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

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Abstract

In this paper, we review econometric methodology that is used to test for jumps and to decompose realized volatility into continuous and jump components. In order to illustrate how to implement the methods discussed, we also present the results of an empirical analysis in which we separate continuous asset return variation and finite activity jump variation from excess returns on various 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 use 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. We also observe that jumps had a significant effect on excess returns during 2008 and 2009; but not in the years before and after the recession.

Keywords: High-frequency jumps, jump spillover, jump risks, excess returns, ETFs, Great Recession, high-frequency data.

JEL classification: G12, C58, C22, G10.

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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 paper 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 paper 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 (2015) 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 paper, 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 paper is organized as follows. Section 2 reviews nonparametric jump tests and decomposition methods. Section 3 outlines the empirical methodology used in our data analysis. Section 4 contains our empirical findings. Finally, concluding remarks are gathered in Section 5.

2 Jump Tests and Jump Decomposition Methods

2.1 Set-up

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

$$Y_t = Y_0 + \int_0^t a_u d_u + \int_0^t \sigma_u dW_u + \int_0^t \int_{\{|y|\le\epsilon\}} y(j-\nu)(du,dy) + \int_0^t \int_{\{|y|>\epsilon\}} yj(du,dy), \quad (1)$$

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, $\int_0^t \int_{\{|y|\le\epsilon\}} y(j-\nu)(du,dy)$ 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:

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

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:

$$[Y]_t = p \lim_{\delta\to 0} \sum_{i=0}^{t/\delta-1} (Y_{t_i} - Y_{t_i})^2, \quad (3)$$

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

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

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

$$QV = [Y_\delta]_t = \sum_{i=1}^{t/\delta} r_{i,t}^2 \quad (4)$$

Another important measure is called integrated volatility, which is defined as $\int_0^t \sigma_u^2 du$. When

[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.

asset prices are continuous on a fixed interval $[0, T]$:

$$[Y]_t \xrightarrow{\mathbb{P}} \int_0^t \sigma_u^2 du, \tag{5}$$

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

$$[Y]_t \xrightarrow{\mathbb{P}} \int_0^t \sigma_u^2 du + \sum_{u \leq t} (\Delta Y_u)^2, \tag{6}$$

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 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 paper, 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)

2.2.1 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:

$$BV_t = \{Y_\delta\}_t^{[1,1]} = \sum_{i=2}^{t/\delta} |r_{i-1,t}||r_{i,t}|. \tag{7}$$

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

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

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:

$$\mu_1^{-2} BV \xrightarrow{\mathbb{P}} \int_0^t \sigma_u^2 du \tag{8}$$

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]

$$QPV_t = \{Y_\delta\}_t^{[1,1,1,1]} = \delta^{-1}\sum_{i=4}^{t/\delta} |r_{i-3,t}||r_{i-2,t}||r_{i-1,t}||r_{i,t}| \xrightarrow{\mathbb{P}} \mu_1^4 \int_0^t \sigma_u^4 du. \quad (9)$$

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

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

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

$$\hat{J} = \frac{\delta^{-1/2}}{\sqrt{\eta max(t^{-1}, \frac{QPV_t}{BV_t^2})}}(\frac{\mu_1^{-2}BV_t}{QV_t} - 1) \xrightarrow{d} N(0,1). \quad (10)$$

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

[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.

jumps on a daily basis, where

$$z_{TP,t} = \frac{RV_t - BV_t}{\sqrt{(v_{bb} - v_{qq})\frac{1}{N}TP_t}} \xrightarrow{d} N(0,1), \tag{11}$$

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

$$TP_t = \delta^{-1}\mu_{4/3}^{-3}\sum_{j=3}^{1/\delta}|r_{i-2,t}|^{4/3}|r_{i-1,t}|^{4/3}|r_{i,t}|^{4/3} \xrightarrow{\mathbb{P}} \int_0^t \sigma_u^4 du \tag{12}$$

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:

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

2.2.2 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.

2.2.3 Truncated Power Variation Tests

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

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

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

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

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.

2.2.4 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

$$\begin{aligned}\widehat{\mu}_{3,T,\delta} &= \frac{1}{T} \sum_{k=1}^{n-1} \left(Y_{(k+1)\delta} - Y_{k\delta} - \frac{Y_{n\delta} - Y_{\delta}}{n} \right)^3 \\ &- \frac{1}{T^+} \sum_{k=1}^{n^+-1} \left(Y_{(k+1)\delta} - Y_{k\delta} - \frac{Y_{n^+\delta} - Y_{\delta}}{n^+} \right)^3 1\left\{ \left| Y_{(k+1)\delta} - Y_{k\delta} \right| \leq \tau(\delta) \right\}, \end{aligned} \tag{13}$$

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:

$$S_{T,\delta} = \frac{T^{1/2}}{\delta} \widehat{\mu}_{3,T,\delta} \xrightarrow{d} N(0, \omega_0). \tag{14}$$

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:

$$\begin{aligned}&\widehat{\sigma}^2_{\lambda,T,\delta}\\&= \frac{1}{T\delta^2}\sum_{k=0}^{n-1}\left(Y_{(k+1)\delta} - Y_{k\delta} - \frac{Y_{n\delta} - Y_{\delta}}{n}\right)^3 I\left\{\left|Y_{(k+1)\delta} - Y_{k\delta}\right| \leq \tau\left(\delta\right)\right\}.\end{aligned} \tag{15}$$

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

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

2.3 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.

$$\begin{aligned}\text{Percentage of total QV due to continuous component } (QVC) &= \tfrac{B(2,u,\delta)}{B(2,\infty,\delta)}\\ \text{Percentage of total QV due to jump component } (QVJ) &= 1 - \tfrac{B(2,u,\delta)}{B(2,\infty,\delta)}\end{aligned} \tag{16}$$

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:

$$\begin{aligned}\text{Percentage of QV due to large jump component } (QVJL) &= \tfrac{U(2,\epsilon,\delta)}{B(2,\infty,\delta)}\\ \text{Percentage of QV due to small jump component } (QVJS) &= \tfrac{B(2,\infty,\delta) - B(2,u,\delta) - U(2,\epsilon,\delta)}{B(2,\infty,\delta)}\end{aligned} \tag{17}$$

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).

3 Empirical Methodology

Two experiments are conducted in this paper. 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 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 1 summarizes the experimental setup used in this paper. 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 2.3 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.

3.1 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 3 and 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

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

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 $k = 22$ for most sectors). 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 of jump spillover effects from market sector j in year h is then $\sum_i\sum_{k=1}^{k=22}|\beta^*_{i,j,k,h}|$, and $j \neq i$.

Of note is that there are a total of 199 parameters in each equation of the VAR model discussed above. This does not pose a problem in our empirical analysis, since the number of daily observations used in each of the yearly regressions that we estimate is much greater than 199. However, informative interpretation of individual coefficient magnitudes in our analysis is not feasible, given multicollinearity across regressors, and given the sheer number of regressors. For this reason, our interpretation of these regressions is based on aggregation of coefficient magnitudes, as discussed above. Another approach to this problem is to utilize machine learning, dimension reduction, and shrinkage methods in order to reduce the dimension of the set of regressors used in the equations in the above VAR. Refer to Kim and Swanson (2014, 2018) for further discussion and references. This is left to future research.

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 $C = 10^{17}$.

4 Empirical Results

4.1 Data

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.

4.2 Empirical Findings

See Sections 3.1 and 3.2 for a discussion of our empirical setup. As discussed in that section, tabulated results in Tables 3 and 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 paper.[5] This is not surprising, given the findings presented in Table 2, where it can be seen that $QVJL5$ is often 0, suggesting that the cut-off level used in the calculation of $QVJL5$ is

[4]Complete regression findings are available upon request, and are omitted here for the sake of brevity.
[5]Complete results are available upon request.

not informative.[6] Interestingly, Table 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 3 and 4, note that Figures 1 - 3 plot jump spillover effects by sector, by year, based on Table 3. Examination of these 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 4 - 6 plot jump contribution levels to excess returns, by year, based on Table 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 3 and 4. A number of clear-cut conclusions emerge upon inspection of the results in these tables. First, consider Table 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,

[6]Table 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.

[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,

XLF, XLV, 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 1 - 3 illustrate this pattern quite clearly.[9]

Drilling down a bit further, the results in Table 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.

Now, consider the results contained in Table 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 4 and Figures 4 and 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

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

between 2007 and 2009 (see Table 4 and Figure 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.

5 Concluding Remarks

This paper 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.

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Table 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 2.3 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 3.1 by calender year, for different jump types.
Step 3b: Jump Contribution to Excess Returns	Ft the model in Section 3.2 by calender year, for different jump types.

Table 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 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 3.

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

QVJ	Lagged QVJ from 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

$QVJL3$	Lagged $QVJL3$ from 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

$QVJS3$	Lagged $QVJS3$ from 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 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 3a.

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

QVJ	Lagged QVJ from 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
$QVJL3$	Lagged $QVJL3$ from 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
$QVJS3$	Lagged $QVJS3$ from 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 3a.

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

QVJ	Lagged QVJ from 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

$QVJL3$	Lagged $QVJL3$ from 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

$QVJS3$	Lagged $QVJS3$ from 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 3a.

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

QVJ	Lagged QVJ from								
	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
$QVJL3$	Lagged $QVJL3$ from								
	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
$QVJS3$	Lagged $QVJS3$ from								
	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 3a.

Table 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 3.

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

	Lagged QVJ from								
Excess Returns of	XLB	XLE	XLF	XLI	XLK	XLP	XLU	XLV	XLY
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 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 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 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 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 4a.

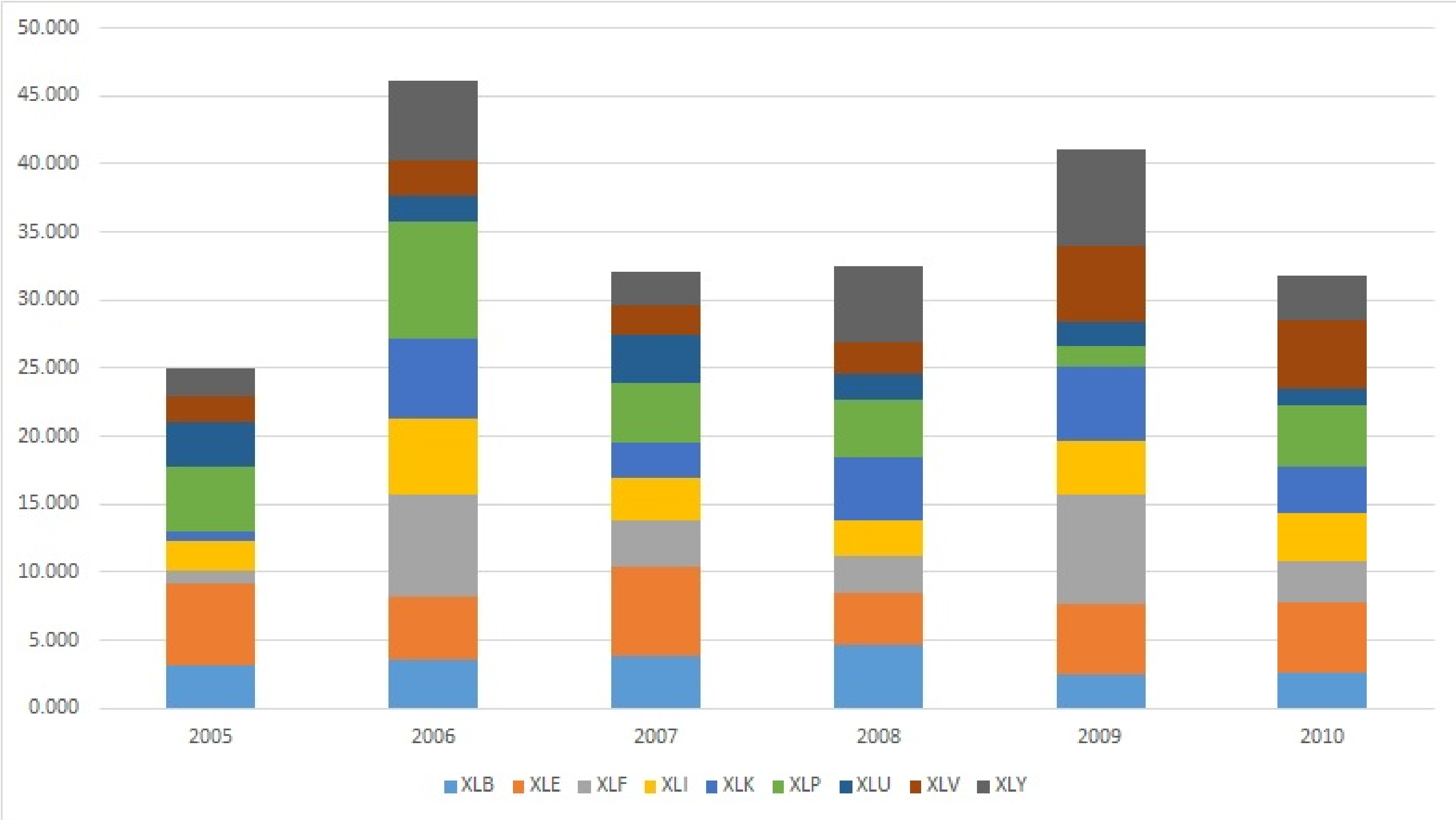

Figure 1: Large Jump Spillover Effects by Year*

* Notes: This figure aggregates the large ($QVJL3$) spillover effects by sector and by year based on the results in Table 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 3.1.

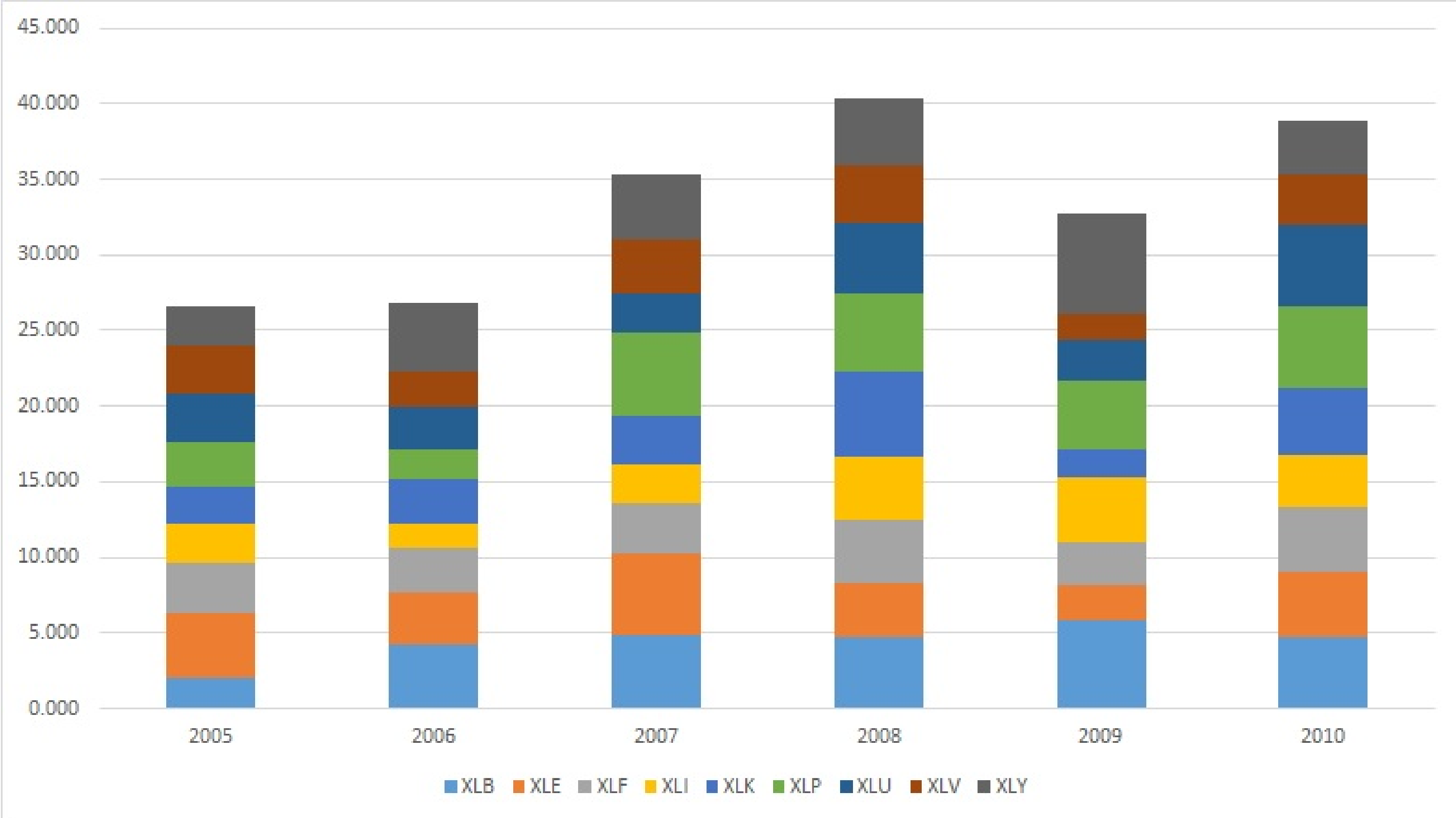

Figure 2: Small Jump Spillover Effects by Year*

* Notes: This figure aggregates the small ($QVJS3$) spillover effects by sector and by year based on the results in Table 3. See notes to Figure 1.

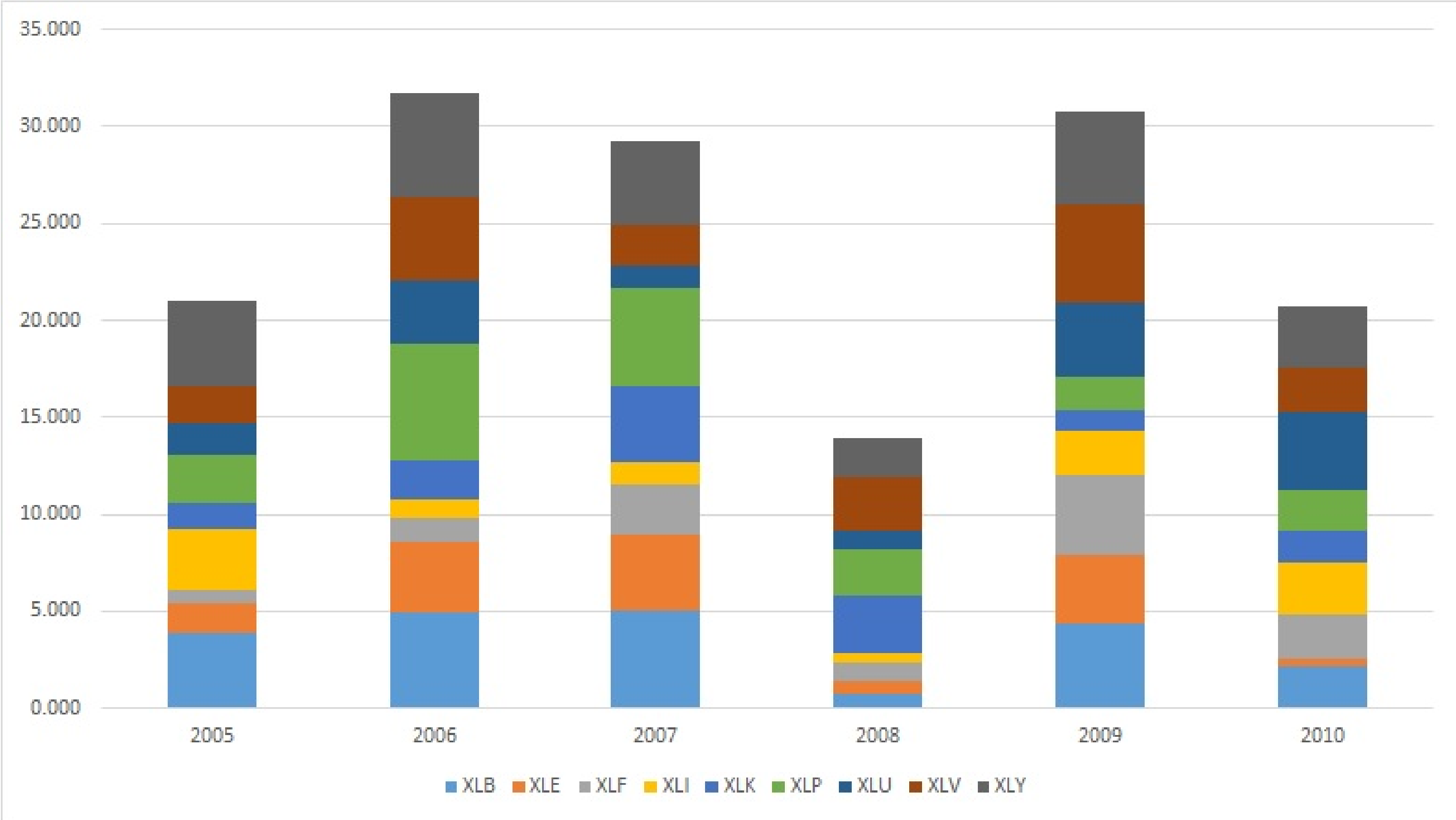

Figure 3: Total Jump Spillover Effects by Year*

* Notes: This figure aggregates the total (QVJ) spillover effects by sector and by year based on the results in Table 3. See notes to Figure 1.

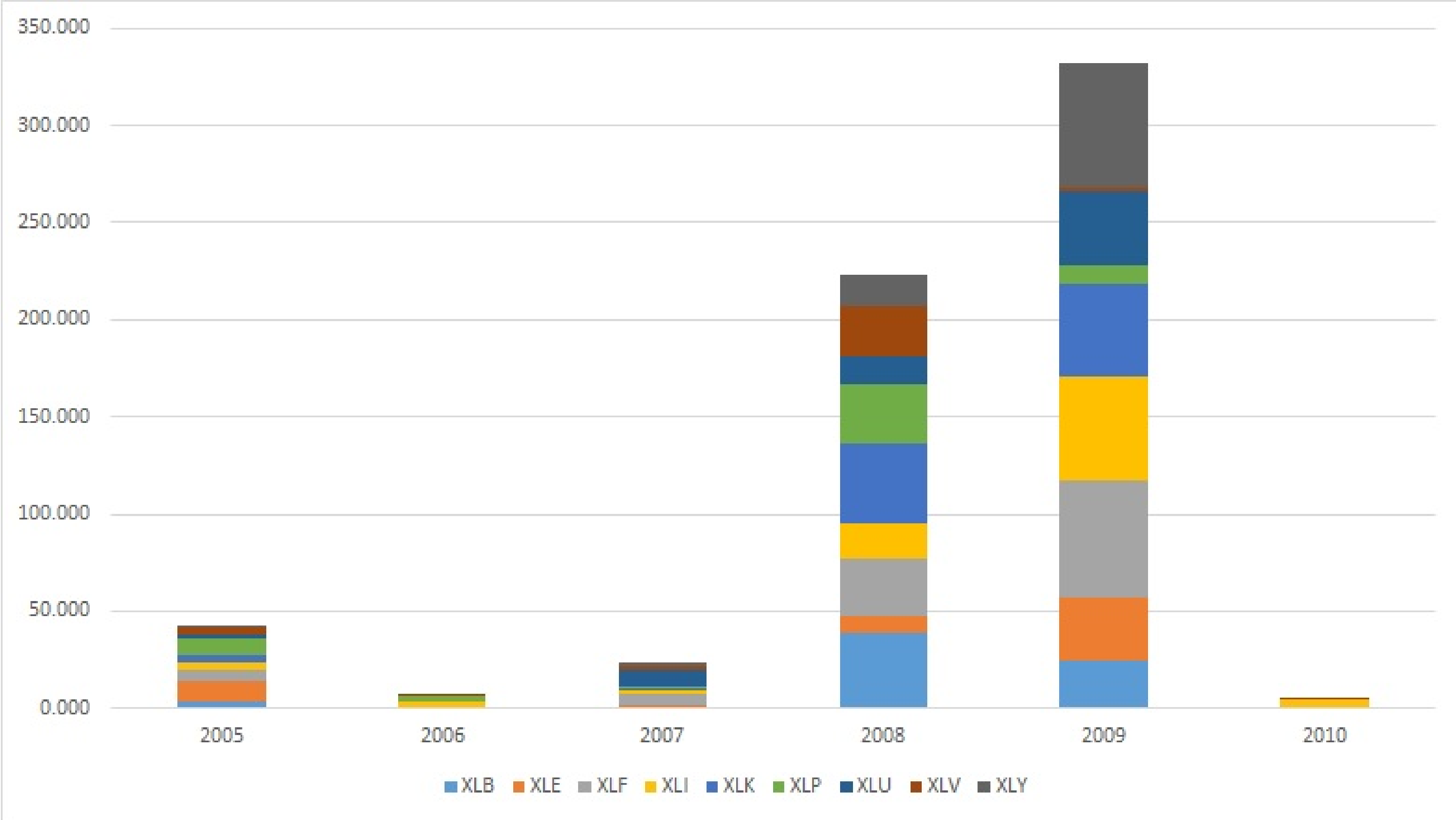

Figure 4: Large Jump Contribution Level to Excess Returns*

* Notes: This figure aggregates large ($QVJL3$) jump contribution level to excess returns by sector and by year based on the results in Table 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 3.2.

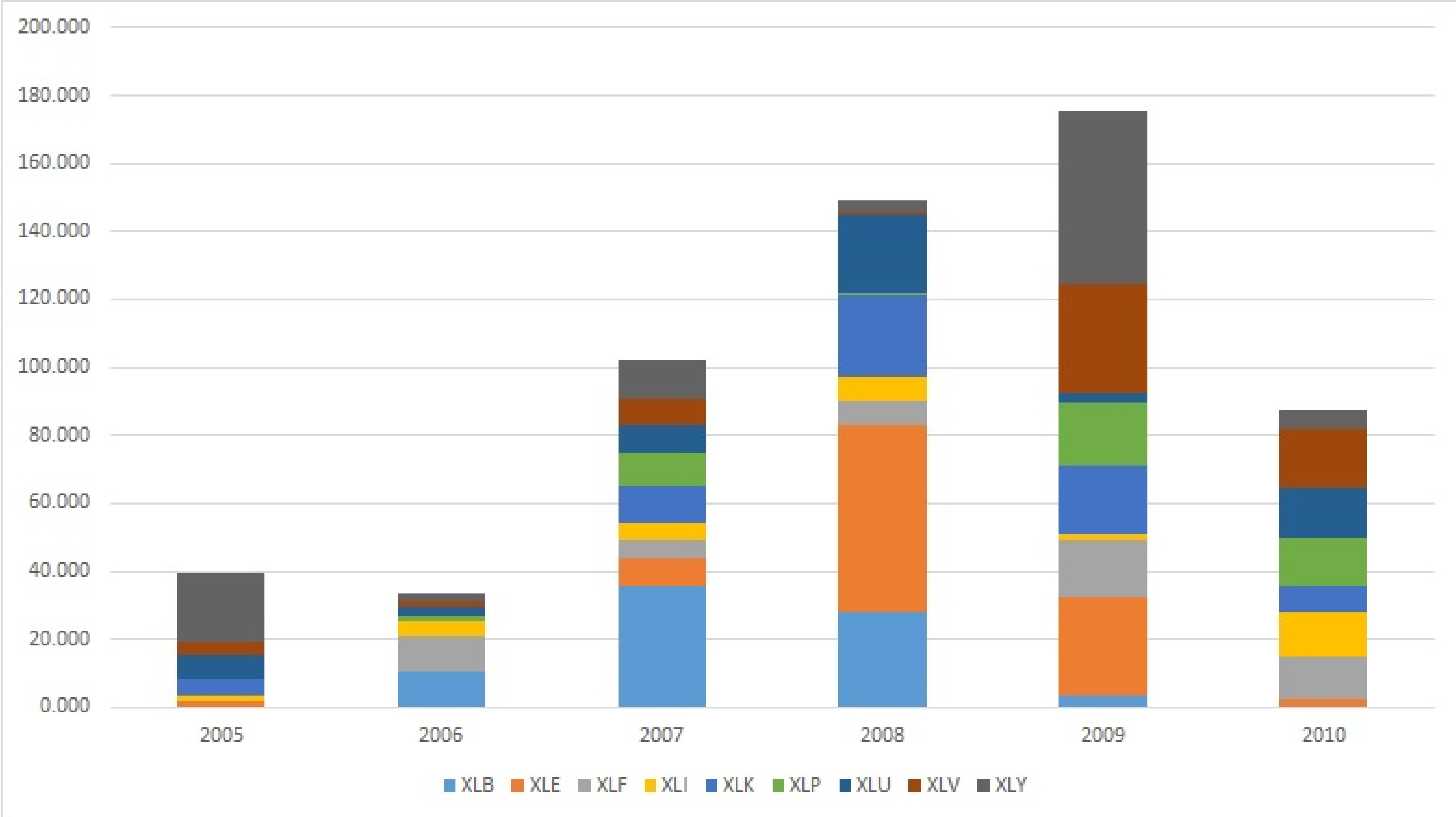

Figure 5: Small Jump Contribution Level to Excess Returns*

* Notes: This figure aggregates the small ($QVJS3$) jump contribution level to excess returns by sector and by year based on the results in Table 4. See notes to Figure 4.

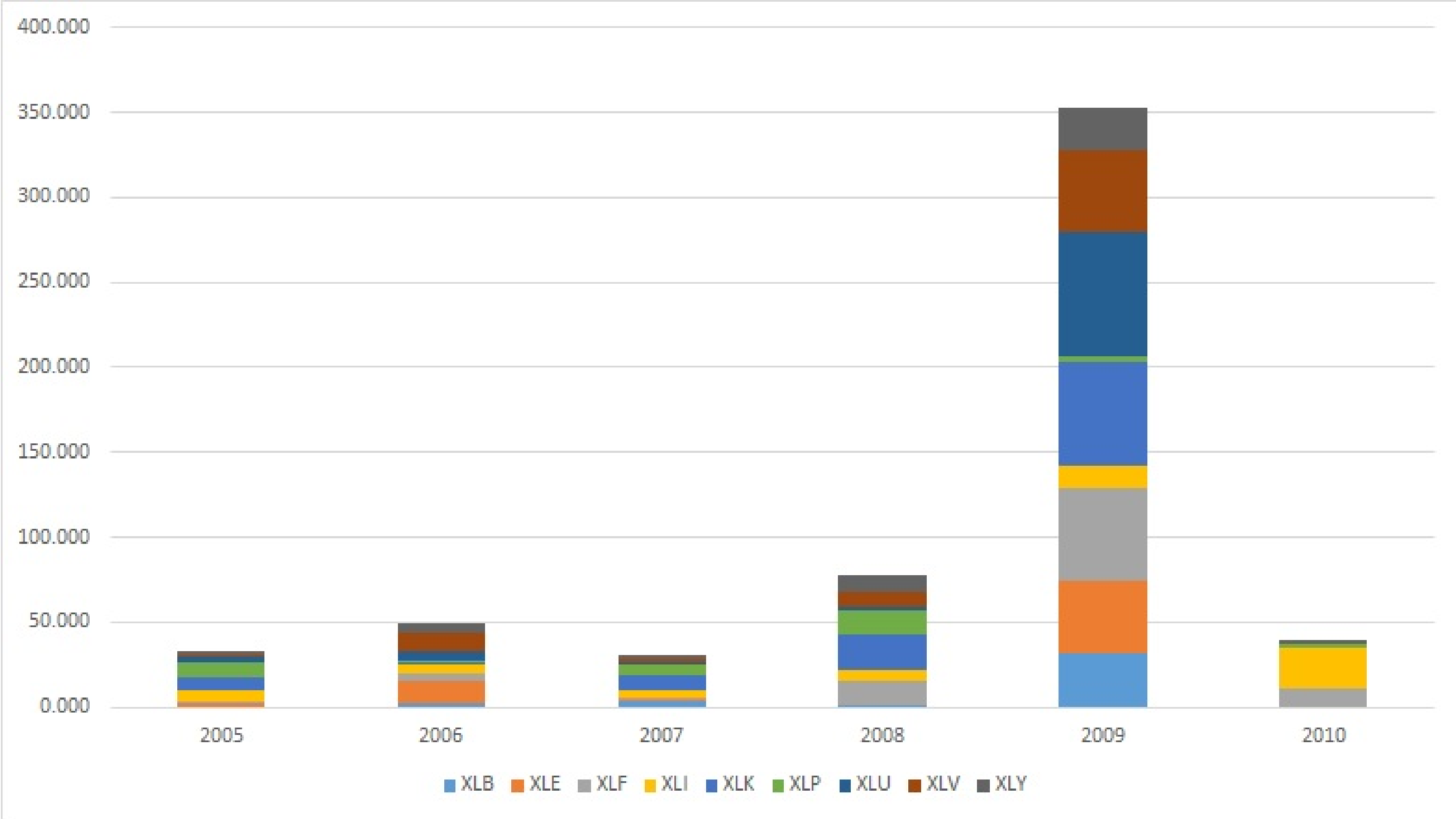

Figure 6: Total Jump Contribution Level to Excess Returns*

* Notes: This figure aggregates the total (QVJ) jump contribution level to excess returns by sector and by year based on the results in Table 4. See notes to Figure 4.