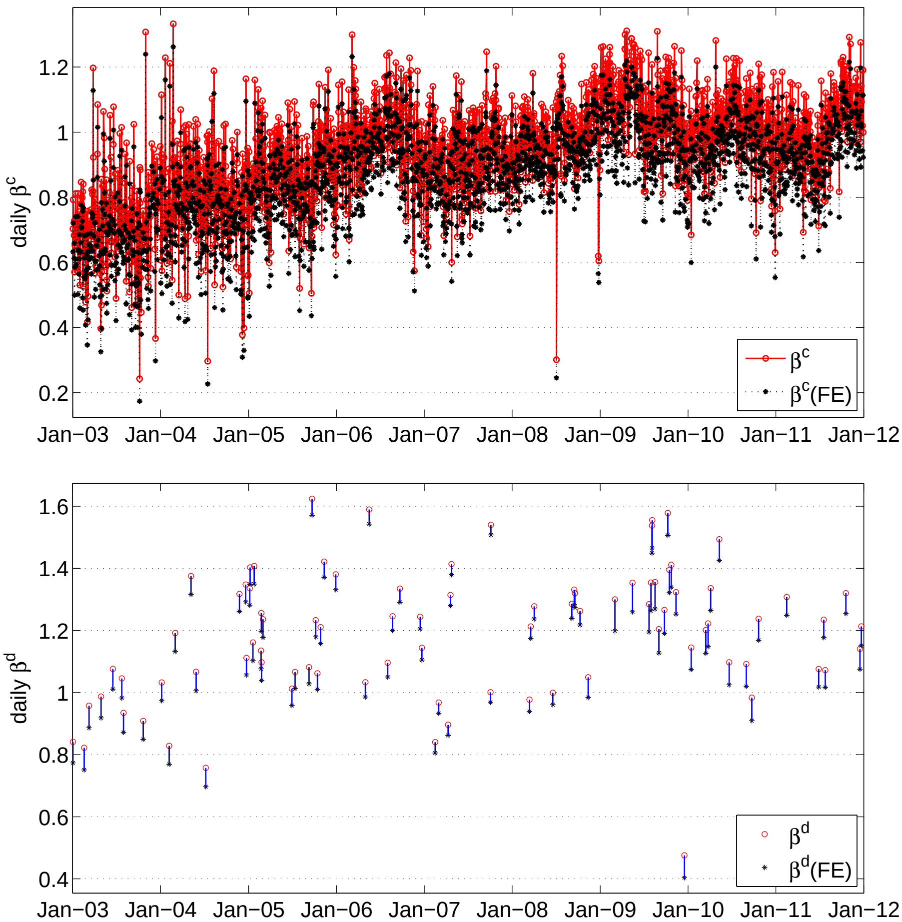
produce almost the same filtered estimates, hence only the fixed effects estimates are reported henceforth. Figure 7 compares the average of filtered estimates and the original estimates for all S&P 500 stocks. The continuous beta is reduced by 0.0755 on average by controlling for the firm characteristics, and the jump beta is reduced by 0.0617. However, the interval estimates of $\tilde{\beta}_i^c$ and $\tilde{\beta}_i^d$ are very wide, thus almost all of the original beta estimates are not statistically different from the filtered estimates. We can conclude that controlling for firm characteristics does not alter the qualitative property of the beta estimates.

4.6 Robustness Test

In this section we investigate the robustness of the empirical results obtained in previous analysis with respect to different choices of the parameter values. Most of these nuisance parameters do not affect the consistency property of the estimators presented in Section 2.2, but they will have impact in any finite sample applications.

Epps (1979) first documented that the correlations among stock returns decrease to zero when their sampling intervals decrease. In the context of the present paper, the Epps effect will cause downward bias in the estimated betas, and is more pronounced for non-liquid stocks. This is the main reason that Todorov and Bollerslev (2010) and Patton and Verardo (2012) choose to use relatively low sampling frequencies in their beta estimates. In order to ensure that our results are not driven by the Epps effect, we construct price and return series at 10, 20 and 30 minutes sampling intervals, and re-calculate $\hat{\beta}_i^c$ and $\hat{\beta}_i^d$ for all 501 stocks in the dataset. Figure 8 plots the monthly $\hat{\beta}_i^c$ for the four smallest firms in terms of *Size*, as they are less liquid and more prone to

Figure 7: The comparison of average daily $\tilde{\beta}_i^c$ and $\hat{\beta}_i^c$, $\tilde{\beta}_i^d$ and $\hat{\beta}_i^d$ for all S&P500 stocks



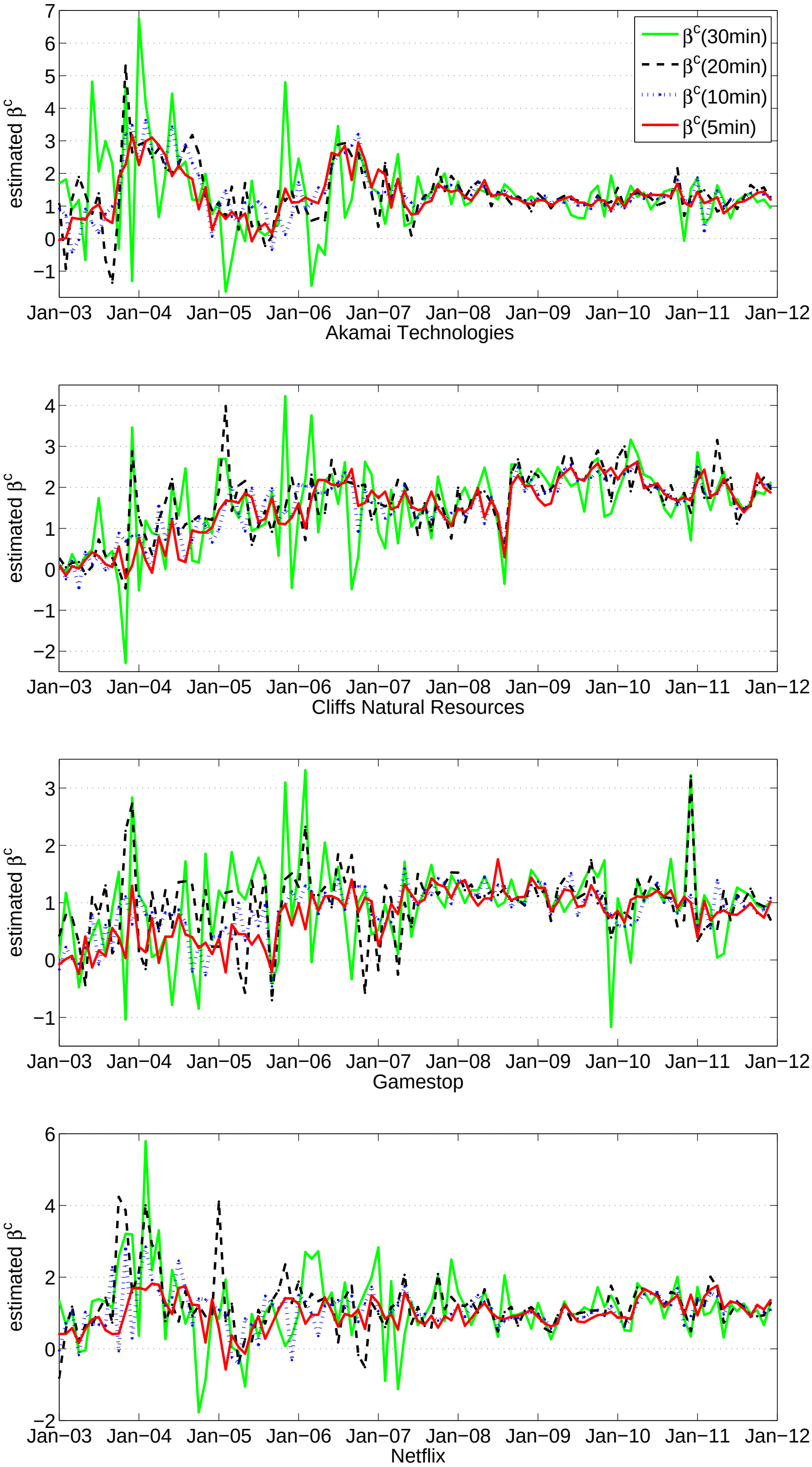
The red circles denote the original beta estimates, whereas the black dots denote the filtered betas using the FE regression. The upper panel plots the daily continuous betas, and the lower panel plots the daily jump betas. The verticle lines connect the two betas obtained from the same day.

the Epps effect. Figure 8 reveals that the original estimates ($\beta^c(5min)$) are less volatile but not necessarily smaller than the $\hat{\beta}_i^c$ calculated using 20-minutes and 30-minutes returns. They exhibit a qualitatively similar pattern over the entire sample period. The same finding still holds for other stocks in this S&P500 dataset.[5]

For monthly estimates of the β's, the value of Δ_n is changing from one month to another, because the number of observations are different. Thus we choose an average number of observations per month to set $\Delta_n = 1/1635$ for all calender months, and calculate the monthly $\hat{\beta}^c$ and $\hat{\beta}^d$ for all stocks. There are still 77 months that contain at least one jump day using the adjusted ratio test by Barndorff-Nielsen and Shephard (2006). Both the point and interval estimates of $\hat{\beta}^c$ and $\hat{\beta}^d$ are almost the same as our previous results. For example for those stocks listed in Table 2, the average values and

[5]The estimated β's with different sampling frequencies for each of the S&P500 constituent stock are available upon request.

Figure 8: The monthly $\hat{\beta}^c$ estimated under different sampling frequencies for small-size firms



the corresponding 95% confidence intervals are the same up to one decimal place.

Next we consider different values for α_i in the truncation threshold $\mathbf{u}_n$ in (11). In previous analysis we set $\alpha_i^d = \sqrt{BV_i^{[0,T]}}$ instead of $2\sqrt{BV_i^{[0,T]}}$ as in Todorov and Bollerslev (2010). The reason for using this less strict classification of price movements that contain jumps is to obtain valid variance estimates for all $\hat{\beta}_i^d$. In equation (14), only those observations that satisfy $|\Delta_j^n p_0| \geq \alpha_0 \Delta_n^{\varpi}$ are retained to calculate the variance estimates. Hence α_i^d and k_n are both chosen according to this principle, so that there are sufficient observations to calculate (14). We experiment with alternative values of α_i^d and k_n, and calculate the variance estimates. Setting $\alpha_i^d = 2\sqrt{BV_i^{[0,T]}}$, we fail to produce an estimated variance for $\hat{\beta}_i^d$ in 12 months out of 77. Using only these 65 estimates to construct confidence bands for the $\hat{\beta}_i^d$ will in general leads to slightly wider interval estimates, but the qualitative results shown in Table 2 do not alter. Similarly, choosing a less restrictive value of α_i^d, such as $\frac{1}{2}\sqrt{BV_i^{[0,T]}}$ reduces the variance estimates by a marginal amount; setting α_i^d to be a reasonable constant value throughout the sample period does not alter our empirical results. In addition, varying the value of k_n has negligible impact on the variance estimates.[6]

Changing the value of α_i^c will affect the number of observations involved in the calculation of $\hat{\beta}_i^c$, and hence affect the two variance estimates in equations (14) and (15) through $\hat{e}_i^c$. Thus we cannot set α_i^c too restrictively in order to retain sufficient observations to estimate (12). By setting $\alpha_i^c = 3\sqrt{BV_i^{[0,T]}}$ we implicitly assume that price movements within 3 standard deviations are associated with the continuous components. There are roughly 30% of the total observations retained. Notice that in equation (12), $|\Delta_j^n p_i| \leq \alpha_i^c \Delta_n^{\varpi}$ need to be satisfied for each $i = 0, 1, \ldots, N$. For large number of N we can lose a large number of observations using this truncation threshold. Thus we only examine the situations where the value of α_i^c is reduced. Results show that the monthly estimates $\hat{\beta}_i^c$ are very robust to more relaxed truncation thresholds.

The last robustness test is to use different test statistics given by Barndorff-Nielsen and Shephard (2006) for detecting jump days. Apart from the adjusted ratio test $\hat{\mathcal{J}}$, there are two other test statistics which have the same asymptotic distribution:

$$\hat{\mathcal{G}} = \frac{1}{\sqrt{\Delta_n}} \frac{\mu_1^{-2} \cdot BV_0^{[0,T]} - QV_0^{[0,T]}}{\theta \mu_1^{-4} \cdot DV_0^{[0,T]}} \xrightarrow{L} \mathcal{N}(0,1), \tag{21}$$

$$\hat{\mathcal{H}} = \frac{1}{\sqrt{\Delta_n}} \frac{1}{\sqrt{\theta \cdot DV_0^{[0,T]} / (BV_0^{[0,T]})^2}} \left(\frac{\mu_1^{-2} \cdot BV_0^{[0,T]}}{QV_0^{[0,T]}} - 1 \right) \xrightarrow{L} \mathcal{N}(0,1). \tag{22}$$

The difference statistic $\hat{\mathcal{G}}$ and the ratio statistic $\hat{\mathcal{H}}$ in general detect more jump days than the adjusted ratio statistic $\hat{\mathcal{J}}$ in equation (16). For the S&P500 index, using $\hat{\mathcal{G}}$

[6] The variance estimates using different parameter values are available upon request.

leads to 284 jump days which are contained in 98 months, and using $\hat{\mathcal{H}}$ leads to 128 jump days which are contained in same 77 months as detected by $\hat{\mathcal{J}}$. The $\hat{\beta}_i^d$'s and their respective 95% confidence intervals calculated using 98 months that contain jumps remain the same up to one decimal place.

5 Conclusion

The recent literature in high-frequency financial econometrics has provided evidence that price discontinuities, or jumps, are important features of the price process (Jacod and Todorov, 2009; Andersen et al., 2007). With the advent of techniques to separate jumps from the continuous component of the price process, we can now distinguish between the continuous and the jump systematic risk components in the market portfolio, as suggested by Todorov and Bollerslev (2010), and capture the time variation in those estimated betas over relatively short intervals, which is of considerable interest.

This paper estimates the CAPM beta for both continuous and jump components for constituent stocks of the S&P500 index over the sample period of 2003 to 2011 using a new 5 minute data set compiled from Thomson Reuters Tick History. We find that the jump betas are usually 30%-40% higher than the continuous betas. These estimates suggest that when news is sufficient to disrupt prices, that is to cause a jump, the speed with which news is disseminated into the market is likely to be even faster than previously estimated using the combined continuous and jump price process as in Patton and Verardo (2012). The continuous betas display some trending property to some extent whereas there is no clear patterns for the jump betas through time. This suggests that firms' responses to continuous systematic risk are easier to predict than the responses to the sudden arrival of news risk.

We compare the beta estimates across different industries, and investigate clustering within the industries. Firms in sectors such as utilities display quite a tight range of continuous beta estimates, consistent with the hypothesis that firms in a single industry face similar opportunities and hence have similar responses to systematic risk – a rationale for implementing an industry based portfolio strategy. Other industries are not as tightly clustered, and we find that there is considerable movement of firms between the interquartile and outerquartile distributions for individual firms – firms are on average in the outerquartile range of their industry about half the time – it is not simple to implement an empirical strategy to select the most representative firms in our industry sectors.

The industry-based average for both the continuous and jump betas show distinct changes over the sample period. Most industries experience significant structural changes in their sensitivities to the continuous systematic risk associated with the global financial crisis, particularly during the last quarter of 2008. Not surprisingly, the financial sector displays the most volatility in the beta estimates in this period. Interestingly, in the financial and some other sectors, the only time when jump betas are not distinctly higher than continuous betas is during periods of high financial stress – in late 2008 and first quarter 2010 due to the emerging Greek crisis. In these periods systematic risk considerations dominate any concerns about individual news events.

These results present evidence in favour of the industry-based portfolio diversification, especially for hedging the continuous component of the systematic risk. An interesting line of future research is to further explore means of obtaining homogeneous groupings for beta estimates. Clustering of the continuous betas at finer level may exist, and will provide more informative portfolio management strategies.

References

Aït-Sahalia, Y. and Jacod, J. (2010), Analyzing the Spectrum of Asset Returns: Jump and Volatility Components in High Frequency Data, NBER Working Papers 15808, National Bureau of Economic Research, Inc.

Anand, Amber, A., Irvine, R., Puckett, A. and Venkataraman, K. (2013), 'Institutional Trading and Stock Resiliency: Evidence from the 2007-2009 Financial Crisis', *Journal of Financial Economics* **108**, 773–797.

Andersen, T. G., Bollerslev, T. and Diebold, F. X. (2007), 'Roughing It Up: Including Jump Components in the Measurement, Modeling, and Forecasting of Return Volatility', *The Review of Economics and Statistics* **89**(4), 701–720.

Andersen, T. G., Bollerslev, T., Diebold, F. X. and Labys, P. (2003), 'Modelling and Forecasting Realized Volatility', *Econometrica* **71**, 579–625.

Andrews, D. W. K. (1993), 'Tests for Parameter Instability and Structural Change With Unknown Change Point', *Econometrica* **61**(4), pp. 821–856.

Andrews, D. W. K. and Ploberger, W. (1994), 'Optimal Tests When a Nuisance Parameter Is Present Only under the Alternative', *Econometrica* **62**(6), 1383–1414.

Bai, J. (1997), 'Estimating Multiple Breaks One at a Time', *Econometric Theory* **13**, 315–352.

Bai, J. and Perron, P. (1998), 'Estimating and Testing Linear Models with Multiple Structural Changes', *Econometrica* **66**(1), 47–78.

Bai, J. and Perron, P. (2003*a*), 'Computation and Analysis of Multiple Structural Change Models', *Journal of Applied Econometrics* **18**(1), 1–22.

Bai, J. and Perron, P. (2003*b*), 'Critical values for Multiple Structural Change Tests', *Econometrics Journal* **6**(1), 72–78.

Bandi, R. and Russell, J. (2006), 'Separating Microstructure Noise from Volatility', *Journal of Financial Economics* **79**, 655–692.

Barndorff-Nielsen, O. E. and Shephard, N. (2006), 'Econometrics of Testing for Jumps in Financial Economics Using Bipower Variation', *Journal of Financial Econometrics* **4**(1), 1–30.

Beber, A. and Pagano, M. (2013), 'Short-Selling Bans Around the World: Evidence from the 2007-09 Crisis', *The Journal of Finance* **68**(1), 343–381.

Bekaert, G., Harvey, C. R., Lundblad, C. T. and Siegel, S. (2011), 'What Segments Equity Markets?', *Review of Financial Studies* **24**(12), 3841–3890.

Bekaert, G., Harvey, C. R., Lundblad, C. T. and Siegel, S. (2013), 'The European Union, the Euro, and Equity Market Integration', *Journal of Financial Economics* **109**(3), 583–603.

Bekaert, G., Hodrick, R. and Zhang, X. (2009), 'International Stock Return Comovements', *The Journal of Finance* **64**(6), 2591–2626.

Blair, B., Poon, S.-H. and Taylor, S. (2001), 'Forecasting S&P500 Volatility: The incremental information content of implied volatilities and high-frequency index returns', *Journal of Econometrics* **105**, 5–26.

Bollerslev, T., Law, T. H. and Tauchen, G. (2008), 'Risk, Jumps, and Diversification', *Journal of Econometrics* **144**(1), 234–256.

Dungey, M., Henry, O. and Hvozdyk, L. (2011), The Impact of Thin Trading and Jumps on Realized Hedge Ratios, manuscript, CFAP, University of Cambridge.

Dungey, M., Luciani, M. and Veredas, D. (2012), Ranking Systemically Important Financial Institutions, Working Papers ECARES 2013/130530, ULB – Universite Libre de Bruxelles.

Dungey, M., McKenzie, M. and Smith, V. (2009), 'Empirical Evidence on Jumps in the Term Structure of the US Treasury Market', *Journal of Empirical Finance* **16**, 430–445.

Ehling, P. and Ramos, S. B. (2006), 'Geographic versus Industry Diversification: Constraints Matter', *Journal of Empirical Finance* **13**, 396–416.

Epps, T. W. (1979), 'Comovements in Stock Prices in the Very Short Run', *Journal of the American Statistical Association* **74**(366), pp. 291–298.

Hoberg, G. and Phillips, G. (2010), 'Real and Financial Industry Booms and Busts', *Journal of Finance* **65**(1), 45–86.

Jacod, J. and Todorov, V. (2009), 'Testing for Common Arrivals of Jumps for Discretely Observed Multidimensional Processes', *The Annals of Statistics* **37**(4), pp. 1792–1838.

King, M. (2011), The Cross-border Contagion and Competition Effects of Bank Bailouts Announced in October 2008, manuscript, University of Western Ontario.

Lahaye, J., Laurent, S. and Neely, C. J. (2005), 'Bond Yields and the Federal Reserve', *Journal of Political Economy* **113**(2), 311–344.

Lahaye, J., Laurent, S. and Neely, C. J. (2011), 'Jumps, Cojumps and Macro Announcements', *Journal of Applied Econometrics* **26**(6), 893–921.

Lai, Y.-S. and Sheu, H.-J. (2010), 'The Incremental Value of a Futures Hedge Using Realized Volatility', *Journal of Futures Markets* **30**(9), 874–896.

Menzly, L. and Ozbas, O. (2010), 'Market Segmentation and Cross-predictability of Returns', *Journal of Finance* **65**(4), 1555–1580.

Patton, A. J. and Verardo, M. (2012), 'Does Beta Move with News? Firm-specific Information Flows and Learning About Profitability', *Review of Financial Studies* **25**, 2789–2839.

Todorov, V. and Bollerslev, T. (2010), 'Jumps and Betas: A New Framework for Disentangling and Estimating Systematic Risks', *Journal of Econometrics* **157**(2), 220–235.