ESSAYS ON HIGH FREQUENCY DATA, JUMPS, AND FORECASTING

by

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ABSTRACT OF THE DISSERTATION

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This dissertation comprises two essays on financial economics and econometrics. The first essay reviews methodology associated with the construction of nonparametric estimators of integrated volatility, jump tests, and realized volatility decompositions. In an empirical analysis that draws on this methodology, we separate continuous asset return variation and finite activity jump variation from U.S. excess returns on U.S. market sector exchange traded funds (ETFs) during and around the Great Recession of 2008. Our objective is to characterize the financial contagion that was present during one of the greatest financial crises in U.S. history. In particular, we study how shocks, as measured by jumps, propagate through nine different market sectors. One element of our analysis involves the investigation of causal linkages associated with jumps (via the analysis of vector autoregressions), and another involves the examination of the predictive content of jumps for excess returns. We find that as early as 2006, jump spillover effects became more pronounced in the markets. Another important findings that we see is that jumps have a significant effect on excess returns during 2008 and 2009. Thus, jumps play an important role in asset pricing during volatile episodes. In the second essay, we utilize measures of jumps in the markets in order to construct daily indexes of unexpected jump spillover risk associated with major news announcements and events. The methodology that we implement is based on two novel new tools recently developed in the financial econometric and machine learning literatures. First, we implement the jump decomposition methods detailed in Aït-Sahalia and Jacod (2012) in order to decompose quadratic variation into continuous components and jump components; and we further separate large and small jump variations. We then carry out shrinkage via application of ridge, elastic net (EN), least absolute shrinkage operator (LASSO), and a cross validated convex combination ridge, EN and LASSO methods in order to quantify (Granger) causal jump spillover effects across sectors and markets, and construct risk indexes. In an empirical analysis illustrating the methodology proposed for constructing jump based risk indexes, we analyze equally spaced 5-minute high frequency trading data on nine market sector ETFs as well as the S&P500 and the VIX for the period 2005 - 2010.In summary, we believe the indexes proposed in this paper are usefully condensed indicators of the risk associated with unexpected events in the markets, and should be of interest to market participants interested in hedging such risk.

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Dedication

To my parents, Huiying Chen and Zuqiang Jiang,

And my husband and my son, Justin S. Schlossberg and Lee A. Schlossberg

Without whom none of my achievements would be possible

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Chapter 1

Introduction

This dissertation will present empirical research in the field of high frequency volatility jumps. Since 2006, High frequency trading has grown to become an essential part of the trading market. According to Credit Suisse, which cited data from TABB Group, high frequency trading contributed to roughly half of all equity trading in 2016. High frequency has reshaped the financial industry. As a result, high frequency volatility jumps has received tremendous attention from both financial economists and investors. We aim to expand the current literature on this topic, specifically in two areas: jump spillover and jump contribution to excess returns. The economic rationale for the dissertation draws on the idea that jumps are associated with specific economic events, which was found empirically (See Andersen, Bollerslev, Diebold, and Vega (2003), Huang (2007), Bollerslev, Law, and Tauchen (2008), Lee and Mykland (2008), Lahaye, Laurent, and Neely (2010), Asgharian and Nossman (2011), Evans (2011), Lahaye, Laurent, and Neely (2011), Jiang and Verdelhan (2011), Chatrath, Miao, Ramchander, and Villupuram (2014), Jawadi, Louhichi, and Cheffou (2015), Aït-Sahalia and Xiu (2016)) . In the second chapter, we review some recent advances in econometric methodology of analyzing jumps using the high frequency data, such as the bipower-variation-based tests of Barndorff-Nielsen and Shephard (2006a, 2006b, 2006c), Huang and Tauchen (2005), Andersen, Bollerslev and Diebold (2007), and Lee and Mykland (2008); the swap-variance-based test due to Jiang and Oomen (2008); and the truncated-power-variation based tests due to Aït-Sahalia and Jacod(2008, 2009a, 2009b) and Lee and Hanning (2010). We also discuss a so-called long time span jump test dues to Corradi, Silvapulle and Swanson (2018), which is consistent (the above fixed time span tests are not consistent, in the sense that power does not go to unity as the sample size increases). Our main findings are: (1) strong large and total jump spillover effects (i.e., jumps from one sector (Granger) causing jumps from another sector) were seen as early as in 2006, and weakened as the recession unfolded. With small jumps, the opposite occurred. In particular, 2008 was the weakest year for large and total jump spillover effects and strongest year for small jumps. This can be understood by examining the causes of jumps of different sizes. (2) Large jump spillover effects seem to correlate with major news and events, while small jump spillover effects are harder to interpret and seem more correlated with heterogeneous agent and firm specific characteristics. (3) With regard to the jump contributions to excess returns, total jump and large jump contributions were close to zero in years other than 2008 and 2009. This provides strong evidence that jumps play an important role in asset pricing during crisis times.

The third chapter extends the findings in the second chapter and attempts to construct a new type of daily frequency index that is associated with the jump spillover risks. The implemented methodology is based recently developed tools in financial econometrics and machine learnings. The first step is to decompose jump variation via methods detailed in Aït-Sahalia and Jacod (2012). We then implement shrinkage through ridge, elastic net (EN), LASSO and a cross validated convex combination ridge, EN and LASSO methods in order to quantify (Granger) causal jump spillover effects across sectors and markets. Last, we construct indexes for the U.S. market using equal weighted and float-adjusted market capitalization weighted, as well as indexes for each market sector. We then apply Markov regime switching models to analyze and compare our indexes with S&P500 and VIX. We believe that the indexes proposed in this chapter are useful condensed indicators of the jump spillover risk, which are connected to unexpected events and should be of interest to market participants intereseted in hedging such risk.

Chapter 2

Jump Spillover and Risk Effects on Excess Returns in the United States During the Great Recession

2.1 Introduction

The so-called Great Recession of 2008-2009 has received considerable attention in the economics and finance professions in recent years. Indeed, countless academic papers have studied its causes, impact, and aftermath. This chapter provides a fresh perspective by looking at this important event through the lens of high frequency trading data. First, we survey recent advances in the econometric methodology of analyzing jumps using high frequency financial data. Then, we utilize five-minute trading data and apply the aforementioned econometric methods to analyze jump spillover effects and jump contributions to excess returns in U.S. markets during and around the Great Recession.

The economic rationale for the chapter draws on the idea that jumps are associated with specific economic events. Andersen, Bollerslev, Diebold, and Vega (2003) study foreign exchange markets and find that unexpected news announcements result in conditional mean jumps; and that negative news has a greater impact than positive news. Huang (2007) analyzes jumps using intra-day high frequency data in equity and fixed-income markets, and finds that more large jumps are present on days with news than on days without news. Evans (2011) discovers that approximately one third of jumps between July 1998 and June 2006 in the U.S. futures markets are connected with U.S. macroeconomic news announcements, and that these news announcements lead to large jumps. Jiang and Verdelhan (2011) find that pre-announcement liquidity shocks can be used to predict jumps in treasury bond markets and are therefore useful for asset pricing. Lee and Mykland (2008) apply nonparametric tests to search for jumps in equity markets. Their results suggest that different pricing models should be applied for individual equity options and index options, due to the fact that jumps in individual stocks are associated with company-specific news events. Lahaye, Laurent, and Neely (2011) focus on futures markets, and find that the size, frequency and timing of jumps in futures markets are related to economic shocks. Bollerslev, Law, and Tauchen (2008) examine jumps in both individual stocks and an aggregate market index. They conclude that the existence and pattern of co-jumps provides evidence of a relationship between jumps and macroeconomic news announcements. Similar results can also be seen in the currency markets. For example, Chatrath, Miao, Ramchander, and Villupuram (2014) find that correlation exists between jumps and news announcements. They also find evidence of co-jumps. Some authors focus on international markets rather than just domestic markets. For example, Asgharian and Bengtsson (2006) focus on the U.S. market and several European markets and find that significant jump spillover effects exist in countries that have features in common, such as industry structure or geographic location. Asgharian and Nossman (2011) inspect jumps in equity markets in several regions and conclude that local European markets are under the influence of U.S. markets. Jawadi, Louhichi, and Cheffou (2015) use nonparametric econometric methods to test contagion hypotheses, and provide evidence of dependence between jumps in three European markets and U.S. markets. Lahaye, Laurent, and Neely (2010) find that payroll announcements are important in stock and bond futures markets, while trade related news often creates co-jumps in exchange rate markets. Aït-Sahalia and Xiu (2016) provide strong evidence of correlation between financial crises and increase in the quadratic variation of assets.

In this chapter, we extend the findings of Asgharian and Bengtsson (2006), Asgharian and Nossman (2011), Jawadi, Louhichi, and Cheffou (2015), and Aït-Sahalia and Xiu (2016) in three ways. First, our research centers on the domestic jump spillover effects in the U.S. during the 2008 financial crisis. Particularly, we look at jump spillover effects across nine market sectors. Second, we decompose jumps based on their size and investigate financial market interactions using different sized jumps. By using truncation in order to identify (small and large) jumps, we are able to investigate how different economic shocks affect U.S. markets. This is important, since macroeconomics news events often cause large jumps, while many (asset) price movements are associated with small jumps. Our approach is to remain agnostic about the cause of jumps, and to instead focus on the relationship among different jumps (in different market sectors, for example).

Third, we focus attention on the importance of jumps for explaining excess returns.

Following the methodology used in much of the extant literature on jumps in financial markets, our approach to examining jump propagation is based on the use of nonparametric tools. In particular, we apply nonparametric jump tests and decomposition methods, which are discussed in detail in the sequel, in order to characterize jumps. We then perform two regression analyses. In a first analysis, we test the hypothesis that jump spillovers exists across different market sectors. Our main findings are as follows. First, large jump spillover effects that impact multiple markets seem to be correlated with the major news and events and can be industry-specific. This is because large jumps are known to be related to unexpected major news and events. Second, total jump spillover effects are similar to large jump spillover effects, as large jumps usually dominate the jump process. Third, strong large and total jump spillover effects are observed prior to the onset of the 2008-2009 recession, and weakened in 2008; while small jump spillover effects intensified as the recession unfolded. This can be explained by the different origins of large jumps and small jumps. It is also consistent with a hypothesis that that jumps are affected by trader's behavior in the markets. Finally, jumps from the XLF (i.e., the financial sector) are not a major player in our findings, as might be expected. this might be explained in part by unmodelled nonlinear correlation across market sectors, for example.

In a second regression analysis we study the contribution of jumps to excess returns. We find that jumps are statistically significant in models of excess returns. Moreover, we observe a sharp increase in jump contribution to sector excess returns in 2008 and 2009. This provides evidence that jumps are important in asset pricing, especially in turbulent times.

The rest of the chapter is organized as follows. Section 2.2 reviews nonparametric jump tests and decomposition methods. Section 2.3 outlines the empirical methodology used in our data analysis. Section 2.4 contains our empirical findings. Finally, concluding remarks are gathered in Section 2.5.

2.2 Jump Tests and Jump Decomposition Methods

2.2.1 Set-up

Define log prices as $Y_t = log(P_t)$, and assume that they follow an Itô semimartingale process,

$$Y_t = Y_0 + \int_0^t a_u d_u + \int_0^t \sigma_u dW_u + \int_0^t \int_{\{|y|\leq\epsilon\}} y(j-\nu)(du,dy) + \int_0^t \int_{\{|y|>\epsilon\}} yj(du,dy), \qquad (2.1)$$

where $Y_0 + \int_0^t a_u d_u + \int_0^t \sigma_u dW_u$ is a Brownian semi-martingale. Here, $\int_0^t a_u d_u$ is the drift term, with a_t being the instantaneous drift, and $\int_0^t \sigma_u dW_u$ is the continuous part. with σ_t being the spot volatility. Additionally, j is the jump measure of Y_t, and its predictable compensator is the Lévy measure ν. Finally, $\int_0^t \int_{\{|y|\leq\epsilon\}} y(j-\nu)(du,dy)$ is the so-called small jump component, and $\int_0^t \int_{\{|y|>\epsilon\}} yj(du,dy)$ is the so-called large jump component, with ϵ being an arbitrary cutoff level specified in order to differentiate between small and large jumps.

Volatility is a latent variable, and realized measures are often employed to consistently estimate it.[1] In the high frequency literature, one of the most widely known measures is realized volatility (RV). Suppose that $t > 0$ is a fixed time period, for example, one trading day, and the ith log-price of an asset observed during day t is $Y_{i,t}$. The intra-ith return on day t is $r_{i,t} = Y_{i,t} - Y_{i-1,t}$, where $i = 1, 2, ..., t/\delta$ and δ is the sampling frequency. For one trading day, we have the explicit expression for RV:

$$RV_t = \sum_{i=1}^{t/\delta} r_{i,t}^2. \qquad (2.2)$$

When sampling is at a high and fixed frequency (such as $N \to \infty$ or $\delta \to 0$), then realized volatility converges to so-called quadratic variation which is defined as follows:

$$[Y]_t = p \lim_{\delta \to 0} \sum_{i=0}^{t/\delta - 1} (Y_{t_i} - Y_{t_i})^2, \qquad (2.3)$$

for any sequence of partitions $t_0 = 0 < t_1 < ... < t_n = t$, with $sup_i\{t_{i+1} - t_i\} \to 0$ for $\delta \to 0$. Thus

$$RV_t \xrightarrow{\mathbb{P}} [Y]_t$$

[1]Sometimes, in financial econometrics, the word variance is used interchangeably with volatility. Here we follow the convention of equating volatility with sums of squared returns.

where $\mathbb{P}$ denotes convergence in probability. Thus, realized quadratic variation (QV) is expressed as:

$$QV = [Y_\delta]_t = \sum_{i=1}^{t/\delta} r_{i,t}^2 \tag{2.4}$$

Another important measure is called integrated volatility, which is defined as $\int_0^t \sigma_u^2 du$. When asset prices are continuous on a fixed interval $[0, T]$:

$$[Y]_t \xrightarrow{\mathbb{P}} \int_0^t \sigma_u^2 du, \tag{2.5}$$

and when asset prices also have a discontinuous component on $[0, T]$ (like in Equation (1)):

$$[Y]_t \xrightarrow{\mathbb{P}} \int_0^t \sigma_u^2 du + \sum_{u \leq t} (\Delta Y_u)^2, \tag{2.6}$$

where $\sum_{u \leq t}(\Delta Y_u)$ is a pure jump process and a jump at time s is defined as $\Delta Y_t = Y_u - Y_{u-}$. Here, $\sum_{u \leq t}(\Delta Y_u)^2$ is the variation of the jump component.

2.2.2 Jump Testing

The literature on jump testing has been active since 2002. Testing whether or not jumps are present in a process is particularly useful to do prior to constructing realized measures of jump and continuous components of a variable. For early relevant discussions in this area, see Andersen, Benzoni, and Lund (2002) and Chernov et al. (2003), as well as Aït-Sahalia (2002) and Johannes (2004). In this chapter, we discuss three different tests including: the bipower-variation-based tests of Barndorff-Nielsen and Shephard (2006a, 2006b, 2006c), Huang and Tauchen (2005), Andersen, Bollerslev and Diebold (2007), and Lee and Mykland (2008); the swap-variance-based test due to Jiang and Oomen (2008); and the truncated-power-variation based tests due to Aït-Sahalia and Jacod(2008, 2009a, 2009b) and Lee and Hanning (2010). We also discuss a so-called long time span jump test dues to Corradi, Silvapulle and Swanson (2018), which is consistent (the above fixed time span tests are not consistent, in the sense that power does not go to unity as the sample size increases)

Bipower Variation Tests

Under the assumption of Equation (1), Equation (6) shows that if the theoretical integrated volatility can be properly estimated, jumps can be measured using the difference between QV and realized integrated volatility. This is the key idea underpinning bipower variation based tests. Barndorff-Nielsen and Sharphard (2004) suggest using bipower variation to estimate integrated volatility. Barndorff-Nielsen and Shephard (2006a) propose various bipower variation based jump test statistics.

The quadratic variation defined in equation (3) is a special case of power variation. Additionally, sth power variation is defined as:

$$\{Y\}_t^{[s]} = p\lim_{\delta\to 0} \delta^{1-s/2} \sum_{i=1}^{t/\delta} |r_{i,t}|^s,$$

where $s > 0$. The bipower variation process is defined as:

$$\{Y\}_t^{[s_1,s_2]} = p\lim_{\delta\to 0} \delta^{1-(s_1+s_2)/2} \sum_{i=1}^{[t/\delta]-1} |r_{i,t}|^{s_1} |r_{i+1,t}|^{s_2},$$

where $s_1, s_2 > 0$. When $s_1 = s_2 = 1$, $\{Y\}_t^{[1,1]}$ can be consistently estimated using realized bipower variation (BV), defined as follows:

$$BV_t = \{Y_\delta\}_t^{[1,1]} = \sum_{i=2}^{t/\delta} |r_{i-1,t}||r_{i,t}|. \tag{2.7}$$

Barndorff-Nielsen and Shephard (2004) show that the power variation and bipower variation can be expressed as:

$$\mu^{-1}\{Y\}_t^{[s]} = \begin{cases} \int_0^t \sigma_u^s du & s \in (0,2) \\ \big[Y\big]_t & s = 2 \\ \infty & s > 2 \end{cases}$$

and

$$\mu_{s_1}^{-1}\mu_{s_2}^{-1}\{Y\}_t^{[s_1,s_2]} = \begin{cases} \int_0^t \sigma_u^{s_1+s_2} du & max(s_1,s_2) \in (0,2) \\ x_t^* & max(s_1,s_2) = 2 \\ \infty & max(s_1,s_2) > 2 \end{cases}$$

where x_t^* is some stochastic process.

A special case is when $s_1 = s_2 = 1$,

$$\mu_1^{-2}\{Y\}_t^{[1,1]} = \int_0^t \sigma_u^2 du.$$

Thus, integrated volatility can be consistently estimated as:

$$\mu_1^{-2} BV \xrightarrow{\mathbb{P}} \int_0^t \sigma_u^2 du \tag{2.8}$$

where $\mu_1 = E[u] = \sqrt{2}/\sqrt{\pi} \simeq 0.79788$, and u is $N(0,1)$ random variable.

The bipower jump test null hypothesis is that no jumps are present. Barndorff-Nielsen and Shephard (2006a) propose a linear jump test statistic G, and a ratio jump test statistic H:

$$G = \frac{\delta^{-1/2}(\mu_1^{-2} BV_t - QV_t)}{\sqrt{\int_0^t \eta \sigma_u^4 du}} \xrightarrow{d} N(0,1)$$

and

$$H = \frac{\delta^{-1/2}(\frac{\mu_1^{-2} BV_t}{QV_t} - 1)}{\sqrt{\eta \frac{\int_0^t \sigma_u^4 du}{\{\int_0^t \sigma_u^2 du\}^2}}} \xrightarrow{d} N(0,1),$$

where $\eta = (\pi^2/4) + \pi - 5 \simeq 0.6090$ and d means convergence in distribution. Here, $\int_0^t \sigma_u^4 du$ is the integrated quarticity and can be estimated using realized quadpower variation (QPV): [2]

$$QPV_t = \{Y_\delta\}_t^{[1,1,1,1]} = \delta^{-1} \sum_{i=4}^{t/\delta} |r_{i-3,t}||r_{i-2,t}||r_{i-1,t}||r_{i,t}| \xrightarrow{\mathbb{P}} \mu_1^4 \int_0^t \sigma_u^4 du. \tag{2.9}$$

Additionally, $\int_0^t \sigma_u^2 du$ can be estimated using BV. This yields the following feasible linear jump and ratio jump statistics, $\hat{G}$ and $\hat{H}$:

$$\hat{G} = \frac{\delta^{-1/2}(\mu_1^{-2} BV_t - QV_t)}{\sqrt{\eta \mu_1^{-4} QPV_t}} \xrightarrow{d} N(0,1).$$

and

$$\hat{H} = \frac{\delta^{-1/2}}{\sqrt{\eta QPV_t / BV_t^2}} (\frac{\mu_1^{-2} BV_t}{QV_t} - 1) \xrightarrow{d} N(0,1),$$

[2] Barndorff-Nielsen et al. (2005) discuss a more general case for realized multipower variation, and Barndorff-Nielsen, Shephard, and Winkel (2006) analyze the case where the jump component is a Lèvy or non-Gaussian Ornstein-Uhlenbeck (OU) process.

Inference using these tests is straightforward, as both test statistics have limiting standard normal distributions. Clearly, the ratio $\frac{\int_0^t \sigma_u^4 du}{\mu_1^{-4} BV^2} \geq 1/t$, and Barndorff-Nielsen and Shephard (2006a) suggest replacing $\hat{H}$ by the adjusted ratio jump test

$$\hat{J} = \frac{\delta^{-1/2}}{\sqrt{\eta max(t^{-1}, \frac{QPV_t}{BV_t^2})}} \big(\frac{\mu_1^{-2} BV_t}{QV_t} - 1 \big) \xrightarrow{d} N(0,1). \tag{2.10}$$

Huang and Tauchen (2005), Andersen, Bollerslev, and Diebold (2007) analyze the statistical properties of bipower variation based jump tests using S&P index data, exchange rates, and bond yields; as well as via Monte Carlo simulation. They suggest using a daily statistic, $z_{TP,t}$, to test for jumps on a daily basis, where

$$z_{TP,t} = \frac{RV_t - BV_t}{\sqrt{(v_{bb} - v_{qq}) \frac{1}{N} TP_t}} \xrightarrow{d} N(0,1), \tag{2.11}$$

with $v_{qq} = 2$, $v_{bb} = (\frac{\pi}{2})^2 + \pi - 3$, Here, realized tripower quarticity (TP) is defined and estimated as follows:

$$TP_t = \delta^{-1} \mu_{4/3}^{-3} \sum_{j=3}^{1/\delta} |r_{i-2,t}|^{4/3} |r_{i-1,t}|^{4/3} |r_{i,t}|^{4/3} \xrightarrow{\mathbb{P}} \int_0^t \sigma_u^4 du \tag{2.12}$$

Additionally, the asymptotic covariance of

$$\delta^{-1/2} \begin{pmatrix} RV_t - \int_0^t \sigma_u^2 du \\ BV_t - \int_0^t \sigma_u^2 du \end{pmatrix}$$

is $\Pi \int_0^t \sigma_u^4 du$, where

$$\Pi = \begin{pmatrix} Var(u^2) & 2\mu_1^{-2} Cov(u^2, |u||u'|) \\ 2\mu_1^{-2} Cov(u^2, |u||u'|) & \mu_1^{-4} (Var(|u||u'|) + 2Cov(|u||u'|, |u'||u''|)) \end{pmatrix}$$

$$= \begin{pmatrix} v_{qq} & v_{qb} \\ v_{qb} & v_{bb} \end{pmatrix}$$

with $v_{qb} = 2$. Inference is carried out by rejecting the null of no jumps if $z_{TP,t}$ exceeds the critical value, Φ_α, leading to a conclusion that there are jumps during the day. A common choice for the critical value is 1.96, equivalent to 5% significant level.

Lee and Mykland (2008) focus on detecting jump at time t without assuming that there are (or are not) jumps before or after time t. Their objective is to detect jumps over time. The main idea behind Lee and Mykland (2008) centers around the difference between observed high returns caused by jumps and by spot volatility. They standardize the return using instantaneous volatility $\sigma(ti)$, which only includes the local variance from the continuous part of the process. The instantaneous volatility is consistently measured using realized bipower variation. The test statistic that they propose is constructed as follows.

$$LM(ti) = \frac{r_{i,t}}{\widehat{\sigma_{i,t}}},$$

where

$$\widehat{\sigma_{i,t}} = \frac{1}{K-2} \sum_{j=i-K+2}^{i-1} |r_{i,t}||r_{i-1,t}|,$$

and K is the window size of a local movement of the process, and is chosen so that the effect of jumps on the volatility estimator disappears. They suggest to choosing $K = 10$, when sampling at a 5-minute frequency. Asymptotically, $LM(ti)$ follows a normal distribution. Namely:

$$\sqrt{\frac{2}{\pi}} LM(ti) \xrightarrow{d} N(0,1).$$

Swap Variance Based Tests

Inspired by the comparison between bipower variation and realized variance, as proposed in Barndorff-Nielsen and Shephard (2004, 2006), Jiang and Oomen (2008) propose comparing a jump sensitive variance measure and the realized variance. Their idea comes from a well known observation about market microstructure noise in the finance literature. Namely, in the absence of jumps the accumulated difference between the simple return and the log return captures one half of the integrated variance in the continuous-time limit. Since this relation is the foundation of a variance swap replication strategy, the accumulated difference between simple returns and log returns is called the swap variance. They compare this value to the realized variance in order to test for jumps.

Intuitively, when jumps are absent, the difference between the swap variance and the realized variance should be indistinguishable from zero, while when jumps are present, it will reflect the replication error of the variance swap, which leads to jump detection. The swap variance is defined as:

$$SwV_t = 2\sum_{i=1}^{t/\delta}(R_{i,t} - r_{i,t}),$$

where $R_{i,t} = \frac{P_{i,t}}{P_{i-1,t}} - 1$, and $r_{i,t} = Y_{i,t} - Y_{i-1,t}$.

Three types of swap variance jump tests are developed by these authors. Namely, they propose the difference test

$$\frac{t/\delta}{\sqrt{\Omega_{SwV}}}(SwV_t - RV_t) \xrightarrow{d} N(0,1),$$

the logarithmic test

$$\frac{BV * N}{\sqrt{\Omega_{SwV_t}}}(lnSwV_t - lnRV_t) \xrightarrow{d} N(0,1),$$

and the ratio test

$$\frac{BV * N}{\sqrt{\Omega_{SwV_t}}}(lnSwV_t - lnRV_t) \xrightarrow{d} N(0,1),$$

where $\Omega_{SwV_t} = \frac{\mu_6}{9}\frac{N^3\mu_{6/s}^{-s}}{N-s+1}\sum_{i=0}^{N-s}\prod_{k=1}^{s}|r_{i+1}|^{6/s}$, $N = t/\delta$, and $\mu_s = E(|x|^s)$ for $x \sim N(0,1)$. Setting s equal to either 4 or 6 (as a robust estimation of Ω_{SwV_t}) is recommended.

Jiang and Oomen (2008) provide Monte Carlo simulation evidence that their SwV test is more sensitive to jumps than the bipower variation tests discussed above, but the requirement of estimating the sixticity can be challenging in practice. They also provide a useful discussion of jumps when the sampling frequency is ultra-high and market microstructure noise needs to be taken into consideration when testing for jumps.

Truncated Power Variation Tests

The truncated sth realized power variation as defined in Aït-Sahalia and Jacod (2012) is expressed as follows.

$$B(s,u,\delta) = \sum_{i=1}^{t/\delta}|r_{i,t}|^s I_{\{|r_{i,t}|\le u\}}.$$

Here, the truncation level u is set equal to $b\delta^\omega$, for some constant $\omega \in (0,1/2)$, with $b > 0$, which results in u shrinking to 0. As above, δ is the sampling frequency. In this framework, $\omega < 1/2$ ensures that all increments "mainly" contain a Brownian contribution. Note, when u is set to infinity, the truncated realized power variation becomes $B(s,\infty,\delta)$, in which case no truncation is applied.

When $\delta \to 0$, $B(s,\infty,\delta)$ converges in probability as follows.

$$\begin{cases} s > 2 \text{ all } Y_t & \Rightarrow B(s,\infty,\delta) \xrightarrow{\mathbb{P}} J(s) \\ \text{all } s \text{ on } \Omega_T^c & \Rightarrow \frac{\delta^{1-s/2}}{\mu_1^s} B(s,\infty,\delta) \xrightarrow{\mathbb{P}} \int_0^t |\sigma_u|^s d_u \end{cases}$$

where μ_1^s is the sth absolute moment of a standard normal random variable, and Ω_T^c $=\{Y$ is continuous in $[0,T]\}$ is a set defined pathwise on $[0,T]$. Also, define Ω_T^W $=\{Y$ has a Wiener component in $[0,T]\}$, and Ω_T^J $=\{Y$ has jumps in $[0,T]\}$,which are additional sets defined pathwise on $[0,T]$. They recommend using the following test statistic:

$$AJ(s,k,\delta) = \frac{B(s,\infty,k\delta)}{B(s,\infty,\delta)},$$

where $s > 2$, and $k > 2$ is an integer that controls the sampling frequency. These authors show that:

$$AJ(s,k,\delta) \to \begin{cases} 1 & \text{on } \Omega_T^J \\ k^{s/2-1} & \text{on } \Omega_T^c \cap \Omega_T^W \end{cases}$$

$\Omega_T^c \cap \Omega_T^W$ means Y_t is continuous and has a Wiener component in $[0,T]$.

Thus, when jumps are present, the variation converges to a finite limit and so the ratio, $AJ(s,k,\delta)$, tends to 1, while when there are no jumps, the variation converges to 0, and so $AJ(s,k,\delta)$ tends to a limit that is greater than 1, and depends on the choice of k. Essentially, this test compares the estimator of integrated variance using different sampling frequencies, and is motivated by the fact that sampling frequency should have no influence on the estimator when there are jumps.

Lee and Hanning (2010) also utilize truncated power variation, and develop a related test for jump detection that is robust to infinite activity jumps. Their test is quite similar to the test developed by Lee and Mykland (2008), although the Lee and Mykland test is designed to have power against Poisson-type (finite activity) jumps. Namely, they propose using:

$$LH(ti) = \frac{r_{i,t}}{\hat{\sigma}_{i,t}\delta^{1/2}} \xrightarrow{d} N(0,1),$$

with

$$\hat{\sigma}_{i,t}^{1/2} = \frac{\delta^{-1}}{K} \sum_{j=i-K}^{i-1} r_{j-m+1,t}^2 I_{\{|r_{j-m+1,t}| \le g\delta^{\omega}\}}$$

where δ is the sampling frequency, $g > 0$, $0 < \omega < 1/2$, and K is the window size, which is usually set to be $b\delta^c$, with $-1 < c < 0$, and b a constant. As recommended by the Lee and Manning, $g = 1.2$, $\omega = 0.47$, $K = b\delta^c$ with $-1 < c < 0$ for some constant b.

Long Time Span Jump Tests

Building on the work by Aït-Sahalia (2002, 2012), Corradi, Silvapulle, and Swanson (2018) construct a jump test to detect jumps in the data by examining the intensity parameter in the data generating process. In particular, they develop a jump test for the null hypothesis that the probability of a jump is zero. Their test is based on realized third moments, and uses observations over an increasing time span. The test offers an alternative to the standard finite time span jump tests discussed above, and is designed to detect jumps in the data generating process rather than detecting realized jumps over a fixed time span. They also provide a test for self-excitement (i.e., is the intensity parameter constant or does the intensity follow a Hawkes diffusion process (as discussed in Andersen, Benzoni, and Lund (2002), Aït-Sahalia, Cacho-Diaz, and Laeven (2015)).

Let

$$\begin{aligned}\widehat{\mu}_{3,T,\delta} &= \frac{1}{T}\sum_{k=1}^{n-1}\left(Y_{(k+1)\delta} - Y_{k\delta} - \frac{Y_{n\delta}-Y_{\delta}}{n}\right)^3 \\ &\quad - \frac{1}{T^+}\sum_{k=1}^{n^+-1}\left(Y_{(k+1)\delta} - Y_{k\delta} - \frac{Y_{n^+\delta}-Y_{\delta}}{n^+}\right)^3 1\left\{\left|Y_{(k+1)\delta}-Y_{k\delta}\right| \le \tau\left(\delta\right)\right\}, \qquad (2.13)\end{aligned}$$

where $\tau(\delta)$ is a truncation parameter, δ is the sampling frequency, T and T^+ are time spans (with $T^+/T \to \infty$) , and $n = \frac{T}{\delta}$ and n^+ are analogously defined, but denote the number of observations, as discussed in CSS (2018). Now, define the statistic for testing no null of no jumps as follows:

$$S_{T,\delta} = \frac{T^{1/2}}{\delta}\widehat{\mu}_{3,T,\delta} \xrightarrow{d} N\left(0,\omega_0\right). \qquad (2.14)$$

where ω_0 is defined in CSS (2018).

The test has power not only against constant and self-exciting intensity, but also against affine jump diffusions where the intensity is an affine function of volatility, for example. As the variance of the statistic is of larger order under the alternative of positive jump intensity, one cannot construct a variance estimator which is consistent under all hypotheses. Thus, the authors construct an estimator for the variance of $S_{T,\delta}$ which is consistent under the null of no jumps and bounded in probability under the (union of) alternatives. This is done by using a threshold variance estimator, which filters out the contribution of the jump component. In particular, define:

$$\begin{aligned}
&\widehat{\sigma}^2_{\lambda,T,\delta} \\
&= \frac{1}{T\delta^2} \sum_{k=0}^{n-1} \left(Y_{(k+1)\delta} - Y_{k\delta} - \frac{Y_{n\delta} - Y_{\delta}}{n} \right)^3 I \left\{ \left| Y_{(k+1)\delta} - Y_{k\delta} \right| \leq \tau(\delta) \right\}. \qquad (2.15)
\end{aligned}$$

It follows that the t-statistic version of this jump test is,

$$t_{\lambda,T,\delta} = \frac{S_{T,\delta}}{\widehat{\sigma}_{\lambda,T,\delta}}.$$

2.2.3 Jump Decompositions

In our empirical application, we utilize the jump decomposition methods discussed in Aït-Sahalia and Jacod (2012) in order to decompose quadratic variation into continuous components and jump components. Furthermore, we consider large jump and small jump components, as discussed above. When considering truncated sth realized power variation, if the power, $s < 2$, then the continuous component in the process dominates, while if $s > 2$ then the jump component dominates. When $s = 2$ both components have equal influence on the process. Thus, we can obtain important information about quadratic variation by decomposing realized power variation into continuous and jumps components, as follows.

$$\begin{aligned}
\text{Percentage of total QV due to continuous component } (QVC) &= \tfrac{B(2,u,\delta)}{B(2,\infty,\delta)} \\
\text{Percentage of total QV due to jump component } (QVJ) &= 1 - \tfrac{B(2,u,\delta)}{B(2,\infty,\delta)}
\end{aligned} \qquad (2.16)$$

In our empirical section, we use the value of u used in code available from Aït-Sahalia and Jacod (2012). We denote the variation due to jumps (i.e., increments "larger" than u) as:

$$\begin{aligned}
U(s,u,\delta) &= \sum_{i=1}^{t/\delta} |r_{i,t}|^s I_{\{|r_{i,t}|>u\}} \\
&= B(s,\infty,\delta) - B(s,u,\delta)
\end{aligned}$$

Jump decompositions based on this metric can be calculated as:

$$\begin{aligned}
\text{Percentage of QV due to large jump component } (QVJL) &= \tfrac{U(2,\epsilon,\delta)}{B(2,\infty,\delta)} \\
\text{Percentage of QV due to small jump component } (QVJS) &= \tfrac{B(2,\infty,\delta) - B(2,u,\delta) - U(2,\epsilon,\delta)}{B(2,\infty,\delta)}
\end{aligned} \qquad (2.17)$$

The large jump cut-off level is $\epsilon = b\delta^{\omega}$, which is arbitrarily chosen, by experimenting with multiple values of ϵ.[3] In our analysis, we set $b = 3$ and $b = 5$. We consider the following variations: QVJ, $QVJL3$, $QVJL5$, $QVJS3$, and $QVJS5$ (where the "3" and "5" values correspond to the values of b that we utilized in our empirical analysis).

2.3 Empirical Methodology

Two experiments are conducted in this chapter. In the first experiment, "jump spillover effects" are examined by carrying out a regression analysis in which the causal linkages between quadratic jump variations in nine SPDR sector ETFs (see Section 2.4.1 for complete details) are examined. In the second experiment, causal linkages between excess returns from each of the sectors that we examine and jump variations from all nine sectors are examined. Excess returns are defined to be the difference between daily log-returns of an asset and the daily log-returns of the market. We use an ETF based on S&P500 called SPY to obtain the log-returns of the market.

We adopt the year over year (YoY) method from finance to compare our results, which means results are compared based on each calendar year. More specifically, for each experiment we fit vector autoregression (VAR) models for each calendar year. Moreover, we categorize our analysis by jump types (total jumps, large jumps, small jumps), as discussed above. To summarize, there are five jump types (QVJ, $QVJL3$, $QVJL5$, $QVJS3$, $QVJS5$), nine market sectors, and six calendar years in our dataset. Thus, we have 270 models for each experiment.

Table 2.1 summarizes the experimental setup used in this chapter. First, we run $\hat{J}$ tests for each trading day in our sample, and record the dates when we reject the null of no jumps. Second, we use the methods described in Section 2.2.3 in order to obtain QVJ,$QVJL3$, $QVJL5$,$QVJS3$ and $QVJS5$ on trading days when we reject the null. On days when we do not reject the null, $QVJ = QVJL3 = QVJL5 = QVJS3 = QVJS5 = 0$, as no jumps are present. Finally, we conduct regression analysis for each calender year using daily data and the two VAR models described below.

[3] Recall that u is set equal to $b\delta^{\omega}$. In our calculations, we set $b = 2$ when calculating u.

2.3.1 Modeling Jump Spillover Effects

Jump spillover effects measure whether or not jumps in a given sector (Granger) cause jumps in other sectors. In our empirical experiment, we fit a linear VAR model to test for such effects. In our tabulated results (i..e, Tables 2.3 and 2.4), we collect coefficients on jumps variables in a given sector that are significantly different from zero at a 95% level of confidence (based on application of t-tests), take the absolute value of these, and report the sum thereof, of each regression in our VAR. This sum represents jump spillover effects of a given sector on one of the other sectors. The VAR model that we fit is the following:

$$\begin{bmatrix} Sector_{1,t,h} = \beta_{1,0,h} + \sum_{j=1}^{9} \sum_{k=1}^{k=22} \beta_{1,j,k,h} Sector_{j,t-k,h} + \epsilon_{1,t,h} \\ Sector_{2,t,h} = \beta_{2,0,h} + \sum_{j=1}^{9} \sum_{k=1}^{k=22} \beta_{2,j,k,h} Sector_{j,t-k,h} + \epsilon_{2,t,h} \\ Sector_{3,t,h} = \beta_{3,0,h} + \sum_{j=1}^{9} \sum_{k=1}^{k=22} \beta_{3,j,k,h} Sector_{j,t-k,h} + \epsilon_{3,t,h} \\ Sector_{4,t,h} = \beta_{4,0,h} + \sum_{j=1}^{9} \sum_{k=1}^{k=22} \beta_{4,j,k,h} Sector_{j,t-k,h} + \epsilon_{4,t,h} \\ Sector_{5,t,h} = \beta_{5,0,h} + \sum_{j=1}^{9} \sum_{k=1}^{k=22} \beta_{5,j,k,h} Sector_{j,t-k,h} + \epsilon_{5,t,h} \\ Sector_{6,t,h} = \beta_{6,0,h} + \sum_{j=1}^{9} \sum_{k=1}^{k=22} \beta_{6,j,k,h} Sector_{j,t-k,h} + \epsilon_{6,t,h} \\ Sector_{7,t,h} = \beta_{7,0,h} + \sum_{j=1}^{9} \sum_{k=1}^{k=22} \beta_{7,j,k,h} Sector_{j,t-k,h} + \epsilon_{7,t,h} \\ Sector_{8,t,h} = \beta_{8,0,h} + \sum_{j=1}^{9} \sum_{k=1}^{k=22} \beta_{8,j,k,h} Sector_{j,t-k,h} + \epsilon_{8,t,h} \\ Sector_{9,t,h} = \beta_{9,0,h} + \sum_{j=1}^{9} \sum_{k=1}^{k=22} \beta_{9,j,k,h} Sector_{j,t-k,h} + \epsilon_{9,t,h} \end{bmatrix}$$

where $Sector_{i,t,h}$ is the variation of the jump component of the ith market sector at time t in year h, with $i = 1, ..., 9$ representing our nine market sectors. $Sector_{j,t-k,h}$ is the k^{th} lagged variation of the jump component of the j^{th} market sector in year h, with $j = 1, ..., 9$ representing nine market sectors. Here, $h = 2005, ..., 2010$ denotes the calendar year. Variations used as regressors in the above model are QVJ,$QVJL3$, $QVJL5$,$QVJS3$ and $QVJS5$. $\beta_{i,0,h}$ is the intercept for market sector i in year h. $\beta_{i,j,k,h}$ denotes the coefficient on the k^{th} lagged jump in sector j, in the regression of the i^{th} sector in year h. Clearly, the βs quantify the causal or spillover effects for a given year. The number of lags is chosen based on use of the Akaike Information Crietion (AIC). Additionally, we believe that jump spillover effects can last for a long period, and in particular at least one month (i.e., 22 trading days). Our use of the AIC confirms our choice (i.e., we find that $k = 22$). Augmented Dickey-Fuller tests were conducted to ensure that variables are stationary.

Maximum likelihood is used to estimate the model. As discussed above, jump spillover effects of market sector j on market sector i ($j \neq i$) is calculated as $\sum_{k=1}^{k=22} |\beta^*_{i,j,k,h}|$, where $|\beta^*_{i,j\neq i,k,h}|$ is set to zero if not significantly different from zero based on application of a 5% level t-test. The total jump spillover effects of market sector j in year h is then $\sum_i \sum_{k=1}^{k=22} |\beta^*_{i,j,k,h}|$, and $j \neq i$.

2.3.2 Modeling Jump Contributions to Excess Returns

Our assessment of jump risk in excess returns measures the impact of jumps on excess returns of an market sector return. As done above, we fit a linear VAR model in order to quantify jump risk. Our tabulated results are presented in the same fashion as results based on our jump spillover effect analysis. The VAR model is also the same, except that dependent variables are now excess market sector returns rather than jump variations.

$$\begin{bmatrix}
SectorEX_{1,t,h} = \beta_{1,0,h} + \gamma_{1,1,h} SectorEX_{1,t-1,h} + \sum_{j=1}^{9} \sum_{k=0}^{k=22} \beta_{1,j,k,h} Sector_{j,t-k,h} + \epsilon_{1,t,h} \\
SectorEX_{2,t,h} = \beta_{2,0,h} + \gamma_{2,1,h} SectorEX_{2,t-1,h} + \sum_{j=1}^{9} \sum_{k=0}^{k=22} \beta_{2,j,k,h} Sector_{j,t-k,h} + \epsilon_{2,t,h} \\
SectorEX_{3,t,h} = \beta_{3,0,h} + \gamma_{3,1,h} SectorEX_{3,t-1,h} + \sum_{j=1}^{9} \sum_{k=0}^{k=22} \beta_{3,j,k,h} Sector_{j,t-k,h} + \epsilon_{3,t,h} \\
SectorEX_{4,t,h} = \beta_{4,0,h} + \gamma_{4,1,h} SectorEX_{4,t-1,h} + \sum_{j=1}^{9} \sum_{k=0}^{k=22} \beta_{4,j,k,h} Sector_{j,t-k,h} + \epsilon_{4,t,h} \\
SectorEX_{5,t,h} = \beta_{5,0,h} + \gamma_{5,1,h} SectorEX_{5,t-1,h} + \sum_{j=1}^{9} \sum_{k=0}^{k=22} \beta_{5,j,k,h} Sector_{j,t-k,h} + \epsilon_{5,t,h} \\
SectorEX_{6,t,h} = \beta_{6,0,h} + \gamma_{6,1,h} SectorEX_{6,t-1,h} + \sum_{j=1}^{9} \sum_{k=0}^{k=22} \beta_{6,j,k,h} Sector_{j,t-k,h} + \epsilon_{6,t,h} \\
SectorEX_{7,t,h} = \beta_{7,0,h} + \gamma_{7,1,h} SectorEX_{7,t-1,h} + \sum_{j=1}^{9} \sum_{k=0}^{k=22} \beta_{7,j,k,h} Sector_{j,t-k,h} + \epsilon_{7,t,h} \\
SectorEX_{8,t,h} = \beta_{8,0,h} + \gamma_{8,1,h} SectorEX_{8,t-1,h} + \sum_{j=1}^{9} \sum_{k=0}^{k=22} \beta_{8,j,k,h} Sector_{j,t-k,h} + \epsilon_{8,t,h} \\
SectorEX_{9,t,h} = \beta_{9,0,h} + \gamma_{9,1,h} SectorEX_{9,t-1,h} + \sum_{j=1}^{9} \sum_{k=0}^{k=22} \beta_{9,j,k,h} Sector_{j,t-k,h} + \epsilon_{9,t,h}
\end{bmatrix}$$

where $SectorEX_{i,t,h}$ is the excess return of the i^{th} market sector at time t in year h, and other variables and coefficients are discussed above. The jump contribution level of market sector j on excess returns of market sector i is calculated as $C\sum_{k=0}^{k=22} |\beta^*_{i,j,k,h}|$, where $|\beta^*_{i,j,k,h}|$ is set to zero if not significantly different from zero based on application of a 5% level t-test and C is a constant to adjust the contribution level, because the βs are very close to zero. The total jump contribution level of market sector j in year h is then $C\sum_i \sum_{k=0}^{k=22} |\beta^*_{i,j,k,h}|$, where $C = 10^{17}$.

2.4 Empirical Results

2.4.1 Data Description

We obtain daily millisecond trading data for the period January 2005 - December 2010 from the TAQ database through the Wharton Research Data Services portal. To reduce the micro-structure noise effects, we follow convention and choose a sampling frequency of 5 minutes, which yields roughly 78 observations per day. When there is no price at an exact time stamp, we use the closest one available.

Our dataset consists of nine SPDR market sector ETFs. These nine sector ETFs are XLY (consumer discretionary sector), XLP (consumer staples sector), XLE (energy sector), XLF (financials sector), XLV (health care sector), XLI (industrials sector), XLB (materials sector), XLK (technology sector), and XLU (utilities sector). According to the SPDR website, XLY includes companies from industries like: media, retail (specialty, multiline, internet and catalog), hotels, restaurants and leisure, textiles, apparel and luxury goods, household durables, automobiles, auto components, distributors, leisure products, and diversified consumer services. XLP includes food and staples, retailing, household products, food products, beverages, tobacco, and personal products. XLE includes companies in oil, gas and consumable fuels, and energy equipment and services. XLF includes diversified financial services, insurance, banks, capital markets, mortgage real estate investment trusts (REITs), consumer finance, and thrifts and mortgage finance. XLV includes companies in pharmaceuticals, health care equipment and supplies, health care providers and services, biotechnology, life sciences tools and services, and health care technology. XLI includes a wide range of industries, such as aerospace and defense, industrial conglomerates, marine, transportation infrastructure, machinery, road and rail, air freight and logistics, commercial services and supplies, professional services, electrical equipment, construction and engineering, trading companies and distributors, airlines, and building products. XLB includes a collection of companies in chemicals, metals and mining, paper and forest products, containers and packaging, and construction materials. XLK includes companies in technology hardware, storage, and peripherals, software, diversified telecommunication services, communications equipment, semiconductors and semiconductor equipment, internet software and services, IT services, electronic equipment, instruments and components, and wireless telecommunication services. Finally, XLU includes companies in electric utilities, water utilities, multi-utilities, independent power producers and energy traders, and gas utilities. In 2015, SPDR launched a new ETF targeting real estate management and development and REITs, excluding mortgage REITs, but since our analysis is between 2005 and 2010, we exclude this new sector ETF from our data set.

For our the excess return calculations, we downloaded the S&P 500 index based ETF (SPY) and the nine market sector ETFs from *Yahoo Finance* at a daily frequency for the period January 2005 - December 2010.

2.4.2 Empirical Findings

See Sections 2.3.1 and 2.3.2 for a discussion of our empirical setup. As discussed in that section, tabulated results in Tables 2.3 and 2.4 collect coefficients on jumps variables in a given sector that are significantly different from zero at a 95% level of confidence (based on application of t-tests), take the absolute value of these, and report the sum thereof, for each regression in our VAR.[4] Thus, for each of our 9 market sectors one can assess the impact each of the other 8 sectors has on that sector. Our results based on $QVJL5$ and $QVJS5$ were found to be un-informative, so that tabulated results are presented only for regressions that include QVJ, $QVJL3$ and $QVJS3$ in this chapter.[5] This is not surprising, given the findings presented in Table 2.2, where it can be seen that $QVJL5$ is often 0, suggesting that the cut-off level used in the calculation of $QVJL5$ is not informative.[6] Interestingly, Table 2.2 also indicates that jumps can either contribute as much as 80% of quadratic variation or as little as 20% on a given trading day. This suggests that market sectors are frequently beset by shocks that cause jumps. However, it should be noted that, large jumps usually dominate the quadratic variation, with a few exceptions, such as on January 11 and February 8.

Before turning to our discussion of the results in Tables 2.3 and 2.4, note that Figures 2.1 - 2.3 plot jump spillover effects by sector, by year, based on Table 2.3. Examination of these

[4] Complete regression findings are available upon request, and are omitted here for the sake of brevity.
[5] Complete results are available upon request.
[6] Table 2.2 only contains results for the first 6 weeks in 2005. Similar results were found when constructing $QVJL5$ for the the rest of 2005, and for other calendar years in our sample.

figures indicates that there are jump spillovers across all sectors, broadly speaking. Interestingly, total jump spillovers was greater in 2005, 2006, and 2007 than in 2008, large jump spillovers were greatest in 2006, and small jump spillovers peaked in 2008. This suggests that transmission of jumps of different magnitudes across sectors is asymmetric, and dependent upon the state of the economy. Finally, notice that there were no years where total jump spillover effects were notably fewer than in other years. The same is not the case when one examines the propagation of jumps through excess returns. Figures 2.4 - 2.6 plot jump contribution levels to excess returns, by year, based on Table 2.4. Interestingly, even cursory examination of these figures indicates that excess returns are affected much more significantly by both large and small jumps during 2008 and 2009, than during any other calendar years in our analysis. Indeed, large jumps exhibit almost no correlation with excess returns during 2005, 2006, 2007, or 2010; whereas there are significant excess return-jump spillovers during 2008 and 2009. Thus, the effects of jump variations on excess returns are a clear indicator of the Great recession, while the same cannot be said when considering jump spillover effects.

We now turn to a discussion of Tables 2.3 and 2.4. A number of clear-cut conclusions emerge upon inspection of the results in these tables. First, consider Table 2.3.

First, large jump spillover effects from each sector seem to coincide with sector-related major events that happened around that time. For example, XLI, XLK, and XLP had the strongest large jump spillover effects in 2006, and large jumps spillovers in XLI and XLP might be related to the volatile housing market at the time. According to a report published by RealtyTrac, the number of total foreclosure filings nationwide rose from about 885,000 in 2005 to 1,259,118 in 2006, which is more than 42% increase. For the same reason, the large jump spillover effects for XLF in 2006 was quite strong as well.[7] In terms of the XLK, 2006 is often called a “tech bubble” year. For example, Youtube was sold for $1.65 billion during 2006. Also, six prominent tech companies filed their IPOs in 2006, but only one of them was profitable. Moreover, quite a few tech companies experienced skyrocketing stock prices until early 2006, and slid dramatically afterwards.[8] In 2009, XLF, XLV,

[7]For more details see: https://www.housingwire.com/articles/us-foreclosure-filings-42-percent-2006 for more details.

[8]For more details see:
http://www.nytimes.com/2006/10/10/technology/10deal.html,
http://money.cnn.com/2006/05/16/technology/pluggedin_fortuneipos0516/index.htm,

and XLY exhibited their most spillovers. Similar news events can be used to explain many of the other incidences of large spillover effects.

Second, small jump spillover effects are quite different from large jump effects. Most sectors had their strongest spillover effects between 2007 and 2010. This discrepancy between the large jump case and the small jump case can perhaps be best interpreted as a result of the different causes of large jumps and small jumps: large jumps are associated with major news and events, while small jumps are likely the result of things like high frequency trading and company specific events.

Third, total jump spillover effects (both large and small) are interesting. For example, it is worth noting that 2008 was a relatively quiet year for all sectors as none of the sectors showed the strongest spillover effects in that year. This may be related to the fact that 2008 was the peak of the recession and fear dominated the market, which led to liquidity problems (Reavis (2012)). These issues in turn may have affect the ease with which spillover effects occurred.

Fourth, a YoY comparison indicates that large jump spillover effects and total jump spillover effects in the whole U.S. market peaked in 2006, bottomed in 2008. Small jump spillover effects started to increase in 2006, peaked in 2008, dropped in 2009, and rose up again in 2010. This is intriguing, since 2006 was the year of the "slowdown". According to the Center for American Progress, the U.S. economy experienced a fall in both economic growth and consumption growth in 2006, for the first time in more than three years, indicating high risks in certain areas in the market. Figures 2.1 - 2.3 illustrate this pattern quite clearly.[9]

Drilling down a bit further, the results in Table 2.3 does no show jumps from XLF dominating the spillover effects prior to the recession. This is different from what we expected, as the financial sector was the main cause of the recession. What we instead observe is that the large jump spillover effects and total jump spillover effects peaked in 2006 and bottomed in 2008. This implies that prior to the Great Recession, the market was more volatile but not necessarily concentrated only in the financial sector.

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and
https://seekingalpha.com/article/308397-we-may-be-nearing-a-third-tech-bubble-collapse

[9]For more details see: https://www.americanprogress .org/issues/economy/news/2006/12/21/2420/the-u-s-economy-in-review-2006,
http://money.cnn.com/2008/09/15/markets/markets_newyork2,
and
http://www.nytimes.com/2012/05/07/business/stock-trading-remains-in-a-slide-after-08-crisis.html

Now, consider the results contained in Table 2.4. Again, a number of clear-cut conclusion emerge upon inspection of the results in this table.

First, there were scarcely any large jump and total jump contributions to excess returns before and after the recession (see Table 2.4 and Figures 2.4 and 2.6). Additionally, large jump contributions were only prevalent during 2008 and 2009. This provides evidence that jumps, especially large jumps should not be neglected in asset pricing, particularly in a volatile markets. Second, small jump contribution levels were rather significant across all sampling years, and became intensified between 2007 and 2009 (see Table 2.4 and Figure 2.5). It is also worth noting that while large and total jump spillover effects weakened during the recession, the impact of jumps on excess returns escalated, as discussed above. Finally, and similar to the spillover case, we do not observe jumps from XLF contributing to excess returns more than jumps from other sectors.

2.5 Concluding Remarks

This chapter begins with a review of jump testing and variation decomposition methodology. Thereafter, an empirical analysis is presented in which jump spillover effects in nine market sectors over a six year period around the Great Recession of 2008-2009 are examined. Broadly speaking, strong large and total jump spillover effects (i.e., jumps from one sector (Granger) causing jumps from another sector) were seen as early as in 2006, and weakened as the recession unfolded. With small jumps, the opposite occurred. In particular, 2008 was the weakest year for large and total jump spillover effects and strongest year for small jumps. This can be understood by examining the causes of jumps of different sizes. Large jump spillover effects seem to correlate with major news and events, while small jump spillover effects are harder to interpret and seem more correlated with heterogeneous agent and firm specific characteristics. With regard to the jump contributions to excess returns, total jump and large jump contributions were close to zero in years other than 2008 and 2009. This provides strong evidence that jumps play an important role in asset pricing during crisis times.

Table 2.1: **Experimental Setup**

Sample Period:	Jan. 3, 20005 to Dec. 31, 2010
Sampling Frequency:	5 minutes.
Regression Estimation Scheme:	VAR estimation with time span equal to one calender year.
Jump types:	Total jumps (QVJ), large jumps at cutoff level $b = 3$ ($QVJL3$), large jumps at cutoff level $b = 3$ ($QVJL5$), small jumps at cutoff level $b = 3$ ($QVJS3$), small jumps at cutoff level $b = 5$ ($QVJS5$).
Evaluation Criterion:	Coefficients are summed that are significant using a 5% level t-test.
Step 1: Jump Test	Test for jumps on each trading day during sample period. For this, the bipower variation based test $z_{TP,t}$ described in Section 2.2.1 is applied with significance level $\alpha = 5\%$. The null hypothesis is that no jumps are present.
Step 2: Jump Decomposition	For trading days which reject the null in Step 1, the decomposition method in Section 2.2.3 is applied to extract QVJ, $QVJL3$, $QVJL5$, $QVJS3$, and $QVJS5$ on that day. For trading days for which the null is not rejected in Step 1, jump quadratic variation is set equal to 0.
Step 3a: Jump Spillover Analysis	Fit the model in Section 2.3.1 by calender year, for different jump types.
Step 3b: Jump Contribution to Excess Returns	Ft the model in Section 2.3.2 by calender year, for different jump types.

Table 2.2: **Disaggregate Quadratic Variation in the XLB Sector***

Date	QVJ	$QVJL3$	$QVJL5$	$QVJS3$	$QVJS5$
1/3/2005	0.4352	0.2521	0	0.1831	0.4352
1/4/2005	0.2594	0	0	0.2594	0.2594
1/5/2005	0.84	0.8006	0.7301	0.0394	0.1099
1/6/2005	0.3481	0.1494	0	0.1987	0.3481
1/7/2005	0.3668	0.2417	0	0.1251	0.3668
1/10/2005	0.5789	0.3394	0	0.2395	0.5789
1/11/2005	0.5809	0.2611	0	0.3198	0.5809
1/12/2005	0.577	0.4163	0.2563	0.1607	0.3207
1/13/2005	0.3918	0.2224	0	0.1694	0.3918
1/14/2005	0.5241	0.2987	0	0.2254	0.5241
1/18/2005	0.6349	0.3646	0	0.2703	0.6349
1/19/2005	0	0	0	0	0
1/20/2005	0.5473	0.419	0	0.1283	0.5473
1/21/2005	0.3142	0.1824	0	0.1318	0.3142
1/24/2005	0.5531	0.387	0.387	0.1661	0.1661
1/25/2005	0.7079	0.5185	0.5185	0.1894	0.1894
1/26/2005	0.4206	0.2352	0	0.1854	0.4206
1/27/2005	0.5888	0.3594	0.3594	0.2294	0.2294
1/28/2005	0.3973	0.2494	0	0.1479	0.3973
1/31/2005	0.4323	0.3689	0.3689	0.0634	0.0634
2/1/2005	0.4831	0.3397	0.3397	0.1434	0.1434
2/2/2005	0.45	0.1362	0	0.3138	0.45
2/3/2005	0	0	0	0	0
2/4/2005	0.3565	0.1941	0	0.1624	0.3565
2/7/2005	0.4154	0.1396	0	0.2758	0.4154
2/8/2005	0.505	0	0	0.505	0.505
2/9/2005	0.7931	0.7931	0.6389	0	0.1542
2/10/2005	0.5243	0	0	0.5243	0.5243
2/11/2005	0.5517	0.2765	0	0.2752	0.5517
2/14/2005	0.3892	0.3229	0.3229	0.0663	0.0663
2/15/2005	0.3822	0	0	0.3822	0.3822
2/16/2005	0.4734	0	0	0.4734	0.4734
2/17/2005	0.629	0.4126	0.4126	0.2164	0.2164
2/18/2005	0	0	0	0	0

* Notes: This table shows the percentage of quadratic variation (QV) that is due to total jumps, jumps at the $b = 3$ cutoff level, and jumps at the $b = 5$ cutoff level, for the period January 2005 - March 2005. Similar results for other time periods and market sectors are omitted for the sake of brevity, but are available upon request.

Table 2.3: **Jump Spillover Analysis of Nine SPDR Sector ETFs**

a: Results Based on Analysis of 2005 Jump Variation Data*

	Lagged QVJ from								
QVJ	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	0.000	0.000	0.440	0.000	0.000	0.000	0.000	0.000
XLE	0.336	NA	0.705	1.474	1.040	0.359	0.731	0.538	0.505
XLF	2.040	0.000	NA	0.000	0.000	0.436	0.000	0.000	1.716
XLI	0.472	0.000	0.000	NA	0.000	0.000	0.399	0.000	0.873
XLK	0.757	0.000	0.000	0.894	NA	0.431	0.000	0.365	0.399
XLP	0.000	0.000	0.000	0.309	0.348	NA	0.000	0.000	0.352
XLU	0.000	0.992	0.000	0.000	0.000	0.498	NA	0.501	0.575
XLV	0.324	0.478	0.000	0.000	0.000	0.415	0.478	NA	0.000
XLY	0.000	0.000	0.000	0.000	0.000	0.362	0.000	0.440	NA
	Lagged $QVJL3$ from								
$QVJL3$	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	0.000	0.000	0.000	0.000	0.469	0.430	0.394	0.000
XLE	0.461	NA	0.000	0.000	0.254	0.219	0.000	0.000	0.465
XLF	0.000	0.000	NA	0.590	0.000	0.512	0.000	0.000	0.000
XLI	0.808	1.300	0.000	NA	0.000	0.609	0.977	0.420	0.000
XLK	0.283	1.020	0.000	0.257	NA	0.000	0.317	0.000	0.486
XLP	0.000	0.796	0.000	0.273	0.000	NA	0.000	0.664	0.000
XLU	0.000	0.649	0.000	0.390	0.000	0.463	NA	0.463	0.664
XLV	0.790	2.259	0.000	0.677	0.000	1.652	0.779	NA	0.454
XLY	0.792	0.000	0.911	0.000	0.476	0.866	0.710	0.000	NA
	Lagged $QVJS3$ from								
$QVJS3$	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	0.502	0.865	0.406	0.443	0.000	1.378	0.941	0.000
XLE	0.000	NA	0.703	0.934	0.000	0.338	0.656	0.584	1.032
XLF	0.000	0.000	NA	0.000	0.382	0.000	0.000	0.000	0.000
XLI	1.132	2.847	0.325	NA	0.394	1.853	0.437	0.383	0.496
XLK	0.000	0.000	0.000	0.000	NA	0.000	0.000	0.000	0.000
XLP	0.000	0.525	0.391	0.000	0.347	NA	0.415	0.000	0.000
XLU	0.859	0.000	0.754	1.168	0.578	0.748	NA	0.000	0.735
XLV	0.000	0.416	0.361	0.000	0.000	0.000	0.000	NA	0.365
XLY	0.000	0.000	0.000	0.000	0.330	0.000	0.340	1.229	NA

* Notes: Entries are "aggregate spillover effects" of lagged jumps from a given sector (see first row of entries) on the jumps in each of the sectors listed in the first column of the table. Aggregate spillover effects are aggregated absolute coefficient magnitudes, summed for statistically significant (at a 5% level, based on application of t-statistics) coefficients on the lags in the VAR associated with the regression pertaining to each sector listed in the first column of the table, for all lags in the regression pertaining to the sector listed in the first row of entries in the table. For further details refer to Section 2.3.

b: Results Based on Analysis of 2006 Jump Variation Data*

	Lagged QVJ from								
QVJ	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	0.362	0.000	0.347	0.508	0.766	0.929	1.836	0.772
XLE	0.861	NA	0.000	0.000	0.000	0.000	0.000	0.402	0.608
XLF	1.233	0.768	NA	0.398	0.588	2.179	0.328	0.966	0.780
XLI	0.000	0.338	0.369	NA	0.000	0.000	0.819	0.000	1.107
XLK	1.046	0.522	0.806	0.000	NA	1.003	0.806	1.117	1.633
XLP	0.000	0.000	0.000	0.000	0.000	NA	0.000	0.000	0.000
XLU	0.558	0.000	0.000	0.000	0.343	0.000	NA	0.000	0.000
XLV	0.364	1.707	0.000	0.000	0.581	1.679	0.000	NA	0.396
XLY	0.839	0.000	0.000	0.281	0.000	0.379	0.350	0.000	NA
	Lagged $QVJL3$ from								
$QVJL3$	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	0.000	0.875	0.404	1.168	0.420	0.431	0.000	0.490
XLE	0.000	NA	1.100	0.000	0.000	0.000	0.000	0.000	0.000
XLF	0.000	1.223	NA	1.816	0.317	2.329	0.520	0.849	1.359
XLI	0.000	0.000	0.348	NA	0.000	0.354	0.000	0.000	0.000
XLK	0.000	0.000	1.028	0.000	NA	0.000	0.428	0.000	0.000
XLP	0.000	0.000	0.000	0.557	0.000	NA	0.535	0.000	0.499
XLU	3.211	2.889	2.807	1.741	4.453	3.005	NA	1.136	2.840
XLV	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA	0.000
XLY	0.291	0.532	1.352	0.320	0.000	1.501	0.000	0.567	NA
	Lagged $QVJS3$ from								
$QVJS3$	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	0.820	0.000	0.823	0.694	0.000	0.703	0.335	1.205
XLE	0.457	NA	0.000	0.000	0.964	0.000	0.424	0.000	1.308
XLF	0.882	0.500	NA	0.000	0.000	0.343	0.000	0.000	0.000
XLI	0.745	0.000	0.310	NA	0.000	0.797	0.000	0.000	0.000
XLK	0.516	0.962	0.787	0.325	NA	0.450	0.835	0.325	0.500
XLP	1.181	0.714	1.184	0.391	0.670	NA	0.415	0.916	0.405
XLU	0.457	0.000	0.000	0.000	0.337	0.364	NA	0.357	1.140
XLV	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA	0.000
XLY	0.000	0.503	0.311	0.000	0.338	0.000	0.363	0.465	NA

* Notes: See notes to Table 2.3a.

c: Results Based on Analysis of 2007 Jump Variation Data*

	Lagged QVJ from								
QVJ	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	0.000	0.000	0.000	0.370	0.403	0.000	0.000	0.000
XLE	0.458	NA	0.000	0.000	0.000	0.360	0.000	0.363	0.888
XLF	1.168	0.459	NA	0.334	1.033	0.732	0.000	0.000	0.838
XLI	1.557	0.587	0.000	NA	0.000	0.599	0.433	0.902	0.000
XLK	0.000	0.352	0.445	0.357	NA	0.465	0.000	0.372	0.511
XLP	0.000	0.583	0.525	0.000	0.481	NA	0.000	0.459	0.000
XLU	1.037	0.445	0.544	0.425	1.316	0.947	NA	0.000	1.019
XLV	0.468	1.062	0.548	0.000	0.377	0.488	0.000	NA	1.007
XLY	0.342	0.437	0.532	0.000	0.346	1.087	0.739	0.000	NA
	Lagged $QVJL3$ from								
$QVJL3$	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	0.609	0.000	0.000	0.000	0.462	0.373	0.000	0.000
XLE	1.402	NA	1.075	1.216	0.336	0.428	0.802	0.634	0.788
XLF	0.463	0.000	NA	0.000	0.000	0.000	0.470	0.000	0.000
XLI	0.000	1.232	0.000	NA	0.815	0.521	0.000	0.000	0.573
XLK	0.787	0.691	0.599	1.037	NA	0.000	0.551	0.623	0.000
XLP	0.582	1.412	0.522	0.000	1.015	NA	0.446	0.550	0.598
XLU	0.000	1.601	0.452	0.000	0.000	2.060	NA	0.000	0.000
XLV	0.000	0.000	0.000	0.000	0.000	0.993	0.469	NA	0.000
XLY	0.566	0.994	0.749	0.889	0.441	0.000	0.418	0.321	NA
	Lagged $QVJS3$ from								
$QVJS3$	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	0.827	0.406	0.364	0.977	0.325	1.072	0.364	0.738
XLE	0.429	NA	0.000	0.000	0.365	0.406	0.000	0.000	0.000
XLF	0.858	0.877	NA	0.248	1.178	0.805	1.207	1.474	0.772
XLI	0.496	0.400	0.545	NA	0.000	0.000	0.000	0.000	0.954
XLK	0.514	1.079	0.938	0.958	NA	1.591	0.399	0.863	1.792
XLP	0.000	0.000	0.000	0.000	0.000	NA	0.000	0.000	0.000
XLU	1.761	2.184	0.441	0.659	0.326	1.228	NA	0.840	0.000
XLV	0.444	0.000	0.980	0.385	0.000	0.378	0.000	NA	0.000
XLY	0.351	0.000	0.000	0.000	0.317	0.775	0.000	0.000	NA

* Notes: See notes to Table 2.3a.

d: Results Based on Analysis of 2008 Jump Variation Data*

	Lagged QVJ from								
QVJ	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
XLE	0.000	NA	0.000	0.000	0.542	0.833	0.000	0.366	0.884
XLF	0.000	0.000	NA	0.000	0.000	0.000	0.522	1.086	0.651
XLI	0.000	0.000	0.274	NA	0.786	0.000	0.000	0.000	0.000
XLK	0.354	0.332	0.000	0.000	NA	0.000	0.000	0.447	0.000
XLP	0.000	0.000	0.392	0.442	0.000	NA	0.000	0.000	0.000
XLU	0.000	0.375	0.000	0.000	0.919	0.000	NA	0.414	0.000
XLV	0.385	0.000	0.286	0.000	0.000	0.872	0.390	NA	0.428
XLY	0.000	0.000	0.000	0.000	0.741	0.674	0.000	0.504	NA
	Lagged $QVJL3$ from								
$QVJL3$	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	0.000	0.000	0.000	0.000	0.470	0.000	0.000	0.000
XLE	0.540	NA	0.396	0.433	0.563	1.193	0.390	0.342	1.059
XLF	0.000	0.000	NA	0.000	0.000	0.000	0.000	0.000	0.520
XLI	1.028	0.448	0.324	NA	2.220	1.131	1.140	1.214	1.910
XLK	1.884	1.740	1.172	0.969	NA	1.402	0.361	0.294	0.974
XLP	0.414	1.043	0.000	1.241	0.617	NA	0.000	0.000	0.000
XLU	0.374	0.656	0.445	0.000	1.302	0.000	NA	0.462	1.139
XLV	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA	0.000
XLY	0.360	0.000	0.324	0.000	0.000	0.000	0.000	0.000	NA
	Lagged $QVJS3$ from								
$QVJS3$	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	0.451	0.875	0.918	0.665	0.797	0.654	0.716	1.377
XLE	0.378	NA	0.000	0.468	0.942	0.000	0.000	0.000	0.000
XLF	0.408	0.360	NA	0.887	0.334	0.434	1.284	0.000	0.752
XLI	2.109	0.743	0.660	NA	1.563	0.825	1.303	0.353	0.302
XLK	0.531	0.000	0.456	0.000	NA	0.000	0.000	0.000	0.413
XLP	0.426	1.114	1.363	0.000	0.000	NA	0.560	1.791	0.865
XLU	0.494	0.432	0.462	0.489	0.312	0.998	NA	0.495	0.399
XLV	0.000	0.469	0.358	1.333	0.000	2.151	0.383	NA	0.366
XLY	0.440	0.000	0.000	0.000	1.391	0.000	0.517	0.386	NA

* Notes: See notes to Table 2.3a.

e: Results Based on Analysis of 2009 Jump Variation Data*

	Lagged QVJ from								
QVJ	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	1.112	0.000	0.000	0.000	0.000	0.000	0.684	0.419
XLE	0.726	NA	0.000	0.545	0.000	0.900	0.474	0.830	0.697
XLF	1.000	0.000	NA	0.000	0.000	0.471	0.896	1.565	0.521
XLI	0.355	0.557	0.000	NA	0.000	0.000	0.920	0.442	1.173
XLK	0.000	0.703	0.801	0.000	NA	0.000	0.000	0.357	0.000
XLP	0.819	0.377	0.653	0.291	0.000	NA	1.095	0.418	0.000
XLU	0.370	0.400	1.139	0.367	1.035	0.347	NA	0.398	1.048
XLV	0.331	0.375	1.125	0.409	0.000	0.000	0.482	NA	0.963
XLY	0.762	0.000	0.384	0.705	0.000	0.000	0.000	0.331	NA
	Lagged $QVJL3$ from								
$QVJL3$	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	2.769	4.471	1.648	2.612	0.819	0.418	1.719	1.762
XLE	0.716	NA	0.340	0.365	0.501	0.283	1.406	0.642	1.471
XLF	0.000	0.529	NA	0.436	0.000	0.000	0.000	1.451	1.459
XLI	0.905	0.431	0.861	NA	1.092	0.396	0.000	0.539	0.526
XLK	0.344	0.440	0.389	0.431	NA	0.000	0.000	0.387	0.000
XLP	0.000	0.969	0.997	1.038	1.226	NA	0.000	0.000	0.484
XLU	0.000	0.000	1.048	0.000	0.000	0.000	NA	0.429	1.423
XLV	0.548	0.000	0.000	0.000	0.000	0.000	0.000	NA	0.000
XLY	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA
	Lagged $QVJS3$ from								
$QVJS3$	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	0.000	0.000	0.463	0.000	0.000	0.000	0.000	0.439
XLE	0.426	NA	0.387	0.000	0.371	0.456	0.506	0.881	0.506
XLF	0.587	0.267	NA	0.801	0.328	0.000	0.694	0.323	0.000
XLI	0.000	0.000	0.845	NA	0.791	0.000	0.000	0.000	0.421
XLK	0.419	0.000	0.000	0.000	NA	0.000	0.000	0.000	0.000
XLP	0.000	0.000	0.000	0.000	0.000	NA	0.000	0.000	0.000
XLU	0.000	1.039	0.436	0.000	0.000	1.265	NA	0.000	0.904
XLV	3.408	1.108	1.112	2.649	0.000	2.390	0.830	NA	3.510
XLY	0.967	0.000	0.000	0.332	0.000	0.517	0.313	0.431	NA

* Notes: See notes to Table 2.3a.

f: Results Based on Analysis of 2010 Jump Variation Data*

	Lagged QVJ from								
QVJ	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	0.000	0.384	0.000	0.000	0.000	0.000	0.000	0.000
XLE	0.000	NA	0.000	0.405	0.000	0.000	0.000	0.000	0.000
XLF	0.415	0.000	NA	0.397	0.485	0.000	0.000	0.399	0.488
XLI	0.347	0.000	0.667	NA	0.338	1.189	0.389	0.000	0.000
XLK	0.000	0.388	0.430	0.733	NA	0.895	1.513	0.000	0.450
XLP	1.426	0.000	0.833	1.080	0.000	NA	1.531	1.418	2.240
XLU	0.000	0.000	0.000	0.000	0.000	0.000	NA	0.000	0.000
XLV	0.000	0.000	0.000	0.000	0.000	0.000	0.000	NA	0.000
XLY	0.000	0.000	0.000	0.000	0.841	0.000	0.571	0.469	NA
	Lagged $QVJL3$ from								
$QVJL3$	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	0.353	0.000	0.433	0.854	0.000	0.334	0.000	0.000
XLE	0.000	NA	0.000	0.000	0.000	0.000	0.000	0.000	0.000
XLF	0.336	1.118	NA	0.513	0.000	0.528	0.000	0.420	1.288
XLI	0.000	0.000	0.368	NA	0.000	0.000	0.000	0.000	0.000
XLK	0.000	0.562	0.569	0.640	NA	1.688	0.000	2.114	0.600
XLP	1.029	0.848	0.704	0.953	0.904	NA	0.549	2.129	0.831
XLU	0.000	0.597	0.000	0.000	0.000	0.000	NA	0.000	0.000
XLV	0.822	0.708	0.310	0.482	0.000	1.328	0.000	NA	0.486
XLY	0.434	0.945	1.108	0.559	1.554	0.994	0.425	0.351	NA
	Lagged $QVJS3$ from								
$QVJS3$	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	NA	0.356	0.000	0.000	0.399	0.377	0.000	0.333	0.000
XLE	0.379	NA	1.239	1.103	1.152	0.665	0.722	0.430	1.142
XLF	0.000	0.382	NA	0.526	1.342	0.928	1.056	0.335	1.048
XLI	0.485	0.634	0.632	NA	0.359	1.503	1.419	1.211	0.981
XLK	0.388	0.896	0.538	0.588	NA	0.000	0.409	0.393	0.000
XLP	0.750	0.000	0.000	0.000	0.000	NA	0.282	0.293	0.000
XLU	0.440	0.000	0.468	0.442	0.000	0.583	NA	0.339	0.402
XLV	1.878	2.021	0.951	0.784	0.666	1.386	0.747	NA	0.000
XLY	0.420	0.000	0.451	0.000	0.486	0.000	0.745	0.000	NA

* Notes: See notes to Table 2.3a.

Table 2.4: **Jump Contribution to Excess Returns For Nine SPDR Sector ETFs**

a: Results Based on Analysis of 2005 Jump Variation Data*

	Lagged QVJ from								
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	0.000	0.000	0.000	1.255	0.000	2.858	0.000	0.000	1.360
XLE	0.000	1.949	0.996	0.860	0.883	1.332	0.000	1.502	0.792
XLF	0.000	0.000	0.000	0.000	0.000	0.211	0.000	0.000	0.000
XLI	0.000	0.000	0.000	0.000	0.000	0.371	0.000	0.000	0.139
XLK	0.000	0.000	0.000	3.164	6.182	2.348	2.458	0.000	0.000
XLP	0.000	0.241	0.141	0.000	0.181	0.324	0.000	0.000	0.305
XLU	0.000	0.000	0.000	0.786	0.816	0.748	0.328	0.000	0.000
XLV	0.000	0.000	0.000	0.308	0.000	0.243	0.000	0.000	0.000
XLY	0.000	0.000	0.000	0.000	0.308	0.000	0.000	0.000	0.000
	Lagged $QVJL3$ from								
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	1.062	1.382	1.244	0.000	0.000	1.169	0.000	1.020	0.000
XLE	1.099	1.558	0.000	0.554	0.721	0.000	0.000	0.518	0.000
XLF	0.187	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
XLI	0.126	0.267	0.129	0.081	0.264	0.348	0.000	0.198	0.105
XLK	0.000	7.106	4.254	2.618	3.642	5.234	2.180	1.807	0.000
XLP	0.000	0.000	0.000	0.000	0.000	0.118	0.000	0.000	0.000
XLU	0.643	0.511	0.000	0.000	0.000	0.637	0.000	0.000	0.000
XLV	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.167	0.000
XLY	0.203	0.235	0.000	0.000	0.000	0.251	0.000	0.000	0.000
	Lagged $QVJS3$ from								
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	0.000	0.000	0.000	0.000	1.505	0.000	1.790	2.064	5.254
XLE	0.000	0.000	0.000	0.979	0.000	0.000	0.000	1.056	1.364
XLF	0.000	0.000	0.000	0.368	0.000	0.000	0.000	0.000	0.409
XLI	0.000	0.332	0.000	0.192	0.000	0.000	0.000	0.000	0.259
XLK	0.000	0.000	0.000	0.000	3.122	0.000	3.696	0.000	9.986
XLP	0.000	0.567	0.000	0.246	0.153	0.000	0.625	0.214	0.790
XLU	0.000	0.717	0.000	0.000	0.394	0.000	0.579	0.599	1.278
XLV	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.410
XLY	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.464

* Notes: Entries are "aggregate jump effects on excess returns" of lagged jumps from a given sector (see first row of entries) on the excess return for each of the sectors listed in the first column of the table. Aggregate jump effects on excess returns are aggregated absolute coefficient magnitudes, summed for statistically significant (at a 5% level, based on application of t-statistics) coefficients on the lags in the VAR associated with the regression pertaining to each sector listed in the first column of the table, for all lags in the regression pertaining to the sector listed in the first row of entries in the table. For further details refer to Section 2.3.

b: Results Based on Analysis of 2006 Jump Variation Data*

Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
				Lagged QVJ from					
XLB	0.000	1.523	0.000	0.000	0.000	0.000	0.955	1.458	0.000
XLE	0.000	1.653	1.611	1.189	0.000	0.000	1.239	1.530	1.063
XLF	0.000	0.575	0.218	0.000	0.000	0.000	0.214	0.308	0.227
XLI	0.000	0.703	0.000	0.621	0.274	0.000	0.249	0.648	0.644
XLK	0.468	1.203	0.728	0.447	0.390	0.000	0.782	2.108	0.385
XLP	0.871	2.522	0.000	0.769	0.000	0.000	0.924	1.287	0.930
XLU	0.000	0.938	0.509	0.000	0.000	0.000	0.328	0.000	0.000
XLV	1.025	2.615	1.225	2.476	0.000	1.209	0.816	2.492	1.836
XLY	0.000	1.308	0.000	0.000	0.000	0.000	0.459	0.847	0.000
				Lagged $QVJL3$ from					
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.763	0.000
XLE	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
XLF	0.000	0.000	0.226	0.227	0.000	0.192	0.000	0.160	0.000
XLI	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
XLK	0.000	0.000	0.000	0.369	0.000	0.373	0.000	0.000	0.000
XLP	0.000	0.000	0.000	0.952	0.000	0.847	0.000	0.000	0.000
XLU	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.268	0.000
XLV	0.000	0.000	0.000	0.972	0.000	0.931	0.000	0.000	0.000
XLY	0.000	0.000	0.000	0.544	0.000	0.515	0.000	0.346	0.000
				Lagged $QVJS3$ from					
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	3.959	0.000	1.660	1.620	0.000	0.000	0.000	0.000	0.000
XLE	2.108	0.000	1.954	0.000	0.000	0.000	1.588	0.000	0.000
XLF	0.421	0.000	0.402	0.000	0.000	0.000	0.000	0.000	0.000
XLI	0.503	0.000	0.000	0.000	0.000	0.000	0.419	0.000	0.540
XLK	0.000	0.000	0.742	0.000	0.000	0.000	0.000	0.000	0.000
XLP	0.000	0.000	2.825	1.580	0.000	1.526	1.160	1.290	0.000
XLU	0.615	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
XLV	1.973	0.000	1.581	1.263	0.000	0.000	0.000	0.000	1.695
XLY	1.026	0.000	0.981	0.000	0.000	0.000	0.000	0.000	0.000

* Notes: See notes to Table 2.4a.

c: Results Based on Analysis of 2007 Jump Variation Data*

	Lagged QVJ from								
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	0.000	0.000	0.000	1.107	1.732	1.317	0.000	0.000	1.737
XLE	2.423	0.000	0.000	1.226	1.969	1.218	0.949	0.988	0.000
XLF	0.000	0.000	0.000	0.850	1.432	1.046	0.000	0.000	0.000
XLI	0.630	0.433	0.154	0.184	1.084	0.696	0.312	0.126	0.285
XLK	0.220	0.447	0.405	0.337	1.100	0.747	0.241	0.522	0.588
XLP	0.000	0.000	0.000	0.281	0.528	0.346	0.000	0.000	0.000
XLU	0.000	0.000	0.299	0.207	0.000	0.229	0.000	0.000	0.000
XLV	0.000	0.000	0.000	0.407	0.716	0.474	0.000	0.000	0.000
XLY	0.227	0.000	0.000	0.000	0.195	0.365	0.000	0.229	0.000
	Lagged $QVJL3$ from								
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	0.000	0.000	1.431	0.000	0.000	0.000	1.954	0.000	0.000
XLE	0.000	0.000	0.000	0.000	0.000	0.000	1.575	0.000	0.000
XLF	0.000	0.000	1.228	1.041	0.000	0.000	1.567	0.000	1.063
XLI	0.000	0.830	0.246	0.204	0.462	0.279	0.553	0.203	0.263
XLK	0.000	0.647	0.274	0.454	0.466	0.274	0.688	1.003	0.312
XLP	0.000	0.000	0.412	0.405	0.000	0.000	0.936	0.372	0.000
XLU	0.000	0.338	0.727	0.000	0.353	0.000	0.311	0.000	0.000
XLV	0.000	0.000	0.582	0.000	0.000	0.000	0.670	0.000	0.000
XLY	0.299	0.000	0.000	0.287	0.000	0.215	0.271	0.000	0.000
	Lagged $QVJS3$ from								
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	7.860	1.975	0.000	0.000	1.544	0.000	0.000	1.717	1.509
XLE	6.079	1.941	1.503	0.000	2.799	3.131	1.891	1.348	3.072
XLF	10.805	1.864	1.592	0.968	2.285	2.943	2.824	1.563	2.512
XLI	0.364	0.245	0.000	0.221	0.252	0.516	0.191	0.456	1.001
XLK	1.757	0.000	0.638	0.554	0.614	0.864	0.257	0.350	0.263
XLP	1.816	0.459	0.000	0.684	0.767	0.488	0.000	0.371	0.387
XLU	1.251	0.920	0.902	0.698	0.000	0.296	0.617	0.297	1.007
XLV	3.968	0.732	0.000	0.992	1.569	1.312	1.214	0.779	0.708
XLY	1.530	0.328	0.916	0.602	0.937	0.463	1.036	0.680	1.175

* Notes: See notes to Table 2.4a.

d: Results Based on Analysis of 2008 Jump Variation Data*

	Lagged QVJ from								
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	0.000	0.000	5.318	0.000	4.341	3.399	0.000	1.608	1.908
XLE	0.180	0.181	0.000	0.000	0.238	0.439	0.506	0.232	0.562
XLF	0.000	0.000	1.027	1.727	2.185	1.332	0.000	1.506	1.655
XLI	0.000	0.000	2.541	0.000	3.953	2.262	0.000	1.251	1.302
XLK	0.000	0.000	0.000	0.000	2.929	1.719	0.883	0.905	0.921
XLP	0.000	0.000	1.543	0.000	2.607	1.926	0.000	1.040	1.178
XLU	0.000	0.000	2.030	2.575	4.329	2.347	0.000	1.414	1.269
XLV	0.475	0.000	1.311	2.587	0.690	0.632	0.000	0.617	0.514
XLY	0.236	0.000	0.213	0.000	0.000	0.000	0.264	0.614	0.242
	Lagged $QVJL3$ from								
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	5.715	0.000	2.583	3.032	5.530	4.535	1.943	1.743	0.000
XLE	1.281	1.313	0.859	0.579	1.000	1.406	1.444	1.091	2.059
XLF	4.947	0.000	2.197	0.000	5.508	4.302	1.937	4.035	2.151
XLI	3.733	0.000	3.287	1.878	3.944	3.163	1.281	2.695	1.432
XLK	3.010	0.000	2.435	1.422	4.264	2.420	0.998	2.035	0.000
XLP	4.862	0.000	2.879	2.745	5.331	2.809	1.325	3.687	1.220
XLU	11.193	6.285	12.577	6.376	12.264	9.282	3.588	7.181	6.544
XLV	2.184	0.000	1.688	1.000	2.170	0.867	0.658	1.655	0.736
XLY	1.857	0.930	1.460	0.525	1.752	1.698	1.173	1.053	2.737
	Lagged $QVJS3$ from								
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	3.633	10.667	0.000	0.000	3.759	0.000	2.744	0.000	0.000
XLE	0.000	0.000	0.000	0.000	0.708	0.000	0.413	0.000	0.000
XLF	6.898	12.000	6.824	3.493	8.858	0.000	9.562	0.000	0.000
XLI	4.361	7.352	0.000	0.000	2.854	0.000	0.000	0.000	0.000
XLK	1.699	5.255	0.000	0.000	1.884	0.000	1.311	0.000	0.000
XLP	6.263	7.300	0.000	2.283	2.396	0.000	3.993	0.000	1.487
XLU	4.972	8.400	0.000	0.000	2.950	0.000	2.149	0.000	0.000
XLV	0.000	4.595	0.000	1.529	0.000	0.000	2.839	0.000	2.124
XLY	0.000	0.000	0.000	0.000	0.433	0.462	0.000	0.524	0.000

* Notes: See notes to Table 2.4a.

e: Results Based on Analysis of 2009 Jump Variation Data*

	Lagged QVJ from								
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	3.134	2.922	4.434	0.885	4.933	0.000	5.807	5.157	3.197
XLE	4.841	8.950	8.662	2.693	4.988	2.398	7.035	8.543	6.908
XLF	6.728	11.083	13.736	2.934	19.275	0.000	22.079	13.582	4.253
XLI	0.498	0.596	1.025	0.186	1.079	0.207	0.781	0.521	0.326
XLK	1.820	2.210	3.418	0.607	3.155	0.000	4.279	2.682	1.731
XLP	3.794	4.623	6.767	1.311	7.525	0.000	8.664	4.891	4.562
XLU	5.691	6.468	8.408	1.749	11.409	0.000	13.116	8.053	0.000
XLV	2.246	3.715	4.685	2.274	5.347	0.000	6.222	2.176	3.128
XLY	2.803	2.517	3.111	0.616	3.735	0.000	4.903	2.843	0.924
	Lagged $QVJL3$ from								
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	0.000	1.485	3.585	1.735	1.946	0.000	1.316	0.892	5.074
XLE	2.131	1.387	5.301	4.211	3.337	0.000	3.726	0.000	3.405
XLF	9.185	18.613	19.640	21.273	21.665	4.287	11.449	0.000	27.862
XLI	0.370	0.000	0.839	0.543	0.000	0.398	0.680	0.235	0.000
XLK	1.816	1.208	2.630	2.423	1.658	0.000	1.120	0.000	1.670
XLP	1.784	2.315	4.898	2.714	3.328	0.000	4.365	0.000	5.484
XLU	5.593	3.598	11.883	11.540	8.914	2.704	9.382	0.000	9.509
XLV	1.545	2.170	6.682	4.529	4.627	0.000	3.995	0.000	7.153
XLY	2.169	1.350	5.418	4.540	1.795	2.110	2.493	0.720	3.666
	Lagged $QVJS3$ from								
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	0.000	2.242	2.132	0.000	1.925	0.000	0.000	4.873	4.227
XLE	0.000	1.936	1.638	0.000	1.724	3.211	0.000	3.033	5.869
XLF	0.000	8.467	0.000	0.000	7.602	0.000	0.000	0.000	7.216
XLI	0.665	0.555	2.065	1.788	0.946	1.129	2.226	2.216	1.831
XLK	0.000	1.664	0.000	0.000	1.426	2.825	0.000	0.000	1.575
XLP	3.026	0.000	0.000	0.000	2.583	0.000	0.000	0.000	5.777
XLU	0.000	8.165	8.282	0.000	0.000	8.443	0.000	14.484	15.314
XLV	0.000	2.357	3.009	0.000	2.489	0.000	0.000	6.500	2.714
XLY	0.000	3.119	0.000	0.000	1.368	3.170	0.000	1.556	5.798

* Notes: See notes to Table 2.4a.

f: Results Based on Analysis of 2010 Jump Variation Data*

	Lagged QVJ from								
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	0.000	0.000	0.000	2.205	0.000	0.000	0.000	0.000	0.000
XLE	0.000	0.000	3.229	6.696	0.000	0.000	0.000	0.000	0.000
XLF	0.000	0.000	1.105	2.479	0.000	0.000	0.000	0.000	0.000
XLI	0.000	0.000	1.067	1.728	0.000	0.000	0.000	0.000	0.000
XLK	0.000	0.000	1.371	1.431	0.000	0.610	0.000	0.000	0.614
XLP	0.000	0.000	0.000	2.384	0.000	0.000	0.000	0.000	0.000
XLU	0.000	0.000	0.000	0.727	0.000	0.000	0.000	0.000	0.929
XLV	0.332	0.000	0.693	0.348	0.000	0.000	0.000	0.000	0.000
XLY	0.000	0.000	3.671	5.368	0.000	2.236	0.000	0.000	0.000
	Lagged $QVJL3$ from								
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
XLE	0.000	0.000	0.000	4.984	0.000	0.000	0.000	0.000	0.000
XLF	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
XLI	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
XLK	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
XLP	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
XLU	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
XLV	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.483	0.000
XLY	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	Lagged $QVJS3$ from								
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
XLB	0.000	0.000	0.000	0.000	0.000	0.000	0.721	0.000	0.000
XLE	0.000	0.000	0.000	4.551	0.000	4.809	0.000	4.007	0.000
XLF	0.000	0.000	0.000	0.000	0.000	0.000	1.693	1.505	0.000
XLI	0.000	0.000	0.000	0.000	0.000	0.819	0.948	0.825	0.811
XLK	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
XLP	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
XLU	0.000	0.000	0.000	0.000	0.000	0.000	1.174	0.000	1.087
XLV	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
XLY	0.000	2.272	12.386	9.018	7.471	8.746	10.176	10.696	3.685

* Notes: See notes to Table 2.4a.

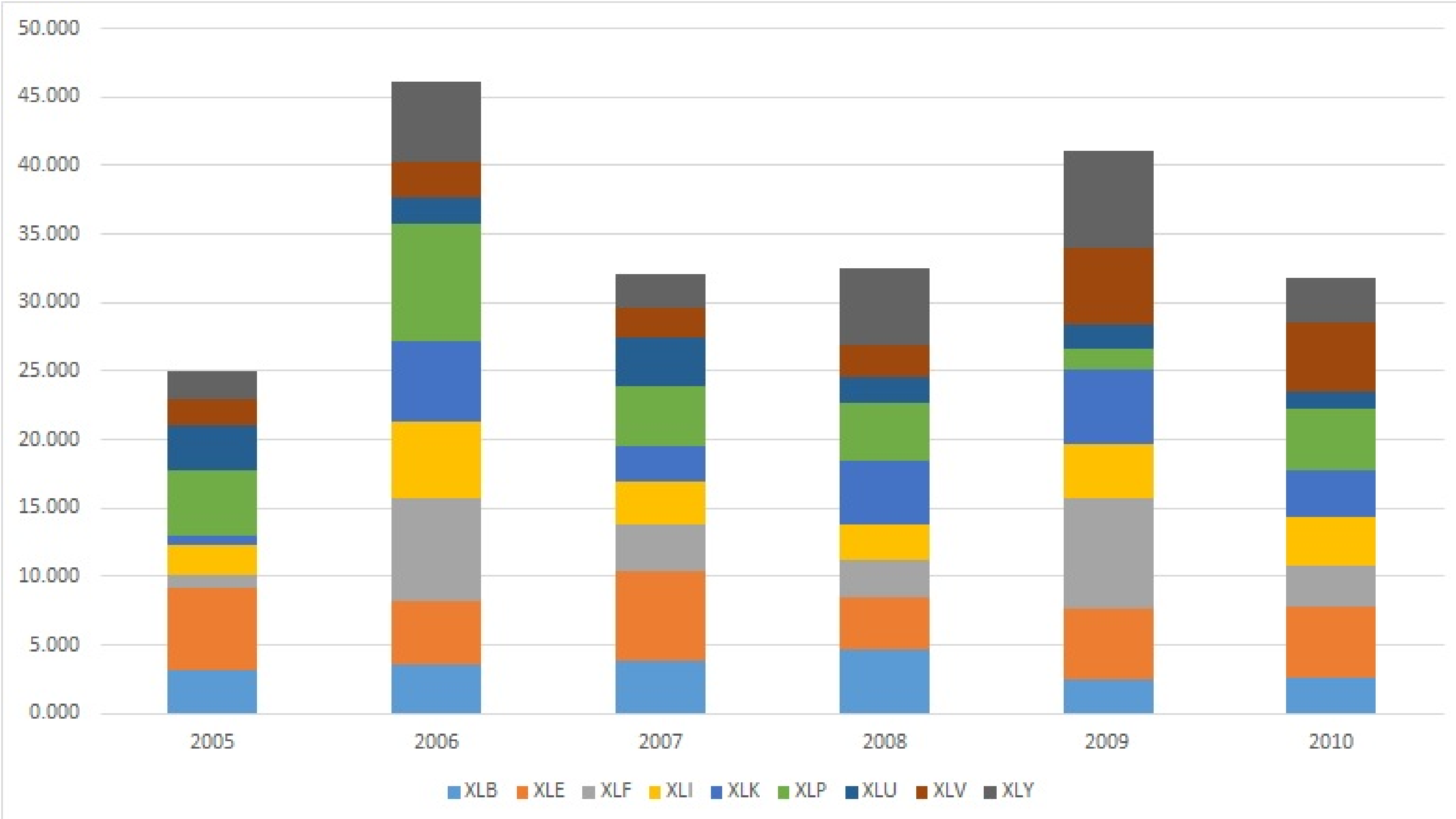

Figure 2.1: Large Jump Spillover Effects by Year*

* Notes: This figure aggregates the large ($QVJL3$) spillover effects by sector and by year based on the results in Table 2.3. NA is treated as 0. Each color block in the graph represents the spillover effects of sector j in year h, and is calculated as $\sum_i \sum_{k=1}^{k=22} |\beta^*_{i,j,k,h}|$ $(j \neq i)$ as discussed in Section 2.3.1.

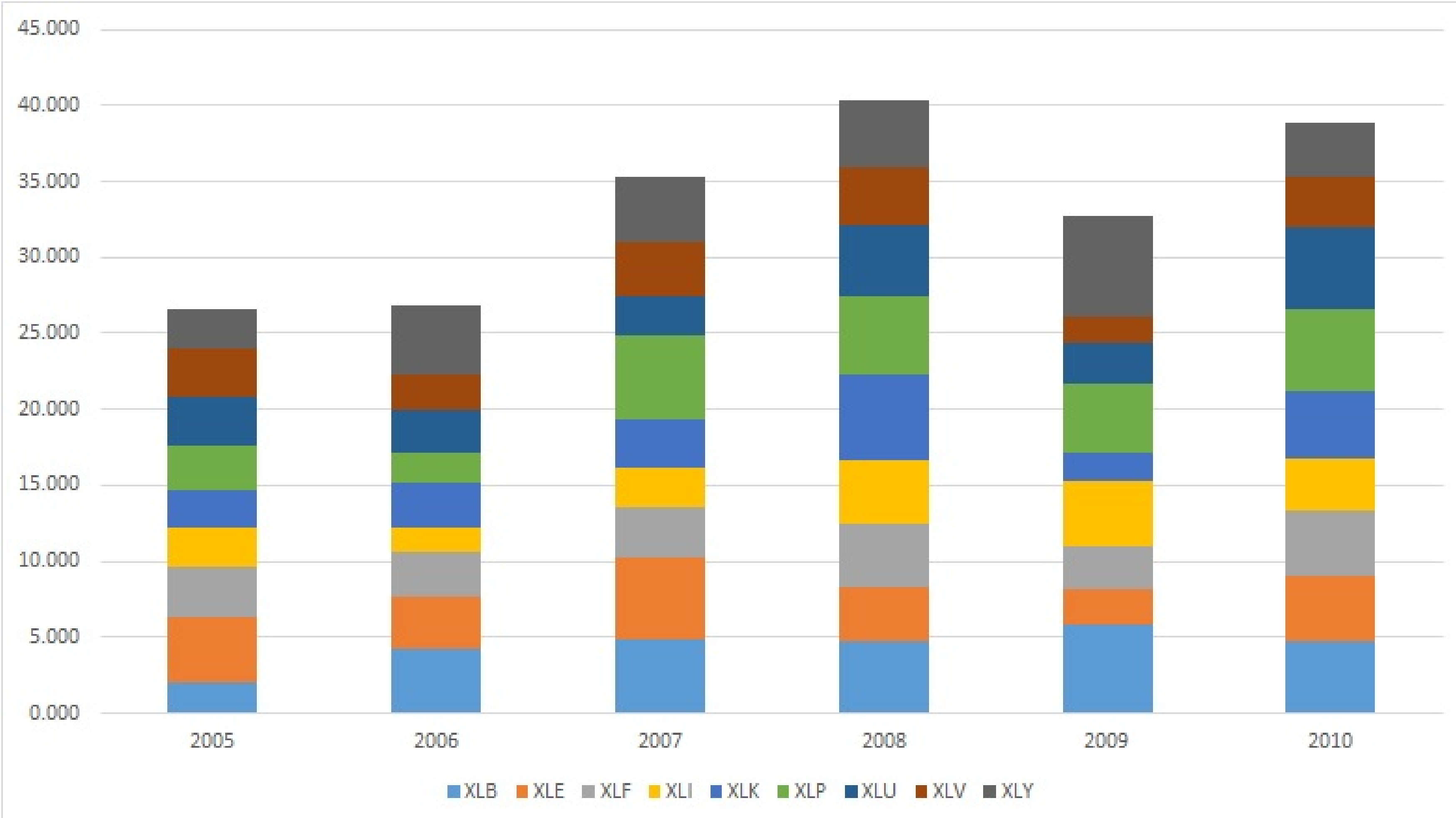

Figure 2.2: Small Jump Spillover Effects by Year*

* Notes: This figure aggregates the small ($QVJS3$) spillover effects by sector and by year based on the results in Table 2.3. See notes to Figure 2.1.

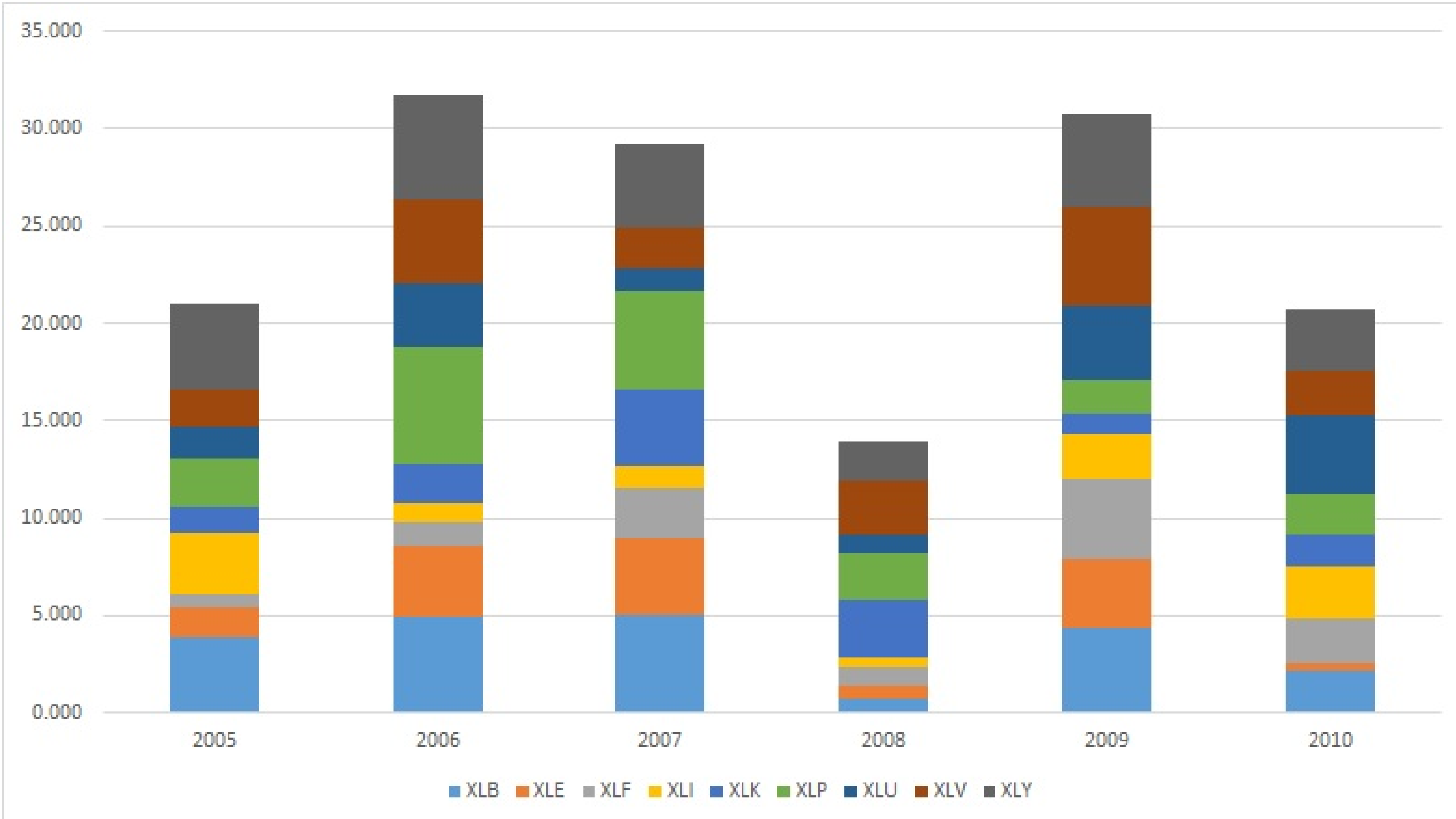

Figure 2.3: Total Jump Spillover Effects by Year*

* Notes: This figure aggregates the total (QVJ) spillover effects by sector and by year based on the results in Table 2.3. See notes to Figure 2.1.

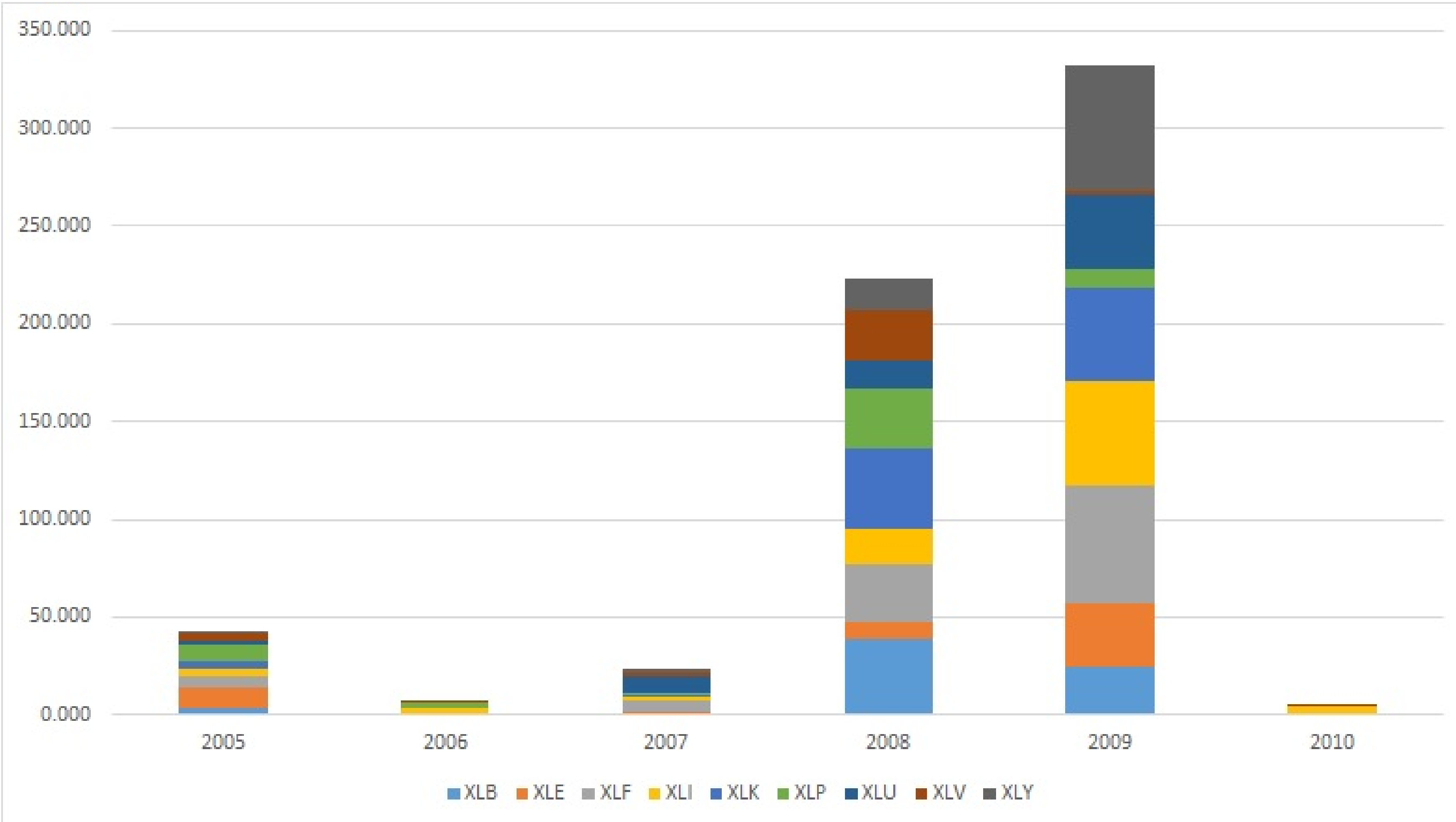

Figure 2.4: Large Jump Contribution Level to Excess Returns by Year*

* Notes: This figure aggregates large ($QVJL3$) jump contribution level to excess returns by sector and by year based on the results in Table 2.4. Each color block in the graph represent the contribution level of jumps in sector j in year h, and is calculated as $C\sum_i \sum_{k=0}^{k=22} |\beta^*_{i,j,k,h}|$ as seen in Section 2.3.2.

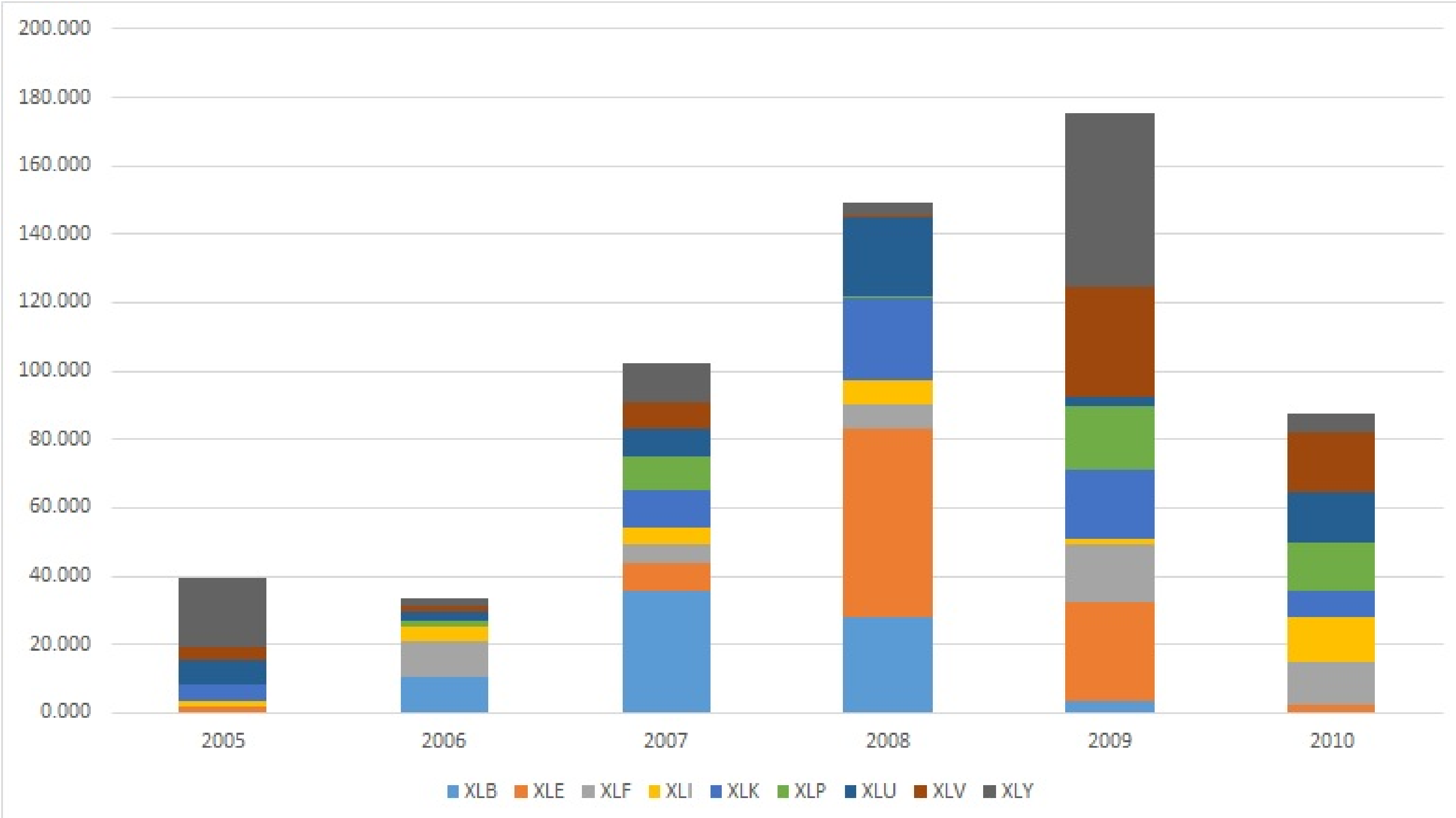

Figure 2.5: Small Jump Contribution Level to Excess Returns by Year*

* Notes: This figure aggregates the small ($QVJS3$) jump contribution level to excess returns by sector and by year based on the results in Table 2.4. See notes to Figure 2.4.

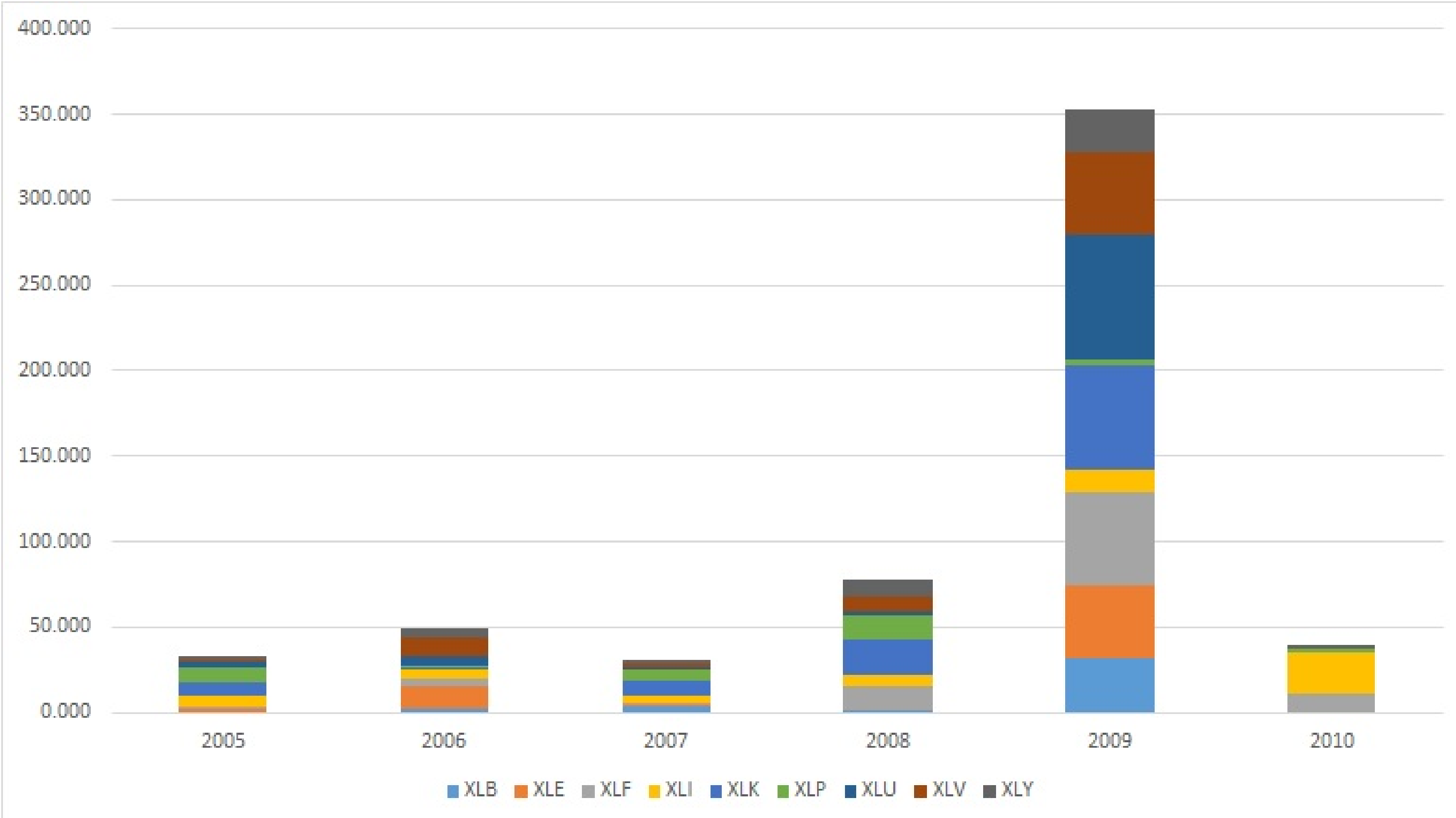

Figure 2.6: Total Jump Contribution Level to Excess Returns by Year*

* Notes: This figure aggregates the total (QVJ) jump contribution level to excess returns by sector and by year based on the results in Table 2.4. See notes to Figure 2.4.

Chapter 3
Jump Spillover Based Risk Indexes

3.1 Introduction

We like indexes because they are straightforward, they are easy to interpret, and they can be simple signals for something quite complicate, like the U.S. economy. In this chapter, we attempt to construct a group of indexes that could serve as indicators for a particular type of risk in the U.S. market - risks associated with unexpected events. To be specific, this type of risk is quantified through a concept called jump spillover effects. The theoretical background and empirical findings of the relationship between jumps and unexpected news announcements can be found in numerous financial econometric papers, such as in Andersen, Bollerslev, Diebold, and Vega (2002), Huang (2007), Bollerslev, Law, and Tauchen (2008), Evans (2011), and Chatrath, Miao, Ramchander, and Villupuram (2014). Based on such observation, financial econometricians are interested in studying the interaction across financial markets. Asgharian and Bengtsson (2006) find that the U.S. market and several European markets show significant jump spillover in countries that have features in common, such as industry structure or geographic location. Asgharian and Nossman (2011) conclude that local European equity markets are under the influence of the U.S. market and regional markets through jumps. Jawadi, Louhichi, and Cheffou (2015) provide evidence showing the dependence between jumps in three European markets and U.S. markets. Aït-Sahalia and Xiu (2016) find the correlation between financial crisis and an increase in the quadratic variation of an asset in the futures market. Chapter 2 finds jump spillover effects across nice market sectors increased right prior to the Great Recession and dropped as the recession unfolded. This gives us some clues on revealing risks related to jumps.

We extend the findings in Chapter 2 to construct daily frequency indexes based on the jump spillover effects across the market sectors for the U.S. market. The main idea is that the index represents risks associated with jumps and are presented through spillover effects. Since there are nine sectors, we calculate this risks in each sector and then the whole U.S. market.

The reason we have a need for such indexes is because, to the best knowledge of the authors, there have been no similar indicators for unexpected risks in the market. One of the biggest reason is the complication of the causes of such risks. We know that the market is changing all the time, and is affected by countless events that make it impossible to track all of them. In this chapter, we propose our indexes as a simple way to solve this complex issue. Instead of trying to track all possible events that can sway, we look at the end-results - volatility jumps. Despite of the causes of the jumps, we can directly measure the changes of the market through these jumps. Thus, we find a straightforward and feasible method to quantify risks related to market-related events.

Moreover, what differentiate our indexes and some of the most popular indexes, like S&P500 and VIX, are their unique characteristics. VIX is the most well-known index to measure market risks. It is calculated using the implied volatility over the following 30 days. It is fair to say, VIX is based on future/unknown knowledge. In this sense, our indexes are completely different from VIX. First, we are not based on expected information from the future, instead, we are based on what happened in the past. Second, we are interested in identifying the dynamics of risk transmission and not the volatility in the market. Knowing how the risk transmits from one market sector to another, or from one asset from another, enables us to hedge loss during trading. Third, VIX only covers the whole U.S. market, while our indexes offers the option for the whole U.S. market and nine market sectors. Comparing to existing indexes, our indexes offer a fresh prospective to evaluate the market.

Several features are selected to construct our indexes. First, we segregate various types of jumps. Following the jump testing and jump separation methods shown in the first chapter, we obtain daily quadratic variation caused by jumps, large jumps and small jumps. Doing so allows us to analyze risks caused by unexpected events overall, major news announcements, and small-scale price fluctuation respectively. Truncation level is chosen arbitrarily as shown in Aït-Sahalia and Jacod (2012). Based on the results in Schlossberg and Swanson (2018), we applied the same truncation level to obtain the decomposed jump information. For simplicity, we denote each type of jumps as QVJ - quadratic variation due to jumps, $QVJL$ - quadratic variation due to large jumps, $QVJS$ - quadratic variation due to small jumps. For each data type, we use rolling window method to extract the spillover coefficients among nine market sectors. We adopt the SPDR market sector ETF for accurate sector trading information, as these ETFs are a microcosm of its corresponding industry. During this process, we run into the number of parameters exceeds the number of observations. We rely on three popular shrinkage and regularization methods in machine learning to tackle the problem: Ridge, LASSO, and elastic net. At last, we construct a group of indexes for the U.S. market and its sectors. In addition, for the U.S. market index, we provide two versions: equal weighted and float adjusted market capitalization weighted. We also account for seasonality and periodicity.

We find that float adjusted market capitalization weighted index works better than the equal weighted version. Index based on QVJ is preferred than index based on $QVJL$ or $QVJS$, no matter it is for the sector or the whole market. The best shrinkage and regularization method is to let the data decide which shrinkage and regularization method to apply.

The rest of the chapter is organized as follows. Section 3.2 reviews nonparametric jump tests, decomposition methods, and data shrinkage and regularization methods. Section 3.3 outlines the empirical methodology used in our data analysis. Section 3.4 contains our empirical findings. Finally, concluding remarks are gathered in Section 3.5.

3.2 Theoretical Background

The construction of this index is achieved through a series of steps, involving statistical testing and analysis:

- Jump test and decomposition
- Volatility jump spillover based risk quantification

3.2.1 Jump Test and Decomposition

Jump test and decomposition obtains jump information from 5-min trading data. First, a bipower variation based jump test is applied to identify whether or not there are jumps in an asset on a trading day. Then, a truncated method power variation based method is used to decompose jumps from the variation process. We denote QVC as percentage of quadratic variation caused by continuous component, QVJ as percentage of quadratic variation caused by jumps, $QVJL$ as percentage of quadratic variation by large jumps, and $QVJS$ as percentage of quadratic variation by small jumps. For days when no jumps are present, $QVJ = QVJL = QVJS = 0$. Below is the detailed theoretical background.

The information presented in this section is quite similar to what is described in Chapter 2.

Set-up

Define log prices as $Y_t = log(P_t)$, and assume that they follow an Itô semimartingale process,

$$Y_t = Y_0 + \int_0^t a_u d_u + \int_0^t \sigma_u dW_u + \int_0^t \int_{\{|y|\leq\epsilon\}} y(j-\nu)(du,dy) + \int_0^t \int_{\{|y|>\epsilon\}} yj(du,dy), \qquad (3.1)$$

where $Y_0 + \int_0^t a_u d_u + \int_0^t \sigma_u dW_u$ is a Brownian semi-martingale. Here, $\int_0^t a_u d_u$ is the drift term, with a_t being the instantaneous drift, and $\int_0^t \sigma_u dW_u$ is the continuous part with σ_t being the spot volatility. Additionally, j is the jump measure of Y_t, and its predictable compensator is the Lévy measure ν. Finally, $\int_0^t \int_{\{|y|\leq\epsilon\}} y(j-\nu)(du,dy)$ is the so-called small jump component, and $\int_0^t \int_{\{|y|>\epsilon\}} yj(du,dy)$ is the so-called large jump component, with ϵ being an arbitrary cutoff level specified in order to differentiate between small and large jumps.

Several important concepts are presented here: realized volatility (RV), quadratic variation, and integrated volatility.

Suppose that $t > 0$ is a fixed time period, for example, one trading day, and the ith log-price of an asset observed during day t is $Y_{i,t}$. The intra-ith return on day t is $r_{i,t} = Y_{i,t} - Y_{i-1,t}$, where $i = 1, 2, ..., t/\delta$ and δ is the sampling frequency. For one trading day, we have the explicit expression for RV:

$$RV_t = \sum_{i=1}^{t/\delta} r_{i,t}^2. \qquad (3.2)$$

Quadratic variation is defined as:

$$[Y]_t = p \lim_{\delta\to 0} \sum_{i=0}^{t/\delta-1} (Y_{t_i} - Y_{t_i})^2, \qquad (3.3)$$

for any sequence of partitions $t_0 = 0 < t_1 < ... < t_n = t$, with $sup_i\{t_{i+1} - t_i\} \to 0$ for $\delta \to 0$. When sampling is at a high and fixed frequency (such as $N \to \infty$ or $\delta \to 0$),

$$RV_t \xrightarrow{\mathbb{P}} [Y]_t$$

where $\mathbb{P}$ denotes uniform convergence in probability. Thus, realized quadratic variation (QV) is expressed as:

$$QV = [Y_\delta]_t = \sum_{i=1}^{t/\delta} r_{i,t}^2 \tag{3.4}$$

The definition of integrated volatility is $\int_0^t \sigma_u^2 du$. When asset prices are continuous on a fixed interval $[0, T]$,

$$[Y]_t \xrightarrow{\mathbb{P}} \int_0^t \sigma_u^2 du, \tag{3.5}$$

and when asset prices also have a discontinuous component on $[0, T]$ (like in Equation (1)),

$$[Y]_t \xrightarrow{\mathbb{P}} \int_0^t \sigma_u^2 du + \sum_{u \leq t} (\Delta Y_u)^2, \tag{3.6}$$

where $\sum_{u \leq t}(\Delta Y_u)$ is a pure jump process and a jump at time s is defined as $\Delta Y_t = Y_u - Y_{u-}$. Here, $\sum_{u \leq t}(\Delta Y_u)^2$ is the variation of the jump component.

Jump Test

Under the assumption of Equation (1), Equation (6) shows that if the theoretical integrated volatility can be properly estimated, jumps can be measured using the difference between QV and realized integrated volatility. This is the key idea underpinning bipower variation based tests.

The sth power variation is defined as:

$$\{Y\}_t^{[s]} = p \lim_{\delta \to 0} \delta^{1-s/2} \sum_{i=1}^{t/\delta} |r_{i,t}|^s,$$

where $s > 0$.

The bipower variation process is defined as:

$$\{Y\}_t^{[s_1, s_2]} = p \lim_{\delta \to 0} \delta^{1-(s_1+s_2)/2} \sum_{i=1}^{[t/\delta]-1} |r_{i,t}|^{s_1} |r_{i+1,t}|^{s_2},$$

where $s_1, s_2 > 0$. More importantly, when $s_1 = s_2 = 1$,

$$\mu_1^{-2} \{Y\}_t^{[1,1]} = \int_0^t \sigma_u^2 du.$$

Thus, integrated volatility can be consistently estimated as:

$$\mu_1^{-2} BV = \mu_1^{-2} \sum_{i=2}^{t/\delta} |r_{i-1,t}||r_{i,t}| \xrightarrow{\mathbb{P}} \int_0^t \sigma_u^2 du \tag{3.7}$$

where $\mu_1 = E[u] = \sqrt{2}/\sqrt{\pi} \simeq 0.79788$, and u is $N(0,1)$ random variable.

Barndorff-Nielsen and Shephard (2006a) suggest an adjusted ratio jump test

$$\hat{J} = \frac{\delta^{-1/2}}{\sqrt{\eta max(t^{-1}, \frac{QPV_t}{BV_t^2})}}\big(\frac{\mu_1^{-2}BV_t}{QV_t} - 1\big) \xrightarrow{d} N(0,1). \tag{3.8}$$

where d denotes convergence in distribution, and QPV is the realized quadpower variation

$$QPV_t = \{Y_\delta\}_t^{[1,1,1,1]} = \delta^{-1}\sum_{i=4}^{t/\delta} |r_{i-3,t}||r_{i-2,t}||r_{i-1,t}||r_{i,t}| \tag{3.9}$$

Huang and Tauchen (2005), Andersen, Bollerslev, and Diebold (2007) extends the test by Barndorff-Nielsen and Shephard (2006a) and suggest using a daily statistic, $z_{TP,t}$, to test for jumps on a daily basis:

$$z_{TP,t} = \frac{RV_t - BV_t}{\sqrt{(v_{bb} - v_{qq})\frac{1}{N}TP_t}} \xrightarrow{d} N(0,1), \tag{3.10}$$

with $v_{qq} = 2$, $v_{bb} = (\frac{\pi}{2})^2 + \pi - 3$, Here, realized tripower quarticity (TP) is defined and estimated as follows:

$$TP_t = \delta^{-1}\mu_{4/3}^{-3}\sum_{j=3}^{1/\delta} |r_{i-2,t}|^{4/3}|r_{i-1,t}|^{4/3}|r_{i,t}|^{4/3} \xrightarrow{\mathbb{P}} \int_0^t \sigma_u^4 du \tag{3.11}$$

Inference is carried out by rejecting the null of no jumps if $z_{TP,t}$ exceeds the critical value, Φ_α, leading to a conclusion that there are jumps during the day. A common choice for the critical value is 1.96, equivalent to 5% significant level.

Jump Decomposition

In our empirical application, we utilize the jump decomposition methods discussed in Aït-Sahalia and Jacod (2012) in order to decompose quadratic variation into continuous components and jump components. Furthermore, we consider large jump and small jump components, as discussed above. When considering truncated sth realized power variation, if the power, $s < 2$, then the continuous component in the process dominates, while if $s > 2$ then the jump component dominates. When $s = 2$ both components have equal influence on the process. Thus, we can obtain important information about quadratic variation by decomposing realized power variation into continuous and jumps components, as follows.

The truncated sth realized power variation as defined in Aït-Sahalia and Jacod (2012) is expressed as follows.

$$B(s,u,\delta) = \sum_{i=1}^{t/\delta} |r_{i,t}|^s I_{\{|r_{i,t}| \le u\}}.$$

Here, the truncation level u is set equal to $b\delta^{\omega}$, for some constant $\omega \in (0, 1/2)$, with $b > 0$, which results in u shrinking to 0. As above, δ is the sampling frequency. In this framework, $\omega < 1/2$ ensures that all increments "mainly" contain a Brownian contribution. Note, when u is set to infinity, the truncated realized power variation becomes $B(s,\infty,\delta)$, in which case no truncation is applied.

$$\begin{aligned} \text{Percentage of total QV due to continuous component } (QVC) &= \tfrac{B(2,u,\delta)}{B(2,\infty,\delta)} \\ \text{Percentage of total QV due to jump component } (QVJ) &= 1 - \tfrac{B(2,u,\delta)}{B(2,\infty,\delta)} \end{aligned} \tag{3.12}$$

In our empirical section, we use the value of u used in code available from Aït-Sahalia and Jacod (2012). We denote the variation due to jumps (i.e., increments "larger" than u) as:

$$\begin{aligned} U(s,u,\delta) &= \sum_{i=1}^{t/\delta} |r_{i,t}|^s I_{\{|r_{i,t}| > u\}} \\ &= B(s,\infty,\delta) - B(s,u,\delta) \end{aligned}$$

Jump decompositions based on this metric can be calculated as:

$$\begin{aligned} \text{Percentage of QV due to large jump component } (QVJL) &= \tfrac{U(2,\epsilon,\delta)}{B(2,\infty,\delta)} \\ \text{Percentage of QV due to small jump component } (QVJS) &= \tfrac{B(2,\infty,\delta) - B(2,u,\delta) - U(2,\epsilon,\delta)}{B(2,\infty,\delta)} \end{aligned} \tag{3.13}$$

The large jump cut-off level is $\epsilon = b\delta^{\omega}$, which is arbitrarily chosen, by experimenting with multiple values of ϵ.[1] Based on the findings in Chapter 2 we set $b = 3$. We consider the following variations: QVJ, $QVJL$, $QVJS$.

3.2.2 Volatility Jump Spillover Based Risk Quantification

Volatility jump spillover based risk quantification allows us to quantify risks through jump spillover effects, which ultimately are related to major news/events and high frequency trading strategies. After we obtain QVJ, $QVJL$, $QVJS$, we would like to quantify the jump spillover effects across

[1] Recall that u is set equal to $b\delta^{\omega}$. In our calculations, we set $b = 2$ when calculating u.

all market sectors on a particular day. Several questions we need to ask first:

(1) which data to use: total jumps (QVJ), large jumps ($QVJL$), or small jumps ($QVJS$)

(2) how to obtain the spillover effects on a daily basis

(3) how to decide number of lags in the regression

(4) how to solve the problem that the number of regressors is larger than the observations

Empirical evidence shows that large jumps are usually associated with major news announcement and events, and small jumps are a result of high frequency trading strategies. Thus, we conduct our linear regression analysis on each type of jumps: QVJ, $QVJL$, $QVJS$. In order to obtain jump spillover effects at a daily frequency, we adopt the rolling window method. We choose the length of the rolling window to be half a year - 132 days (assuming each month has 22 trading days). This length is chosen based on the economic logic that half a year seems to be a reasonable length for any particular events to take an effect. Then for each rolling window, we conduct linear regression for each sector in the form as below:

$$Sector_{i,t,h} = \beta_{i,0,h} + \sum_{j \neq i} \sum_{k=1}^{k=22} \beta_{i,j,k,h} Sector_{j,t-k,h} + \epsilon_{1,t,h} \tag{3.14}$$

where $Sector_{i,t,h}$ is the variation of the jump component of the ith market sector at time t in year h with $i = 1, ..., 9$ representing nine market sectors. $Sector_{j,t-k,h}$ is the k lagged variation of the jump component of the jth market sector in year h with $j = 1, ..., 9$ representing nine market sectors. $h = 2005, ..., 2010$ is the calendar year. Variation of the jump component are categorized as QVJ,$QVJL$, and $QVJS$. $\beta_{i,0,h}$ is the intercept for market sector i in year h. $\beta_{i,j,k,h}$ denotes the coefficient of kth lagged jump in sector j in regards to the jump in ith sector in year h. Clearly, these βs quantify the spillover effects in that year. The number of lags is chosen based on both economic analysis and Akaike information criterion (AIC). We believe that jump spillover effects can last for a long period, such as one month (22 trading days). AIC also confirms this choice ($k = 22$). We did not use BIC because it penalizes large models and results in neglecting lagged regressors from multiple market sectors. Augmented DickeyFuller test is conducted to ensure all input data meeting the stationary requirement. Maximum likelihood is used to estimate the model. The jump spillover effects of market sector j on market sector i ($j \neq i$) is calculated as $\sum_{k=1}^{k=22} |\hat{\beta}_{i,j,k,h}|$, where $\hat{\beta}$ is the estimated coefficient of lagged jumps in market sectors. The jump spillover effects contained in sector i is then $\sum_{j\neq i}\sum_{k=1}^{k=22}|\hat{\beta}_{i,j,k,h}|$, which is the base of our index.

For each regression, there are 199 parameters while our observation has only 132 (22*6) data points, we now face a high dimensional issue. This issue arises when when the number of regressors are larger than the number of observations. The traditional least squares fitting procedure estimates the coefficients β_j by minimizing sum of squared errors

$$\min \sum_{i=1}^{n}(y_i - \sum_{j=1}^{p}\beta_j x_{ij})^2 \tag{3.15}$$

This method only works when the number of the regressors is much smaller than the number of observations. If not, there will be either infinite solutions to this minimization problem or the estimate have poor predictive accuracy. We apply shrinkage and dimensional reduction methods from machine learning, particularly Ridge, LASSO (least absolute shrinkage and selection operator), and elastic-net method to estimate the coefficients.

Ridge Regression

Ridge regression is proposed to constrain βs so that we can solve the problem that the number of regressors exceed the number of observations. The ridge regression is constructed as below:

$$PRSS(\beta)_{l_2} = \sum_{i=1}^{n}(y_i - \sum_{j=1}^{p}\beta_j x_{ij})^2 + \lambda\sum_{j}^{n}\beta_j^2 \tag{3.16}$$

where PRSS stands for penalized residual sum of squares, λ is the tuning parameter and controls the impact of the shrinkage penalty $\lambda\sum_j^n \beta_j^2$ in the minimization problem. When $\lambda = 0$, there is no penalization and we have p parameters. When $\lambda \to \infty$, the parameters are mostly constrained and the degrees of freedom is decreasing to 0. Moreover, x is assumed to have mean 0 and unit variance, while y is assumed to be centered.

Now the problem becomes to minimize $PRSS$, and since $PRSS(\beta)_{l_2}$ is convex, it has a unique solution. The *beta* here is biased and called the ridge estimator, denoting as β_{ridge}. If we calculate the ratio between the squared loss with ridge and without ridge (the traditional one), we can see that the ridge regression can reduce the expected squared loss despite being a biased estimator.

LASSO Regression

One pitfall of the ridge regression is the difficult interpretation, as no regressors are eliminated from the regression. As a result, Tibshirani (1996) proposes LASSO (least absolute shrinkage and selection operator) to shrink the estimates of β_j towards zero.

$$\hat{\beta}_\lambda = \arg\min\{\sum_{i=1}^{n}(y_i - \sum_{j=1}^{p}\beta_j x_{ij})^2 + \lambda\sum_{j}^{n}|\beta_j|\} \tag{3.17}$$

similar to ridge regression, λ is the tuning parameter and controls the impact of the shrinkage penalty $\lambda\sum_j^n|\beta_j|$ in the minimization problem.

Unlike ridge regression, LASSO has no closed form. Efron et al. (2004) suggest using the LARS algorithm and prove that the LASSO solution paths grow piecewise linearly in a predictable way. In this chapter, we rely on the *glmnet* packages in R, which is discussed at the end of this section.

Elastic Net Regression

Zou and Hastie (2005) build their work on LASSO and proposed the elastic net regularization method. Similar to LASSO, it serves a way to select and regulate regression models; and unlike LASSO, it emphasizes the grouping effect, where correlated regressors tend to stay in and leave the model together.

$$\min\sum_{i=1}^{N}(y_i - \beta_0 - x_i^T\beta)^2 + \lambda[(1-\alpha)||\beta||_2^2/2 + \alpha||\beta||_1] \tag{3.18}$$

where $\lambda \geq 0$ is the tuning parameter as before and $0 < \alpha < 1$ is the mixing parameter balancing the effect of ridge and LASSO. Clearly, when $\alpha = 1$, the minimization problem becomes LASSO and when $\alpha = 0$, the minimization problem becomes ridge.

Zou and Hastie (2005) propose an algorithm called LARS-EN to solve the elastic net efficiently, which is very similar to the LARS algorithm of Efron et al. (2004). The coordinate decent in the *glmnet* packages in R is applied in this chapter.

R *glmnet* packages

The *glmnet* packages in R applies the coordinate descent to provide solutions to the three shrinkage and regularization methods above. Specifically, suppose the current estimates are $\tilde{\beta}$s. The updated estimates are obtained by computing the gradient at the current estimates. Without loss of generality, the objective function for the Gaussian family can be written as:

$$\min \frac{1}{2N}\sum_{i=1}^{N}(y_i - \beta_0 - x_i^T\beta)^2 + \lambda[\alpha||\beta||_1 + (1-\alpha)||\beta||_2^2/2] \tag{3.19}$$

where λ and α is the tuning and mixing parameter as described above.
Then the update of the estimates is calculated as

$$\beta_{update} \leftarrow \frac{S(\frac{1}{N}x_{ij}(y_i - y_i^{\widetilde{update}}), \lambda\alpha)}{1+\lambda(1-\alpha)} \tag{3.20}$$

where $\tilde{y}_i^{update} = \tilde{\beta}_0 + \sum_{i \neq j} x_{ij}\tilde{\beta}_j$. $S(z, \gamma)$ is the soft-thresholding operator with value $sign(z)(|z| - \gamma)_+$.

The requirement for the above three shrinkage methods is to standardize our data to have a unit variance for each rolling window. To find the best tuning parameter λ and best mixing parameter α, the cross validation method recommended by Rob Hyndman is applied. [2] The common K-fold cross validation is not always suitable because of the inherent serial correlation and possible non-stationarity in time series data as discussed in Arlot and Celisse (2010), Bergmeir, Hyndman, and Koo(2018). In our chapter, we first define a default shrinkage and regularization method, such as ridge, LASSO, and elastic net by setting the $\alpha = 0$, $\alpha = 1$, $0 < \alpha < 1$ respectively. To complete our experiments, we also create a case where we let the data in each rolling window decide which shrinkage and regularization method to use. We call it mixed. So in total, we have four cases: ridge, LASSO, elastic net, and mixed.

3.3 Empirical Methodology

3.3.1 Index Creation

From section 3.2, we obtain jump spillover coefficients for each sector for each trading day. Since our data are always between 0 and 1 (it is a percentage), our coefficients are in the same scale. Each index is constructed following the steps below:

- Take the absolute value of the coefficients $\hat{\beta}_{i,j,k,h}$, called it AbsCoefficient $|\hat{\beta}_{i,j,k,h}|$, based on the targeting market, jump variation type, and data shrinkage and regularization method.

[2] For more details see: https://robjhyndman.com/hyndsight/tscv/

- In rolling window h, sum all the AbsCoefficients appears in the regression on jumps in sector i and denote it as $Ind_i = \sum_{j \neq i} \sum_{k=1}^{22} |\hat{\beta}_{i,j,k,h}|$. It is worth noting that $i \neq j$ is to ensure to exclude the coefficients from the autoregression process and only account for the jump spillover effects. For example, the jump spillover affects jumps in XLB in window h is $Ind_{XLB} = \sum_{j \neq 1} \sum_{k=1}^{22} |\hat{\beta}_{1,j,k,h}|$, where $h = 1, ..., 1380$.

- For market index, we construct two versions: equal weighted index and float-adjusted weighted index. To calculate weights for each market sectors, we obtain the historical S&P500 sector weightings between 2005 and 2010 from the SPDR website. Appendix 3.I describes more detailed information.

  Specifically, the equal weighted market index and the float adjusted weighted market index are constructed as below:

$$Ind_{FW} = W_{XLB} * Ind_{XLB} + W_{XLE} * Ind_{XLE} + W_{XLF} * Ind_{XLF} + W_{XLI} * Ind_{XLI} + W_{XLK} * Ind_{XLK} + W_{XLP} * Ind_{XLP} + W_{XLU} * Ind_{XLU} + W_{XLV} * Ind_{XLV} + W_{XLY} * Ind_{XLY} \tag{3.21}$$

  The equal weighted indexes for the U.S. market is constructed by adding the spillover coefficients from each market sector assuming each sector has the same weight.

$$Ind_{EW} = Ind_{XLB} + Ind_{XLE} + Ind_{XLF} + Ind_{XLI} + Ind_{XLK} + Ind_{XLP} + Ind_{XLU} + Ind_{XLV} + Ind_{XLY} \tag{3.22}$$

- To construct the index for the whole U.S. market, we can choose to time the impact from each sector with or without its corresponding weight. For the index for each market sector, we just change the weight of the corresponding sector to be 1 and the rest of the weights to be 0. For example, our initial market index for one day is $Index_{temp} = \sum_{i=1}^{9} W_i * Ind_i$, where i is the ith sector.

- The final step is to factor the seasonality and periodicity. We first apply the apply the exponential function on the trend $I_{exp} = e^{Index_{temp}}$, which aims to enhance the contrast between unexpected-events period and normal period, and then use *stl* package in R to extract the trend of I_{exp} to obtain our final Index Ind.

As a result, a total of 132 indexes are constructed based on the different choices made in each step. First, there are three types of data that we want to obtain the jump spillover coefficients: QVJ, $QVJL$, and $QVJS$. Second, we have four cases to conduct the regression analysis: ridge, LASSO, elastic net, and mixed. Last, we can construct the U.S. market index by summing up the spillover coefficients from nine market sectors using equal weights or their equivalent weights from the S&P 500 index, as well as indexes for each market sector. Appendix 3.II shows the complete list of 132 indexes.

3.3.2 Markov Regime Switching Model

To better illustrate our indexes, the markov regime switching model is applied to use our indexes to detect different economic regimes, and then the results are compared with regime detection using a S&P500 based ETF called SPY and VIX. The joint likelihood of observation $Y_t = \{y_1, ..., y_n\}$ and latent states $S_t = \{s_1, ..., s_n\}$ is expressed as:

$$P(Y_t, S_t) = P(s_1)P(y_1|s_1)\prod_{2}^{n} P(s_t|s_{t-1})P(y_t|s_t) \tag{3.23}$$

where s_i is the state at time i and can take two values s_a and s_b. In other words, at any time t, we have two possible states s_a and s_b. $P(s_1)$ is the prior probability distribution on the initial state. $P(s_t|s_{t-1})$ describes the probability of a transition from the state at time $t-1$ to the state at time t. $P(y_t|s_t)$ is the observation/measurement probability.

To obtain the maximum likelihood estimates of te model parameters, the marginal likelihood of the observation is calculated using dynamic programming. In this chapter, we adopt *depmixS4* package from R to estimate the parameters, which is achieved by the expectation-maximization (EM) algorithm. Interested readers can read more in Visser and Speekenbrink (2010).

3.4 Empirical Results

3.4.1 Data Description

We obtain daily millisecond trading data between January 2005 to December 2010 from TAQ database though Wharton Research Data Services (WRDS). To reduce the micro-structure noise effects, we follow literature standard and choose the sampling frequency to be at the 5 minute frequency between 9:30am to 4pm, which yields roughly 78 observations per day. When there is no price at the exact time stamp, we use the closest one available.

We choose nine market sector ETFs constructed by SPDR. These nine sector ETFs are XLY (consumer discretionary sector), XLP (consumer staples sector), XLE (energy sector), XLF (financials sector), XLV (health care sector), XLI (industrials sector), XLB (materials sector), XLK (technology sector), and XLU (utilities sector).

According to SPDR website, XLY includes companies from industries like: media, retail (specialty, multiline, internet and catalog), hotels, restaurants and leisure, textiles, apparel and luxury goods, household durables; automobiles; auto components, distributors, leisure products, and diversified consumer services. XLP covers food and staples retailing, household products, food products; beverages, tobacco, and personal products. XLE consists of companies in oil, gas and consumable fuels, and energy equipment and services. XLF is about diversified financial services, insurance, banks, capital markets, mortgage real estate investment trusts ("REITs"), consumer finance, and thrifts and mortgage finance. XLV provides a picture of companies in pharmaceuticals, health care equipment and supplies, health care providers and services, biotechnology, life sciences tools and services, and health care technology. XLI has a wide range of industries, including aerospace and defense, industrial conglomerates, marine, transportation infrastructure, machinery, road and rail, air freight and logistics, commercial services and supplies, professional services, electrical equipment, construction and engineering, trading companies and distributors, airlines, and building products. XLB is a collection of companies in chemicals, metals and mining, paper and forest products, containers and packaging, and construction materials. XLK aggregate companies in technology hardware, storage, and peripherals, software, diversified telecommunication services, communications equipment, semiconductors and semiconductor equipment, internet software and services, IT services, electronic equipment, instruments and components, and wireless telecommunication services. XLU provides information about companies in electric utilities, water utilities, multi-utilities, independent power producers and energy traders, and gas utilities. In 2015, SPDR launched a new ETF targeting real estate management and development and REITs, excluding mortgage REITs, but since our analysis is between 2005 and 2010, we exclude this new sector ETF from our data set.

To compare our indexes with industry benchmarks, we download the S&P 500 index based ETF

SPY and VIX from Yahoo!Finance at a daily frequency between January 2005 to December 2010, so that we can use Markov regime-switching model on the SPY, VIX and our indexes.

3.4.2 Empirical Findings

Based on the three different jump types and four data shrinkage and regularization methods, as well as market types, we created 132 indexes. Among those 132 indexes, 24 of them focus on the whole U.S. market with 12 using equal weighted methods and 12 float-adjusted market capitalization weighted methods. The rest are 12 incices for each market sectors. Due to the large amount of information, only key points and results are presented in this chapter. indexes result in redundant or useless information are omitted from discussion.

Market Indexes

As described above, two types of market indexes are constructed: the equal weighted indexes and float-adjusted market capitalization weighted indexes. For each weighting type, we categorize indexes based on the type of jumps considered: total jump variation QVJ, large jump variation $QVJL$, and small jump variation $QVJS$. For each jump type, four shrinkage and regularization cases are applied to find the spillover coefficients: ridge, LASSO, elastic net, and mixed.
USIndex1 to USIndex 12 are the float-adjusted market capitalization weighted indexes after adjusting seasonality and periodicity. Weights for each sector is calculated using the method in Appendix 3.III. Figure 3.1 compares the USIndex group with SPY and VIX. Several conclusions can be made. First, prior to the Great Recession, we see an increase in jump spillover based index for indicex using total and large jump variation. This matches the findings in Chapter 2. Second, we see LASSO and ridge works better for large and small jump variation (USIndex5, USIndex6, USIndex11, USIndex12) respectively, while elastic net works better for total jump variation (USIndex1). This can be explained by the theoretical background of those methods. As explained in Section 3.2.2, LASSO penalizes large models and ridge keeps all the explanatory variables. LASSO is able to catch rare and meaningful regressors, and Ridge can preserve information on all possible jumps that affect the dependent variable. In some way, both methods are capable to explain the dynamics among a specific type of jump variation. However, for the same reason, LASSO does not work that

well in the total jump case (USIndex4), which is probably due to some information are lost during shrinking regressors. Ridge method results (USIndex10) can be noisy and misleading. While elastic net aims to filter regressors as a group. We can say that it looks at only partial information when balancing regressors, so no strong patterns for USIndex2 and USIndex3, but works well when data are total jumps (USIndex1). Mixed, which uses data to decide the shrinkage and regularization method, seems to provide a good justification in all cases (as seen USIndex7, USIndex8, USIndex9). Third, total jumps, large jumps, and small jumps captures different aspects in the market movements, comparing USIndex7, USIndex8, and USIndex9. Large jump risks appeared as early as in late 2006, due to the housing bubble, while small jump risks spiked right before the recession started. Total jump risks shows that 2007 is a volatile year.

USIndexEW1 to USIndexEW12 are the equal weighted indexes for the U.S. market using different types of jumps and data shrinkage and regularization methods. Figure 3.2 aggregates them with SPY and VIX. We see huge spikes appearing in various places along the timeline, which is quite different from the float-adjusted case. While each spikes can be associated with some major economic events, such as the housing bubble in 2006, the rise and fall of crude oil prices between 2005 and 2009, the Great Recession, etc., the drastic changes in levels of the index can be deceptive. In other words, graphs is not the most reliable way for analysis. Thus, we turn to Hidden Markov models described earlier to investigate the regime states in these indexes and comparing them to SPY and VIX. The *depmixS4* R package is applied to achieve this goal. Figure 3.3 presents the regime posterior probabilities using SPY, VIX, USIndex7 and USIndexEW7. Clearly that SPY and VIX indicate the business cycles changed around mid-2008, while USIndex7 and USIndexEW7 present regimes at a finer grid. Both USIndex7 and USIndexEW7 show that regime switching happened more frequently between 2006 and 2007. Yet USIndex7 fluctuates more in 2008-2009 period, while USIndexEW7 not so much. However, all of these observations provide some clues for our economy. To conclude, float-adjusted weighted and equal weighted indexes are both useful in terms of detecting regimes, and jump sizes affect the type of risks showing in the indexes.

Market Sector Indexes

To expand our experiments, we attempt to construct jump-spillover-based indexes for each market sectors. Similar to the whole market indexes, we categorize indexes based on the type of jumps considered: total jump variation, large jump variation, and small jump variation. For each jump type, four shrinkage and regularization cases are applied to find the spillover coefficients: ridge, LASSO, elastic net, and mixed.

XLB indexes target jump spillover risks in the XLB (materials) sector (Figure 3.4). We still focus on indexes using mixed data shrinkage and regularization method. XLBIndex7, which is based on the total jump variation, shows spikes in late 2006, late 2007 and early 2008, while XLBIndex8 focusing large jumps indicates spikes happening in early 2009, and XLBIndex9 shows small jumps based spikes appearing in 2005 and 2010. Different timestamps with spikes lead to the conclusion that jump sizes associate with different types of risks presented here. The industry is affected both by the overall economic environment (the recession), specific industry news (2009 chemical industry faced sharp declines), and unknown causes.[3]

XLE indexes target jump spillover risks in the XLE (energy) sector (Figure 3.5). We focus on indexes using mixed data shrinkage and regularization method. XLEIndex7, which is based on the total jump variation, shows spikes in late 2005, early 2007, while XLEIndex8 focusing large jumps indicates spikes happening in 2007 and mid-2010, and XLEIndex9 sees small jumps based spikes appearing in 2005, 2006, 2009 and 2010. Different timestamps with spikes lead to the conclusion that jump sizes associate with different types of risks presented here. The industry is affected both by the many events (strong growth in 2005, Hurricane Katrina in Aug. 2005, decline in 2007 for the U.S. market), specific industry news (a volatile global energy market in 2007), and unknown causes. [4]

XLF indexes target jump spillover risks in the XLF (financials) sector (Figure 3.6). We focus on indexes using mixed data shrinkage and regularization method. XLFIndex7, which is based on the total jump variation, shows spikes in mid-2006, mid-2007, late 2009 and mid-2010, while

[3]For more details see: https://pubs.acs.org/cen/coverstory/88/8827cover.html for details

[4]For more details see:
https://www.ferc.gov/market-oversight/reports-analyses/reports-analyses.asp
http://www.nytimes.com/2005/08/30/us/hurricane-katrina-slams-into-gulf-coast-dozens-are-dead.html

XLFIndex8 focusing on large jumps indicates spike happening in late 2005, mid-2007, and mid-2008, and XLFIndex9 sees small jumps based spikes appearing in early 2007 and late 2009, as well as in 2010. Different timestamps with spikes lead to the conclusion that jump sizes associate with different types of risks presented here. The industry is affected both by the overall economic environment (total jumps - housing bubble in 2006-2007, a recovering U.S. economy in late 2009 with Dow ended above 10,000 the first time in a year, and impact of European debt crisis and weaker-than-expect June job report with Dow closed at a 7 month low in July 2010), specific industry news (an unexpected sudden fall in the economy in 2005 and the beginning of the financial crisis and Great Recession in 2007 and 2008) and unknown causes. [5]

XLI indexes target jump spillover risks in the XLI (industrials) sector (Figure 3.7). We focus on indexes using mixed data shrinkage and regularization method. XLIIndex7, which is based on the total jump variation, shows spikes concentrate on times prior to the Great Recession, while XLIIndex8 focusing large jumps indicates spikes happening in 2005-early 2007, 2009, and 2010, and XLIIndex9 sees small jumps based spikes appearing between 2008 and 2009. Different timestamps with spikes lead to the conclusion that jump sizes associate with different types of risks presented here. The industry is affected both by the overall economic environment, specific industry news, and unknown causes.

XLK indexes target jump spillover risks in the XLK(technology) sector (Figure 3.8). We focus on indexes using mixed data shrinkage and regularization method. XLKIndex7, which is based on the total jump variation, shows spikes concentrate during 2006-2007, while XLKIndex8 focusing large jumps indicates spikes happening in late 2005, and XLKIndex9 sees small jumps based spikes appearing between 2008 and 2009. Different timestamps with spikes lead to the conclusion that jump sizes associate with different types of risks presented here. The industry ETF is affected both by the economic environment (a sharp slowdown in late 2005 and in late 2006), and unknown causes. [6]

[5] For more details see:
http://www.nytimes.com/2009/10/15/business/15markets.html
http://money.cnn.com/2010/12/31/markets/2010_stock_market_review/index.htm
http://www.nytimes.com/2006/01/28/business/us-economy-slowed-sharply-at-end-of-2005.html

[6] For more details see:
http://www.nytimes.com/2006/01/28/business/us-economy-slowed-sharply-at-end-of-2005.html
https://www.americanprogress.org/issues/economy/news/2006/12/21/2420/the-u-s-economy-in-review-2006/

XLP indexes target jump spillover risks in the XLP (consumer staples) sector (Figure 3.9). We focus on indexes using mixed data shrinkage and regularization method. XLPIndex7, which is based on the total jump variation, shows spikes in late-2008, late 2009, and late 2010, while XLPIndex8 focusing large jumps indicates spikes happening in early 2005, late 2008, and late 2009, and XLPIndex9 sees small jumps based spikes appearing between 2007 and 2008. Different timestamps with spikes lead to the conclusion that jump sizes associate with different types of risks presented here. It is quite interesting to see that in the XLP case, indexes based on total jumps and large jumps are quite similar. This is due to the nature of the sector, which is an industry that people behave the same way regardless of their financial situations. The industry is affected mainly by the need from consumers, which is affected by the overall economy.

XLU indexes target jump spillover risks in the XLU (utilities) sector (Figure 3.10). We focus on indexes using mixed data shrinkage and regularization method. XLUIndex7, which is based on the total jump variation, shows spikes in 2005, 2006 and 2007, while XLUIndex8 focusing large jumps indicates spikes happening around the same time as XLUIndex7 shows, and XLUIndex9 sees small jumps based spikes appearing in early 2007. Different timestamps with spikes lead to the conclusion that jump size associate with different types of risks presented here. Moreover, we can see XLUIndex7 and XLUIndex8 is quite similar to XLFIndex8, this is because the housing market is closely related to the real estate companies as well as construction and utility companies.

XLV indexes target jump spillover risks in the XLV (health care) sector (Figure 3.11). We focus on indexes using mixed data shrinkage and regularization method. XLVIndex7, which is based on the total jump variation, shows spikes concentrate on late 2005 and early 2007, while XLVIndex8 focusing large jumps indicates spikes happening in early 2009, and XLVIndex9 sees small jumps based spikes appearing across sampling years. Different timestamps with spikes lead to the conclusion that jump sizes associate with different types of risks presented here. The industry is affected by the economic environment, specific industry news (Hurricane Katrina in Aug. 2005, the Deficit Reduction Act of 2005 in October, the development of Obamacare in 2009-2010), and price movement due to causes that are hard to quantify (such as the E. coli breakout in Sep. 2006).[7]

[7] For more details see:
http://www.nytimes.com/2005/08/30/us/hurricane-katrina-slams-into-gulf-coast-dozens-are-dead.html
https://www.congress.gov/bill/109th-congress/senate-bill/1932

XIY indexes target jump spillover risks in the XLY (consumer discretionary) sector (Figure 3.12). We focus on indexes using mixed data shrinkage and regularization method. XLYIndex7, which is based on the total jump variation, shows spikes in 2008, while XLYIndex8 focusing large jumps indicates spikes happening in early 2005 and late 2010, and XLYIndex9 sees small jumps based spikes appearing in 2007-2008 and 2009-2010. The different time with spikes lead to the conclusion that jump sizes associate with different types of risks presented here. Since this industry is mainly affected by the consumer financial situation, it is not surprising to see that the spikes in total jump and small parts based indexes corresponds to the overall economic environment, while large jump variation based index to the industry specific events, such as strong consumer confidence in early 2005 and an unexpected gain in consumer borrowing in 2010.

3.5 Concluding Remarks

This chapter experiments a novel way to construct a new type of index that aims at risks associated with volatility jump spillovers. Volatility jumps are generally believed to be related to major news announcement/events, as well as high frequency trading strategies. Thus, in some sense, our indexes offer a way to reveal information that are quite complicated, because news announcement/event worldwide and trading strategies are not easy to keep track with. We find some evidence that our indexes provide useful information to signal the market, as well as market sectors.

https://www.cnn.com/2013/06/28/health/e-coli-outbreaks-fast-facts/index.html

Appendix 3.I

The historical S&P500 sector weightings between 2005 and 2010 are obtained from the webpage: http://www.sectorspdr.com/sectorspdr/Pdf/All%20Funds%20Documents/Document%20Resources/10%20Year%20Sector%20Returns

Sector Historical Weights in S&P500

Sector	Sector ETF	2005	2010
Consumer Discretionary	XLY	10.7	10.6
Consumer Staples	XLP	9.6	10.6
Energy	XLE	9.3	12.0
Financials	XLF	21.3	16.1
Health Care	XLV	13.3	10.9
Industrials	XLI	11.4	10.9
Information Technology	XLK	15.3	18.8
Materials	XLB	3.0	3.7
Telecom		5.5	3.1
Utilities	XLU	3.8	3.3

The above data is obtained from the sector returns document from sectorspdr.com and its source is quoted as Standard and Poor's. While it is not clear how the XLK (technology) sector is related to the Information Technology and Telecom, we decide to only use the Information Technology to represent the weight of the XLK.

Since our data run between 2005 and 2010, we take the average of the 2005 and 2010 weights to apply it over the 5-year period. The weights for each sector is listed as below:

Sector Weights Used In Our Research

Sector ETF	2005 - 2010
Consumer Discretionary XLY	10.65
Consumer Staples XLP	10.1
Energy XLE	9.65
Financials XLF	18.7
Health Care XLV	12.1
Industrials XLI	11.15
Information Technology XLK	34.1
Materials XLB	3.35
Utilities XLU	3.55

Appendix 3.II

List of Indices

Index Name	Index Description	Index Name	Index Description	Index Name	Index Description	Index Name	Index Description
USIndex1	weighted_elastic net QVJ	XLBIndex10	xlb_ridge QVJ	XLIIndex7	xli_mixed QVJ	XLUIndex4	xlu_lasso QVJ
USIndex2	weighted_elastic net $QVJL$	XLBIndex11	xlb_ridge $QVJL$	XLIIndex8	xli_mixed $QVJL$	XLUIndex5	xlu_lasso $QVJL$
USIndex3	weighted_elastic net $QVJS$	XLBIndex12	xlb_ridge $QVJS$	XLIIndex9	xli_mixed $QVJS$	XLUIndex6	xlu_lasso $QVJS$
USIndex4	weighted_lasso QVJ	XLEIndex1	xle_elastic net QVJ	XLIIndex10	xli_ridge QVJ	XLUIndex7	xlu_mixed QVJ
USIndex5	weighted_lasso $QVJL$	XLEIndex2	xle_elastic net $QVJL$	XLIIndex11	xli_ridge $QVJL$	XLUIndex8	xlu_mixed $QVJL$
USIndex6	weighted_lasso $QVJS$	XLEIndex3	xle_elastic net $QVJS$	XLIIndex12	xli_ridge $QVJS$	XLUIndex9	xlu_mixed $QVJS$
USIndex7	weighted_mixed QVJ	XLEIndex4	xle_lasso QVJ	XLKIndex1	xlk_elastic net QVJ	XLUIndex10	xlu_ridge QVJ
USIndex8	weighted_mixed $QVJL$	XLEIndex5	xle_lasso $QVJL$	XLKIndex2	xlk_elastic net $QVJL$	XLUIndex11	xlu_ridge $QVJL$
USIndex9	weighted_mixed $QVJS$	XLEIndex6	xle_lasso $QVJS$	XLKIndex3	xlk_elastic net $QVJS$	XLUIndex12	xlu_ridge $QVJS$
USIndex10	weighted_ridge QVJ	XLEIndex7	xle_mixed QVJ	XLKIndex4	xlk_lasso QVJ	XLVIndex1	xlv_elastic net QVJ
USIndex11	weighted_ridge $QVJL$	XLEIndex8	xle_mixed $QVJL$	XLKIndex5	xlk_lasso $QVJL$	XLVIndex2	xlv_elastic net $QVJL$
USIndex12	weighted_ridge $QVJS$	XLEIndex9	xle_mixed $QVJS$	XLKIndex6	xlk_lasso $QVJS$	XLVIndex3	xlv_elastic net $QVJS$
USIndexEW1	equal weight_elastic net QVJ	XLEIndex10	xle_ridge QVJ	XLKIndex7	xlk_mixed QVJ	XLVIndex4	xlv_lasso QVJ
USIndexEW2	equal weight_elastic net $QVJL$	XLEIndex11	xle_ridge $QVJL$	XLKIndex8	xlk_mixed $QVJL$	XLVIndex5	xlv_lasso $QVJL$
USIndexEW3	equal weight_elastic net $QVJS$	XLEIndex12	xle_ridge $QVJS$	XLKIndex9	xlk_mixed $QVJS$	XLVIndex6	xlv_lasso $QVJS$
USIndexEW4	equal weight_lasso QVJ	XLFIndex1	xlf_elastic net QVJ	XLKIndex10	xlk_ridge QVJ	XLVIndex7	xlv_mixed QVJ
USIndexEW5	equal weight_lasso $QVJL$	XLFIndex2	xlf_elastic net $QVJL$	XLKIndex11	xlk_ridge $QVJL$	XLVIndex8	xlv_mixed $QVJL$
USIndexEW6	equal weight_lasso $QVJS$	XLFIndex3	xlf_elastic net $QVJS$	XLKIndex12	xlk_ridge $QVJS$	XLVIndex9	xlv_mixed $QVJS$
USIndexEW7	equal weight_mixed QVJ	XLFIndex4	xlf_lasso QVJ	XLPIndex1	xlp_elastic net QVJ	XLVIndex10	xlv_ridge QVJ
USIndexEW8	equal weight_mixed $QVJL$	XLFIndex5	xlf_lasso $QVJL$	XLPIndex2	xlp_elastic net $QVJL$	XLVIndex11	xlv_ridge $QVJL$
USIndexEW9	equal weight_mixed $QVJS$	XLFIndex6	xlf_lasso $QVJS$	XLPIndex3	xlp_elastic net $QVJS$	XLVIndex12	xlv_ridge $QVJS$
USIndexEW10	equal weight_ridge QVJ	XLFIndex7	xlf_mixed QVJ	XLPIndex4	xlp_lasso QVJ	XLYIndex1	xly_elastic net QVJ
USIndexEW11	equal weight_ridge $QVJL$	XLFIndex8	xlf_mixed $QVJL$	XLPIndex5	xlp_lasso $QVJL$	XLYIndex2	xly_elastic net $QVJL$
USIndexEW12	equal weight_ridge $QVJS$	XLFIndex9	xlf_mixed $QVJS$	XLPIndex6	xlp_lasso $QVJS$	XLYIndex3	xly_elastic net $QVJS$
XLBIndex1	xlb_elastic net QVJ	XLFIndex10	xlf_ridge QVJ	XLPIndex7	xlp_mixed QVJ	XLYIndex4	xly_lasso QVJ
XLBIndex2	xlb_elastic net $QVJL$	XLFIndex11	xlf_ridge $QVJL$	XLPIndex8	xlp_mixed $QVJL$	XLYIndex5	xly_lasso $QVJL$
XLBIndex3	xlb_elastic net $QVJS$	XLFIndex12	xlf_ridge $QVJS$	XLPIndex9	xlp_mixed $QVJS$	XLYIndex6	xly_lasso $QVJS$
XLBIndex4	xlb_lasso QVJ	XLIIndex1	xli_elastic net QVJ	XLPIndex10	xlp_ridge QVJ	XLYIndex7	xly_mixed QVJ
XLBIndex5	xlb_lasso $QVJL$	XLIIndex2	xli_elastic net $QVJL$	XLPIndex11	xlp_ridge $QVJL$	XLYIndex8	xly_mixed $QVJL$
XLBIndex6	xlb_lasso $QVJS$	XLIIndex3	xli_elastic net $QVJS$	XLPIndex12	xlp_ridge $QVJS$	XLYIndex9	xly_mixed $QVJS$
XLBIndex7	xlb_mixed QVJ	XLIIndex4	xli_lasso QVJ	XLUIndex1	xlu_elastic net QVJ	XLYIndex10	xly_ridge QVJ
XLBIndex8	xlb_mixed $QVJL$	XLIIndex5	xli_lasso $QVJL$	XLUIndex2	xlu_elastic net $QVJL$	XLYIndex11	xly_ridge $QVJL$
XLBIndex9	xlb_mixed $QVJS$	XLIIndex6	xli_lasso $QVJS$	XLUIndex3	xlu_elastic net $QVJS$	XLYIndex12	xly_ridge $QVJS$

Appendix 3.III

Experimental Setup

Sample Period:	Jan. 3, 20005 to Dec. 31, 2010
Sampling Frequency:	5 minutes.
Regression Estimation Scheme:	Linear Regression.
Jump types:	Total jumps (QVJ), large jumps ($QVJL$), and small jumps ($QVJS$).
Evaluation Criterion:	Three data shrinkage and regularization methods: Ridge, LASSO, and Elastic net.
Step 1a: Jump Test Step 1b: Jump Decomposition	Test for jumps on each trading day during sample period. For this, the bipower variation based test $z_{TP,t}$ described in Section 2.1.2 is applied with significance level $\alpha = 5\%$. The null hypothesis is that no jumps are present. For trading days which reject the null in Step 1a, the decomposition method in Section 2.1.3 is applied to extract QVJ, $QVJL$, and $QVJS$ on that day. For trading days for which the null is not rejected in Step 1a, jump quadratic variation is set equal to 0.
Step 2: Volatility jump spillover based risk quantification	Fit the model in Section 2.2 for each jump variation type and each market sector.
Step 3: Jump Construction	Follow the instructions in Section 3.1 to construct a group of indices for the U.S. market and each market sector.

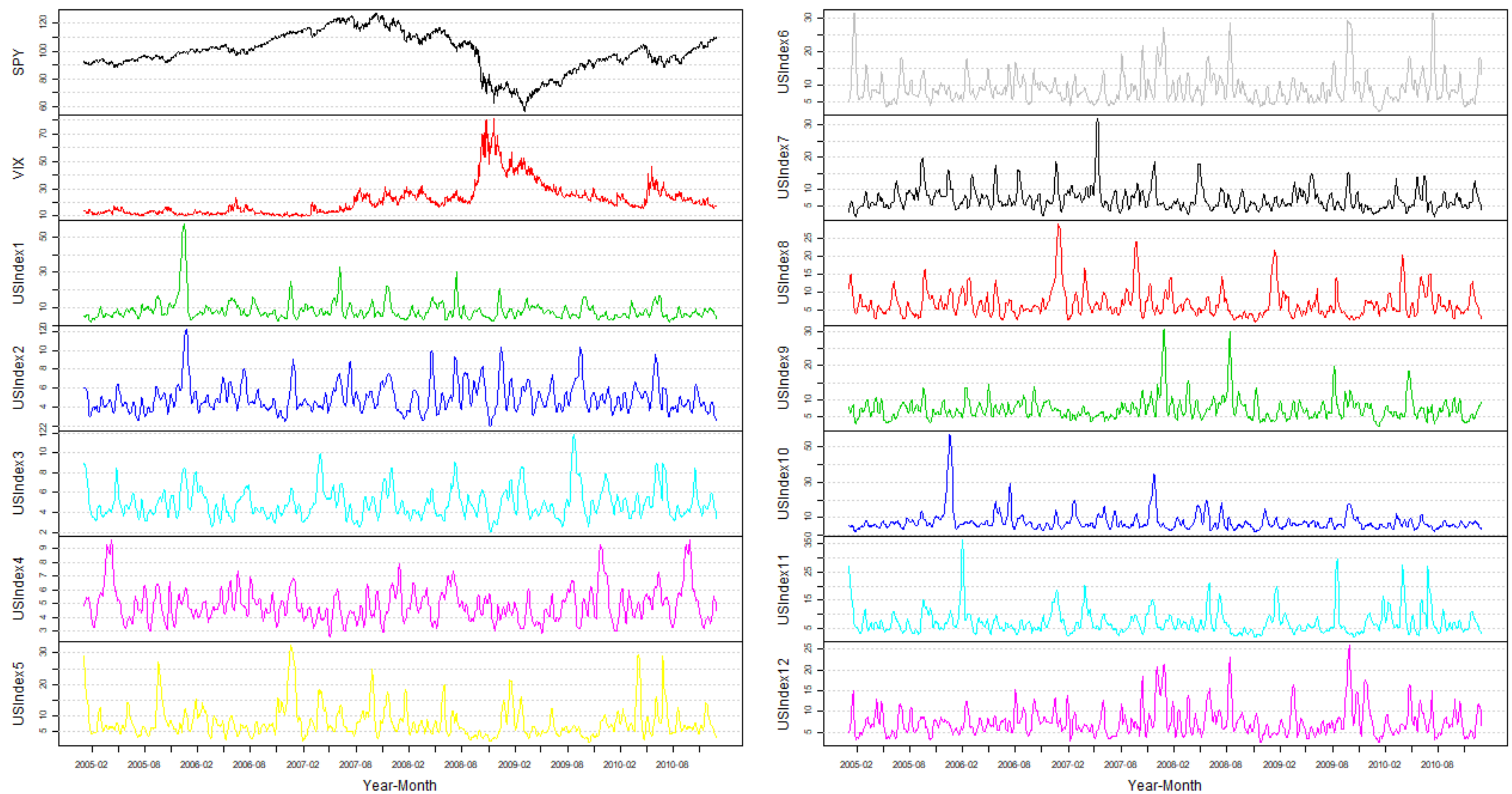

Figure 3.1: Float-Adjusted Weighted Indexes for the Whole U.S. Market with SPY and VIX*

* Notes: Indexes are constructed using the float-adjusted weighted method based on various jump variation spillovers and data shrinkage and regularization methods. See Section 3.3.1 for details.

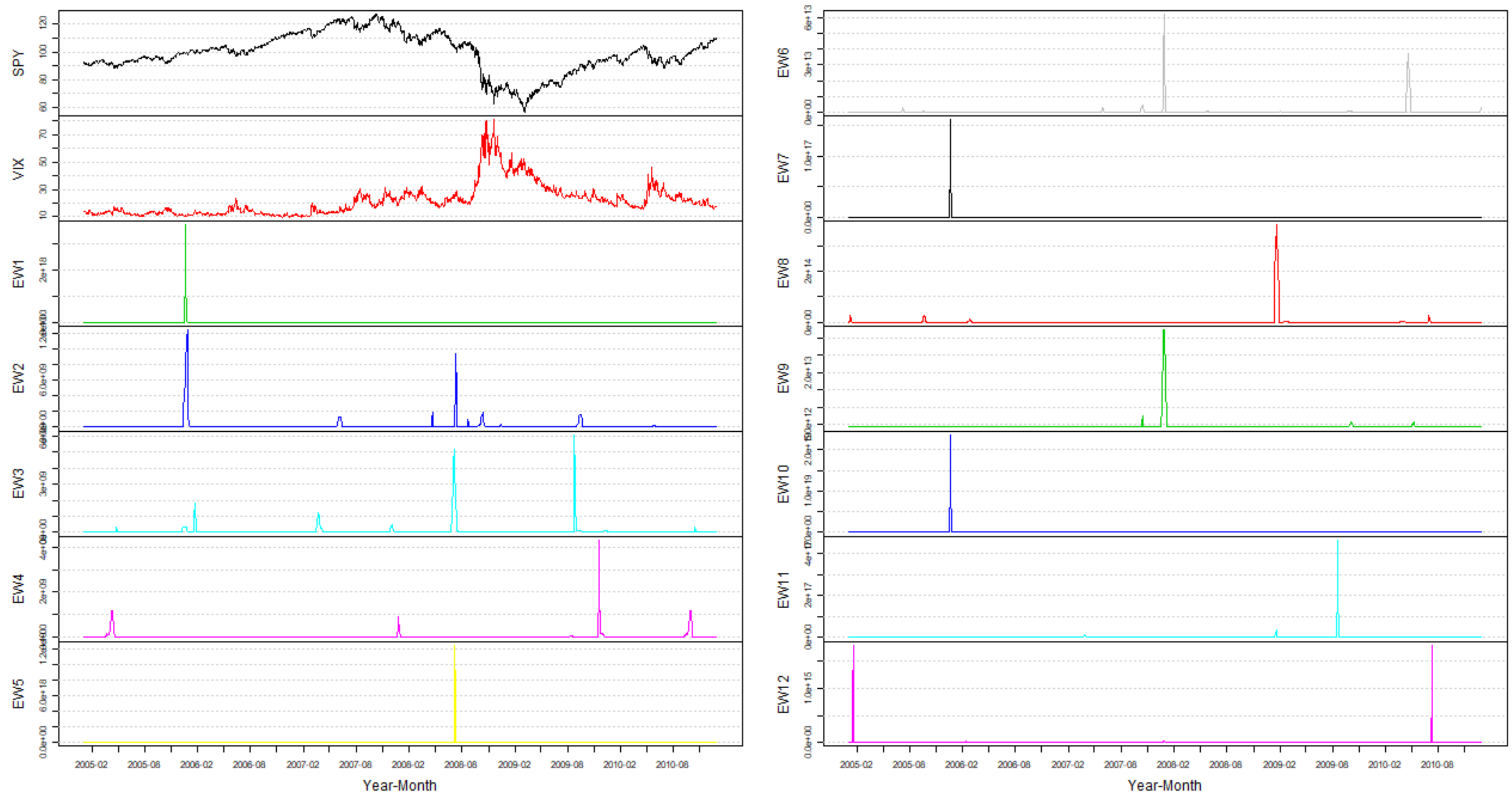

Figure 3.2: Equal Weighted Indexes for the Whole U.S. Market with SPY and VIX*

* Notes: Indexes are constructed using equal weighted method based on various jump variation spillovers and data shrinkage and regularization methods. See Section 3.3.1 for details.

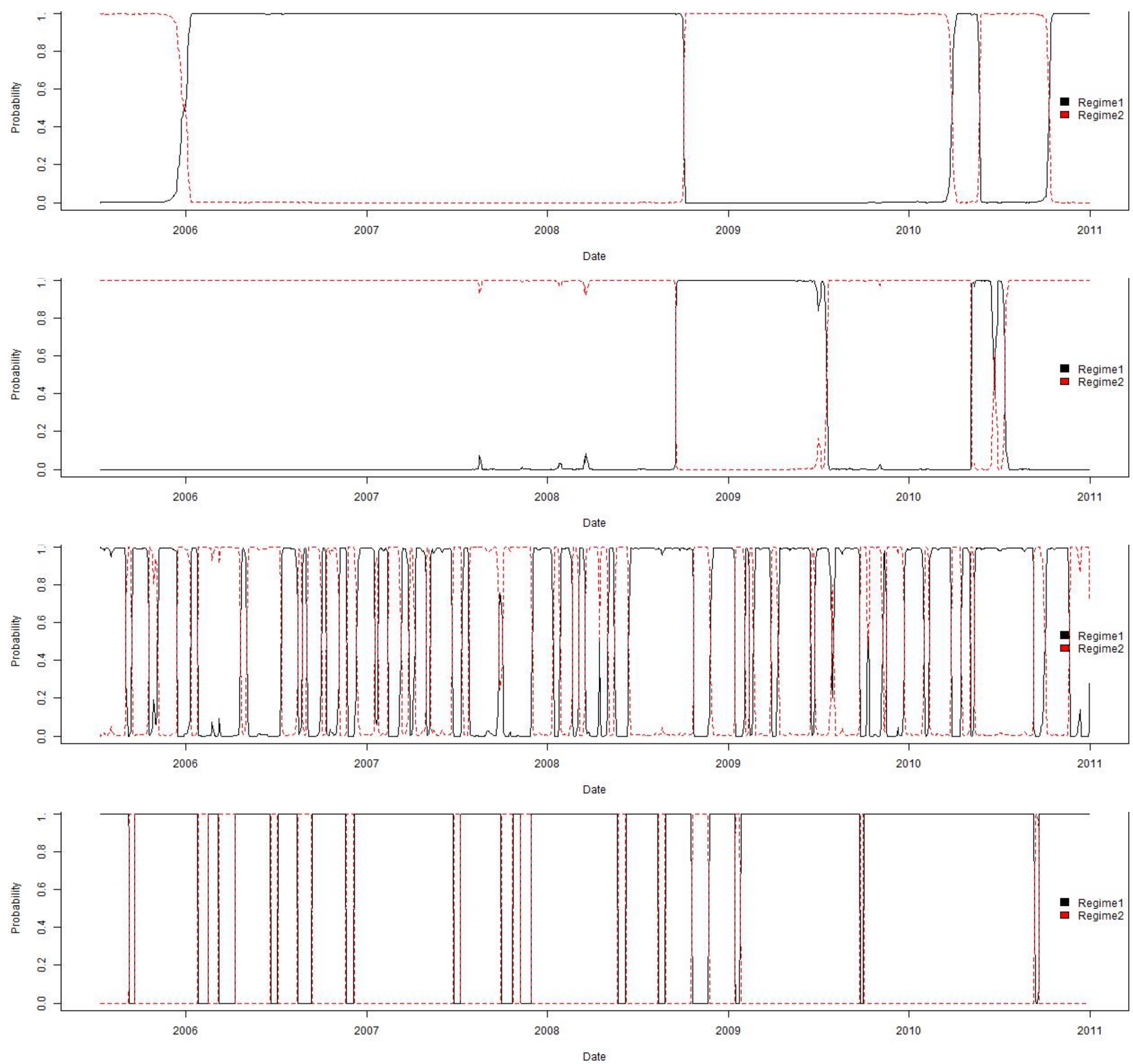

Figure 3.3: Regime Detection Based on SPY, VIX, USIndex7 and USIndexEW7*

* Notes: Figures from top to bottom are regime detection using hidden markov switching model based on SPY, VIX, USIndex7, and USIndexEW 7. See Section 3.3.2 for details.

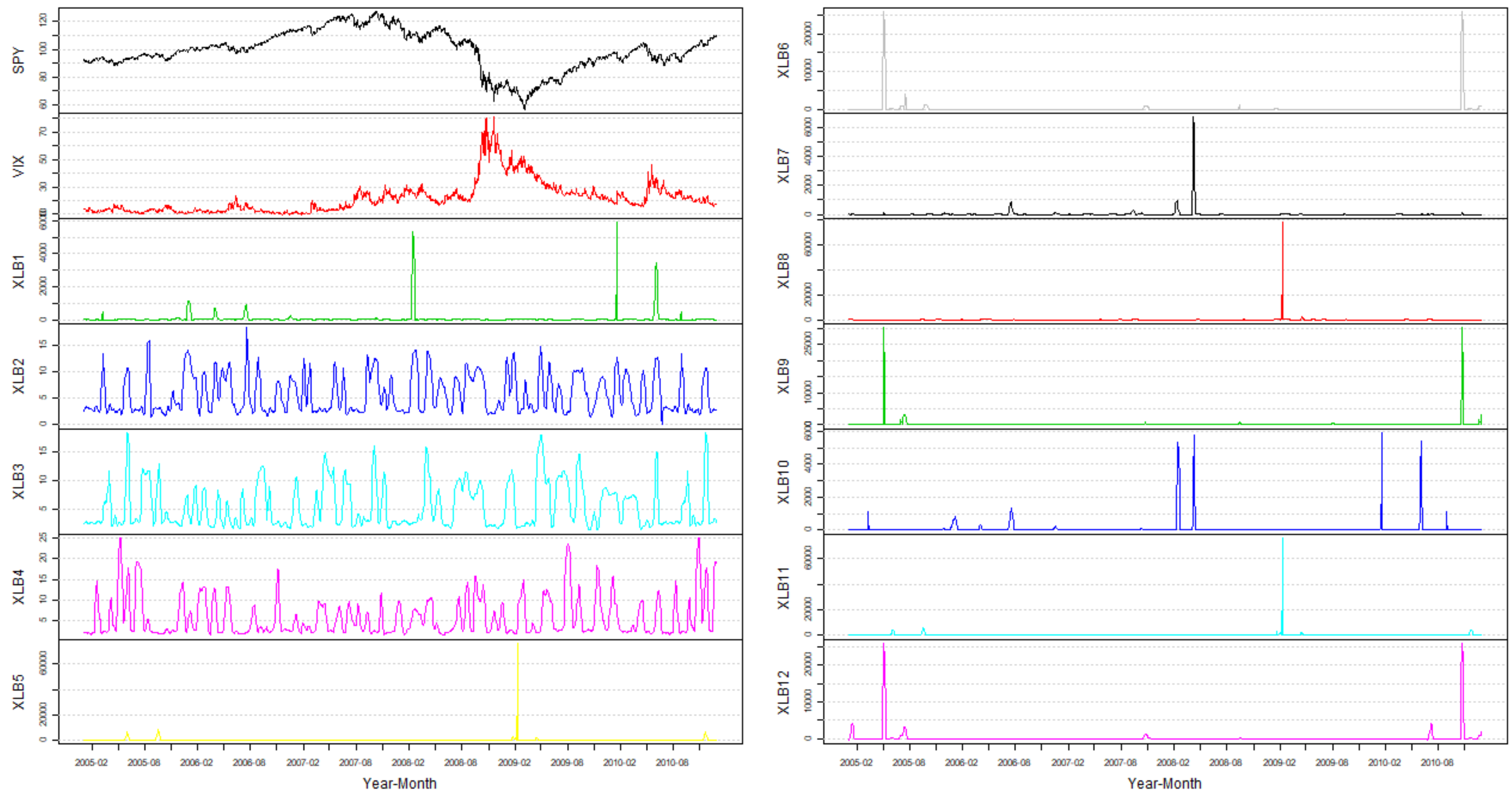

Figure 3.4: Indexes for XLB Sector with SPY and VIX*

* Notes: Index is constructed for risk in the XLB sector. See Section 3.3.1 for details.

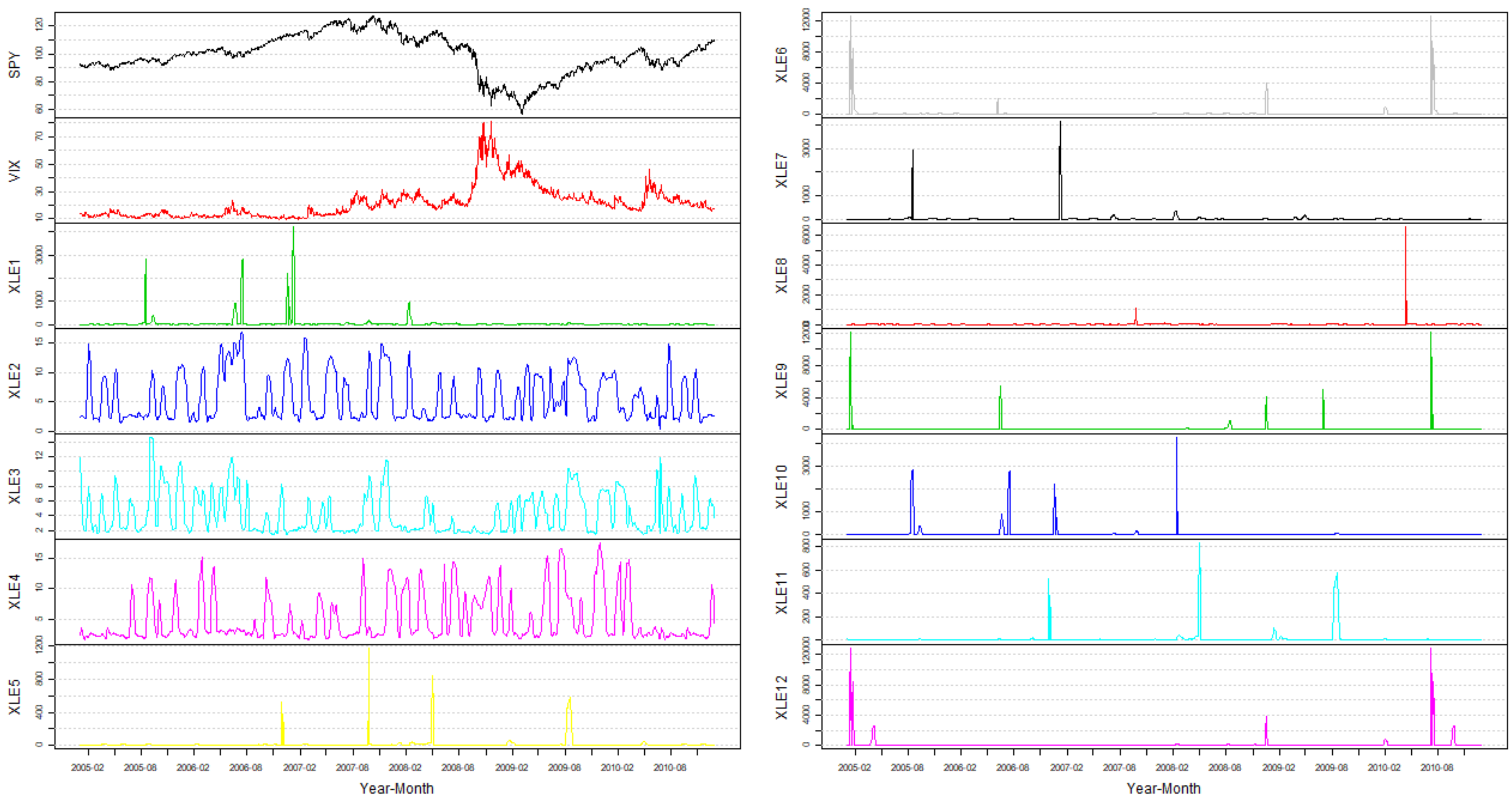

Figure 3.5: Indexes for XLE Sector with SPY and VIX*

* Notes: Index is constructed for risk in the XLE sector. See Section 3.3.1 for details.

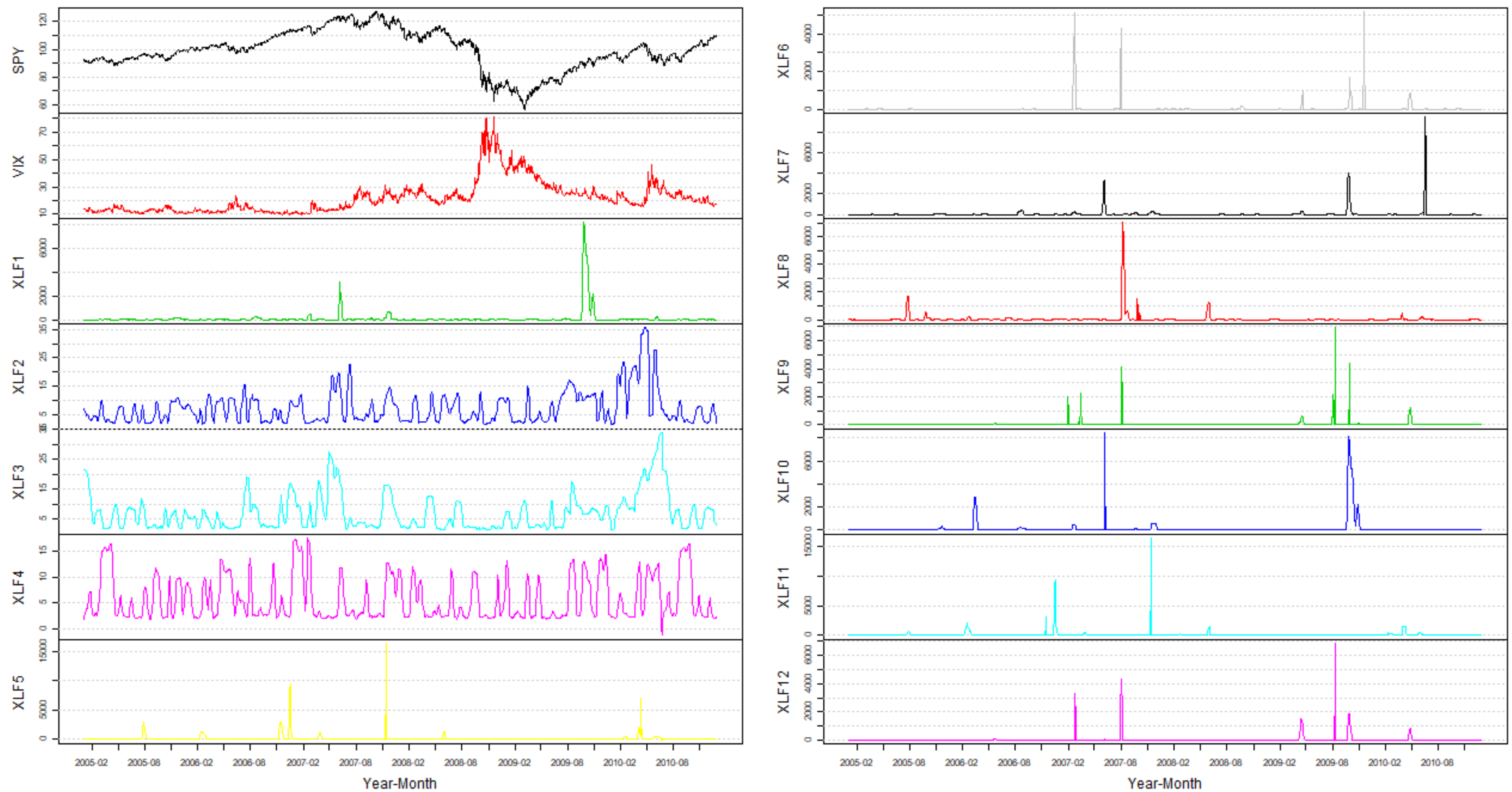

Figure 3.6: Indexes for XLF Sector with SPY and VIX*

* Notes: Index is constructed for risk in the XLF sector. See Section 3.3.1 for details.

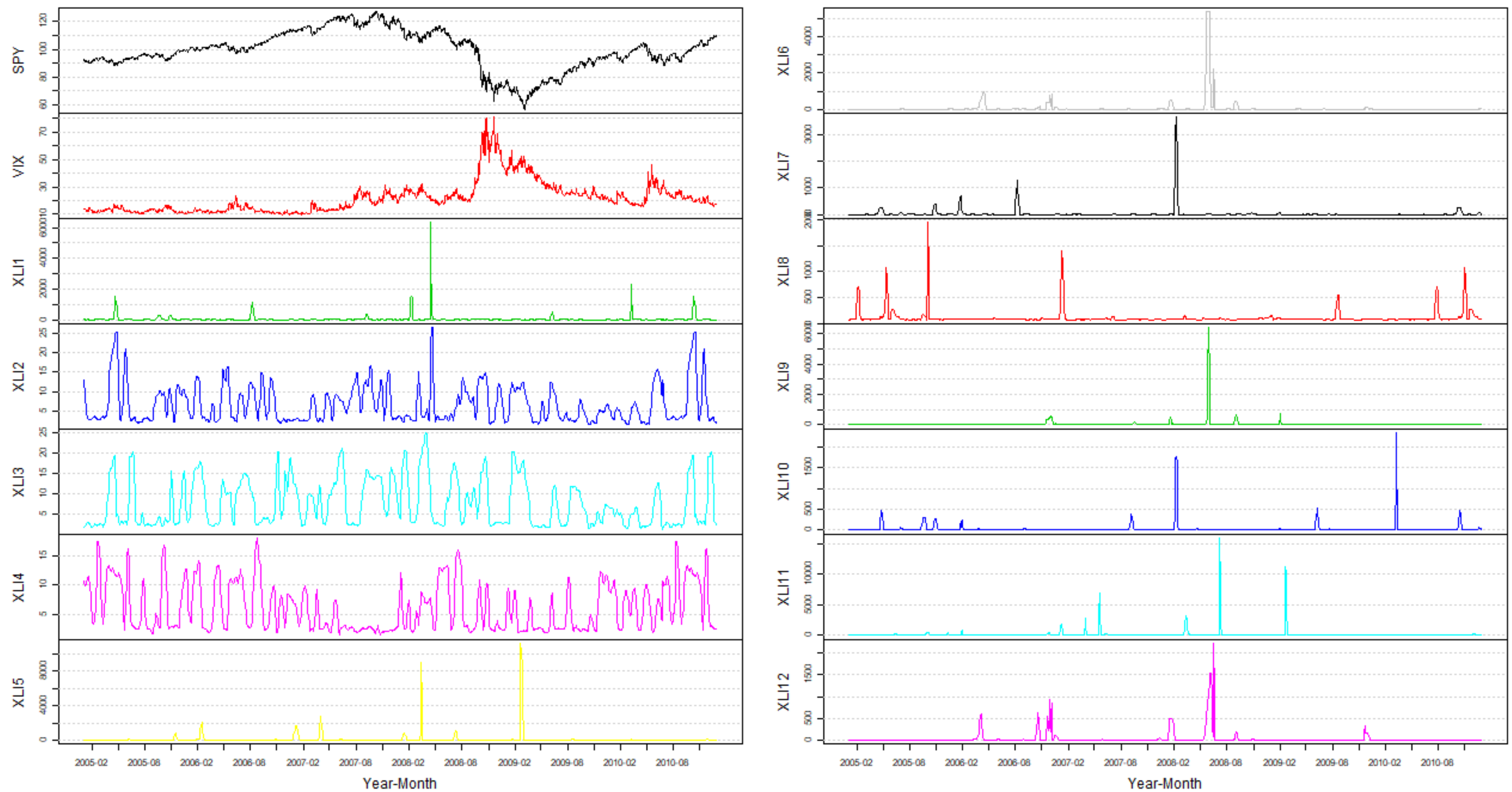

Figure 3.7: Indexes for XLI Sector with SPY and VIX*

* Notes: Index is constructed for risk in the XLI sector. See Section 3.3.1 for details.

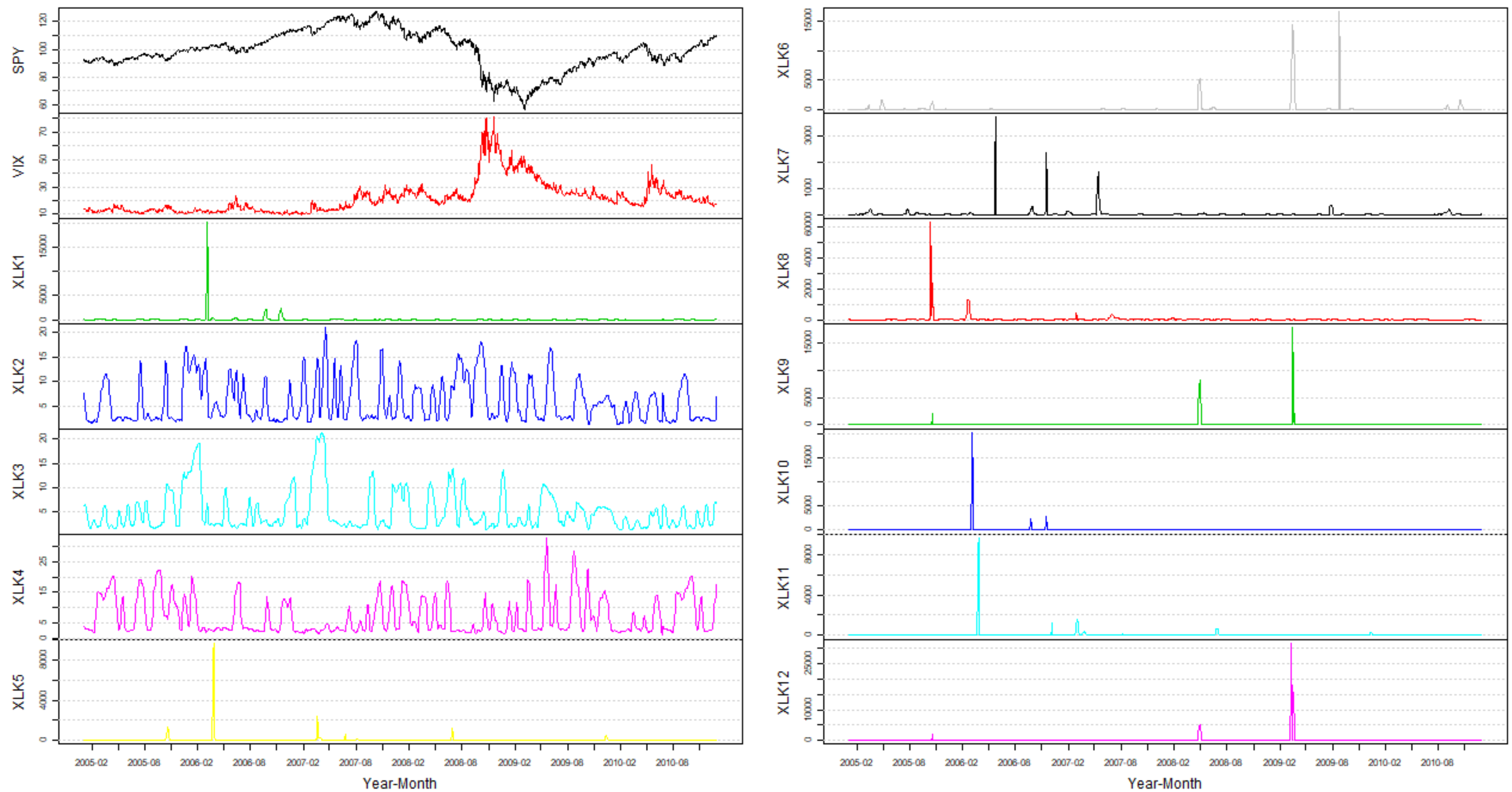

Figure 3.8: Indexes for XLK Sector with SPY and VIX*

* Notes: Index is constructed for risk in the XLK sector. See Section 3.3.1 for details.

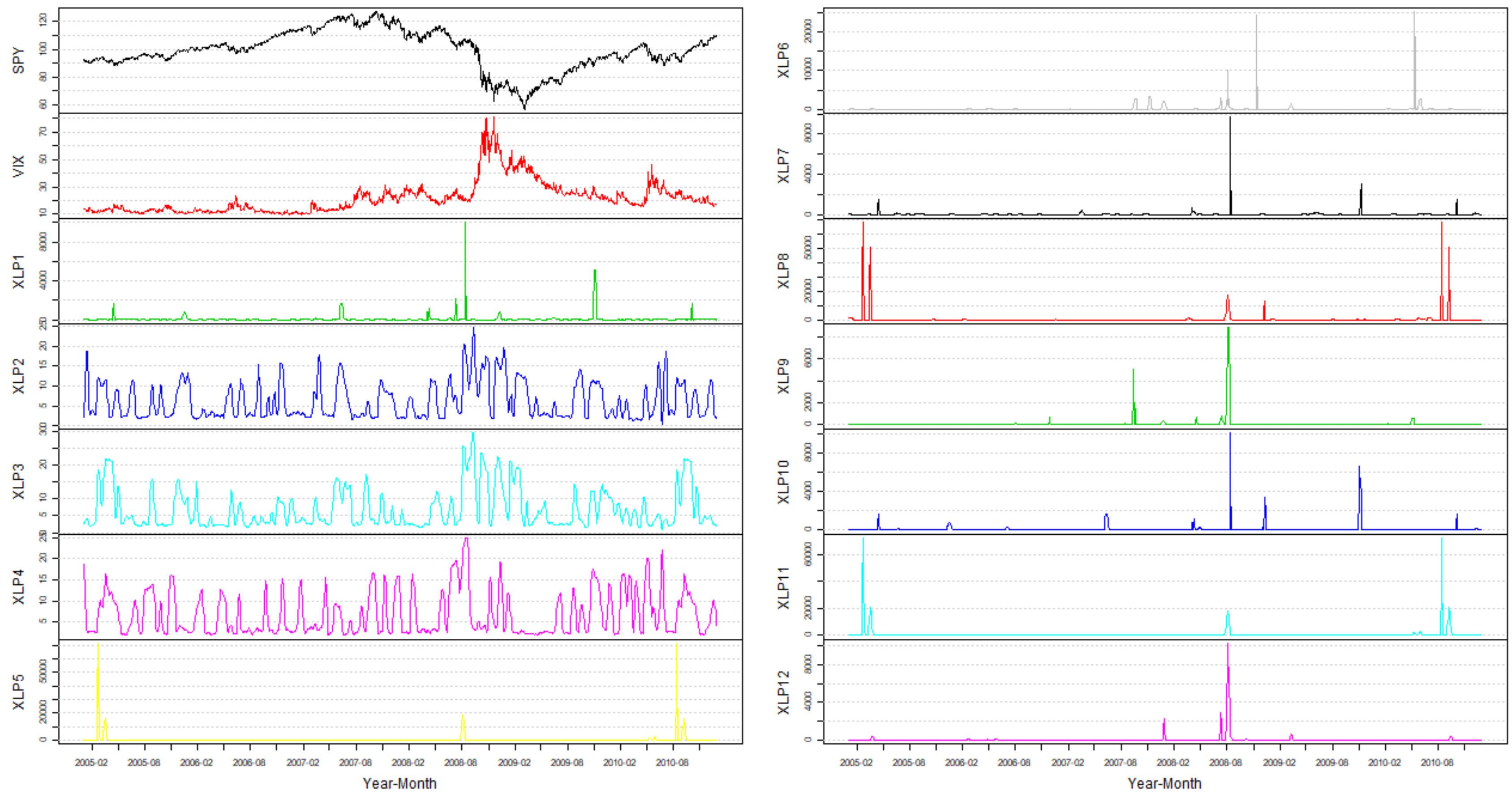

Figure 3.9: Indexes for XLP Sector with SPY and VIX*

* Notes: Index is constructed for risk in the XLP sector. See Section 3.3.1 for details.

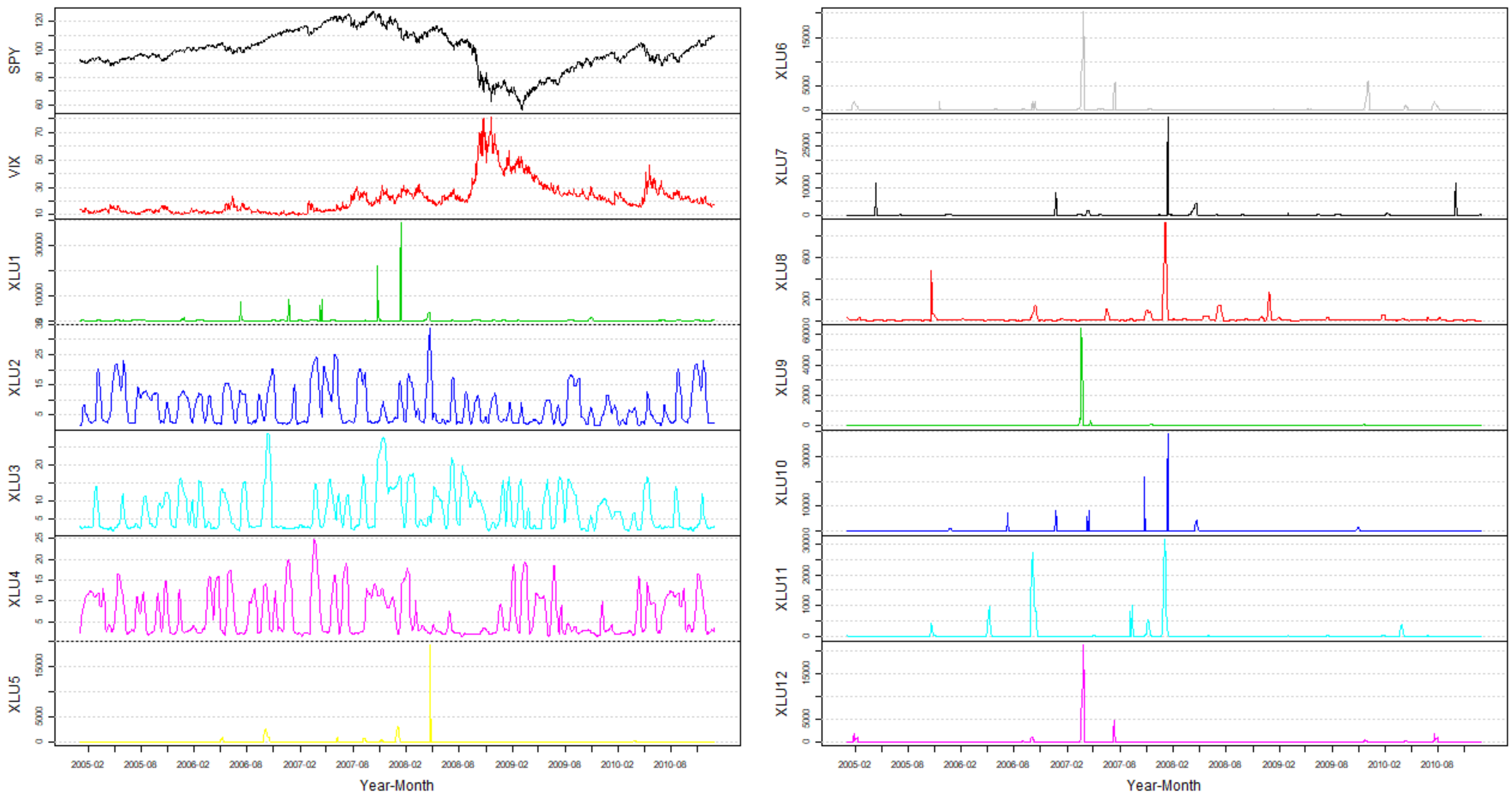

Figure 3.10: Indexes for XLU Sector with SPY and VIX*

* Notes: Index is constructed for risk in the XLU sector. See Section 3.3.1 for details.

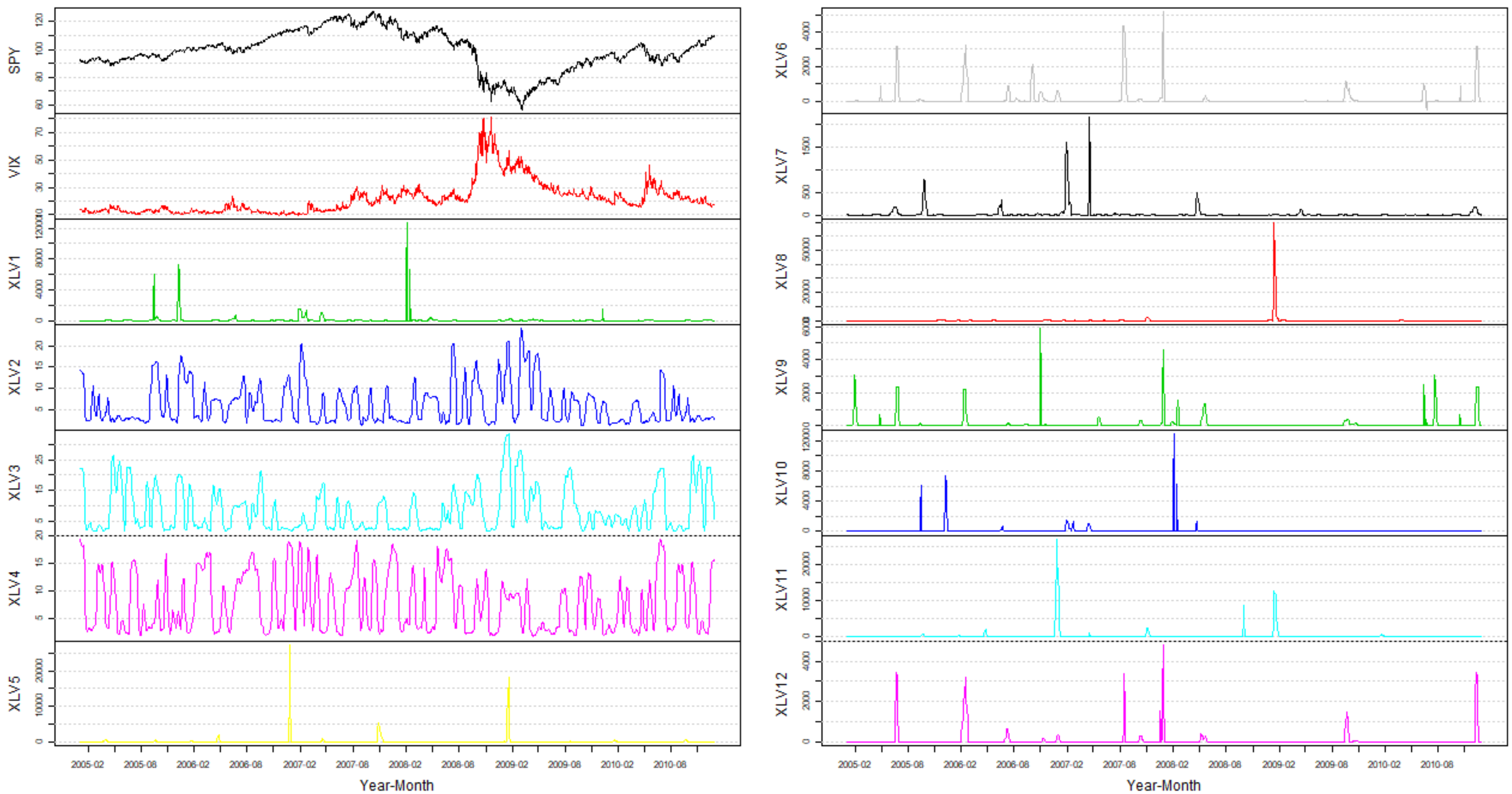

Figure 3.11: Indexes for XLV Sector with SPY and VIX*

* Notes: Index is constructed for risk in the XLV sector. See Section 3.3.1 for details.

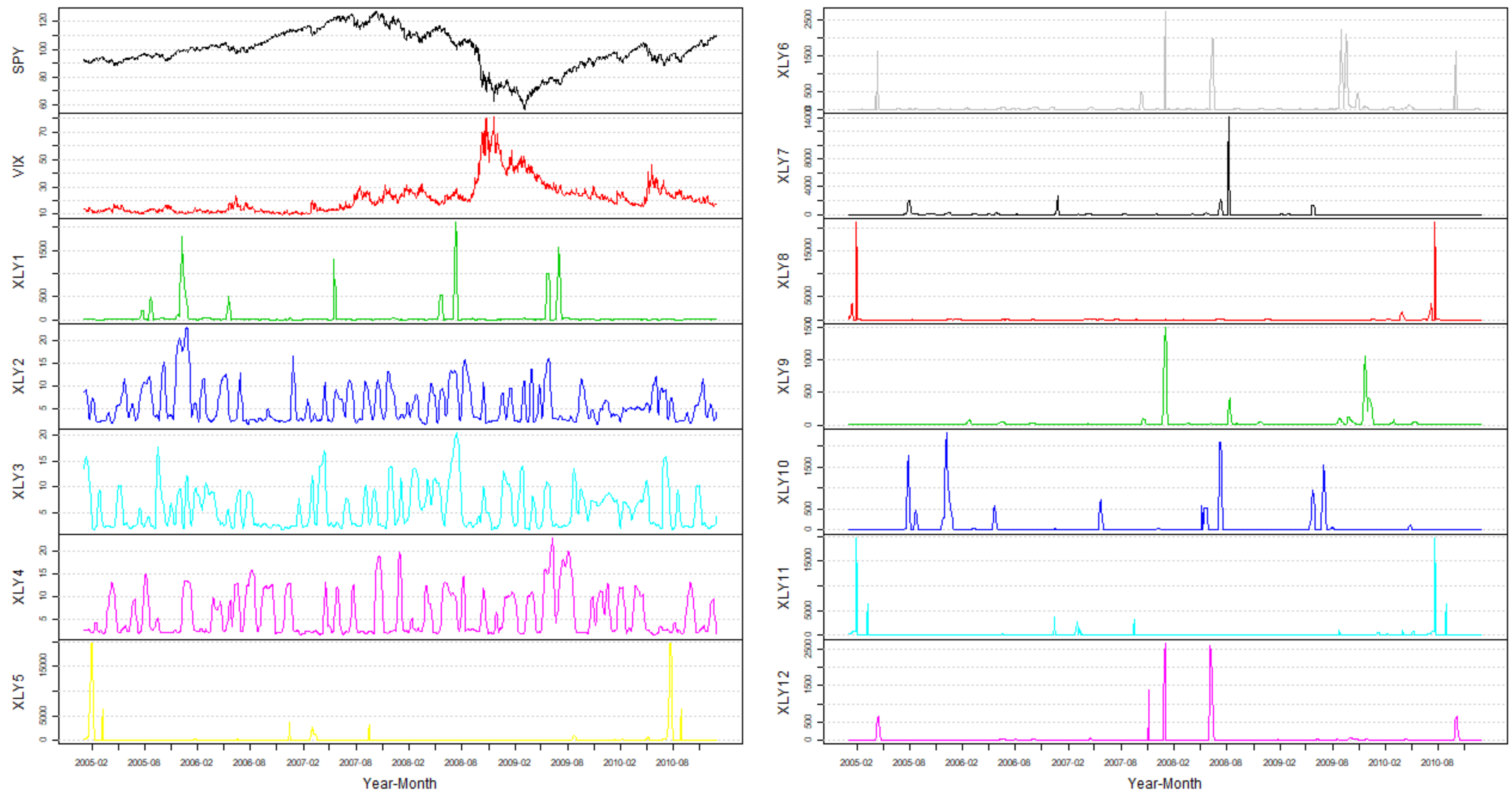

Figure 3.12: Indexes for XLY Sector with SPY and VIX*

* Notes: Index is constructed for risk in the XLY sector. See Section 3.3.1 for details.

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