



Essays in international finance : risk, jumps and diversification

Oussama M'Saddek

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**THÈSE DE DOCTORAT DE
L'UNIVERSITÉ CLERMONT AUVERGNE**

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**Essays in International Finance: Risk, Jumps and
Diversification**

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Abstract

This thesis consists of an introductory chapter and three empirical studies that contribute to the international finance literature by investigating the dynamics of cojumps between major equity markets and assessing their impact on international portfolio allocation and asset pricing.

The first study (chapter 2) examines the impact of cojumps between international stock markets on asset holdings and portfolio diversification benefits. Using intraday index-based data for exchange-traded funds (SPY, EFA and EEM) as proxies for international equity markets, we document evidence of significant intraday cojumps, with the intensity increasing during the global financial crisis of 2008-2009. The application of the Hawkes process also shows that jumps propagate from the US and other developed markets to emerging markets. However, the evidence of jump spillover from emerging markets to developed markets is weak. To assess the impact of cojumps on international asset holdings, we consider a representative American investor who allocates his wealth among one domestic risky asset, the SPY fund, and two foreign risky assets, the EFA and EEM funds and compute the optimal portfolio composition from the US investor perspective by minimizing the portfolio's risk. We find that the demand of foreign assets is negatively correlated to jump correlation, implying that a domestic investor will invest less in foreign markets when the frequency of cojumps between domestic and foreign assets increases. In contrast, idiosyncratic jumps are found to increase the diversification benefits and foreign asset holdings in international equity portfolios. Finally, we examine the impact of higher-order moments induced by idiosyncratic and systematic jumps on the optimal portfolio composition by considering an investor who recognizes jump risks as well as another investor who ignores them. Our results show that both investors have almost the same portfolio composition, which indicates that the impact of jump higher-order moments on optimal portfolio composition is not significant.

The second study (chapter 3) tackles the issue of pricing of both continuous and jump risks in the cross-section of international stock returns. We contribute to the literature on

international asset pricing by considering a general pricing framework involving six separate market risk factors. We first decompose the systematic market risk into intraday and overnight components. The intraday market risk includes both continuous and jump parts. We then consider the asymmetry and size effects of market jumps by separating the systematic jump risk into positive vs. negative and small vs. large components. Using the intraday data of a set of country exchange traded funds covering developed, emerging and frontier markets, we show that continuous and downside discontinuous risks are positively rewarded in the cross-section of expected stock returns during the pre-financial crisis period whereas the upside and large jump risks are negatively priced during the crisis and post-crisis periods. We also provide evidence on the strong negative relationship between market price movements and market volatility changes, suggesting that both price and volatility risks share compensations for common underlying risk factors.

The third study (chapter 4) examines how international equity markets respond to aggregate market jumps at price and volatility levels. Using intraday data of ten exchange-traded funds covering major developed and emerging markets and two international market volatility indices (VIX and VXEEM), we show that both price and volatility jump betas are time-varying and exhibit asymmetric effects across upside and downside market movements. Looking at the relation between future stock market returns and aggregate market price and volatility jumps, we measure the proportion of future excess returns explained by market price and volatility jumps and provide evidence of a significant predictive power that market price and volatility jumps have on future stock returns.

Overall, our results suggest that the jump risks play an important role in determining the market risk premium and portfolio allocation decisions in an international setting.

Keywords: cojumps, international diversification, home bias, risk premium, leverage effect, high frequency data.

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Chapter 1

General Introduction

1.1 Background

This dissertation consists of an introductory chapter and three research essays that contribute to the existing literature on international finance by focusing especially on the effects of jump and cojump risks on international portfolio allocation and asset pricing. The nature of international stock market comovements is an important issue that has been extensively studied in the international finance literature (see, among others, Karolyi and Stulz (1996), De Santis and Gerard (1997), Ang and Bekaert (2002)). The topic of international stock market interdependencies has gained an increased interest among researchers for at least two main reasons. First, the nature and degree of cross-market linkages have a direct effect on international diversification. The modern portfolio theory suggests that diversification is an efficient tool to minimize the portfolio's risk. Investors, either individual or institutional, can reduce the risk of their portfolios by holding assets that are not perfectly correlated. On the contrary, in the context of an increased cross-market correlation, the benefit of portfolio diversification will be reduced. Motivated by the increased capital market integration covering both developed and emerging markets during the last decades, many researchers questioned if cross-country correlations would increase and thus the international diversification benefits would decrease.

Second, the study of correlations has been also boosted by the recurrence of financial crises that occurred in both developed and emerging countries during the last three decades. Understanding the nature of interdependencies between international stock markets in period of crisis is of great interest for both investors and policy makers who want to guard against an excessive correlation between international markets, known also as contagion risk. Several studies (Ang et al., 2006 and Lettau et al., 2014) provide evidence of a significant downside

risk in equity markets and have documented the high correlation of large down moves in international markets (see, among others, Longin and Solnik (2001), Ang and Bekaert (2002), Ang and Chen (2002) and Hartmann et al. (2004)).

More recently, researchers have especially focused on studying the comovement of stock returns in the tail of the distribution, also called tail dependence or tail risk. It is well documented in the finance literature that financial asset prices often violate the log-normality assumptions and exhibit large discontinuities or jumps in their trajectories. Thanks to the availability of high frequency data, the recent development of nonparametric jump detection techniques (see, among others, Barndorff-Nielsen and Shephard (2004, 2006), Andersen et al. (2007), Lee and Mykland (2008) and Ait-Sahalia and Jacod (2009)) provides strong evidence in favor of the presence of jumps in asset prices. The main objective of this dissertation is to contribute to the existing literature on international stock market correlations by empirically investigating the dynamics of cojumps in international equity markets and assessing their impact on portfolio allocation decisions and asset pricing.

The remainder of this introductory chapter is organized as follows. Section 1.2 goes through the existing literature on international diversification, jump and cojump risks in international stock markets. Section 1.3 summarizes the three essays and highlights their main contributions.

1.2 Diversification, jump and cojump risks in international stock markets

This section goes through the main works in the literature that motivated our study. The objective is not to provide an exhaustive list of all studies on jump and cojump risks in international stock markets, but to shed light on the main strands of the literature that are directly linked to the topics addressed in this thesis.

The literature on jump and cojump risks in financial markets can be decomposed on three

strands. The first one focused on the issue of jump identification. The works in this era have been motivated by the availability of high frequency data and the development of new jump identification techniques. Others studies were interested in studying simultaneous jumps or cojumps and developed new statistical techniques to detect the occurrence of cojumps across assets. The tools proposed in these studies are very useful for detecting both individual and common arrivals of jumps which is a key building block in studying jump dependencies.

The second branch of the literature examines the question of international diversification in presence of jumps and cojumps between assets. As mentioned earlier, the main question here is to analyze how asset allocation decisions of investors will move when considering asset jumps' dependencies.

The third branch of the literature explores the relationship between jumps in asset prices with those of aggregate risk factors and develops new econometrical tools for measuring the sensitivity of individual assets to market jumps, known also as the jump beta. These tools are very useful in practice especially for researchers who are interested in the pricing of individual assets and the understanding of the cross-section of asset returns.

1.2.1 Jump identification techniques

Numerous detection techniques have been proposed in the literature to resolve price jump identification issues. These techniques are often derived from the statistical test theory. They aim to study the dynamics of jumps' arrivals using high frequency data. The seminal work in this area was Barndorff-Nielsen and Shephard (2004, 2006) who distinguish between two measures of integrated variance. The first one takes into account the jump component of the price process when measuring the integrated variance while the second one is a jump robust measure. Authors develop a nonparametric test which indicates if a sample contains jumps using the reported measures.

Lee and Mykland (2008) notice the impact of the sensitivity of intraday volatility patterns on Barndorff-Nielsen and Shephard nonparametric test, that leads to spurious detection of

jumps. The basic idea behind their statistical test is to distinguish movements of the realized return that are caused by jumps from those that are induced by a high level of volatility. Thus, they develop a new statistical test by scaling returns by a local volatility measure. Bajgrowicz et al. (2015) also propose a technique to eliminate spurious detection of jumps on available test statistics using specific thresholds. Mancini (2001, 2009) has also developed a nonparametric test for measuring jump arrival times from high-frequency data using threshold-based methods.

A different approach (known as the "swap variance" approach) was proposed by Jiang and Oomen (2008) who consider the third and higher-order return moments to identify jumps at day level. They were inspired from the "swap variance" replication strategy to construct their statistical test. Ait-Sahalia and Jacod (2009) also examine the difference between high order moments of returns at two different sampling frequencies to detect jumps in a daily basis.

Although these statistical tests are designed to detect the same jumps, studies show that their results are often incoherent. Schwert (2008) finds, for example, that the amount and the timing of jumps depend on the choice of the sampling frequency. In an attempt to find the optimal level of sampling frequency, he mentions that the microstructure noise has a significant impact on different test statistics.¹ He proposes to sample market data at intervals of five to eleven minutes to reduce the effects of microstructure noise. Dumitru and Urga (2012) provide a comparison study between various univariate tests through Monte Carlo procedures and find that the intraday jump test of Lee and Mykland outperforms other jump identification procedures especially when the volatility is not high. The test of Lee and Mykland has also the advantage to identify jumps intradaily compared to others jump tests that have been designed to determine if a day (or a given time window) contains price jumps.

¹The microstructure noise is the deviation of the asset price from its fundamental value due to market frictions such as bid-ask bounce, latency, and asymmetric information.

1.2.2 Cojump identification techniques

In addition to univariate jump identification techniques, econometric tools have been developed to detect common arrivals of asset jumps, also called multivariate jump tests. However, the literature on cojump identification is relatively recent and scarcer compared to univariate jump tests. The most intuitive way to detect cojumps is to identify jump occurrences for each individual asset using an univariate jump test and then apply the co-exceedance rule proposed by Bae et al. (2003). A cojump is identified if two or more assets jump within the same intraday time interval. Bollerslev et al. (2008) use the mean of cross products of returns of a large number of stocks as a test statistic to detect common arrival of jumps at portfolio level. Their test statistic is sensitive to the number of stocks considered in the portfolio. Indeed, a large number of stocks is required to diversify away asset idiosyncratic jumps.

Jacod and Todorov (2009) develop a bivariate jump identification test using the ratio of power variation estimators. However, their approach can only be applied to detect if a particular day contains cojumps. Gobbi and Mancini (2012) propose a daily cojump test by applying thresholding techniques. Gnabo et al. (2014) use the product of assets' intraday returns and parametric bootstrapping techniques to identify intraday cojumps. Their approach complements the univariate jump detection tests in the sense that it aims to identify potential cojumps, which are not, detected through univariate jump tests. However, Gnabo et al. (2014) show that univariate tests remain satisfactory and best-suited for detecting jumps and cojumps as long as the jumps sizes are sufficiently large and have the same sign as the assets' correlation.

1.2.3 Jumps and cojumps in equity markets

Motivated by the development of nonparametric jump detection tests, researchers examine the dynamics of jumps in different stock markets. Gilder et al. (2012) use univariate jump detection techniques to identify intraday jumps in the US stock market and examine the frequency of cojumps between individual stocks and the market portfolio. They find a

tendency for a relatively large number of stocks to be involved in systematic cojumps, which are defined as cojumps between a stock and market portfolio. Lahaye et al. (2010) and Evans (2011) examine the link between asset cojumps and new macro announcements and find that cojumps are partially associated with macroeconomic news. Bormetti et al. (2015) study the dynamics of intraday jumps in the Italian stock market and show that Hawkes one-factor model is more suitable to capture the high synchronization of jumps across assets than the multivariate Hawkes model (1971). Using daily data, Ait-Sahalia et al. (2015) develop a multivariate Hawkes jump-diffusion model to capture the propagation of jumps over time and across markets. They provide strong evidence for jumps to arrive in clusters within the same market and to propagate to other international stock markets. Pukthuanthong and Roll (2015) also use daily data to examine jump correlation across international stock markets. In the first essay, we extend the existing literature by studying the dynamics of jumps in an international setting. Our approach is based on the use of high frequency data and the application of nonparametric jump identification tests. We also examine the time (within same market) and space (across markets) clustering properties of intraday jumps using the multivariate Hawkes model.

1.2.4 International diversification in presence of correlated jumps

International stock markets are characterized by jumps that have tendency to occur at the same time across markets especially in bearish market conditions marked by large downturns and high volatility. This excessive correlation between jumps leads researchers to question whether the jump risk reduces the gains from the international diversification. Das and Uppal (2004) examine this question by considering a multivariate system of jump-diffusion processes where jumps are infrequent and occur simultaneously across assets. They find that systemic jump risk reduces the gains of portfolio diversification especially if the considered portfolio includes a risk free asset. Cvitani et al. (2004) consider the optimal portfolio strategy of a representative investor with CRRA utility where the risky asset is modeled as a pure jump process with non-trivial higher moments. They find that ignoring higher moments in the

portfolio optimization problem leads to an over-investment in risky assets and results in a substantial wealth loss. Ait Sahalia et al. (2009) examine the problem of portfolio allocation in presence of jumps and propose a closed-form solution for it.

The benefits from international portfolio diversification have been widely documented in the finance literature (see, among others, Grubel (1968), Levy and Sarnat (1970), Lessard (1973), and Solnik (1974)). However, studies show that in practice investors have tendency to overweight their portfolios with assets from their home country market, meaning that those portfolios tend to be less diversified internationally than would be optimal according to modern portfolio theory (Markowitz, 1952). In the finance literature, this lack of international portfolio diversification is called the home bias puzzle.

The equity home bias was first documented by French and Poterba (1991). They studied the home bias phenomenon in five major countries and they found that at the end of 1989, US investors hold more than 92% of their equity in domestic stock (Japan, 95%; United Kingdom, 92%; Germany, 79% and France, 89%). Tesar and Werner (1998) show the same figures. These empirical data are largely different from those predicted by theoretical studies that demonstrate that the share of domestic assets in optimal portfolio composition should be in line with the share of the domestic equity market compared to the total world equity market. More recently, many researchers studied the evolution of the phenomenon over the past three decades. Karolyi and Stulz (2003) found that international diversification has increased slightly for US investors from 1973 through 2001. This decrease in home bias could be explained by changes that experienced equities market in the nineties including the advent of internet, the development of emerging markets, deregulation and markets liberalization. In spite of this decrease in home bias, several studies report that investors are still far from taking all the gains from international diversification and differences between the theoretical share of foreign assets that should be held by investors and the real share effectively held are largely disproportionate.

The home bias puzzle was extensively studied in the financial literature and there have

been various theoretical explanations that were given to rationalize investors' behaviour and thus the lack of international diversification observed in financial markets.² A first potential explanation for equity home bias is that domestic equities provide a better hedge for risks that are home-country specific such as domestic inflation risk, exchange rate risk and hedges against wealth that is not traded in capital markets. Empirical studies show that there is a weak correlation between domestic stock returns and domestic inflation rate (exchange rate, non-tradable income) indicating that hedging domestic risks fails to explain the observed home bias.

An alternative explanation for international under-diversification is the existence of various barriers and relatively important transaction costs for foreign investments. However, none of the studies that consider barriers and transaction costs as an explanation to home bias succeeds to provide plausible empirical proofs. Moreover, recent studies show that costs and barriers to foreign investments have decreased considerably due to market liberalization in the early nineties. Thus, the home bias in equities cannot be explained by international capital controls or transaction costs.

A different explanation is suggested by recent empirical studies (Chan et al., 2005) that consider information asymmetries between domestic and foreign investors as the main cause of home bias. In order to examine the link between information asymmetries and international portfolio choice, researchers mainly use econometric regression models to measure the impact of each explanatory variable. The physical distance between two countries or the fact to share a common language or culture is often used as a proxy for information asymmetries in those models. Contrary to the information-based explanation of home bias, others researchers criticize the fact that this theory implicitly assumes that domestic investors have superior access to the domestic market in an environment of global information access. It seems that there is no consensus between researchers on the role of information asymmetries as a cause to the observed home bias. This is also related to difficulties to provide a convincing empirical study about the effect of information asymmetries on the portfolio choice due to the lack in

²Refer to Lewis (1999) for a review of the home bias literature.

practice of data necessary to measure these asymmetries.

The explanations reported below are based on the assumption of perfectly rational behaviour of individuals. As it seems that the home bias cannot only be explained by rational behaviour of investors, recent studies rely on recent findings of behavioral finance in order to explain international under-diversification. Researchers examined if the irrational behaviour of investors could be explained by behavioural biases such as overconfidence, familiarity with domestic stocks, patriotism and specific investor characteristics (sophisticated investor or not, age, gender, income).

The puzzle has led to an extensive research effort in both traditional and behavioral finance. So far, several explanations have been presented, but a solution generally accepted by the researchers remains elusive. In the first essay, we contribute to the existing literature on the lack of international diversification by investigating how the cojumps between international stock markets will affect the demand of foreign assets and the gains from international diversification. To the best of our knowledge, we are the first study that examines the impact of intraday cojumps on portfolio allocation decisions in an international setting. Our approach is based on the identification of cojumps using high frequency data. We use mean-variance and mean-CVaR approaches to determine the optimal portfolio composition and examine how the demand of foreign assets varies with jumps' correlation. The impact of higher-order moments induced by jumps on the optimal portfolio composition is also examined.

1.2.5 The pricing of jump risks in the cross-section of returns

The finance theory establishes that investors should be compensated for bearing non-diversifiable risks. Aggregate market jumps are a potential source of systematic risk. Therefore, understanding how individual assets are linked to aggregate market jumps plays a key role in measuring, managing and pricing jump risks. In this field, Bollerslev et al. (2016) and Li et al. (2017) develop new econometrical tools for estimating the sensitivity of individual assets to market jumps. Using these new tools, Bollerslev et al. (2016) and Alexeev

et al. (2017) document that the jump risk carries a significant positive premium. However, the scope of their empirical works is restricted to the US market. Using option data and by constructing suitable option trading strategies, Cremers et al. (2015) provide evidence that both aggregate jump and volatility are priced risk factors, but both of them carry negative market risk prices.

More recently, studies (Bandi and Reno (2016), Jacod and Todorov (2010), Todorov and Tauchen (2011)), show that jumps in prices are often associated with strongly anti-correlated, contemporaneous, discontinuous changes in volatility, suggesting that both the price and volatility jump risks are derived by common underlying risk factors and thus should be handled jointly by investors. Other studies (Bandi and Reno (2016), Davies (2016)) suggest that market volatility jumps are also a source of systematic risk and they should be priced in the cross-section of stock returns.

The asset pricing literature that investigates the role of tail risks on explaining the cross-section of stock returns worldwide also includes Weigert (2016) who provides evidence of a significant positive premium for holding stocks with a strong sensitivity to extreme market downturns, with a risk premium particularly high in countries with higher income per capita and negative market skewness. In contrast, Oordt and Zhou (2016) find the reward for holding stocks that strongly comove with the market during extreme market crashes is not significant. Their study is, however, limited to the US stock market.

In the second essay, we contribute to the existing literature by decomposing the non-diversifiable market risk into continuous and discontinuous components and systematic jump risks into positive vs. negative and small vs. large components. We examine their association with equity risk premia across major equity markets. To the best of our knowledge, we are the first study that examines the market risk across major developed, emerging and frontier markets using a general pricing framework involving six separate market betas measuring the sensitivity of individual country stock markets to respectively continuous, overnight, discontinuous up, discontinuous down, discontinuous small and discontinuous large intraday

movements of the market. As jumps in prices are closely linked to jumps in the volatility, we study, in the third essay, how developed and emerging markets react to jumps of an aggregate market index both at price and volatility levels and examine the role of market price and volatility jumps in forecasting international stock market returns.

1.3 Essays

1.3.1 First essay

The first essay aims to examine the impact of cojumps between international stock markets on asset holdings and portfolio diversification benefits. The paper extends previous studies that investigate how international diversification varies with the correlation between stock markets by focusing specifically on the role of cojumps. It also contributes to the existing literature by studying the dynamics of intraday jumps in an international setting.

Our empirical investigation is based on the use of intraday returns for three international exchange-traded funds, SPY, EFA, and EEM, which respectively aim to replicate the performance of three international equity market indices: S&P 500, MSCI EAFE (Europe, Australasia and Far East), and MSCI Emerging Markets. The data covers the period going from January 2008 to October 2013. We apply the univariate jump identification test of Lee and Mykland (2008) to identify the intraday jumps of the three funds. In order to capture the dependency between the occurrences of the detected jumps, we employ the bivariate Hawkes process (1971) which is appropriate to model the time and space clustering features of jumps. Under this analysis, we find jumps from the US propagate to other developed markets and emerging markets. However, the evidence of jump spillover from emerging markets to developed markets is weak.

To assess the impact of cojumps on international asset holding, we consider a representative American investor who allocates his wealth among one domestic risky asset, the SPY fund, and two foreign risky assets, the EFA and EEM funds. We then compute the optimal portfolio composition from the US investor perspective by minimizing the portfolio's risk.

Once the optimal composition is determined, we examine how the demand of foreign assets varies with the jump correlation or cojumps. We find that the demand of foreign assets is negatively correlated to jump correlation, implying that a domestic investor will invest less in foreign markets when the frequency of cojumps between domestic and foreign assets increases. We also uncover the negative link between the intensity of cojumps and the conditional diversification benefit measure suggested by Christoffersen et al. (2012). Putting differently, the excessive jump correlation increases the cross-market comovements, and therefore reduces the international diversification benefit and leads investors to prefer home assets. In contrast, we find that idiosyncratic jumps have a positive effect on foreign asset holding and diversification benefits, implying that country-specific jumps are a potential source of portfolio diversification for investors. Finally, we examine the impact of higher-order moments (skewness, co-skewness, kurtosis, and co-kurtosis) induced by idiosyncratic and systematic jumps on the optimal portfolio composition by considering an investor who recognizes idiosyncratic and systematic jump risks and assumes that asset returns are given by a multivariate jump-diffusion process as well as another investor who ignores jumps and assumes a pure-diffusion process for asset returns. Our results show that both investors have almost the same portfolio composition, which indicates that the impact of jump higher-order moments on optimal portfolio composition is not significant.

1.3.2 Second essay

The second research paper tackles the issue of pricing of both continuous and jump risks in the cross-section of international stock returns. We contribute to the literature on international asset pricing by considering a general pricing framework involving six separate market risk factors. We first decompose the systematic market risk into intraday and overnight components. The intraday market risk includes both continuous and jump parts. We then consider the asymmetry and size effects of market jumps by separating the systematic jump risk into positive vs. negative and small vs. large components.

The empirical investigation relies on the intraday data of a set of 37 country exchange-

traded funds covering developed, emerging and frontier markets from July 2003 to December 2014. We follow Todorov and Bollerslev (2010)'s methodology to estimate the exposure of each country fund returns towards the systematic market diffusive and jump risks. We examine the cross-sectional relation between estimated betas and return by forming portfolios ranked on the basis of market betas. We find that there is a positive link between the returns of the sorted portfolios and different factors of risk (except the overnight beta) during the pre-crisis period going from July 2003 to June 2008. During the crisis and pre-crisis period (July 2008 to December 2014), we observe an inversion of the patterns of realized returns for portfolios sorted on jump betas (except for discontinuous downside beta), with a negative relation being more pronounced for discontinuous positive and large betas. This result is consistent with an increasing investor appetite for equities that positively comove with large and positive market jumps during periods of market turmoil. These equities will help investors to better hedge against large movements of market and thus would require lower expected returns.

In order to assess the price of bearing continuous and jump market risks, we follow Fama and MacBeth (1973)'s approach by running a set of cross-sectional regressions in a monthly basis. The results of the cross-sectional Fama and MacBeth (1973) regressions are in line with the portfolio sorting findings. We mainly find that continuous and downside discontinuous risks are positively rewarded in the cross-section of expected stock returns during the pre-crisis period whereas the upside and large jump risks are negatively priced during the crisis and post-crisis periods. By studying the return-volatility relationship over the sample period, we provide evidence on the strong negative covariation between market price movements (both continuous and downside discontinuous) and market volatility changes during the pre-crisis period, suggesting that both price and volatility risks share compensations for common underlying risk factors during the pre-crisis period.

1.3.3 Third essay

The third research article complements the first two essays by examining how international equity markets respond to aggregate market jumps at both price and volatility levels.

Motivated by the recent development of jump regression techniques (Li et al. (2017) and Davies (2016)), we examine the linear relationship between individual stock markets and an aggregate market proxy at jump times at both price and volatility levels.

The empirical work is based on two sets of high frequency data. The first set is composed of ten exchange-traded funds covering major developed and emerging markets. The second set is composed of two volatility indices: the Chicago Board of Options Exchange's (CBOE) Volatility Index (VIX) and CBOE Emerging Markets ETF Volatility Index (VXEEM) serving as proxies for respectively the developed and emerging market volatilities. The sample covers the period going from January 2008 to May 2015. By applying the techniques proposed by Andersen et al. (2007) and Lee and Mykland (2008), we identify intraday jumps and cojumps of all funds and volatility indices in the sample and find that simultaneous jumps between individual country funds and two volatility indices have opposite signs, with a higher proportion of positive volatility and negative return cojumps, suggesting a strong anti-correlation between market volatility jumps and the asset returns when the market is downward and its volatility is high.

By considering jump regression techniques proposed by Li et al. (2017) and Davies (2016), we estimate the sensitivity of individual country markets to respectively market price and volatility jumps and show that both price and volatility jump betas are time-varying over the period of study. We also document asymmetric effects across upside and downside market movements for the price jump betas. The results found for the upside and downside volatility jump betas, are, however, inconclusive.

Looking at the relation between future stock market returns and aggregate market price and volatility jumps, we measure the proportion of future excess returns explained by market price and volatility jumps and provide evidence of a significant predictive power that market price and volatility jumps have on future stock returns, with a stronger degree of predictability obtained with market price jumps.

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Chapter 2

Cojumps and Asset Allocation in International Equity Markets¹

Abstract

This paper examines the patterns of intraday cojumps between international equity markets as well as their impact on international asset holdings and portfolio diversification benefits. Using intraday index-based data for exchange-traded funds as proxies for international equity markets, we document evidence of significant cojumps, with the intensity increasing during the global financial crisis of 2008-2009. The application of the Hawkes process also shows that jumps propagate from the US and other developed markets to emerging markets. Correlated jumps are found to reduce diversification benefits and foreign asset holdings in minimum risk portfolios, whereas idiosyncratic jumps increase the diversification benefits of international equity portfolios. In contrast, the impact of higher-order moments induced by idiosyncratic and systematic jumps on the optimal composition of international portfolios is not significant.

Keywords: Cojumps; Foreign asset holdings; International diversification.

¹A paper based on this chapter has been accepted for publication in Journal of Economic Dynamics and Control.

2.1 Introduction

It is now well established in the finance literature that price discontinuities or jumps should be taken into account when studying asset price dynamics and allocating funds across assets (Bekaert et al., 1998; Das and Uppal, 2004; Guidolin and Ossola, 2009; Branger et al., 2017). In this regard, the recent development of non-parametric jump identification tests has enabled jump detection in financial asset prices. The seminal works in this area include Barndorff-Nielsen and Shephard (2004; 2006a) who test for the presence of jumps at the daily level using measures of bipower variation. The same family of intraday jump identification procedures includes the tests developed by, among others, Jiang and Oomen (2008), Andersen et al. (2012), Corsi et al. (2010), Podolskij and Ziggel (2010), and Christensen et al. (2014). Andersen et al. (2007) and Lee and Mykland (2008) have developed techniques to identify intraday jumps using high frequency data. All of these jump detection techniques provide empirical evidence in favor of the presence of asset price discontinuities or jumps.

More recently, researchers have been interested in studying cojumps between assets (Dungey et al., 2009; Lahaye et al., 2010; Dungey and Hvozdyk, 2012; Pukthuanthong and Roll, 2015; Ait-Sahalia and Xiu, 2016). For instance, Gilder et al. (2012) examine the frequency of cojumps between individual stocks and the market portfolio. They find a tendency for a relatively large number of stocks to be involved in systematic cojumps, which are defined as cojumps between a stock and market portfolio. Lahaye et al. (2010) show that asset cojumps are partially associated with macroeconomic news announcements. Ait-Sahalia et al. (2015) develop a multivariate Hawkes jump-diffusion model to capture jumps propagation over time and across markets. They provide strong evidence for jumps to arrive in clusters within the same market and to propagate to other international markets. Bormetti et al. (2015) find that Hawkes one-factor model is more suitable to capture the high synchronization of jumps across assets than the multivariate Hawkes model.

Our study furthers the above-mentioned literature in two ways. First, we empirically investigate intraday cojumps between international equity markets. Second, we show their

impact on international asset allocation and portfolio diversification benefits. To the best of our knowledge, we are the first study that examines the impact of intraday cojumps on portfolio allocation decisions in an international setting. Past studies focus more on the impact of return correlation without separating between continuous and jump parts. Modern portfolio theory suggests that international diversification is an effective way to minimize portfolio risks given that international assets are often less correlated and driven by different economic factors. However, one might expect that cojumps can lead to an increase in the correlation between these international assets and thus reduce the benefit from international diversification. Inversely, if price jumps of different assets do not occur simultaneously, they are categorized as idiosyncratic jumps and will not affect portfolio allocation decisions in an international setting. Choi et al (2017) show, in contrast to traditional asset pricing theory and in support of information advantage theory, concentrated investment strategies in international markets are associated with higher risk-adjusted returns. Our study complements their study by showing investors prefer concentrated portfolios tilted toward home market because cojumps between home and foreign stock markets significantly reduce diversification benefits.

Accordingly, a risk-averse investor who holds an international portfolio is exposed to two types of jump risks: cojump or systematic jump risk (jumps common to all markets) and idiosyncratic jump risk (jumps specific to one market). If an investor's portfolio is well diversified, the idiosyncratic jump risk will be reduced or even eliminated. On the other hand, the cojump risk cannot be eliminated through diversification, thus making its identification central to asset pricing, asset allocation and portfolio risk hedging. Identifying cojumps is also important to policy makers attempting to propose the policies to stabilize financial markets.

Our empirical tests rely on the use of intraday returns for three dedicated international exchange-traded funds (ETFs) – SPY, EFA, and EEM – which respectively aim to replicate the performance of three international equity market indices: S&P 500, MSCI EAFE (Europe,

Australasia and Far East), and MSCI Emerging Markets.² We use the technique proposed by Andersen et al. (2007) and Lee and Mykland (2008) to empirically identify all intraday jumps and cojumps of the three funds from January 2008 to October 2013. Lee and Mykland (2008) show that the power of their non-parametric jump identification test increases with the sampling frequency and that spurious detection of jumps is negligible when high frequency data are used. Unlike Ait-Sahalia et al. (2015) who use low frequency data to study the dynamics of jumps, we employ a bivariate Hawkes model to reproduce the time clustering features of intraday jumps and the dynamics of their propagation across markets. The application of the Hawkes process allows us to capture the dependence between the occurrences of jumps which cannot be reproduced by, for example, the standard Poisson process, owing to the hypothesis of independence of the increments (i.e., the numbers of jumps on disjoint time intervals should be independent). Under this analysis, we find jumps from the US propagate to other developed markets and emerging markets. However, the evidence of jump spillover from emerging markets to developed markets is weak.

Finally, we assess the impact of cojumps on international portfolio allocation by considering a domestic risk-averse investor who selects the portfolio composition based on one domestic asset and two foreign assets in a way to maximize his expected utility.³ As investors are concerned about negative movements of asset returns, we take the risk of extreme events into account using the Conditional Value-at-Risk or CVaR (Rockafellar and Uryasev, 2000) as a risk measure in our portfolio allocation problem. Unlike the standard mean-variance approach, which typically underestimates the risk of large movements of asset returns, the mean-CVaR approach allows us to provide a fairly accurate estimate of the downside risk induced by negative cojumps of asset returns. As to cojumps, we apply two approaches to assess how assets jumps are linked to each other. The first one is cojump intensity measure obtained from the co-exceedance rule (Bae et al., 2003) and univariate jump identification tests proposed by Andersen et al. (2007) and Lee and Mykland (2008). The second one

²S&P 500 index is used as a proxy for the US market. MSCI EAFE index is the benchmark for developed markets excluding the US and Canada, whereas the MSCI Emerging Markets is used to capture the performance of emerging equity markets.

³The domestic country is defined as a reference country considered to be the home country for our investors.

is based on the realized jump correlation measure proposed by Jacod and Todorov (2009). Contrary to the first approach, that only measures the frequency of simultaneous jumps, the correlated jump approach captures both the intensity and size effects of cojumps. It has also the advantage to be robust to jump identification tests.

Once the optimal portfolio composition is determined, we analyze how jumps and cojumps affect investor demand for domestic and foreign assets. Our results show evidence of a negative and significant link between the demand for foreign assets and the jump correlation between the domestic and foreign markets. We also find a negative effect of cross-market cojumps on diversification benefits. In contrast, we find that idiosyncratic jumps have a positive effect on foreign asset holding and diversification benefits.

We also examine how higher-order moments (skewness, co-skewness, kurtosis, and co-kurtosis) induced by idiosyncratic and systematic jumps affect the optimal portfolio composition. For this purpose, we consider an investor who recognizes idiosyncratic and systematic jump risks and assumes that asset returns are given by a multivariate jump-diffusion process as well as another investor who ignores jumps and assumes a pure-diffusion process for asset returns. Both investors have a power utility function and select their respective portfolios composition in a way to maximize their respective expected utilities. Our results show that both investors have almost the same portfolio composition, which typically indicates that the impact of jump higher-order moments on optimal portfolio composition is not significant.

The remainder of the paper is organized as follows. Section 2.2 introduces the jump and cojump identification techniques used in our study. Section 2.3 presents the portfolio allocation problem. Section 2.4 describes the data. Section 2.5 discusses our main empirical findings. Section 2.6 concludes the paper.

2.2 Jump and cojump identification

This section briefly introduces the methodology that we follow to detect intraday jumps and cojumps. We first begin with the univariate jump identification tests proposed by An-

dersen et al. (2007, henceforth ABD) and Lee and Mykland (2008, henceforth LM).⁴The LM and ABD procedures use the same test statistic, but differ on the choice of the critical value. ABD assumes that the test statistic is asymptotically normal, whereas LM provides critical value from the limit distribution of the maximum of the test statistic.

The LM test statistic compares the current asset return with the bipower variation calculated over a moving window with a given number of preceding observations. It tests on day t at time k whether there was a jump from $k - 1$ to k and is defined as:

$$L_{t,k} = \frac{|r_{t,k}|}{\hat{\sigma}_{t,k}} \quad (2.1)$$

where

$$(\hat{\sigma}_{t,k})^2 = \frac{1}{K-2} \sum_{j=k-K+2}^{k-1} |r_{t,j-1}| |r_{t,j}| \quad (2.2)$$

$r_{t,k}$ is the k^{th} intraday return. $\hat{\sigma}_{t,k}$ refers to the realized bipower variation calculated for a window of K observations and provides a jump robust estimator of the instantaneous volatility. A jump is detected with LM test on day t in intraday interval k if the following condition is satisfied:

$$|L_{t,k}| > -\log(-\log(1 - \alpha)) \times S_M + C_M \quad (2.3)$$

where α is the test significance level. S_M and C_M are function of the number of observations in a day M , introduced in Lee and Mykland (2008).

On the other hand, the ABD test statistic is assumed to be normally distributed in the absence of jumps. A jump is detected with the ABD test on day t in intraday interval k if the following condition is satisfied:

$$\frac{|r_{t,k}|}{\sqrt{\frac{1}{M} BV_t}} > \Phi_{1-\frac{\beta}{2}}^{-1} \quad (2.4)$$

⁴Dumitru and Urga (2012) show that intraday jump tests of LM and ABD outperform other test procedures especially when price volatility is not high.

where BV_t is the bipower variation (Barndorff-Nielsen and Shephard 2004) defined as follows:

$$BV_t = \frac{\pi}{2} \frac{M}{M-1} \sum_{k=2}^M |r_{t,k-1}| |r_{t,k}| \quad (2.5)$$

$\Phi_{1-\frac{\beta}{2}}^{-1}$ represents the inverse of the standard normal cumulative distribution function evaluated at a cumulative probability of $1 - \frac{\beta}{2}$ and $(1 - \beta)^M = 1 - \alpha$, where α represents the daily significance level of the test.

In our study, we identify intraday jumps by relying on the intraday procedure of LM-ABD. A jump is detected with the LM-ABD test on day t in intraday interval k when:

$$\frac{|r_{t,k}|}{\hat{\sigma}_{t,k}} > \theta \quad (2.6)$$

The threshold value θ is calculated for different significance levels. For a daily significance level of 5% and a sampling frequency of 5 minutes (which corresponds to 77 intraday returns per day in our study), we obtain a threshold value of 3.40 and 4.40 using ABD and LM methods, respectively. In our study, we combine both procedures by taking an intermediate threshold value equal to 4.⁵

Once all intraday jumps are identified using the univariate jump detection test of LM-ABD, we apply the following co-exceedance rule to verify if a cojump occurs between assets i and j at intraday time k on day t (Bae et al., 2003):⁶

$$1 \left\{ \frac{|r_{i,t,k}|}{\hat{\sigma}_{i,t,k}} > \theta \right\} \times 1 \left\{ \frac{|r_{j,t,k}|}{\hat{\sigma}_{j,t,k}} > \theta \right\} = \begin{cases} 1 : & \text{a cojump between assets } i \text{ and } j \\ 0 : & \text{no cojump} \end{cases} \quad (2.7)$$

Thus, a cojump exists when asset returns jump simultaneously. We distinguish between an idiosyncratic jump defined as jump of a single asset or jump that occurs independently

⁵This threshold value is also employed by Bormetti and al. (2015). We also consider different threshold values (3 and 5). However, the results remain intact.

⁶See Lahaye et al. (2010) and Dungey et al. (2009) for applications.

of the market movement and cojump defined as jumps of two or more assets that occur simultaneously.

Other techniques have recently been proposed to identify cojumps in the multivariate context using a single cojump test statistic such as those proposed by Barndorff-Nielsen and Shephard (2006b), Bollerslev et al. (2008) and Jacod and Todorov (2009). For instance, Bollerslev et al. (2008) uses the mean of cross products of returns of a large number of stocks as a test statistic to detect common arrival of jumps at portfolio level. Their test statistic is sensitive to the number of the stocks considered in the portfolio. Indeed, a large number of stocks is required to diversify away asset idiosyncratic jumps. Jacod and Todorov (2009) develop a bivariate jump identification test using the ratio of power variation estimators. However, their approach can only be applied to detect if a particular day contains cojumps. Gobbi and Mancini (2012) also propose a daily cojump test by applying thresholding techniques.

The cojump test based on co-exceedance rule is appropriate for our context because it presents simple estimates of precisely timed cojumps with a relatively narrow range of intraday data. Moreover, Gnabo et al. (2014) show that univariate tests we use are satisfactory and best-suited for detecting jumps and cojumps as long as the jumps sizes are sufficiently large and have the same sign as the assets' correlation. This is effective in our case where the intraday jump return is greater than four times the estimate of the local volatility and assets are jumping in the same direction of the correlation.

2.3 Portfolio allocation problem

In this section, we present two different approaches for addressing the portfolio allocation problem and derive the optimal portfolio composition when there are domestic and foreign assets. First, we consider a representative domestic investor with a quadratic utility and show that the optimal weight of foreign asset holdings is a decreasing function of the correlation between assets, provided that the variability of the domestic asset is lower than the foreign

asset. Second, we consider the standard power utility approach and examine how higher-order moments induced by systematic and idiosyncratic jumps affect the optimal portfolio composition.

2.3.1 Optimal portfolio composition and jump correlation

Two-fund case

We consider a risk-averse investor who selects his portfolio composition based on two assets: a domestic risky asset and a foreign risky asset. Both asset returns are expressed in the investor's domestic currency. We consider the standard mean-variance approach initially formulated by Markowitz (1952). The approach defines the risk as the variance of the portfolio return. The domestic investor chooses the proportion of his wealth portfolio to invest in foreign asset (w_f) and domestic asset ($1 - w_f$) to maximize his objective utility function given by:

$$U(w_f) = \mu_P(w_f) - \frac{\gamma}{2} v_P(w_f) \quad (2.8)$$

where μ_P , v_P are respectively the portfolio's mean return and variance. γ is the investor's risk aversion coefficient. The investor's objective function increases with the portfolio mean return and decreases with its variability. $\mu_d(\sigma_d)$ and $\mu_f(\sigma_f)$ denote as the expected returns (volatilities) of the domestic and foreign assets, respectively. The proportion of the foreign asset that maximizes the investor's objective function is given by:

$$w_f^* = \frac{1}{\gamma} \frac{(\mu_f - \mu_d)}{\sigma_f^2 - 2\rho\sigma_f\sigma_d + \sigma_d^2} + \frac{\sigma_d(\sigma_d - \rho\sigma_f)}{\sigma_f^2 - 2\rho\sigma_f\sigma_d + \sigma_d^2} \quad (2.9)$$

where ρ is the correlation coefficient between domestic and foreign assets.

The optimal proportion of foreign asset is composed of two terms. The first one represents the demand stemming from a higher potential return of the foreign asset. This term decreases with the investor's risk aversion. The second term represents the demand of foreign asset that minimizes the portfolio variance. The first order derivative of the optimal proportion of the

foreign asset per correlation is:

$$\frac{dw_f^*}{d\rho} = \frac{1}{\gamma} \frac{2\sigma_f\sigma_d(\mu_f - \mu_d)}{(\sigma_f^2 - 2\rho\sigma_f\sigma_d + \sigma_d^2)^2} + \frac{\sigma_f\sigma_d(\sigma_d^2 - \sigma_f^2)}{(\sigma_f^2 - 2\rho\sigma_f\sigma_d + \sigma_d^2)^2} \quad (2.10)$$

The optimal proportion of the foreign asset in Eq. 2.9 is thus a decreasing function of the correlation if :

$$\sigma_d^2 + \frac{2}{\gamma}(\mu_f - \mu_d) < \sigma_f^2 \quad (2.11)$$

This condition is verified if the domestic asset has a higher expected return and a lower variability than the foreign asset.

The optimal weight of the foreign asset can be approximated by the second term in Eq. 2.9 (minimum variance portfolio) for conservative investors with high risk aversion levels.⁷ In that case, an increase in the correlation between assets will lead to a decrease on the demand of foreign asset provided that the volatility of the foreign asset is greater than the domestic one . In practice, it is likely that the foreign asset's volatility is higher than the domestic asset one, given that the variability of the domestic asset only depends on the stock market whereas the variability of foreign asset depends on the foreign market and the variability of the domestic investor's exchange rate against foreign currency.

The correlation of two assets can be seen as the sum of two components. The first one represents the correlation arising from comovement of smooth returns of two assets whereas the second one represents the correlation stemming from simultaneous jumps. Indeed, the expression of the realized correlation (RC) of assets i and j over a time period $[0, T]$ is given

⁷The demand of the foreign asset is also given by the minimum variance portfolio if the difference between domestic and foreign expected returns is not significantly different from zero.

by:

$$\begin{aligned}
 RC &= \frac{\sum_{k=1}^N r_{i,k} r_{j,k}}{\sqrt{\sum_{k=1}^N r_{i,k}^2 \sum_{k=1}^N r_{j,k}^2}} \\
 &= \frac{\sum_{k=1}^N r_{i,k} r_{j,k} 1_{\left\{\frac{|r_{i,k}|}{\hat{\sigma}_{i,k}} \leq \theta\right\}} 1_{\left\{\frac{|r_{j,k}|}{\hat{\sigma}_{j,k}} \leq \theta\right\}}}{\sqrt{\sum_{k=1}^N r_{i,k}^2 \sum_{k=1}^N r_{j,k}^2}} + \frac{\sum_{k=1}^N r_{i,k} r_{j,k} 1_{\left\{\frac{|r_{i,k}|}{\hat{\sigma}_{i,k}} > \theta\right\}} 1_{\left\{\frac{|r_{j,k}|}{\hat{\sigma}_{j,k}} > \theta\right\}}}{\sqrt{\sum_{k=1}^N r_{i,k}^2 \sum_{k=1}^N r_{j,k}^2}}
 \end{aligned}$$

where $r_{i,k}$ and $r_{j,k}$ are the intraday returns of respectively the i^{th} and j^{th} assets over the k^{th} intraday time interval. N is the number of intraday returns over the time period $[0, T]$. The indicator functions are introduced to disentangle jumps from smooth intraday returns. We assume that the diffusive and jump parts of the return are independent.⁸ We use the estimator provided by Jacod and Todorov (2009) to estimate the realized correlation between assets jumps. This estimator has the advantage to be robust to the jump identification procedure and it is given by:

$$\rho_{i,j}^{jump} = \frac{\sum_{k=1}^N r_{i,k}^2 r_{j,k}^2}{\sqrt{\sum_{k=1}^N r_{i,k}^4 \sum_{k=1}^N r_{j,k}^4}} \quad (2.12)$$

The jump correlation increases with the intensity and the size of cojumps. The squared returns are introduced to filter out smooth returns. As a result, the numerator in the above equation only takes into account simultaneous jumps whereas the denominator is calculated using assets jumps that occurs simultaneously or not. We also introduce the formula that we

⁸This assumption is supported by the fact that the two return components are not determined by the same sources of risk. While fundamental factors such as firm-specific characteristics (e.g., size, earnings, leverage, dividend, and momentum) and macroeconomic variables (e.g., economic growth, interest rate, inflation, and exchange rates) derive smooth price movements, infrequent and large price changes (jumps) are generated by the arrival of important news. For instance, Bollerslev and Todorov (2011) show that jump risk requires a different premium.

will use to estimate the correlation of respectively positive and negative jumps.

$$\rho_{i,j}^{jump,up} = \frac{\sum_{k=1}^N r_{i,k}^2 r_{j,k}^2 1_{\{r_{i,k}>0\}} 1_{\{r_{j,k}>0\}}}{\sqrt{\sum_{k=1}^N r_{i,k}^4 1_{\{r_{i,k}>0\}} \sum_{k=1}^N r_{j,k}^4 1_{\{r_{j,k}>0\}}}} \quad (2.13)$$

$$\rho_{i,j}^{jump,down} = \frac{\sum_{k=1}^N r_{i,k}^2 r_{j,k}^2 1_{\{r_{i,k}<0\}} 1_{\{r_{j,k}<0\}}}{\sqrt{\sum_{k=1}^N r_{i,k}^4 1_{\{r_{i,k}<0\}} \sum_{k=1}^N r_{j,k}^4 1_{\{r_{j,k}<0\}}}} \quad (2.14)$$

In our study, we examine how cojumps between domestic and foreign assets affect the demand of foreign assets. We hypothesize the correlation of jumps between US stock market and foreign stock markets decreases the demand of foreign assets of an US representative investor.

General case

We now consider the general case where the investor selects his portfolio composition based on n assets: one domestic risky asset and $n - 1$ foreign risky assets. We suppose that all asset returns are expressed in the investor's domestic currency. The investor allocates funds across n assets in a way to maximize his utility function as follows:

$$\begin{aligned} \max_w & \left(\mu'w - \frac{\gamma}{2} w' \Sigma w \right) \\ \text{subject to } & e'w = 1 \end{aligned} \quad (2.15)$$

where $w = (w_1, w_2, \dots, w_n)'$ is the vector of portfolio weights and $\mu = (\mu_1, \mu_2, \dots, \mu_n)'$ is the vector of expected returns. $\Sigma = \text{cov}(r_i, r_k)_{1 \leq i, k \leq n}$ the variance-covariance matrix of returns. $e = (1, 1, \dots, 1)'$ denotes the vector of ones. The optimal weights that maximize the investor's utility are given by:

$$w^* = \frac{1}{\gamma} \Sigma^{-1} \mu + \left(1 - \frac{e' \Sigma^{-1} \mu}{\gamma} \right) \frac{\Sigma^{-1} e}{e' \Sigma^{-1} e}$$

where Σ^{-1} is the inverse of the returns covariance matrix.

If the coefficient of the risk aversion γ goes to infinity, we get the optimal weights that minimize the portfolio variance.⁹

$$w^* = \frac{\Sigma^{-1}e}{e'\Sigma^{-1}e}$$

It is established that if the investors have a quadratic utility or asset returns are normally distributed, the mean-variance framework is sufficient to obtain the optimal portfolio weights. To the extent that asset returns are non-normal in the presence of jumps, higher-order moments of the return distribution should be considered in the portfolio optimization problem.

Moreover, the variance, as a symmetric risk measure, fails to differentiate between the upside and downside risks, and often leads to an overestimation of the risk for positively skewed distribution and an underestimation of the risk for negatively skewed distribution. It is also unable to capture the risk of extreme events (large losses and large gains) when returns follow a fat-tailed distribution. Since investors are more concerned about extremely negative movements of asset returns, they pay a particular attention to the downside risk when selecting portfolio assets. The issue of the portfolio allocation under the non-normality of asset returns has been widely studied and several alternatives to the standard mean-variance framework have been proposed by, among others, Jondeau and Rockinger (2006) and Guidolin and Timmermann (2008). These two studies have extended the mean-variance framework to cover higher moments of asset returns by approximating the expected utility using Taylor series expansions. Other studies have considered the downside risk in portfolio optimization and allocation, and proposed several percentile risk measures as an alternative to the variance such as Value-at-Risk or VaR (Basak and Shapiro, 2001; Gaivoronski and Pflug, 1999) and Conditional Value-at-Risk or CVaR (Rockafellar and Uryasev, 2000 and 2002; Krokhmal et al., 2002). The CVaR is also known as mean excess loss, mean shortfall, or tail VaR.

⁹The minimum variance portfolio has the advantage to be robust to the estimation error of expected returns.

The VaR is an estimate of the upper percentile of loss distribution. It is calculated for specified confidence level over a certain period of time. The VaR is widely used by financial practitioners to manage and control risks. On other hand, the CVaR of a portfolio represents the conditional expectation of losses that exceeds the VaR. This definition ensures that VaR is never higher than the CVaR. In portfolio optimization, the CVaR has more attractive financial and mathematical properties than the VaR. Indeed, the CVaR is sub-additive and convex (Rockafellar and Uryasev, 2000) which can provide stable and efficient estimates, and is also considered as a coherent risk measure (Artzner et al., 1997; 1999; Pflug, 2000).¹⁰

The mean-CVaR portfolio problem under budget's constraint (weights summing to 1) and a target portfolios expected return $\bar{\mu}$ is formulated as follows:¹¹

$$\begin{aligned} \min_{\alpha, w} \quad & \alpha + \frac{1}{q(1-\beta)} \sum_{i=1}^q u_i \\ \text{subject to} \quad & \begin{cases} e'w = 1, \quad u_i \geq 0 \\ \mu'w = \bar{\mu} \\ u_i + w'r^{(i)} + \alpha \geq 0, \quad i = 1, \dots, q \end{cases} \end{aligned} \quad (2.16)$$

where α is the VaR of the portfolio loss function. β is the confidence level of the VaR and CVaR and $(r^{(1)}, r^{(2)}, \dots, r^{(q)})$ is a random collection of the vector of returns $r = (r_1, r_2, \dots, r_n)'$. u_i is an auxiliary variable defined in Appendix 2.B.

The mean-CVaR optimization problem in Eq. 2.16 can be solved using linear programming techniques. We note that if asset returns are normally distributed and $\beta \geq 0.5$, the values of the mean-variance and mean-CVaR approaches are equivalent and give the same optimal portfolio weights (Rockafellar and Uryasev, 2000). In this paper, we consider both approaches to determine the optimal portfolio composition and examine how the departure from the

¹⁰The lack of sub-additivity implies that VaR of a portfolio with two instruments may be greater than the sum of the individual VaRs of these two instruments (Artzner et al., 1997; 1999). Additionally, since the VaR is non-convex and non-smooth, the portfolio optimization may become very unstable and lead to multiple local extrema.

¹¹See Appendix 2.B for more details about the mean-CVaR optimization problem.

normality caused by the presence of jumps affects the optimal portfolio composition.

2.3.2 Optimal portfolio composition and jump higher-order moments

Asset returns dynamics

In what follows, we introduce a jump-diffusion model that accommodates both systematic and idiosyncratic jumps in asset prices. Systematic jumps are defined as jumps that occur simultaneously across all assets whereas idiosyncratic jumps are asset-specific. Our model also allows for asymmetric effects between positive and negative jumps. The price dynamics of the i^{th} asset is given by:¹²

$$\frac{dS_{t,i}}{S_{t,i}} = \mu_i dt + \sigma_i dZ_{t,i} + \sum_{x \in (up, down)} J_i^{sys,x} dQ^{sys,x} + \sum_{x \in (up, down)} J_i^{id,x} dQ_i^{id,x} \quad (2.17)$$

where $i = 1, \dots, n$ and $0 \leq t \leq T$.

The price process is composed of two components : a diffusion component with a drift μ_i and a volatility σ_i and a jump component that covers the upside and downside changes of both idiosyncratic and systematic price jumps. The upside (downside) jump is a jump with positive (negative) return. The upside systematic jump (respectively downside systematic, upside idiosyncratic and downside idiosyncratic) is characterized with a jump amplitude $J_i^{sys,up}$ (respectively $J_i^{sys,down}$, $J_i^{id,up}$ and $J_i^{id,down}$) and a Poisson process $Q^{sys,up}$ (respectively $Q^{sys,down}$, $Q_i^{id,up}$ and $Q_i^{id,down}$) with intensity $\lambda^{sys,up}$ (respectively $\lambda^{sys,down}$, $\lambda_i^{id,up}$ and $\lambda_i^{id,down}$). We assume that the Brownian motion $Z_{t,i}$, the jump amplitudes and their corresponding Poisson processes are independent and that the jump size $\tilde{J}_i^x = \log(1 + J_i^x)$ has a normal distribution with mean μ_i^x and variance $(\nu_i^x)^2$, where $x \in (sys, up; sys, down; id, up; id, down)$. We also assume that, conditional on a systematic (either positive or negative) jump, the systematic jump sizes are perfectly correlated across assets. We note $\rho_{i,j}$ the correlation coefficient between the Brownian motions of the i^{th} and j^{th} assets. All model parameters are assumed to

¹²This process is an extension of the multivariate jump-diffusion model proposed by Das and Uppal 2004.

be constant over time.¹³

By applying Ito's lemma to the jump-diffusion process, we obtain:

$$d \log(S_{t,i}) = (\mu_i - \frac{\sigma_i^2}{2})dt + \sigma_i dZ_{t,i} + \sum_{x \in (up, down)} J_i^{sys,x} dQ^{sys,x} + \sum_{x \in (up, down)} \tilde{J}_i^{id,x} dQ_i^{id,x}$$

The above stochastic process is useful for model parameters estimation, which is essentially based on the results of jump identification and the method of moments. We first identify all intraday jumps for each asset by applying the LM-ABD technique. We then classify the detected jumps into systematic and idiosyncratic jumps using the co-exceedance rule. The estimate of the intensity of systematic upside (respectively systematic downside, idiosyncratic upside and idiosyncratic downside) jumps is given by the ratio of the number of occurrences of systematic upside (respectively systematic downside, idiosyncratic upside and idiosyncratic downside) jumps to the total number of intraday time intervals over the estimation period. As jump sizes are normally distributed, we estimate the mean and the variance of each distribution from the empirical mean and variance of its corresponding detected jump returns. Finally, we use the method of moments to estimate the diffusive drift vector and the diffusive variance-covariance matrix of the multivariate price processes. For each asset i , the diffusive drift μ_i is set so that the sum of the diffusive and jump mean returns are equal to the mean of total price return:

$$\mu_i - \frac{\sigma_i^2}{2} + \sum_{x \in (up, down)} \lambda^{sys,x} \mu_i^{sys,x} + \sum_{x \in (up, down)} \lambda_i^{id,x} \mu_i^{id,x} = \frac{1}{N} \sum_{k=1}^N r_{i,k}$$

Similarly, the diffusive covariance between two assets i and j , $\{\rho_{i,j} \sigma_i \sigma_j\}_{i,j}$, is set so that the sum of the diffusive and jump covariance components are equal to the total covariance

¹³These assumptions aim to simplify the model calibration and will thus enable us to focus on studying the effects of jump higher-order moments on optimal portfolio composition.

between the two asset returns:¹⁴

$$\begin{aligned} \rho_{i,j}\sigma_i\sigma_j + \sum_{x \in (up, down)} \lambda^{sys,x} (\mu_i^{sys,x} \mu_j^{sys,x} + \nu_i^{sys,x} \nu_j^{sys,x}) + \sum_{x \in (up, down)} \lambda_i^{id,x} (\mu_i^{id,x} \mu_j^{id,x} + \nu_i^{id,x} \nu_j^{id,x}) \\ = \frac{1}{N} \sum_{k=1}^N r_{i,k} r_{j,k} \end{aligned}$$

The method of moments is appropriate for our context because we want to choose the parameters of the multivariate jump-diffusion processes in such a way that the first two moments of the jump-diffusion returns match exactly the first two moments of the pure-diffusion returns. This will then allow us to compare the optimal portfolio weights for an investor who recognizes idiosyncratic and systematic jumps and another investor who ignores them. By matching the first two moments of the pure-diffusion and jump-diffusion returns, we are able to disentangle the difference between two portfolio compositions that is attributed to jump higher-order moments while keeping the impact of the first two moments of returns on the optimal portfolio composition of both investors the same.

Optimal portfolio weights

We now derive the optimal portfolio weights for a representative domestic investor when returns are given by the multivariate jump diffusion process described in Eq. 2.17. The investor selects his portfolio composition based on one riskless asset with an instantaneous riskless rate r , one domestic risky asset and $n - 1$ foreign risky assets. All asset returns are expressed in the investor's domestic currency. The investor wants to maximize the expected utility from terminal wealth W_T under his budget constraint (weights summing to 1). The

¹⁴In our experiment, we have three assets, corresponding to eight diffusive parameters to estimate (three diffusive drifts, three diffusive variances and two diffusive correlations) from eight moment conditions. Each moment condition is then used to estimate its corresponding parameter. The estimation problem thus leads to a unique solution.

investor's problem at time t is given by :

$$\begin{aligned} V(t, W_t) &= \max_w E[U(W_T)] \\ \text{subject to } e'w + w_0 &= 1 \end{aligned} \quad (2.18)$$

where $w = (w_1, w_2, \dots, w_n)'$ is the vector of portfolio weights of n risky assets. w_0 is the weight of the riskless asset and $e = (1, 1, \dots, 1)'$ denotes the vector of ones. U is the CRRA utility function with a constant relative risk aversion (CRRA) coefficient γ :

$$U(W_T) = \begin{cases} \frac{W_T^{1-\gamma}}{1-\gamma} & \text{if } \gamma \neq 1 \\ \log(W_T) & \text{if } \gamma = 1 \end{cases}$$

Using stochastic dynamic programming techniques, we can express the vector of optimal portfolio weights w as a solution of a system of n nonlinear equations as follows :¹⁵

$$\mathbf{0} = R - \gamma \Sigma w + \sum_{x \in (up, down)} \lambda^{sys, x} E[J^{sys, x} (1 + w' J^{sys, x})^{-\gamma}] + \sum_{x \in (up, down)} \lambda^{id, x} \cdot E[J^{id, x} \cdot (e + w \cdot J^{id, x})^{-\gamma}] \quad (2.19)$$

where $\mathbf{0} = (0, 0, \dots, 0)'$ is the vector of zeros. $R = (\mu_1 - r, \mu_2 - r, \dots, \mu_n - r)'$ is the diffusive excess-returns vector. $\Sigma = (\rho_{i,j} \sigma_i \sigma_j)_{1 \leq i, j \leq n}$ is the covariance matrix of the diffusive returns. $\lambda^{id, x} = (\lambda_1^{id, x}, \lambda_2^{id, x}, \dots, \lambda_n^{id, x})'$ is the vector of idiosyncratic (up or down) jump intensities. $J^{id, x} = (J_1^{id, x}, J_2^{id, x}, \dots, J_n^{id, x})'$ is the vector of idiosyncratic (up or down) jump amplitudes whereas $J^{sys, x} = (J_1^{sys, x}, J_2^{sys, x}, \dots, J_n^{sys, x})'$ denotes the vector of systematic (up or down) jump amplitudes. The \cdot operator denotes the element- by-element multiplication of two equally sized vectors.

The above system of non-linear equations can be solved numerically, which we do in Section 2.5.3. In the case of a pure-diffusion investor ($\lambda^{sys, x} = 0; \lambda^{id, x} = \mathbf{0}$), Eq. 2.19 leads to

¹⁵The detailed resolution of the portfolio maximization problem is provided in Appendix 2.C.

the same solution as the quadratic utility maximization problem presented in Section 2.3.1:

$$w^* = \frac{1}{\gamma} \Sigma^{-1} R$$

In what follows, we try to provide some insights on how higher-order moments of returns affect the optimal portfolio composition by considering the case when there is one risky asset and approximate the non-linear term of Eq. 2.19 using a second-order Taylor approximation:¹⁶

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$$(1 + w_1 J_1^{sys,x})^{-\gamma} \approx 1 - \gamma(w_1 J_1^{sys,x}) + \frac{\gamma(\gamma + 1)}{2} (w_1 J_1^{sys,x})^2$$

$$(1 + w_1 J_1^{id,x})^{-\gamma} \approx 1 - \gamma(w_1 J_1^{id,x}) + \frac{\gamma(\gamma + 1)}{2} (w_1 J_1^{id,x})^2$$

Using these approximations, the optimal weight w_1 of the risky asset is the solution of the following quadratic equation:

$$0 = \mu_1^t - \gamma v_1^t w_1 + \frac{\gamma(\gamma + 1)}{2} s_1^t w_1^2$$

where :

$$\mu_1^t = \mu_1 + \sum_{x \in (up, down)} \lambda^{sys,x} \mu_1^{sys,x} + \sum_{x \in (up, down)} \lambda_1^{id,x} \mu_1^{id,x} - r$$

$$v_1^t = \sigma_1^2 + \sum_{x \in (up, down)} \lambda^{sys,x} [(\mu_1^{sys,x})^2 + (\nu_1^{sys,x})^2] + \sum_{x \in (up, down)} \lambda_1^{id,x} [(\mu_1^{id,x})^2 + (\nu_1^{id,x})^2]$$

$$s_1^t = \sum_{x \in (up, down)} \lambda^{sys,x} \mu_1^{sys,x} [(\mu_1^{sys,x})^2 + 3(\nu_1^{sys,x})^2] + \sum_{x \in (up, down)} \lambda_1^{id,x} \mu_1^{id,x} [(\mu_1^{id,x})^2 + 3(\nu_1^{id,x})^2]$$

μ_1^t , v_1^t and s_1^t are respectively the total (the sum of both the diffusive and jump components) mean excess return, variance and skewness of the risky asset. Note that the skewness depends only on the jump component of the price process.

¹⁶We also employ a Taylor series expansion to approximate the jump amplitude $J_1^{sys,x} = e^{J_1^{sys,x}} - 1 \approx J_1^{sys,x}$.

¹⁷We choose to study the case of a portfolio composed of one risky asset in order to simplify the resolution of Eq. 2.19. By using a second-order Taylor approximation, we only consider the role of the skewness in determining the optimal portfolio composition. The impact of all higher-order moments is considered by resolving numerically Eq. 2.19 in Section 2.5.3.

The explicit expression of the optimal risky asset weight is given by:

$$w_1^* \approx \frac{2\mu_1^t}{\gamma v_1^t + \sqrt{\gamma^2 (v_1^t)^2 - 2\gamma(\gamma + 1)\mu_1^t s_1^t}}$$

Note that the optimal weight only depends on the first three moments of the return process because we only consider the first three terms in the Taylor series approximation.

If we consider an investor who ignores the idiosyncratic and systematic jumps and assumes a pure-diffusion model for the price process, the optimal risky asset weight can be written as:¹⁸

$$w_1^* \approx \frac{\mu_1^t}{\gamma v_1^t}$$

The difference between the optimal portfolio composition of the investor who considers idiosyncratic and systematic jumps and the investor who ignores jumps depends on the sign of the jump skewness s_1^t . If the skewness is negative, the investor who accounts for jumps will invest less in risky asset than the investor who ignores jumps. This result can be generalized to the case with several risky assets. The jump-diffusion investor will invest less in risky assets than the diffusion investor if the skewness and co-skewness of asset returns are negative. Also, the investor who considers jump risks will prefer risky assets with better higher-order moments (higher skewness and co-skewness and lower kurtosis and co-kurtosis).¹⁹

2.4 Data

We use intraday data of three international exchange-traded funds: SPDR S&P 500 (SPY), iShares MSCI EAFE (EFA) and iShares MSCI Emerging Markets (EEM). The SPDR S&P 500 ETF aims to replicate the performance of S&P 500 index by holding a portfolio of the common stocks that are included in the index, with the weight of each stock in the portfolio substantially corresponding to the weight of such stock in the index. The S&P 500 index

¹⁸ μ_1^t and v_1^t estimates are the same for both the pure-diffusion and jump-diffusion processes.

¹⁹Higher-order co-moments are only induced by systematic jumps.

is a US stock market index containing the stocks of 500 large-Cap corporations, and thus a proxy for the whole US stock market. The iShares MSCI EAFE ETF aims to replicate the performance of the MSCI EAFE index, which captures the stock market performance of developed markets outside of the US and Canada and thus a proxy for Europe, Australia and Far East equity markets. The iShares Emerging Markets ETF seeks to replicate the performance of the MSCI Emerging Markets index. The latter captures the stock market performance of emerging markets, currently covers over 800 securities across 21 markets, and represents approximately 11% of world market cap. Our empirical analysis is based on intraday prices of the three funds from January 2008 to October 2013. Prices are sampled every five minutes from 9:30 am to 15:55 pm (UTC-4 time zone) to smooth the impact of market microstructure noise.

2.5 Empirical findings

2.5.1 Intraday jump identification

This section summarizes the results from applying LM-ABD intraday jump detection test. A particular attention is given to the intraday volatility pattern (Dumitru and Urga, 2012), which can lead to spurious jump detection. We correct the intraday volatility pattern using a jump robust corrector proposed by Bollerslev et al. (2008) to improve the robustness of our jump detection procedure.²⁰

We estimate the realized bipower variation using a window of 155 intraday returns, which corresponds to two days of intraday returns sampled at a frequency of five minutes. Jumps are detected with a threshold value $\theta = 4$, which means that the intraday jump return size is at least four times greater than the estimate of the local volatility. We also apply threshold values of 3 and 5 to study the robustness of our results.²¹

²⁰Appendix 2.A provides a detailed description of the volatility pattern corrector used in our study.

²¹Detailed results for the threshold values of 3 and 5 are available upon request.

Table 2.1: Summary statistics of jump occurrences, jump sizes and intraday returns.

This table shows summary statistics of total and jump returns in Panels A and B, respectively. Jumps statistics include the total number of jumps, positive and negative jumps, mean, standard deviation, skewness and kurtosis of jump returns of the three ETFs including SPY, EFA, and EEM. The percentage of positive jumps and negative jumps from all jumps are reported in brackets next to the number of positive and negative jumps. Jumps are detected using the LM-ABD procedure with a critical value $\theta = 4$. See Section 2.2 for the detail of jump test statistics. The intraday prices of the three ETFs from January 2008 to October 2013 are included. Prices are sampled every five minutes from 9:30 am to 15:55 pm.

	SPY	EFA	EEM
Panel A: Jumps statistics			
Intraday jumps	1119	1114	1024
Positive jumps	475 (42%)	495 (44%)	455 (44%)
Negative jumps	644 (58%)	619 (56%)	569 (56%)
Mean of jump returns	-4.3e-04	-2.5e-04	-2.1e-04
Std of jump returns	0.0048	0.0047	0.0058
Skewness of jump returns	-0.59	0.27	-0.006
Kurtosis of jump returns	14.00	8.40	15.60
Panel B: Returns statistics			
Mean of total returns	2.4e-06	4.7e-06	3.5e-06
Std of total returns	0.0014	0.0013	0.0017
Skewness of total returns	-0.12	0.11	0.09
Kurtosis of total returns	36.66	24.40	38.33

Table 2.1 provides the number of total, positive and negative intraday jumps detected over the study period. We identify 1119, 1114 and 1024 intraday jumps for SPY, EFA and EEM funds respectively, or 0.989%, 0.986% and 0.900% of the total number of intraday returns. The number of detected intraday jumps is higher in developed markets (US and EFA) than in emerging markets, suggesting a higher degree of asset comovement within developed markets. A positive (negative) jump is a jump with positive (negative) return. The results show that the number of negative jumps is more than 56% of total number of detected jumps for each fund. Stock markets thus tend to experience more price jumps when markets are bearish. Table 2.1 also reveals that the mean of intraday jump returns of SPY (-4.3e-04) in absolute value is two times higher than the one for EFA and EEM (-2.5e-04 and -2.1e-04, respectively).

This result indicates that negative intraday price movements are larger for the US market. However, the intraday jump return volatility is higher for emerging markets (0.0058) than for developed ones (around 0.0047).

At a daily level, Table 2.2 shows that the percentage number of days with at least one intraday jump is around 40% of the total number of days of the study period (1468 days). The high proportion of jump days might be explained by a higher jump activity during the financial crisis period. It is also related to the high level of sampling frequency (five minutes) used in our paper.

Table 2.3 shows some statistics of detected cojumps. Over the study period, we find 585 cojumps between SPY and EFA funds, 509 cojumps between EEM and SPY funds, and 458 cojumps between EEM and EFA funds. This finding indicates that developed equity markets are more linked to the US market than emerging markets. The three funds are involved in 365 cojumps, with the number of negative cojumps (61%) being higher than positive cojumps.

Table 2.2: Summary statistics of jump occurrences at day level.

This table presents the number of days with no jumps, one jump, and two jumps up to more than 5 jumps of the price of the three ETFs (SPY, EFA and EEM). The last row shows the percentage of days with at least one jump. Jumps are detected using LM-ABD procedure with a critical value $\theta = 4$. See Section 2.2 for the detail of jump test statistics. The intraday prices of the three ETFs from January 2008 to October 2013 are included. Prices are sampled every five minutes from 9:30 am to 15:55 pm.

	SPY	EFA	EEM
0	843	843	879
1	357	365	353
2	139	147	128
3	75	50	60
4	30	37	26
5	12	13	9
More than 5	12	13	13
At least one jump	42%	42%	40%

Table 2.3: Summary statistics of cojump occurrences.

This table reports the number of total positive and negative detected cojumps among ETFs including SPY and EFA (column 1), SPY and EEM (column 2), EFA and EEM (column 3) and SPY, EFA and EEM (column 4). The percentage of cojumps compared to the total number of detected jumps is shown in brackets next to intraday cojumps. Jumps are detected using the LM-ABD procedure with a critical value $\theta = 4$. See Section 2.2 for the detail of jump and cojump identification procedure. The intraday prices of the three ETFs from January 2008 to October 2013 are included. Prices are sampled every five minutes from 9:30 am to 15:55 pm.

	SPY / EFA	SPY/EEM	EFA/EEM	SPY/EFA/EEM
Intraday cojumps	585 (53%)	509 (50%)	458 (45%)	365 (36%)
Positive cojumps	242	203	193	144
Negative cojumps	343	306	265	221

Table 2.4 shows the probability to have at least one cojump between SPY and EFA is 0.27 at the daily level. This probability is lower for SPY and EEM (0.23) and for EFA and EEM (0.22). The probability that the three funds simultaneously experience a cojump is 0.18.

Table 2.4: Summary statistics of cojump occurrences at day level.

This table presents the number of days with no cojumps, one cojump, two cojumps up to more than four cojumps among ETFs including SPY and EFA in column 2, SPY and EEM in column 3, EFA and EEM in column 4, and SPY, EFA, and EEM in column 5. The last row shows the percentage of days with at least one cojump. Jumps are detected using the LM-ABD procedure with a critical value $\theta = 4$. See Section 2.2 for jump and cojump identification procedure. The intraday prices of the three funds are from January 2008 to October 2013. Prices are sampled every five minutes from 9:30 am to 15:55 pm.

	SPY/EFA	SPY/EEM	EFA/EEM	SPY/EFA/EEM
0	1071	1130	1147	1208
1	282	233	233	193
2	70	61	57	39
3	27	28	19	20
4	12	11	6	5
More than 4	3	5	6	3
At least one cojump	27%	23%	22%	18%

Table 2.5: Summary statistics of cojumps between EUR/USD exchange rate and international equity funds.

The number of detected cojumps between EUR/USD exchange rate and respectively SPY (row 2), EFA (row 3), EEM (row 4), SPY and EFA (row 5), SPY and EEM (row 6), EFA and EEM (row 7) are reported. The percentage of cojumps compared to the total number of detected jumps is shown in brackets next to intraday cojumps. Jumps are detected using the LM-ABD procedure with a critical value $\theta = 4$. See Section 2.2 for jump and cojump identification procedure. The sample includes the intraday prices of the three ETFs from January 2008 to October 2013. Prices are sampled every five minutes from 9:30 am to 15:55 pm.

	EUR/USD
SPY	162 (14.48%)
EFA	268 (24.06%)
EEM	162 (15.82%)
SPY/EFA	133 (11.94%)
SPY/EEM	110 (10.75%)
SPY/EFA/EEM	101 (9.86%)

We also examine if detected jumps and cojumps can be explained by exchange rates movements. Table 2.5 reports the number of cojumps that involve EUR/USD exchange rate with one or more of the three funds. We apply EUR and USD as they are the two major currencies in the world. The probability of cojumps between the EUR/USD and EFA is the highest (24%) whereas the probability of cojumps with SPY and EEM is respectively 14% and 16%. The exposure to currency risk is relatively higher for EFA given that it is composed largely of stocks that are quoted in EUR whereas the whole fund is traded in USD. The probability that two or three funds jump at the same time as the EUR/USD exchange rate remains less than 12%. These results suggest that only 12% of detected cojumps of three funds are induced by exchange rate movements.

To examine the variation of the jump and cojump intensities over time, we calculate the time-varying daily intensities of jumps (JI) and cojumps (CJI) using a rolling 6-month window of observations as follows:

$$JI = \frac{\sum_k 1_{\{Jump_k^i\}}}{N_{days}} \quad \text{and} \quad CJI = \frac{\sum_k 1_{\{Jump_k^i \cap Jump_k^j\}}}{N_{days}}$$

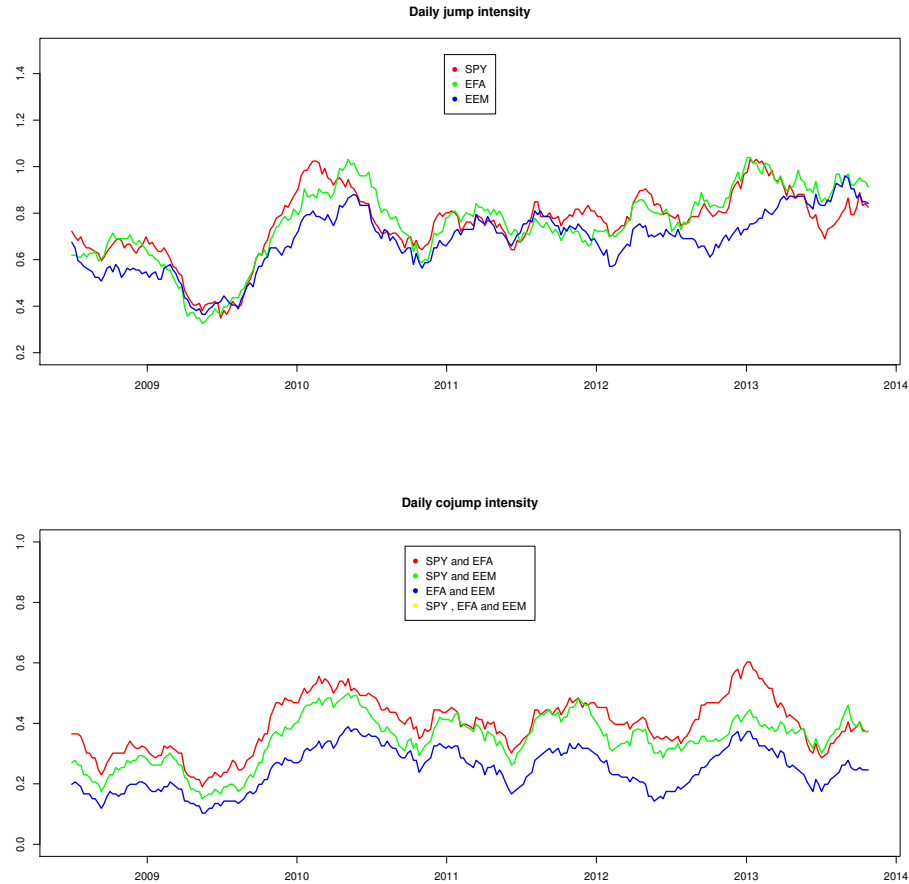


Figure 2.1: Jump and cojump occurrences.

These figures show the variation of the daily jump and cojump intensities of the three funds (SPY, EFA, and EEM) from January 2008 to October 2013. The daily intensity of jumps (cojumps) is defined as the daily average number of jumps (cojumps that involve two or three funds). These time-varying jump intensities are calculated weekly using a rolling six-month window of observations. Prices are sampled every five minutes from 9:30 am to 15:55 pm. Jumps are detected using the LM-ABD procedure with a critical value $\theta = 4$. See Section 2.2 for jump and cojump identification procedure.

where N_{days} is the number of days of the observation period (120 business days in our case). $1_{\{Jump_k^i\}}$ is an indicator function of jump occurrence for the i^{th} asset at the intraday interval k . $1_{\{Jump_k^i \cap Jump_k^j\}}$ is an indicator function of cojump occurrence for the i^{th} and j^{th} assets at the intraday interval k .

Figure 2.1 uncovers that the daily jump and cojump intensities have significantly increased during the financial crisis of 2008-2009 for the three funds. There is a pattern that the US market was the first to reach the peak of the jump intensity during the crisis followed by other developed markets and then emerging markets, particularly during a peak in January 2010, a drop in December 2010, and a jump in December 2012. The results support the evidence in Ait-Sahalia et al. (2015). The cojump intensity is highest between funds of the US and other developed markets, followed by funds of the US and emerging markets, and finally the funds of other developed markets and emerging markets. The intensity of simultaneous jumps of three funds is lowest. Overall, the lead/lag interaction of jumps is similar to pattern of lead/lag during the financial crisis, i.e., the unusual increase of the intraday jumps seems to be triggered in the US market and then propagated to the rest of the world.

2.5.2 Time and space clustering of intraday jumps

This section examines the dependencies between intraday jumps both within and across markets. Figure 2.2 shows jumps in SPY tend to occur simultaneously with jumps in EFA and EEM and their cojumps are clustered during the periods from June 21, 2010 to June 24, 2010 and August 23, 2010 to August 27, 2010. Thus, international intraday jumps are likely to propagate both in time (in the same market) and in space (across markets).

We formally test jump propagation using the Hawkes process (Hawkes, 1971).²² This process is a self-excited point process whose intensity depends on the path followed by the point process and has been extensively used in different domains such as seismology and neurology, but only recently in finance to model the dynamics of microstructure prices (Lee

²²Note that this dependence pattern cannot be reproduced by the standard Poisson process, which assumes the hypothesis of independence of the increments (jumps in our case) on disjoint time intervals.

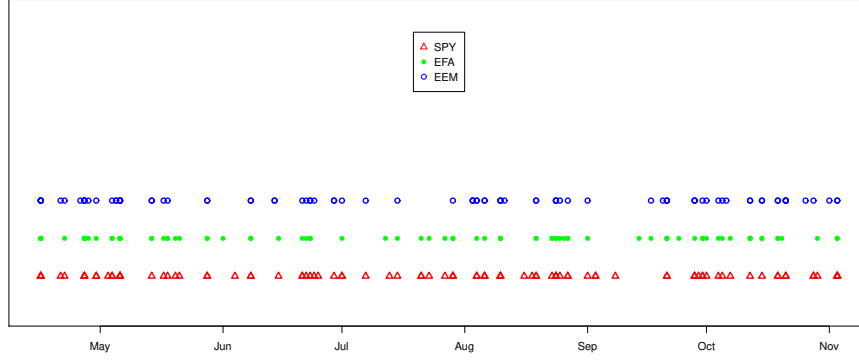


Figure 2.2: Time and space clustering of intraday jumps.

This figure shows the arrival times of intraday jumps of the three funds from April 2010 to November 2010. The intraday prices of the three ETFs including SPY, EFA, and EEM are included. Prices are sampled every five minutes from 9:30 am to 15:55 pm.

and Seo, 2017), trading activity, and asset jumps in financial markets (Ait-Sahalia et al., 2015; Bormetti et al., 2015). For example, Ait-Sahalia et al. (2015) use a multivariate Hawkes jump-diffusion model to investigate the financial contagion in the international equity markets at daily level. Bormetti et al. (2015) employ high frequency data and the Hawkes processes to reproduce the time clustering of jumps for 20 high-cap Italian stocks.

The univariate Hawkes process we use to capture the time clustering of intraday jumps for each of the ETFs is given by:

$$d\lambda_t = \beta(\lambda_\infty - \lambda_t)dt + \alpha dN_t \quad (2.20)$$

where N_t is the number of jumps occurring in the time interval $[0, t]$. A jump occurrence at a given time will increase the intensity or the probability of another jump (self excitation). The intensity increases by α whenever a jump occurs, and then decays back towards a level λ_∞ at a speed β . These parameters can be estimated using the maximum likelihood method.

Given the jump arrival times t_1, t_2, \dots, t_q , the likelihood function is written as:²³

$$L(t_1, t_2, \dots, t_q) = -\lambda_\infty t_q + \sum_{i=1}^q \frac{\alpha}{\beta} \left(e^{-\beta(t_q - t_i)} \right) + \sum_{i=1}^q \log(\lambda_\infty + \alpha A(i)) \quad (2.21)$$

where $A(i) = \sum_{t_j < t_i} e^{-\beta(t_i - t_j)}$ for $i \geq 2$ and $A(1) = 0$.

The univariate Hawkes process can be extended so that it captures the time and space clustering of intraday jumps between n markets, such as:

$$d\lambda_{i,t} = \beta_i(\lambda_{i,\infty} - \lambda_{i,t})dt + \sum_{j=1}^n \alpha_{i,j} dN_{j,t}, \quad i = 1, \dots, n \quad (2.22)$$

Under this model, a jump in market j increases not only the jump intensity within the same market through $\alpha_{j,j}$ (self excitation) but also the cross-market jump intensity through $\alpha_{i,j}$ (cross excitation). $\alpha_{j,j}$ implies a degree where jumps are re-created within the same market whereas $\alpha_{i,j}$ suggests the propagation rate of jumps from market j to market i . The jump intensity of market i reverts exponentially to its average level $\lambda_{i,\infty}$ at a speed β_i . Since the numerical resolution of the trivariate Hawkes model for three ETFs is problematic owing to the large number of parameters to be estimated, we limit the calibration procedure to the bivariate model whereby the vector of unknown parameters only contains 8 parameters, $\Theta = (\lambda_{1,\infty}, \lambda_{2,\infty}, \beta_1, \beta_2, \alpha_{1,1}, \alpha_{1,2}, \alpha_{2,1}, \alpha_{2,2})$, as follows:

$$\begin{cases} d\lambda_{1,t} = \beta_1(\lambda_{1,\infty} - \lambda_{1,t})dt + \alpha_{1,1}dN_{1,t} + \alpha_{1,2}dN_{2,t} \\ d\lambda_{2,t} = \beta_2(\lambda_{2,\infty} - \lambda_{2,t})dt + \alpha_{2,1}dN_{1,t} + \alpha_{2,2}dN_{2,t} \end{cases} \quad (2.23)$$

Panels A, B and C of Table 2.6 show the estimation results of the bivariate Hawkes model for SPY/EFA, SPY/EEM and EFA/EEM, respectively. All the model parameters are significant at conventional levels, implying that the bivariate Hawkes model satisfactorily fits the data of intraday jump occurrences of three funds.

²³See Ogata (1978) and Ozaki (1979) for the details of the maximum likelihood estimation.

Table 2.6: Maximum likelihood estimation of the bivariate Hawkes model.

The table below shows the results of the maximum likelihood estimation of the bivariate Hawkes model for pairs of ETFs including SPY/EFA (panel A), SPY/EEM (panel B) and EFA/EEM (panel C). See Section 2.5.2 for the detail of Hawkes process. The sample includes the intraday prices of the three ETFs from January 2008 to October 2013. Prices are sampled every five minutes from 9:30 am to 15:55 pm. The values of the estimate, standard error, z- statistic and p-value are reported for each parameter of the bivariate model. ***, **, and * represent 0.1 percent, 1 percent and 5 percent significance levels, respectively.

Panel A: SPY/EFA

	Estimate	Std. Error	z value	Pr(z)
$\lambda_{spy,\infty}$	1.6305e-03	6.4929e-05	25.1122	<2.2 e-16***
$\lambda_{efa,\infty}$	1.5445e-03	6.4217e-05	24.0505	<2.2 e-16 ***
β_{spy}	4.2957e-02	5.2288e-03	8.2154	<2.2 e-16 ***
β_{efa}	1.9230e-02	1.6585e-03	11.5942	<2.2 e-16 ***
$\alpha_{spy,spy}$	1.2004e-02	1.8520e-03	6.4816	9.074 e-11 ***
$\alpha_{spy,efa}$	1.7864e-03	5.5554e-04	3.2156	0.001302 **
$\alpha_{efa,efa}$	3.7166e-03	4.9845e-04	7.4563	8.896 e-14 ***
$\alpha_{efa,spy}$	2.4015e-03	4.6676e-04	5.1452	2.673 e-07 ***

Panel B: SPY/EEM

	Estimate	Std. Error	z value	Pr(z)
$\lambda_{spy,\infty}$	1.5452e-03	6.4580e-05	23.9268	<2.2 e-16***
$\lambda_{eem,\infty}$	1.4443e-03	6.3741e-05	22.6583	<2.2 e-16 ***
β_{spy}	1.8364e-02	1.6053e-03	11.4395	<2.2 e-16 ***
β_{eem}	1.8342e-02	1.6588e-03	11.0573	<2.2 e-16 ***
$\alpha_{spy,spy}$	4.0540e-03	5.3480e-04	7.5804	3.445 e-14***
$\alpha_{spy,eem}$	2.1598e-03	4.6120e-04	4.6829	2.828 e-06 ***
$\alpha_{eem,eem}$	3.8814e-03	5.5318e-04	7.0164	2.277 e-12 ***
$\alpha_{eem,spy}$	2.2278e-03	4.2694e-04	5.2181	1.808 e-07 ***

Panel C: EFA/EEM

	Estimate	Std. Error	z value	Pr(z)
$\lambda_{efa,\infty}$	1.5471e-03	6.2625e-05	24.7045	<2.2 e-16***
$\lambda_{eem,\infty}$	1.4194e-03	6.2419e-05	22.7400	<2.2 e-16 ***
β_{efa}	2.6309e-02	2.7030e-03	9.7335	<2.2 e-16 ***
β_{eem}	2.5798e-02	2.7876e-03	9.2544	<2.2 e-16 ***
$\alpha_{efa,efa}$	4.0065e-03	5.2480e-04	7.6342	2.272 e-14 ***
$\alpha_{efa,eem}$	2.1582e-03	4.7037e-04	4.5882	4.470 e-06 ***

$\alpha_{eem,eem}$	3.7661e-03	5.5861e-04	6.7418	1.564 e-11 ***
$\alpha_{eem,efa}$	2.5773e-03	4.4460e-04	5.7969	6.754 e-09 ***

The large value of the parameters $\alpha_{1,1}$ and $\alpha_{2,2}$ provides clear evidence that intraday jumps of the US market, other developed markets and emerging markets are strongly recreated within individual market. Panel A indicates that the self-excitation activity for the US market is higher than that of other developed markets. Compared to emerging markets, the self-excitation activity for the US (Panel B) and for the other developed market (Panel C) is greater. The higher degree of market efficiency in the US and other developed market might explain their high level of self-excitation activity. On the other hand, the value of the parameters $\alpha_{1,2}$ and $\alpha_{2,1}$, which measure the degree of jump transmission between markets, is smaller than the self-excitation parameters. The degree of jump transmission between markets is asymmetric with a stronger transmission from the US market to other developed markets ($\alpha_{efa,spy} = 2.40 \text{ e-03}$) than from the US market to emerging markets ($\alpha_{eem,spy} = 2.23 \text{ e-03}$). The transmission of jumps in the other way around is also significant but the strength is weaker. The emerging markets receive more jump spillover from the other developed markets than what they transmit to other markets.

2.5.3 Cojumps and optimal portfolio composition

We now examine the effect of cojumps on the optimal portfolio composition within the mean-variance and mean-CVaR frameworks from the US investor perspective. More precisely, we study how the demand of foreign assets varies with cojumps between domestic and foreign assets. The portfolio we consider is composed of one domestic asset (represented by the SPY fund) and two foreign assets (represented by EFA and EEM funds). All funds are expressed from the US investor's perspective and thus in USD. Assets weights can be negative, meaning that the domestic investor can take short position on the domestic and foreign assets. The demand of foreign assets is defined as the sum of optimal allocation weights of EFA and EEM funds resulting from our portfolio optimization procedure based on daily historical returns

(1469 observations for each fund) and the variance and CVaR approaches. The portfolio optimization is performed each week using a rolling window of about 120 daily returns (6 months) that immediately precede the optimization day. We also consider different rolling window sizes (3, 9, 12, 15 and 18 months), and the results remain intact.²⁴

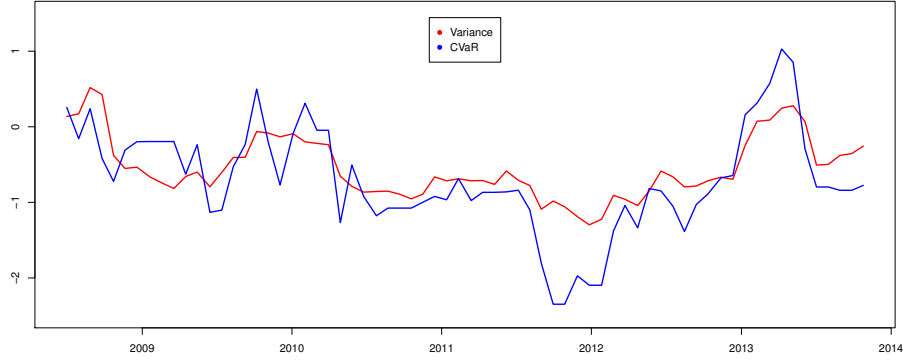


Figure 2.3: The variation of the optimal proportion of foreign assets.

This figure shows the variation of the optimal proportion of the foreign assets (EFA and EEM) obtained from variance and CVaR minimization approaches. The optimal portfolio composition is determined in a monthly basis, using a rolling six-month window of daily returns. The portfolio is composed of one domestic asset (SPY) and two foreign assets (EFA and EEM).

Our optimization problem consists of minimizing the portfolio risk (standard deviation or CVaR) under the budget's constraint of weights summing to one. Figure 2.3 shows the dynamic changes in the optimal proportion of the foreign assets (EFA and EEM) for variance and CVaR approaches. Both approaches lead to similar portfolio compositions over the study period, but the minimum CVaR portfolio composition is more volatile than the minimum variance portfolio. This might be because CVaR is determined using few extreme observations in the lower tail of the returns distribution whereas the variance takes into account all available observations. Panels A and B of Figure 2.4 show that the standard deviation and CVaR are varying in a similar fashion over time. Moreover, the risk of the domestic market (SPY fund) is often lower than that of foreign markets (EFA and EEM funds), regardless of the risk measures. This might be because from domestic market perspective (here is the US), the foreign market is subject to the variability of both foreign stock market and exchange rate.

²⁴Detailed results for different rolling window sizes (3, 9, 12, 15 and 18 months) are available upon request.

Panels C, D and F of Figure 2.4 show respectively the variation of the daily return correlation, the realized correlation and realized correlation of SPY/EFA jumps, SPY/EEM jumps and EFA/EEM jumps.²⁵ The graphs suggest that three correlation measures are closely linked to each other. In other words, correlated jumps have similar pattern of comovement to both correlated daily and intraday returns. The correlation of jumps is relatively high over the period of study. It varies between 0.6 and 1 for three pairs of funds. The jump correlation is thus significant and positively high.²⁶ On average, the correlation between SPY/EFA jumps is the highest. It is then followed by SPY/EMM and EFA/EEM jumps.

As the composition of the optimal portfolio becomes available, we are able to study how cojumps between domestic and foreign markets affect the portfolio composition. We hypothesize that a high intensity of cojumps between domestic and foreign markets leads to a decrease in benefit from diversifying internationally and thus foreign asset holding. We begin our analysis with the calculation of the correlation between the daily intensity of cojumps and the optimal proportion of foreign assets that we obtained with variance and CVaR approaches. Although our exercise onward has the US as home market and the rest as foreign markets, our analysis can be generalized to any home and host markets with respect to our theoretical framework in Section 2.3.1, provided that the variability of home market is lower than the variability of host markets.

The main results for the variance approach, summarized in Table 2.7, show a negative correlation between the demand of foreign assets and the daily intensity of cojumps between the domestic market (SPY fund) and each of foreign markets (EFA and EEM funds).²⁷ We find a correlation of -0.10 for SPY/EFA cojumps intensity and -0.20 for SPY/EEM cojumps intensity with foreign asset holding. When we consider the cojumps that involve the three funds, we find a negative correlation of -0.19. We get similar results for positive and negative

²⁵The daily correlation is the standard correlation coefficient calculated monthly using a rolling six-month window of daily returns. The realized total and jump correlations are estimated monthly using a rolling six-month window of intraday returns.

²⁶Refer to Jacod and Todorov (2009) for more details about the accuracy of the jump correlation estimator.

²⁷We find similar results for the CVaR approach. Detailed results are not presented due to limited space but are available upon request.

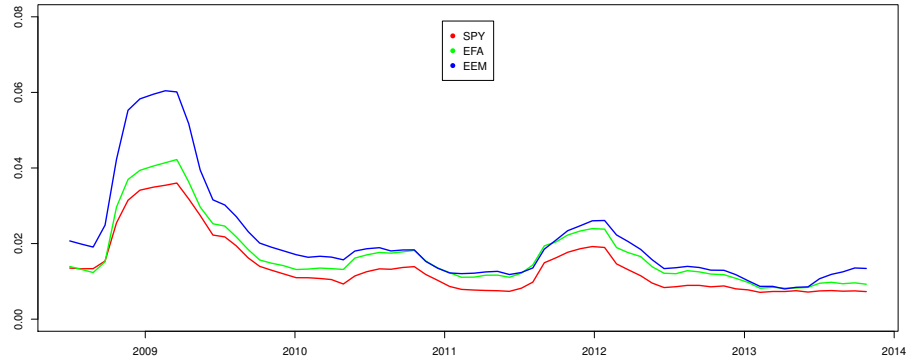
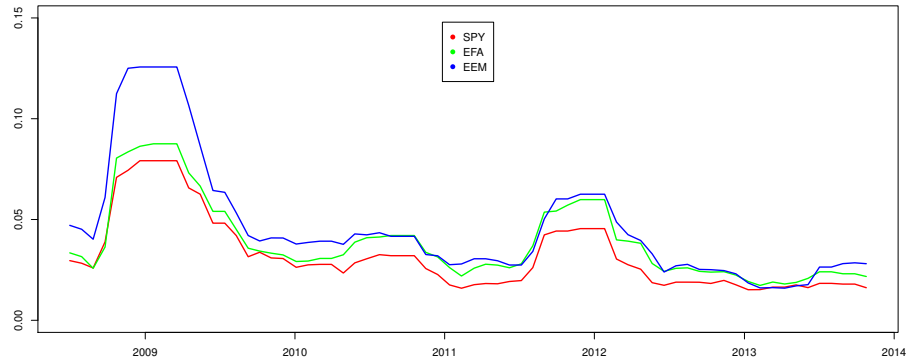
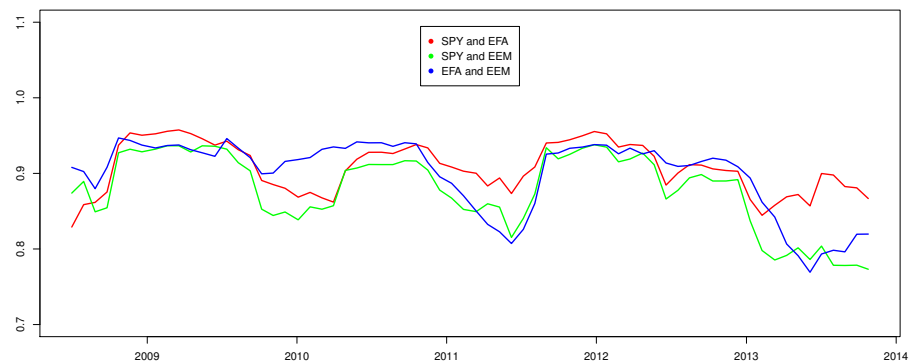
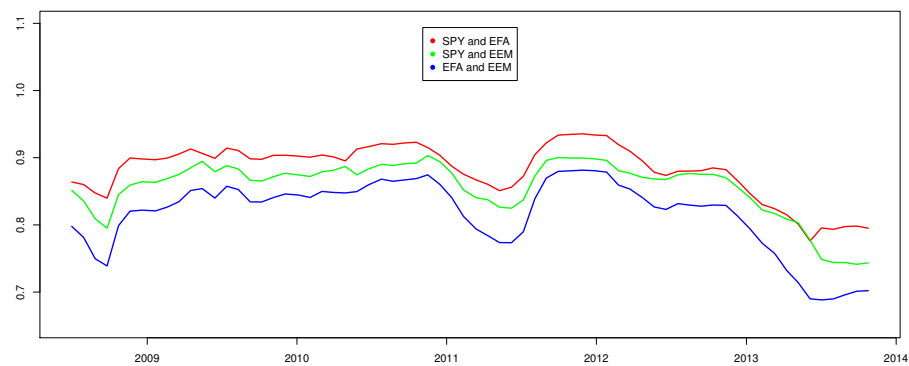
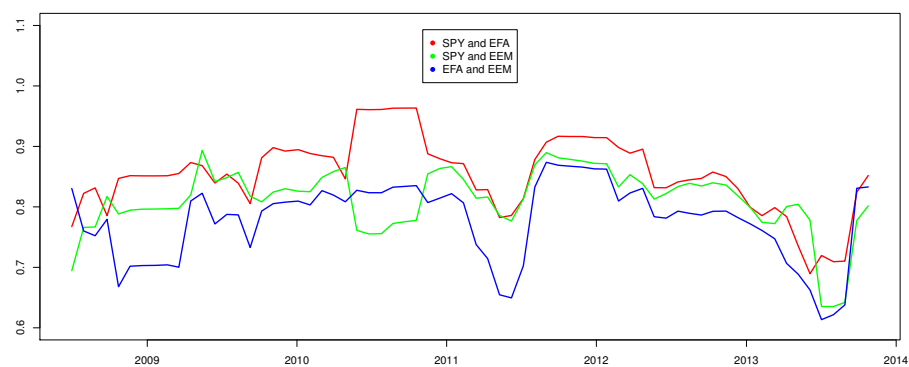
Panel A: Standard deviation of SPY, EFA and EEM**Panel B: CVaR of SPY, EFA and EEM**

Figure 2.4: Standard deviation, CVaR and correlations of domestic and foreign assets.

These figures show the variation of the standard deviation, CVaR and the correlation, respectively of SPY, EFA and EEM. Panels A and B present moving standard deviation and absolute value of the CVaR, respectively of SPY, EFA and EEM. Panel C presents the time-varying correlation of respectively SPY and EFA, SPY and EEM and EFA and EEM. These variations are calculated monthly for a rolling six-month window of daily returns. The panels D and E represent the variation of the realized correlation and the realized jump correlation, of respectively SPY and EFA, SPY and EEM and EFA and EEM. The realized correlations are calculated monthly for a rolling six-month window of intraday returns. The intraday prices of the three ETFs including SPY, EFA, and EEM from January 2008 to October 2013 are included. Prices are sampled every five minutes from 9:30 am to 15:55 pm.

Panel C: Correlation obtained from daily returns**Panel D: Realized correlation obtained from intraday returns****Panel E: Realized jump correlation obtained from intraday returns**

(Continued.)

cojumps except for positive cojump between SPY/EFA where the correlation with foreign asset holding is not significant. This result implies that, regardless of the sign of returns, investors do not like cojumps between domestic and foreign assets.

In addition to cojumps intensity, we find that the negative relation between correlated jumps and foreign holdings is more pronounced. The measure of jump correlation is shown analytically in Section 2.3.1. It is more appropriate in practice to use the jump correlation to measure the degree of linkage between assets jumps. Contrary to cojump intensity measure, which only takes into account the frequency effect, the jump correlation captures both the jump frequency and size effects. It thus provides a more accurate measure of the degree of jump comovement than the cojump intensity. We find a strong negative correlation of -0.56 for SPY/EFA correlated jumps and -0.39 for SPY/EEM correlated jumps. Negative and positive jump correlations are also negatively correlated to foreign asset holdings. The correlation between foreign assets holdings and correlated jumps is higher for the portfolio of SPY and EFA funds than for the portfolio of SPY and EEM funds. This is expected given that the US market has a higher correlation with the other developed ones. We also examine if our results are sensitive to exchange rate jump risk. We exclude all assets jumps that occur simultaneously with EUR/USD exchange rate jumps and repeat the analysis. The significant negative link between jump correlation and the demand of foreign assets remains intact. We find a correlation of -0.50 for SPY/EFA and -0.38 for SPY/EEM.²⁸

In Table 2.8, we examine the correlation between foreign asset holdings and idiosyncratic jumps where idiosyncratic jumps are defined earlier as jumps that occur in a single market. Specifically, we measure the correlation between the daily intensity of idiosyncratic jumps (of respectively SPY, EFA and EEM funds) and the optimal proportion of foreign assets and find a positive correlation for SPY (0.45), EFA (0.35) and EEM (0.40). In contrast to systematic jumps, idiosyncratic jumps increase foreign holdings. That is, investors seem to be aware that holding more foreign assets in their portfolios help them diversify idiosyncratic jump risks.

²⁸Detailed results of the correlation between foreign asset holdings and correlated jumps are not presented for brevity. They are available upon request.

Table 2.7: Correlation between the daily intensity of cojumps and the optimal proportion of the foreign assets.

This table presents the correlation between the daily intensity of cojumps and the optimal proportion of the foreign assets (the sum of optimal weights of EFA and EEM) calculated using the variance minimization approach. Panel A shows the results for all cojumps; Panel B shows the results of cojumps that occur independently of EUR/USD exchange rate jumps. The daily intensity of cojumps is defined as the daily average number of cojumps that involve two or three funds and determined weekly using a six-month rolling window of observations. Positive and negative implies cojumps of positive and negative returns, respectively. See Section 2.2 for jump and cojump identification procedure, and Section 2.5.3 for the estimation of the optimal foreign assets holdings. The sample includes the intraday prices of the three funds from January 2008 to October 2013. Prices are sampled every five minutes from 9:30 am to 15:55 pm. ***, **, and * represent 0.1 percent, 1 percent and 5 percent significance levels, respectively.

Panel A: All cojumps

Assets used to estimate the intensity of cojumps	Estimate (Correlation)	Confidence interval (95%)	T-stat	P-value
SPY and EFA	-0.10	[-0.21, -0.02]	-1.56	0.11
Positive SPY and EFA	0.006	[-0.11, 0.13]	0.10	0.92
Negative SPY and EFA	-0.15	[-0.26, -0.03]	-2.48	0.014*
SPY and EEM	-0.20	[-0.31, -0.08]	-3.24	0.001**
Positive SPY and EEM	-0.15	[-0.26, -0.03]	-2.50	0.013*
Negative SPY and EEM	-0.16	[-0.27, -0.04]	-2.48	0.014*
SPY, EFA and EEM	-0.19	[-0.30, -0.07]	-3.13	0.002**
Positive SPY, EFA and EEM	-0.18	[-0.30, -0.07]	-3.06	0.002**
Negative SPY, EFA and EEM	-0.13	[-0.24, -0.01]	-2.12	0.034*

Panel B: Excluding cojumps that occur simultaneously with EUR and USD exchange rate jump

Assets used to estimate the intensity of cojumps	Estimate (Correlation)	Confidence interval (95%)	T-stat	P-value
SPY and EFA	0.05	[-0.07, 0.16]	0.75	0.45
Positive SPY and EFA	-0.05	[-0.17, 0.07]	-0.78	0.44
Negative SPY and EFA	0.09	[-0.03, 0.21]	1.50	0.13
SPY and EEM	-0.14	[-0.26, -0.02]	-2.37	0.02*
Positive SPY and EEM	-0.18	[-0.30, -0.06]	-2.97	0.003**
Negative SPY and EEM	-0.06	[-0.18, 0.06]	-0.99	0.32
SPY, EFA and EEM	-0.16	[-0.27, -0.04]	-2.66	0.008**
Positive SPY, EFA and EEM	-0.27	[-0.38, -0.16]	-4.62	5.85 e-06***
Negative SPY, EFA and EEM	-0.01	[-0.13, 0.10]	-0.22	0.82

Table 2.8: Correlation between the daily intensity of idiosyncratic jumps and the demand of foreign assets.

This table presents the correlation between the daily intensity of idiosyncratic jumps and the optimal proportion of foreign assets (the sum of optimal weights of EFA and EEM) calculated using the variance minimization approach. The daily intensity of idiosyncratic jumps is defined as the daily average number of jumps that involve only one fund and determined weekly using a six-month rolling window of observations. See Section 2.2 for the detail of jump test statistics and definition of idiosyncratic jumps, and Section 2.5.3 for the estimation of the optimal foreign assets holdings. The sample includes the intraday prices of the three funds from January 2008 to October 2013. Prices are sampled every five minutes from 9:30 am to 15:55 pm. ***, **, and * represent 0.1 percent, 1 percent and 5 percent significance levels, respectively.

Assets used to estimate the intensity of idiosyncratic jumps	Estimate (Correlation)	Confidence interval (95%)	T-stat	P-value
SPY	0.45	[0.35, 0.54]	8.21	9.10e-15***
EFA	0.35	[0.24, 0.45]	6.15	2.76e-09***
EEM	0.40	[0.29, 0.50]	7.10	1.15e-11***

Finally, we examine how higher-order moments induced by idiosyncratic and systematic jumps affect the optimal portfolio composition. For this purpose, we compare the optimal portfolio weights for an investor who recognizes idiosyncratic and systematic jumps and another investor who ignores them and assumes a pure multivariate diffusion process for asset returns. Both investors have the same CRRA utility function and select their portfolio compositions based on one domestic asset (SPY) and two foreign assets (EFA and EEM). The portfolio optimization is performed yearly following the methodology described in Section 2.3.2. The optimal weights are obtained by resolving numerically Eq. 2.19. The risk aversion coefficient is set to three and the risk-free rate to zero. The parameters of the multivariate jump-diffusion process are estimated on a yearly basis using intraday returns of the preceding year. Table 2.9 reports the detail of jump-diffusion model estimation over the whole period. The results in Table 2.10 show that optimal domestic asset weights are almost the same for the pure-diffusion and jump-diffusion investors. The impact of jump higher-order moments on the optimal portfolio composition is thus insignificant.²⁹ This finding is consistent with

²⁹The ratio $\frac{\mu_1^t s_1^t}{(v_1^t)^2}$, defined in Section 2.3.2, is in the order of $10e-4$ ($\ll 1$) for three funds, which explains the insignificant impact of higher-order moments.

Das and Uppal (2004) who find similar results for systemic jumps.³⁰ That is, the difference between the portfolio composition of an investor who cares about systemic jumps and another investor who ignores them is small.

Taken together, the findings in this section show that the jump correlation, which is the normalized second joint moment of jump returns, reduces foreign asset holdings in international portfolios, whereas higher-order moments have no significant effect on portfolio composition.

Table 2.9: Multivariate jump-diffusion model estimation.

The tables report the results of the estimation of the multivariate jump-diffusion model introduced in Section 2.3.2. The estimation is performed using intraday prices of the three funds from January 2008 to October 2013. Prices are sampled every five minutes from 9:30 am to 15:55 pm. Jumps and cojumps are detected using the methodology defined in Section 2.2.

	SPY	EFA	EEM
μ_i	6.8e-06	7.4e-06	5.8e-06
$\mu_i^{sys,up}$	0.00472	0.00475	0.00563
$\mu_i^{sys,down}$	-0.00417	-0.00426	-0.00471
$\mu_i^{id,up}$	0.00328	0.00344	0.00410
$\mu_i^{id,down}$	-0.00312	-0.00308	-0.00363
$\nu_i^{sys,up}$	0.00354	0.00312	0.00467
$\nu_i^{sys,down}$	0.00375	0.00324	0.00357
$\nu_i^{id,up}$	0.00291	0.00319	0.00395
$\nu_i^{id,down}$	0.00310	0.00225	0.00375
$\lambda^{sys,up}$	0.00127	0.00127	0.00127
$\lambda^{sys,down}$	0.00196	0.00196	0.00196
$\lambda_i^{id,up}$	0.00293	0.00310	0.00274
$\lambda_i^{id,down}$	0.00373	0.00352	0.00308
$\{\rho_{i,j}\sigma_i\sigma_j\}_{i,j}$			
SPY	1.7e-06		
EFA	1.5e-06	1.5e-06	
EEM	1.9e-06	1.7e-06	2.5e-06

³⁰Systemic jumps are defined as infrequent, large and highly correlated jumps.

Table 2.10: Optimal portfolio weights using power utility maximization approach.

The table reports the optimal weight of the domestic asset (SPY fund) for a jump-diffusion investor who accounts for idiosyncratic and systematic jumps and another pure-diffusion investor who ignores them. The portfolio optimization is performed yearly using intraday returns of the preceding year. The risk aversion coefficient is set to three and the riskless asset weight to zero. The multivariate jump-diffusion model and the power utility optimization problem are introduced in Section 2.3.2. Jumps and cojumps are detected using the methodology defined in Section 2.2.

	pure-diffusion	jump-diffusion
2008	-1.31	-1.33
2009	-2.40	-2.41
2010	1.89	1.91
2011	1.69	1.64
2012	0.25	0.25
2013	-0.76	-0.76

2.5.4 Cojumps and the benefits of international portfolio diversification

The results of the Section 2.5.3 show that cojumps in international equity markets are an indirect barrier to the holding of foreign assets. To the extent that they amplify the level of equity market comovement, it is expected that they negatively affect the benefits of portfolio diversification. We confirm this by examining the link between the number of cojumps and the measure of international diversification benefits in the spirit of Christoffersen et al. (2012) proposing to measure the conditional diversification benefit (CDB) as follows:

$$CDB_{\beta}(w) = \frac{\bar{\phi}_{\beta} - \phi_{\beta}(w)}{\bar{\phi}_{\beta} - \alpha_{\beta}(w)} \quad (2.24)$$

where $\alpha_{\beta}(w)$ and $\phi_{\beta}(w)$ are the values of the VaR and the CVaR of the portfolio loss function associated with the vector of weights w and the confidence level β .³¹ By construction, the $\alpha_{\beta}(w)$ refers to the lower bound of the portfolio's expected shortfall, while $\bar{\phi}_{\beta}$ is the upper bound of the portfolio's expected shortfall and is defined as the weighted average of the individual assets' CVaRs ($\phi_{\beta,i}$):

$$\bar{\phi}_{\beta} = \sum_{i=1}^n w_i \phi_{\beta,i} \quad (2.25)$$

³¹See Appendix 2.B for more details about the VaR and the CVaR of the portfolio loss function.

Thus, the CDB measure is a positive function with values ranging between 0 and 1, and increases with the level of diversification benefit. The CDB measure does not depend on the expected returns. Furthermore, it takes into account the nonlinearity of asset returns and the potential of their nonlinear dependence (i.e., jumps, cojumps, and extreme movements).³²

We calculate the monthly value of the CDB for our portfolio of three exchange-traded funds based on the intraday data from the previous month (about 1617 intraday returns for each fund per month). The confidence level β is set at 5%. The weights allocated to three funds are chosen monthly in a way to maximize the CDB. Figure 2.5 depicts the variation of the optimal level of the CDB for the portfolio composed of three funds SPY, EFA and EEM. The CDB measure fluctuates between 0.06 (August 2011) and 0.30 (August 2008 and January 2013). It is high at the beginning and the end of the study period and relatively low during the global financial crisis.

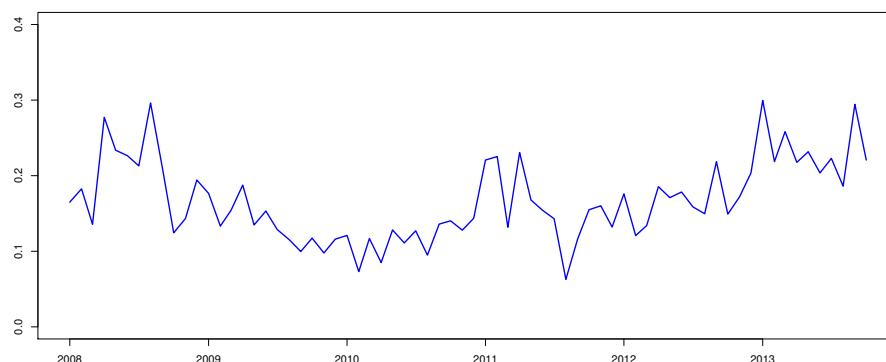


Figure 2.5: The conditional diversification benefit (CDB).

The figure shows the variation of the optimal level of the diversification benefit calculated monthly based on an international portfolio composed of three funds SPY, EFA and EEM. See Section 2.5.4 for the definition of conditional diversification benefit. The intraday prices of the three funds from January 2008 to October 2013 are included. Prices are sampled every five minutes from 9:30 am to 15:55 pm.

To assess the effects of jumps and cojumps on the diversification benefit, we compute the correlation between the optimal level of the CDB and jump comovement, the daily intensity of

³²The high correlation of large down moves in international markets is documented by Longin and Solnik (2001) and Ang and Bekaert (2002).

cojumps and idiosyncratic jumps, both calculated on a monthly basis from the cojumps and jumps detected from the previous month. The daily intensity of cojumps refers to the daily average number of cojumps involving three funds, while the daily intensity of idiosyncratic jumps refers to the daily average number of jumps involving only one fund. We also consider the correlation between the optimal level of CDB and jump comovement.³³ The latter is the monthly average jump correlation of three funds, computed from the previous month intraday data.

The findings in Table 2.11 show that the CDB is negatively correlated with cojumps intensity (-0.37) and correlated jumps (-0.65). In contrast, the CDB is positively correlated with idiosyncratic jumps intensity (0.40). The strong negative dependence between the diversification benefit and jump comovement is also shown in Figure 2.6. Taken together, these results indicate that the international diversification benefit increases with the intensity of idiosyncratic jumps and decreases with the level and intensity of cojumps observed in the international markets. They further confirm our previous findings that domestic (US) investors allocate more money towards home assets in the presence of cojumps between US and foreign markets.

Table 2.11: The impact of simultaneous and idiosyncratic jumps on the optimal level of the diversification benefit.

The table reports the measures of correlation between the conditional diversification benefit (CDB) and correlated jumps, daily cojumps intensity and daily idiosyncratic jumps intensity, respectively. The diversification benefit is defined in Section 2.5.4. The CDB is computed monthly from the previous month intraday data. The correlation of jumps is the average correlation of jumps among the three ETFs including SPY, EFA, and EEM calculated on a monthly basis from the previous month intraday data. See Equations (2.12) to (2.14) for correlated jumps estimation. The daily intensity of cojumps is computed on a monthly basis as the daily average number of cojumps that involve three funds detected from the previous month. The daily intensity of idiosyncratic jumps is measured on a monthly basis as the average daily number of jumps that involve only one market. See Section 2.2 for jump and cojump identification procedure. The intraday prices of the three funds from January 2008 to October 2013 are included. Prices are sampled every five minutes from 9:30 am to 15:55 pm.

Correlation	Estimate (Correlation)	Confidence interval (95%)	T-stat	P-value
Correlated jumps and CDB	-0.65	[-0.77, -0.49]	-7.05	1.1e-09***
Cojumps intensity and CDB	-0.37	[-0.56, -0.15]	-3.3	0.0015**
Idiosyncratic jumps intensity and CDB	0.40	[0.18, 0.58]	3.61	0.0005***

³³The jump correlation measure has been introduced in Section 2.3.1.

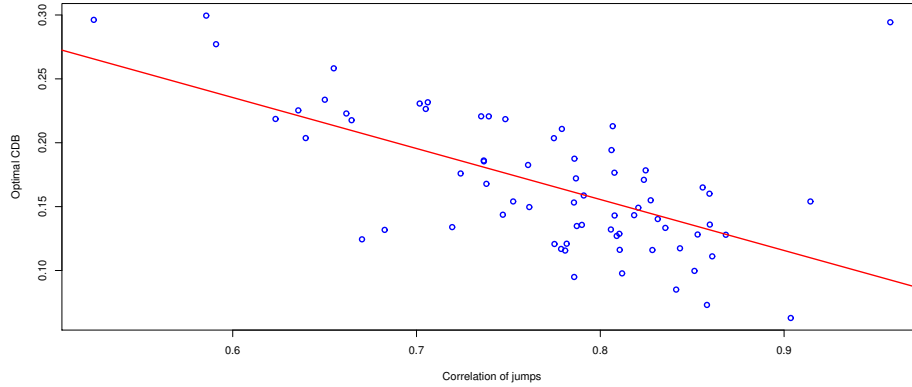


Figure 2.6: Linear regression between the conditional diversification benefit (CDB) and the correlation of jumps.

The figure displays a scatterplot with a regression line showing the linear relationship between the optimal level of the conditional diversification benefit and jump correlation. Diversification benefit is defined in Section 2.5.4. Jump correlation is the average correlation of jumps from different pairs of the three ETFs including SPY, EFA, and EEM computed on a monthly basis. Jump correlation is defined in Section 2.3.1. The intraday prices of the three funds from January 2008 to October 2013 are included. Prices are sampled every five minutes from 9:30 am to 15:55 pm.

2.6 Conclusion

In this paper, we investigate how jumps and cojumps in international equity markets affect international asset allocation and diversification benefits. Using a nonparametric intraday jump detection technique developed by Lee and Mykland (2008) and Anderson et al. (2007) and intraday data from three international exchange-traded funds as proxies for international equity markets, we find that intraday jumps are transmitted both in time (in the same market) and in space (across markets). The markets under consideration also have tendency to be involved in cojumps. The high and significant degree of jumps synchronization in international equity markets suggests that the jump risk is rather systematic and thus could not be eliminated through the diversification.

We study the impact of cojumps on optimal international portfolio based on portfolio variance and CVaR minimisation approaches and find a negative link between the demand for foreign assets and cojumps between domestic and foreign markets. This result implies

that a domestic investor will invest less in foreign markets when the frequency and size of cojumps between domestic and foreign assets increase. We also find the negative link between the intensity of cojumps and the conditional diversification benefit measure suggested by Christoffersen et al. (2012). Putting differently, the high jump correlation increases the cross-market comovement, and therefore reduces the international diversification benefit and leads investors to prefer home assets. In contrast, we find that idiosyncratic jumps have a positive effect on foreign asset holding and diversification benefits. Finally, the impact of higher-order moments induced by idiosyncratic and systematic jumps on optimal international portfolio composition is insignificant.

This work opens interesting avenues for future research. It would be of great interest to broaden the scope of this study by including a larger number of international equity indices and examining the impact of asset cojumps on the demand for foreign assets for a larger panel of countries. Studying the underlying mechanisms of cojumps in international equity markets should also be of interest.

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Appendix 2.A Intraday volatility pattern

It is widely documented (Wood et al. (1985) and Harris (1986)) that intraday returns show a systematic seasonality over the trading day, also called the U-shaped pattern. The intraday volatility is particularly higher at the open and the close of the trading than the rest of the day.

To minimize the effects of intraday volatility on our jump detection test, we modify our procedure by rescaling intraday returns with a volatility jump robust corrector introduced by Bollerslev et al. (2008). The k^{th} rescaled intraday return of day t is defined by:

$$\hat{r}_{t,k} = \frac{r_{t,k}}{\varsigma_k}$$

where:

$$\begin{aligned} \varsigma_1^2 &= \frac{M \sum_{t=1}^T |r_{t,1}| |r_{t,2}|}{\sum_{t=1}^T |r_{t,1}| |r_{t,2}| + \sum_{t=1}^T \sum_{l=2}^{M-1} |r_{t,l-1}|^{\frac{1}{2}} |r_{t,l}| |r_{t,l+1}|^{\frac{1}{2}} + \sum_{t=1}^T |r_{t,M-1}| |r_{t,M}|} \\ \varsigma_k^2 &= \frac{M \sum_{t=1}^T |r_{t,k-1}|^{\frac{1}{2}} |r_{t,k}| |r_{t,k+1}|^{\frac{1}{2}}}{\sum_{t=1}^T |r_{t,1}| |r_{t,2}| + \sum_{t=1}^T \sum_{l=2}^{M-1} |r_{t,l-1}|^{\frac{1}{2}} |r_{t,l}| |r_{t,l+1}|^{\frac{1}{2}} + \sum_{t=1}^T |r_{t,M-1}| |r_{t,M}|}, \quad k = 2, \dots, M-1 \\ \varsigma_M^2 &= \frac{M \sum_{t=1}^T |r_{t,M-1}| |r_{t,M}|}{\sum_{t=1}^T |r_{t,1}| |r_{t,2}| + \sum_{t=1}^T \sum_{l=2}^{M-1} |r_{t,l-1}|^{\frac{1}{2}} |r_{t,l}| |r_{t,l+1}|^{\frac{1}{2}} + \sum_{t=1}^T |r_{t,M-1}| |r_{t,M}|} \end{aligned}$$

T is the total number of days considered in the study and M is the number of observations in a day.

Appendix 2.B Mean-CVaR optimization problem

The mean-CVaR optimization approach initially developed by Rockafellar and Uryasev (2000) can be described as follows. We first define the loss function of a portfolio composed of n assets given the vector of weights w and the random vector of asset returns r such as

$$f(w, r) = - \sum_{i=1}^n w_i r_i = -w' r$$

The probability of $f(w, r)$ not exceeding a threshold α is given by:

$$\Psi(w, \alpha) = \int_{f(w, r) \leq \alpha} p(r) dr$$

where $p(r)$ is the density function of the vector of returns. Ψ is a function of α for a fixed vector of weights w and represents the cumulative distribution function for the loss associated with the vector of weights w .

The values of the VaR and the CVaR of the loss function associated with w and a confidence level β , $\alpha_\beta(w)$ and $\phi_\beta(w)$, can be then determined as:

$$\begin{aligned} \alpha_\beta(w) &= \min(\alpha \in R : \Psi(w, \alpha) \geq \beta) \\ \phi_\beta(w) &= (1 - \beta)^{-1} \int_{f(w, r) \geq \alpha_\beta(w)} f(w, r) p(r) dr \end{aligned}$$

Following Rockafellar and Uryasev (2000), we provide the expression $\phi_\beta(w)$ using the function F_β defined as follows:

$$F_\beta(w, \alpha) = \alpha + (1 - \beta)^{-1} \int [\alpha - f(w, r)]^+ p(r) dr$$

where $[x]^+ = \max(x, 0)$. Rockafellar and Uryasev (2000) show that $F_\beta(w, \alpha)$ is convex and continuously differentiable as a function of α . It is also related to the CVaR of the loss

function through $\phi_\beta(w) = \min_{\alpha \in R} (F_\beta(w, \alpha))$. Moreover, the authors prove that minimizing $\phi_\beta(w)$ over all $w \in R^n$ is equivalent to minimizing $F_\beta(w, \alpha)$ over all $(w, \alpha) \in R^n \times R$, that is $\min_{w \in R^n} \phi_\beta(w) = \min_{(w, \alpha) \in R^n \times R} F_\beta(w, \alpha)$. The expression of F_β can be simplified by generating a random collection of the vector of returns $(r^{(1)}, r^{(2)}, \dots, r^{(q)})$ and approximated with \tilde{F}_β as follows:

$$\tilde{F}_\beta(w, \alpha) = \alpha + \frac{1}{q(1-\beta)} \sum_{i=1}^q \left[f(w, r^{(i)}) - \alpha \right]^+$$

Replacing the loss function by its expression gives:

$$\tilde{F}_\beta(w, \alpha) = \alpha + \frac{1}{q(1-\beta)} \sum_{i=1}^q \left[-w' r^{(i)} - \alpha \right]^+$$

By introducing the auxiliary variable u_i , the minimizing of \tilde{F}_β is equivalent to the linear equation:

$$\begin{aligned} & \alpha + \frac{1}{q(1-\beta)} \sum_{i=1}^q u_i \\ & \text{subject to: } u_i \geq 0, \quad u_i + w' r^{(i)} + \alpha \geq 0 \quad \text{for } i = 1, \dots, q \end{aligned}$$

If we add the budget and the expected target return constraints, the portfolio mean-CVaR optimization problem is given by:

$$\begin{aligned} & \min_{\alpha, w} \alpha + \frac{1}{q(1-\beta)} \sum_{i=1}^q u_i \\ & \text{subject to } \begin{cases} e'w = 1, \quad u_i \geq 0 \\ \mu'w = \bar{\mu} \\ u_i + w' r^{(i)} + \alpha \geq 0, \quad i = 1, \dots, q \end{cases} \end{aligned}$$

Appendix 2.C Expected power utility maximization

The investor's problem at time t is given by :

$$V(t, W_t) = \max_w E[U(W_T)]$$

$$\text{subject to } e'w + w_0 = 1$$

where $w = (w_1, w_2, \dots, w_n)'$ is the vector of portfolio weights of n risky assets. w_0 is the weight of the riskless asset. $e = (1, 1, \dots, 1)'$ denotes the vector of ones and U is the power utility function with a constant relative risk aversion coefficient γ . The dynamics of the wealth W_t is as follows:

$$\frac{dW_t}{W_t} = (w'R + r)dt + w'(\sigma \cdot dZ_t) + \sum_{x \in (up, down)} w' J^{sys, x} dQ^{sys, x} + \sum_{x \in (up, down)} w'(J^{id, x} \cdot dQ^{id, x})$$

where $R = (\mu_1 - r, \mu_2 - r, \dots, \mu_n - r)'$ is the diffusive excess-returns vector. $\sigma = (\sigma_1, \sigma_2, \dots, \sigma_n)'$ the vector of diffusive volatilities. $Z_t = (Z_{t,1}, Z_{t,1}, \dots, Z_{t,n})'$ the vector of Brownian motions. $J^{id, x} = (J_1^{id, x}, J_2^{id, x}, \dots, J_n^{id, x})'$ is the vector of idiosyncratic (up or down) jump amplitudes whereas $J^{sys, x} = (J_1^{sys, x}, J_2^{sys, x}, \dots, J_n^{sys, x})'$ denotes the vector of systematic (up or down) jump amplitudes. $Q^{id, x} = (Q_1^{id, x}, Q_2^{id, x}, \dots, Q_n^{id, x})'$ is the vector of idiosyncratic jump Poisson processes. The \cdot operator denotes the element- by-element multiplication of two equally sized vectors.

By applying Ito's lemma to $V(t, W_t)$ and using stochastic dynamic programming techniques, we obtain the following Hamilton-Jacobi-Bellman equation:

$$\begin{aligned} 0 = \max_w \{ & \frac{\partial V(t, W_t)}{\partial t} + \frac{\partial V(t, W_t)}{\partial W_t} W_t (w'R + r) + \frac{1}{2} \frac{\partial^2 V(t, W_t)}{\partial W_t^2} W_t^2 w' \Sigma w \\ & + \sum_{x \in (up, down)} \lambda^{sys, x} E[V(t, W_t + W_t w' J^{sys, x}) - V(t, W_t)] \\ & + \sum_i \sum_{x \in (up, down)} \lambda_i^{id, x} E[V(t, W_t + W_t w_i J_i^{id, x}) - V(t, W_t)] \} \end{aligned}$$

where $\Sigma = (\rho_{i,j}\sigma_i\sigma_j)_{1 \leq i,j \leq n}$ is the covariance matrix of the diffusive returns.

We guess that the function $V(t, W_t)$ is of the following form :

$$V(t, W_t) = A(t) \frac{W_t^{1-\gamma}}{1-\gamma}$$

Using this guess, the Hamilton-Jacobi-Bellman equation writes :

$$\begin{aligned} 0 = & \max_w \left\{ \frac{1}{A(t)} \frac{dA(t)}{dt} + (1-\gamma)(w'R + r) - \frac{(1-\gamma)\gamma}{2} w' \Sigma w \right. \\ & + \sum_{x \in (up, down)} \lambda^{sys,x} E[(1 + w' J^{sys,x})^{1-\gamma} - 1] \\ & \left. + \sum_i \sum_{x \in (up, down)} \lambda_i^{id,x} E[(1 + w_i J_i^{id,x})^{1-\gamma} - 1] \right\} \end{aligned}$$

Differentiating the above equation with respect to w , we obtain the following system of non linear equation :

$$\mathbf{0} = R - \gamma \Sigma w + \sum_{x \in (up, down)} \lambda^{sys,x} E[J^{sys,x} (1 + w' J^{sys,x})^{-\gamma}] + \sum_{x \in (up, down)} \lambda^{id,x} E[J^{id,x} (e + w \cdot J^{id,x})^{-\gamma}]$$

where $\mathbf{0} = (0, 0, \dots, 0)'$ is the vector of zeros. $\lambda^{id,x} = (\lambda_1^{id,x}, \lambda_2^{id,x}, \dots, \lambda_n^{id,x})'$ is the vector of idiosyncratic (up or down) jump intensities.

By evaluating the Hamilton-Jacobi-Bellman equation at the optimal portfolio weights w^* , we obtain :

$$\begin{aligned} \frac{1}{A(t)} \frac{dA(t)}{dt} = & -\kappa \\ \kappa = & (1-\gamma)(w^{*'} R + r) - \frac{(1-\gamma)\gamma}{2} w^{*'} \Sigma w^* \\ & + \sum_{x \in (up, down)} \lambda^{sys,x} E[(1 + w^{*'} J^{sys,x})^{1-\gamma} - 1] \\ & + \sum_i \sum_{x \in (up, down)} \lambda_i^{id,x} E[(1 + w_i^* J_i^{id,x})^{1-\gamma} - 1] \end{aligned}$$

By integrating the differential equation, we get :

$$A(t) = e^{\kappa(T-t)}, A(T) = 1$$

Chapter 3

Jump Risk Premia Across Major International Equity Markets¹

Abstract

We decompose the non-diversifiable market risk into continuous and discontinuous components and jump systematic risks into positive vs. negative and small vs. large components. We examine their association with equity risk premia across major equity markets. We show that developed markets jumps are more closely linked to the aggregate market index than emerging ones. The reward for bearing both the continuous and downside jump risks is positive during the pre-crisis period whereas the reward for bearing the upside and large jump risks is negative during the crisis and post-crisis periods. We also provide evidence of significant continuous and discontinuous leverage effects during the pre-crisis period, suggesting that both continuous and discontinuous price and volatility risks share compensations for common underlying risk factors.

Keywords: Systematic jump risk; Risk premium; Leverage effect.

¹A paper based on this chapter is currently under revision (R&R) in Journal of Empirical Finance.

3.1 Introduction

The finance theory establishes that there is a tradeoff between risk and return. At the equilibrium, the expected returns on riskier investments are higher than the risk-free rate. Moreover, financial models show that this extra return required by investors to remunerate for risk, the risk premium, is proportional to the systematic risk. Numerous models including the most classical ones such as the capital asset pricing model (CAPM) and the arbitrage pricing theory (APT) estimate the risk premium by matching return and risk expected on different investment opportunities; yet these models take into consideration only continuous risks.

This article contributes to the literature by examining continuous and discontinuous systematic risks and their association with equity risk premia across major equity markets. Thanks to the availability of high frequency data, we decompose the market risk into various components: a continuous component measuring the sensitivity of a single security returns to smooth intraday movements of market returns and a jump component measuring the sensitivity towards discontinuous intraday movements of market returns. The knowledge of how international equity markets react differently to intraday smooth and jump movements of the market will help investors better manage and diversify their portfolios. As investors are often more concerned with large negative movements of the market, we examine whether the systematic jump risk exhibits an asymmetry and size effects by decomposing it into upside versus downside and small versus large components. The upside jump risk measures the sensitivity towards the upward market jumps whereas the downside jump risk captures the sensitivity towards the downward market jumps. The small and large jump risk components capture the response of a single security to respectively small and large market jumps. This jump risk decomposition is likely to provide an efficient tool for investors to manage the portfolio jump risk using suitable hedging tools that optimally reduce the exposure to various sources

of jump risk.²

Our work is motivated by three strands of the literature. The first suggests systematic jump risk exists in the US stock market and requires a risk premium (Alexeev et al., 2017; Bollerslev et al., 2016). Cremers et al. (2015) provide evidence that the aggregate market jump is a priced risk. However, they do not separate between positive and negative jump risks or small and large jump risks. Another branch of the literature examines systematic cojumps between international financial markets. Dungey et al. (2009), Lahaye et al. (2010), Dungey and Hvozdyk (2012), and Gilder et al. (2012) find cojumps are systematic whereas Pukthuanthong and Roll (2015) show jumps are not significantly correlated. Our study extends the previous studies by investigating systematic continuous and jump risks in international stock markets. Bollerslev et al. (2016) study continuous and rough betas including both discontinuous and overnight betas whereas Alexeev et al. (2017) only include continuous and discontinuous betas. Both studies are limited to the US stock market. We extend their model and propose a general pricing framework involving six separate market betas. In addition to continuous and overnight betas, we separate discontinuous betas into up versus down betas and small versus large betas. We also examine whether developed, emerging and frontier markets are exposed similarly to continuous and jump market risks. Our study is also related to the empirical asset pricing literature on systematic tail risks. Different studies examine the comovement of assets with the market return under extreme adverse market conditions (including, among others, Kelly and Jiang (2014), Weigert (2016), Oordt and Zhou (2016)) and propose new measures of the tail risk based on the extreme value theory. In this paper, we propose an alternative approach of measuring the systematic downside jump risk using high frequency data and examine a variety of jump risks including downside, upside, small, and large jump risks.

Our motivation is as follows. Investors apply different hedging tools for different kinds of market risks; thus, it is important to examine these risks individually. Moreover, as jumps

²Hedging instruments including out-of-the-money puts and calls can be used to hedge respectively against large negative and positive jumps. Smooth market variations as well as small market jumps can be hedged using near-and at-the-money options.

are often associated with macroeconomic news announcements (Lahaye et al., 2010; Evans, 2011), we study the jump sensitivity as it captures how fast and intense a security responds to news arrival. Second, the effects of positive and negative jumps on the global jump risk should not be symmetric. Individual assets might be more sensitive to downward jumps of the market due to investors' loss aversion that has been widely documented in the behavioral finance literature. Thus, losses loom larger than gains for loss-averse investors. The jump risk decomposition into upside and downside components is also in line with the evidence of downside risk in equity markets (Ang et al., 2006; Lettau et al., 2014) and the high correlation of large down moves in international markets documented by Longin and Solnik (2001) and Ang and Bekaert (2002). Third, it is common that small jumps are more frequent than large ones. Indeed, the reaction of the stock market to jumps should not depend only on size, but also on frequency and occurrence pattern of jumps. The literature shows large jumps tend to occur simultaneously across countries leading to higher correlations between international stock markets (Das and Uppal, 2004; Ait-Sahalia et al., 2015). The decomposition of jump risk into small and large components will disentangle the effects of frequent small jumps and infrequent large jumps on the global systematic jump risk. Fourth, investors and policy makers tend to care more about large movements of market than smooth ones, especially during the crisis periods. We examine this issue by comparing investors' perception of systematic continuous and discontinuous risks shifts during crisis versus non-crisis periods.

Using the intraday data of 37 country exchange-traded funds (ETFs) covering developed, emerging and frontier markets from July 2003 to December 2014, we apply the techniques proposed by Andersen et al. (2007, henceforth ABD) and Lee and Mykland (2008, henceforth LM) to identify intraday jumps and cojumps. We apply Todorov and Bollerslev (2010)'s methodology to estimate the exposure of each country fund to the systematic market diffusive and jump risks and show that individual country funds are more sensitive to large abrupt movements of market returns than to smooth ones. Defining cojumps or systematic jumps as jumps that occur simultaneously with jumps in the world market index³, we find that

³The world market index is constructed as an equally weighted portfolio of 37 country funds in our sample.

cojumps are more frequent in developed markets than emerging markets which is consistent with the nature of high market integration in developed markets.⁴ The results of the portfolio sorting approach and the cross-sectional Fama and MacBeth (1973) regressions show that both continuous and downside jump systematic risks are rewarded by positive premium during the pre-crisis period whereas the reward for bearing the upside and large jump risks are negative during the crisis and post-crisis periods suggesting that investors prefer stocks that help them hedge against large negative movements of the market. We consider another possible source of jumps and cojumps, exchange rate stemming from all ETFs being U.S. dollar-denominated while their underlying securities are not. We consider the number of cojumps of each fund with EUR/USD exchange rate and an additional factor of risk representing the sensitivity of an asset to EUR/USD exchange rate jump movements. We find the currency jump risk premium is not significant during the pre-crisis, crisis and post-crisis periods. Previous results on continuous and discontinuous equity jump risk premia remain intact after considering currency jump risk. Finally, we provide evidence on the strong negative relationship between market price movements and market volatility changes during the pre-crisis period, consistent with the positive continuous and downside discontinuous risk premia observed during the pre-crisis period. These findings suggest that both continuous and discontinuous price and volatility risks share compensations for common underlying risk factors.

The new jump betas estimation framework that we develop in this article provides a valuable tool for investors to evaluate and hedge jump risks in an efficient way. In accordance with their aversion to jump risk and market conditions (bullish or bearish), investors could limit their exposure to a particular type of jump risk (up, down, small or large) while eliminating remaining sources of jump risks using suitable hedging instruments. As suggested by our study, practitioners should also take advantage of jump risk diversification potential that still offer emerging markets in general and non-Asian emerging markets in particular. The findings in this study also suggest that both continuous and discontinuous price and volatility risks are linked to each other and thus should be managed jointly by investors.

⁴Pukthuanthong and Roll (2015) find similar results. They show jumps are more systematic and correlated in Europe more than the other regions.

The remainder of this paper is organized as follows. Section 3.2 introduces the beta estimation framework. Section 3.3 describes our data. Section 3.4 discusses our main empirical findings. Section 3.5 concludes.

3.2 Betas estimation framework

This section briefly reviews the theoretical framework that we use to disentangle and estimate the sensitivity towards systematic diffusive and jump risks in the context of factor models. We first assume that the intraday log-price processes for the aggregate market index, denoted by $p_{0,t}$, and the asset i , denoted by $p_{i,t}$, follow general continuous-time processes:⁵

$$dp_{0,t} = \alpha_{0,t}dt + \sigma_{0,t}dW_{0,t} + dJ_{0,t}, \quad 0 \leq t \leq T$$

$$dp_{i,t} = \alpha_{i,t}dt + \beta_i^c \sigma_{0,t}dW_{0,t} + \beta_i^d dJ_{0,t} + \sigma_{i,t}dW_{i,t} + dJ_{i,t}, \quad i = 1, \dots, n$$

where $W_{0,t}$ and $W_{i,t}$ denote independent standard Brownian motions; $J_{0,t}$ and $J_{i,t}$ denote pure jump processes for systematic market wide jumps and jumps specific to asset i , respectively. The two betas, β^c and β^d , measure respectively asset i 's sensitivities to continuous and discontinuous movements of the market. Aggregating the individual asset processes over multiple days $[0, T]$ readily implies the linear two-factor relation for the T -day return on asset i :

$$r_i = \alpha_i + \beta_i^c r_0^c + \beta_i^d r_0^d + \epsilon_i \quad (3.1)$$

where α_i is its drift term, and r_0^c and r_0^d are the continuous and the discontinuous parts of the market return, respectively. The idiosyncratic term ϵ_i is defined similarly as temporally aggregated asset specific components. Clearly, when $\beta_i^c = \beta_i^d$, this framework collapses back to the classic, standard one-factor model.

By decomposing the market return into intraday (both diffusive and jump parts) and

⁵This model decomposition is also applied by Alexeev et al. (2017) and Bollerslev et al. (2016).

overnight components, Eq. 3.1 can be rewritten:⁶

$$r_i = \alpha_i + \beta_i^c r_0^c + \beta_i^d r_0^d + \beta_i^{ovn} r_0^{ovn} + \epsilon_i \quad (3.2)$$

where r_0^{ovn} is the aggregated overnight return of the market index over $[0, T]$ and the overnight beta measures asset i 's sensitivity to overnight movements of the market. Overnight period is from 4 pm to 9:30 am (UTC-4 time zone). In Eq. 3.2, we measure separately the sensitivity of the asset i to the market movements that occur respectively during the day and overnight.

We also investigate whether the impact of market jumps is asymmetric by distinguishing between positive and negative market jumps. We obtain the following four-factor model:

$$r_i = \alpha_i + \beta_i^c r_0^c + \beta_i^{d,up} r_0^{d,up} + \beta_i^{d,down} r_0^{d,down} + \beta_i^{ovn} r_0^{ovn} + \epsilon_i \quad (3.3)$$

where $\beta_i^{d,up}$ and $\beta_i^{d,down}$ measure respectively asset i 's sensitivities to positive and negative jumps of the aggregated market index. $r_0^{d,up}$ and $r_0^{d,down}$ are respectively the aggregated positive and negative jump returns of the market index over $[0, T]$.

Finally, we examine separately the reaction of individual assets to respectively small and large market jumps. The model is given by:

$$r_i = \alpha_i + \beta_i^c r_0^c + \beta_i^{d,small} r_0^{d,small} + \beta_i^{d,large} r_0^{d,large} + \beta_i^{ovn} r_0^{ovn} + \epsilon_i \quad (3.4)$$

where $\beta_i^{d,small}$ and $\beta_i^{d,large}$ measure respectively asset i 's sensitivities to small and large jumps of the aggregated market index. $r_0^{d,small}$ and $r_0^{d,large}$ are respectively the aggregated small and large jump returns of the market index over $[0, T]$.

Over the time interval $[0, T]$, suppose that asset prices are observed at discrete time grids $\frac{\tau}{m}$, where m is the number of observations per one time unit, and $\tau = 1, \dots, mT$. $\Delta p_{i,\tau} = p_{i,\frac{\tau}{m}} - p_{i,\frac{\tau-1}{m}}$ is the intraday return of asset i over the $[\frac{\tau-1}{m}, \frac{\tau}{m}]$ intraday time interval.

⁶This three factors model is also used in Bollerslev et al. (2016).

Following Todorov and Bollerslev (2010), we estimate β_i^c and β_i^d using the observed discrete intraday returns of the market and the asset i , $\{\Delta p_{0,\tau}, \Delta p_{i,\tau}\}$ over the period $[0, T]$:

$$\beta_i^c = \frac{\sum_{\tau=1}^{mT} \left[(\Delta p_{i,\tau} + \Delta p_{0,\tau})^2 \mathbb{1}_{\{|\Delta p_{i,\tau} + \Delta p_{0,\tau}| \leq \theta_{i+0,\tau}\}} - (\Delta p_{i,\tau} - \Delta p_{0,\tau})^2 \mathbb{1}_{\{|\Delta p_{i,\tau} - \Delta p_{0,\tau}| \leq \theta_{i-0,\tau}\}} \right]}{\sum_{\tau=1}^{mT} (2\Delta p_{0,\tau})^2 \mathbb{1}_{\{|2\Delta p_{0,\tau}| \leq \theta_{2 \times 0,\tau}\}}}$$

$$\beta_i^d = \text{sign} \left\{ \sum_{\tau=1}^{mT} \text{sign}\{\Delta p_{i,\tau} \Delta p_{0,\tau}\} (\Delta p_{i,\tau} \Delta p_{0,\tau})^2 \right\} \times \left(\frac{\left| \sum_{\tau=1}^{mT} \text{sign}\{\Delta p_{i,\tau} \Delta p_{0,\tau}\} (\Delta p_{i,\tau} \Delta p_{0,\tau})^2 \right|}{\sum_{\tau=1}^{mT} (\Delta p_{0,\tau})^4} \right)^{\frac{1}{2}}$$

The indicator functions $\mathbb{1}_{\{|\Delta p_{i,\tau} + \Delta p_{0,\tau}| \leq \theta_{i+0,\tau}\}}$, $\mathbb{1}_{\{|\Delta p_{i,\tau} - \Delta p_{0,\tau}| \leq \theta_{i-0,\tau}\}}$ and $\mathbb{1}_{\{|2\Delta p_{0,\tau}| \leq \theta_{2 \times 0,\tau}\}}$ are introduced to filter out jumps of $(\Delta p_{i,\tau} + \Delta p_{0,\tau})$, $(\Delta p_{i,\tau} - \Delta p_{0,\tau})$ and $(2\Delta p_{0,\tau})$ processes. Jumps are detected using the technique proposed by Andersen et al. (2007) and Lee and Mykland (2008).⁷ Details about this jump detection method are provided in Appendix 3.A. Similarly, the estimates of $\beta_i^{d,up}$ and $\beta_i^{d,down}$ are given by:

$$\beta_i^{d,up} = \text{sign} \left\{ \sum_{\tau=1}^{mT} \text{sign}\{\Delta p_{i,\tau} \Delta p_{0,\tau}\} (\Delta p_{i,\tau} \Delta p_{0,\tau})^2 \mathbb{1}_{\{\Delta p_{0,\tau} > 0\}} \right\}$$

$$\times \left(\frac{\left| \sum_{\tau=1}^{mT} \text{sign}\{\Delta p_{i,\tau} \Delta p_{0,\tau}\} (\Delta p_{i,\tau} \Delta p_{0,\tau})^2 \mathbb{1}_{\{\Delta p_{0,\tau} > 0\}} \right|}{\sum_{\tau=1}^{mT} (\Delta p_{0,\tau})^4 \mathbb{1}_{\{\Delta p_{0,\tau} > 0\}}} \right)^{\frac{1}{2}}$$

$$\beta_i^{d,down} = \text{sign} \left\{ \sum_{\tau=1}^{mT} \text{sign}\{\Delta p_{i,\tau} \Delta p_{0,\tau}\} (\Delta p_{i,\tau} \Delta p_{0,\tau})^2 \mathbb{1}_{\{\Delta p_{0,\tau} < 0\}} \right\}$$

$$\times \left(\frac{\left| \sum_{\tau=1}^{mT} \text{sign}\{\Delta p_{i,\tau} \Delta p_{0,\tau}\} (\Delta p_{i,\tau} \Delta p_{0,\tau})^2 \mathbb{1}_{\{\Delta p_{0,\tau} < 0\}} \right|}{\sum_{\tau=1}^{mT} (\Delta p_{0,\tau})^4 \mathbb{1}_{\{\Delta p_{0,\tau} < 0\}}} \right)^{\frac{1}{2}}$$

⁷Dumitru and Urga (2012) show that intraday jump tests of LM and ABD outperform other test procedures especially when price volatility is not high. Moreover, Gnabo et al. (2014) show that univariate tests we use are satisfactory and best-suited for detecting jumps and cojumps as long as the jumps sizes are sufficiently large and have the same sign as the assets correlation.

where $\mathbb{1}_{\{\Delta p_{0,\tau} > 0\}}$ and $\mathbb{1}_{\{\Delta p_{0,\tau} < 0\}}$ are indicators for respectively positive and negative market intraday returns.

The estimates of $\beta_i^{d,small}$ and $\beta_i^{d,large}$ are given by:

$$\beta_i^{d,small} = \text{sign} \left\{ \sum_{\tau=1}^{mT} \text{sign}\{\Delta p_{i,\tau} \Delta p_{0,\tau}\} (\Delta p_{i,\tau} \Delta p_{0,\tau})^2 \mathbb{1}_{\{\theta_{i,lower} \leq |\Delta p_{0,\tau}| \leq \theta_{i,upper}\}} \right\} \\ \times \left(\frac{\left| \sum_{\tau=1}^{mT} \text{sign}\{\Delta p_{i,\tau} \Delta p_{0,\tau}\} (\Delta p_{i,\tau} \Delta p_{0,\tau})^2 \mathbb{1}_{\{\theta_{i,lower} \leq |\Delta p_{0,\tau}| \leq \theta_{i,upper}\}} \right|}{\sum_{\tau=1}^{mT} (\Delta p_{0,\tau})^4 \mathbb{1}_{\{\theta_{i,lower} \leq |\Delta p_{0,\tau}| \leq \theta_{i,upper}\}}} \right)^{\frac{1}{2}}$$

$$\beta_i^{d,large} = \text{sign} \left\{ \sum_{\tau=1}^{mT} \text{sign}\{\Delta p_{i,\tau} \Delta p_{0,\tau}\} (\Delta p_{i,\tau} \Delta p_{0,\tau})^2 \mathbb{1}_{\{|\Delta p_{0,\tau}| > \theta_{i,upper}\}} \right\} \\ \times \left(\frac{\left| \sum_{\tau=1}^{mT} \text{sign}\{\Delta p_{i,\tau} \Delta p_{0,\tau}\} (\Delta p_{i,\tau} \Delta p_{0,\tau})^2 \mathbb{1}_{\{|\Delta p_{0,\tau}| > \theta_{i,upper}\}} \right|}{\sum_{\tau=1}^{mT} (\Delta p_{0,\tau})^4 \mathbb{1}_{\{|\Delta p_{0,\tau}| > \theta_{i,upper}\}}} \right)^{\frac{1}{2}}$$

$\theta_{i,upper}$ and $\theta_{i,lower}$ stand for the upper and lower thresholds used to separate between small and large market jumps. $\theta_{i,upper}$ and $\theta_{i,lower}$ are respectively equal to 4.85 and 4 in our study, which corresponds respectively to 1% and 5% confidence level.⁸ The estimate of the overnight beta is obtained by applying the formula of discontinuous beta to overnight returns.

3.3 Data description

We use intraday data of a set of 37 country exchange-traded funds in our empirical investigation covering developed, emerging and frontier markets. We have 18 ETFs for respectively the developed and emerging markets. The frontier markets are represented by one ETF in the sample, the FRN fund.⁹ Table 3.1 provides the detail of the country ETFs used in our study. Our empirical analysis is based on intraday prices from July 2003 to December 2014. Prices are sampled every 20 minutes from 9:30 to 15:55 (UTC-4 time zone), to smooth the

⁸The calculation of the threshold for a given confidence level is detailed in Appendix 3.A.

⁹The FRN fund invests at least 80% of its total assets in securities of issuers from frontier market countries.

impact of market microstructure noise.¹⁰

Table 3.1: Country exchange-traded funds.

The ticker, the name, the inception date and the country of each fund in the sample are reported.

Ticker	Fund	Inception Date	Country
ECH	iShares MSCI Chile Capped ETF	November 12, 2007	Chile
ENZL	iShares MSCI New Zealand Capped ETF	September 1, 2010	New Zealand
EPHE	iShares MSCI Philippines ETF	September 28, 2010	Philippines
EPOL	iShares MSCI Poland Capped ETF	May 25, 2010	Poland
EPU	iShares MSCI All Peru Capped ETF	June 19, 2009	Peru
EWA	iShares MSCI Australia ETF	March 12, 1996	Australia
EWC	iShares MSCI Canada ETF	March 12, 1996	Canada
EWD	iShares MSCI Sweden ETF	March 12, 1996	Sweden
EWG	iShares MSCI Germany ETF	March 12, 1996	Germany
EWH	iShares MSCI Hong Kong ETF	March 12, 1996	Hong Kong
EWI	iShares MSCI Italy Capped ETF	March 12, 1996	Italy
EWJ	iShares MSCI Japan ETF	March 12, 1996	Japan
EWK	iShares MSCI Belgium Capped ETF	March 12, 1996	Belgium
EWL	iShares MSCI Switzerland Capped ETF	March 12, 1996	Switzerland
EWM	iShares MSCI Malaysia ETF	March 12, 1996	Malaysia
EWN	iShares MSCI Netherlands ETF	March 12, 1996	Netherlands
EWO	iShares MSCI Austria Capped ETF	March 12, 1996	Austria
EWP	iShares MSCI Spain Capped ETF	March 12, 1996	Spain
EWQ	iShares MSCI France ETF	March 12, 1996	France
EWS	iShares MSCI Singapore ETF	March 12, 1996	Singapore
EWT	iShares MSCI Taiwan ETF	June 20, 2000	Taiwan
EWU	iShares MSCI United Kingdom ETF	March 12, 1996	United Kingdom
EWV	iShares MSCI Mexico Capped ETF	March 12, 1996	Mexico
EWY	iShares MSCI South Korea Capped ETF	May 9, 2000	South Korea
EWZ	iShares MSCI Brazil Capped ETF	July 10, 2000	Brazil
EZA	iShares MSCI South Africa ETF	February 3, 2003	South Africa
FRN	Guggenheim Frontier Markets ETF	June 12, 2008	Frontier Markets
GREK	Global X FTSE Greece 20 ETF	July 12, 2011	Greece
GXC	SPDR S&P China ETF	March 23, 2007	China

¹⁰We verify the robustness of our results using different sampling frequencies (10, 15, 30 and 60 minutes).

GXG	Global X MSCI Colombia ETF	February 5, 2009	Colombia
IDX	Market Vectors Indonesia Index ETF	January 20, 2009	Indonesia
PIN	Power Shares India Portfolio ETF	March 5, 2008	India
RSX	Market Vectors Russia ETF	April 30, 2007	Russia
SPY	SPDR S&P 500	December 30, 2002	United States
THD	iShares MSCI Thailand Capped ETF	March 26, 2008	Thailand
TUR	iShares MSCI Turkey ETF	March 26, 2008	Turkey
VNM	Market Vectors Vietnam ETF	August 14, 2009	Vietnam

Each country ETF considered in our study can be viewed as a derivative security that aims to replicate the performance of its corresponding country index by holding a portfolio of the common stocks that are included in the underlying index, with the weight of each stock in the portfolio substantially corresponding to the weight of such stock in the index. We choose to conduct our empirical investigation with ETFs rather than underlying indexes for many reasons. First, contrary to ETFs, historical intraday prices are not available for all underlying indexes that we need to conduct our study. Second, the ETF market liquidity is higher than underlying asset markets. Third, all considered ETFs are traded within the same market and during same trading hours. It is easier in practice to work with ETFs synchronous historical prices rather than with underlying assets that are non-synchronously traded in different developed, emerging and frontier markets. However, one might argue that international market jumps that are implied from the ETF market may be substantially different from those that can be retrieved from underlying indices markets. To study this hypothesis, we check if the jump occurrences found using an ETF and its underlying index are the same for the US market. The comparison is done between iShares NYSE 100 ETF and NYSE U.S. 100 Index over the period going from March 2012 to December 2014.¹¹ Prices are sampled every 20 minutes from 9:30 to 15:55. We identify a total number of 161 jumps for iShares NYSE 100 ETF and 163 jumps for the underlying index. The number of cojump occurrences is equal to 161. This result show that the ETF jumps occur simultaneously with

¹¹The iShares NYSE 100 ETF aims to replicate the performance of the NYSE U.S. 100 Index. The underlying index measures the performance of the largest 100 United States companies, based on market capitalization, listed on the New York Stock Exchange (NYSE).

its underlying asset. The ETF market can be thus considered as a good proxy to study jumps of the underlying stock market.

3.4 Empirical Findings

3.4.1 Systematic cojumps

This subsection summarizes the results from applying LM-ABD intraday jump detection test. Table 3.2 shows the number of total, positive and negative intraday jumps detected over the period of study. A positive (negative) jump is a jump with positive (negative) return. We identify 19,599 intraday jumps across all countries in the sample, including the world market index. The world market index is an equal-weighted portfolio created by giving the same weight to country ETFs available in the sample for a given day. We identify 681 jumps (59 jumps per year) for the equal-weighted world market index, which corresponds to 1.24% of the total number of intraday returns over the period of study. We detect 67, 64 and 87 jumps per year on average for respectively developed, emerging and frontier markets. New Zealand, Belgium, Frontier markets, Greece and Peru have the largest number of intraday jumps among all countries studied in our sample. They have more than 80 intraday jumps per year whereas the average number of jumps is 66 per year. United Kingdom, Thailand, Chile and Australia have the lowest jump activity with less than 53 jumps per year. Developed countries like the US, Sweden, France and Germany have similar jump activity to the world market portfolio with a number of jumps between 58 and 62 per year. The results show the number of negative jumps is more than 54% of total number of detected jumps across all funds, which is slightly greater than positive ones. We identify 423 negative systematic jumps for the world market portfolio, which corresponds to 62% of total systematic jumps. This result indicates that stock markets tend to be more linked together when prices are decreasing. The gap between the positive and negative jumps is highest for the world market portfolio, Russia, Indonesia and Brazil, where the number of negative jumps is respectively 62%, 60%, 60% and 59%. The proportions of positive jumps are higher than negative ones for Philippines (54% of detected

jumps are positive). This table shows jump activity of each country fund. A lower jump activity implies lower risk (volatility) for investors. Investors should take into account both the continuous and jump parts of the return before making investment decision.

Table 3.2: Summary statistics of jump occurrences.

The percentage of intraday jumps to the number of intraday returns, the percentage of positive jumps and negative jumps to all jumps are reported in columns 3, 5 and 6, respectively. The total number of days available in the sample by fund and the average number of jumps per year are shown in columns 2 and 4. Aggregated results are also reported for developed, emerging and frontier markets. The world market index is an equal-weighted portfolio created by giving the same weight to country ETFs available in the sample. Jumps are detected by LM-ABD procedure. See Appendix 3.A for the jump measure.

	Days	Intraday jumps	Number of intraday jumps per year	Positive jumps	Negative jumps
Average	-	1.37%	66	46%	54%
Developed markets	-	1.39%	67	45%	55%
Emerging markets	-	1.33%	64	46%	54%
Frontier markets	-	1.83%	87	49%	51%
World Index	2896	681 (1.24%)	59	258 (38%)	423 (62%)
Chile	1518	319 (1.11%)	53	151 (47%)	168 (53%)
New Zealand	817	382 (2.46%)	118	190 (50%)	192 (50%)
Philippines	1052	308 (1.54%)	74	165 (54%)	143 (46%)
Poland	886	207 (1.23%)	59	91 (44%)	116 (56%)
Peru	1372	459 (1.76%)	84	208 (45%)	251 (55%)
Australia	2624	550 (1.1%)	53	246 (45%)	304 (55%)
Canada	2624	592 (1.19%)	57	258 (44%)	334 (56%)
Sweden	2371	556 (1.23%)	59	256 (46%)	300 (54%)
Germany	2624	642 (1.29%)	62	285 (44%)	357 (56%)
Hong Kong	2875	623 (1.14%)	55	275 (44%)	348 (56%)
Italy	2119	556 (1.38%)	66	239 (43%)	317 (57%)
Japan	2894	615 (1.12%)	54	286 (47%)	329 (53%)
Belgium	2371	1074 (2.38%)	114	505 (47%)	569 (53%)
Switzerland	2371	536 (1.19%)	57	243 (45%)	293 (55%)
Malaysia	2371	541 (1.2%)	57	256 (47%)	285 (53%)
Netherlands	2119	655 (1.63%)	78	298 (45%)	357 (55%)
Austria	2624	806 (1.62%)	77	376 (47%)	430 (53%)
Spain	2119	489 (1.21%)	58	219 (45%)	270 (55%)

France	2119	507 (1.26%)	60	214 (42%)	293 (58%)
Singapore	2371	517 (1.15%)	55	253 (49%)	264 (51%)
Taiwan	2880	617 (1.13%)	54	298 (48%)	319 (52%)
United Kingdom	2576	512 (1.05%)	50	221 (43%)	291 (57%)
Mexico	2624	566 (1.14%)	54	249 (44%)	317 (56%)
South Korea	2894	738 (1.34%)	64	337 (46%)	401 (54%)
Brazil	2866	610 (1.12%)	54	250 (41%)	360 (59%)
South Africa	2470	706 (1.5%)	72	343 (49%)	363 (51%)
Greece	500	168 (1.77%)	85	80 (48%)	88 (52%)
China	1939	459 (1.25%)	60	217 (47%)	242 (53%)
Colombia	960	288 (1.58%)	76	138 (48%)	150 (52%)
Indonesia	1199	272 (1.19%)	57	110 (40%)	162 (60%)
India	1700	369 (1.14%)	55	165 (45%)	204 (55%)
Russia	1914	481 (1.32%)	63	193 (40%)	288 (60%)
United States	2896	662 (1.2%)	58	292 (44%)	370 (56%)
Thailand	1431	297 (1.09%)	52	137 (46%)	160 (54%)
Turkey	1684	478 (1.49%)	71	219 (46%)	259 (54%)
Vietnam	1335	370 (1.46%)	70	178 (48%)	192 (52%)

Table 3.3 Panel A provides some statistics of funds' cojumps with the world market index. Systematic cojumps defined as jump in the country fund that occurs at the same intraday interval with jump in the world market index; otherwise, it is called idiosyncratic jump (Gilder et al., 2012; Bormetti et al., 2015) or country specific jump. We identify 7129 systematic cojumps across all country funds, which correspond to 37% of total number of detected jumps. Australia, United Kingdom, United States, France, Spain and Germany have the highest proportion of systematic cojumps with respectively 291 (53% of detected jumps), 269 (53%), 341 (52%), 266 (52%), 252 (52%) and 320 (50%) cojumps. Countries with the lowest proportion of cojumps include Colombia, Vietnam, Greece, Peru and frontier markets, where the proportion of cojumps is less than 15% of detected jumps. In general, jumps in developed countries are more linked to the world market portfolio than emerging and frontier markets. The result is consistent with Pukthuanthong and Roll (2015). Cojumps represent on average 42%, 32% and 14% of all detected jumps for respectively developed, emerging and frontier markets. This

finding is linked to the higher degree of integration observed in developed markets compared to emerging ones, which implies that developed markets are more likely to move together mainly in case of jumps whereas jumps in emerging markets are often country specific. This result might be also explained by the flight-to-safety behavior of market participants who have tendency to flee relatively risky emerging stock markets and prefer to invest in developed stock markets during periods of turmoil, leading to a significant increase in comovement between developed stock markets. Our results are consistent with Pukthuanthong and Roll (2015) who find that jumps are more correlated in developed markets and argue that the rarity of international correlation among jumps suggests that jumps might be caused by local events rather than common global factors such as energy prices. With this argument, it is possible that most of the events that might cause jumps originated in developed markets rather than emerging markets. For instance, the creation of Euro Dollar in 1999 might induce cojumps across Europe, or Internet Bubble burst in 2000 and subprime mortgage crisis in 2009 that were originated in the US and might cause cojumps in other developed markets. The last event is within our sample period.

As for jumps, the number of negative cojumps is higher than positive cojumps for all funds, except for New Zealand, Philippines and Colombia. Negative cojumps represent 57% of all systematic cojumps in average. This result is consistent with the high correlation between large down moves in international markets documented by Longin and Solnik (2001) and Ang and Bekaert (2002).

Table 3.3 Panel B (respectively Panel C) provides some statistics of developed (respectively emerging) market funds cojumps with the aggregated index of developed (respectively emerging) markets. Cojumps represent on average 45% of all detected jumps for developed markets compared to 24% for emerging markets. This result suggests that developed markets jumps are more closely linked to each other than emerging ones. The highest proportions of cojumps with the aggregated index of developed markets are evident for Spain (60%), France (58%), Germany (56%) and United Kingdom (54%) whereas New Zealand has the lowest proportion (15%) among all the developed markets in the sample. Overall, the European

markets have tendency to cojump more frequently with the aggregate index than other developed markets in the sample. Thailand, Indonesia and India have the highest proportions of cojumps with the aggregated index of emerging markets (more than 33% of all detected jumps for each fund) whereas Colombia, Vietnam, Greece and Peru have the lowest proportions (less than 10% of all detected jumps for each fund). Globally, Asian stock markets jumps are more linked to the aggregate index than other emerging markets in the sample. The findings in this section suggest it is more difficult to diversify portfolio jump risk by investing in Asian stock market. The results suggest that investors investing in non-Asian emerging markets may better minimize their exposure to systematic jump risk.

Table 3.3: Summary statistics of systematic cojumps.

Panels A, B and C report the number of cojumps, the percentage of cojumps to the total number of detected jumps, and the percentage of positive and negative cojumps to all cojumps of all country (respectively developed, emerging and frontier) funds with the world market index (respectively the aggregate index of developed markets, the aggregate index of emerging markets). Panels A, B, and C also provide the average proportion of cojumps with the word market index for developed, emerging and frontier markets. The world market index (respectively the developed markets index, emerging market index) is an equal-weighted portfolio created by assigning equal weight to all country (respectively developed, emerging) funds available in the sample. See Appendix 3.A for the cojump measure.

Panel A: Cojumps of all country funds with the world market index

	Cojumps	Positive cojumps	Negative cojumps
Average	37%	43%	57%
Developed markets	42%	43%	57%
Emerging markets	32%	43%	57%
Frontier markets	14%	49%	51%
Chile	66 (21%)	42%	58%
New Zealand	59 (15%)	54%	46%
Philippines	81 (26%)	54%	46%
Poland	95 (46%)	45%	55%
Peru	57 (12%)	46%	54%
Australia	291 (53%)	42%	58%
Canada	236 (40%)	43%	57%
Sweden	256 (46%)	43%	57%
Germany	320 (50%)	41%	59%
Hong Kong	274 (44%)	43%	57%
Italy	235 (42%)	40%	60%

Japan	240 (39%)	46%	54%
Belgium	228 (21%)	42%	58%
Switzerland	221 (41%)	43%	57%
Malaysia	202 (37%)	45%	55%
Netherlands	246 (38%)	41%	59%
Austria	221 (27%)	38%	62%
Spain	252 (52%)	42%	58%
France	266 (52%)	36%	64%
Singapore	249 (48%)	47%	53%
Taiwan	260 (42%)	42%	58%
United Kingdom	269(53%)	45%	55%
Mexico	225 (40%)	41%	59%
South Korea	305 (41%)	42%	58%
Brazil	217 (36%)	36%	64%
South Africa	265 (38%)	42%	58%
Greece	19 (11%)	47%	53%
China	200 (44%)	45%	55%
Colombia	28 (10%)	54%	46%
Indonesia	118 (43%)	41%	59%
India	172 (47%)	39%	61%
Russia	217 (45%)	37%	63%
United States	341 (52%)	40%	60%
Thailand	145 (49%)	41%	59%
Turkey	164 (34%)	37%	63%
Vietnam	36 (10%)	47%	53%

Panel B: Cojumps of developed market funds with the aggregate index of developed markets

	Cojumps	Positive cojumps	Negative cojumps
Average	44%	44%	56%
New Zealand	56 (15%)	57%	43%
Australia	290 (53%)	44%	56%
Canada	230 (39%)	45%	55%
Sweden	285 (51%)	46%	54%
Germany	362 (56%)	41%	59%
Hong Kong	257 (41%)	45%	55%

Italy	275 (49%)	41%	59%
Japan	238 (39%)	51%	49%
Belgium	261 (24%)	42%	58%
Switzerland	245 (46%)	46%	54%
Netherlands	275 (42%)	42%	58%
Austria	243 (30%)	37%	63%
Spain	293 (60%)	43%	57%
France	294 (58%)	37%	63%
Singapore	235 (45%)	48%	52%
United Kingdom	276 (54%)	46%	54%
South Korea	285 (39%)	46%	54%
United States	321 (48%)	42%	58%

Panel C: Cojumps of emerging market funds with the aggregate index of emerging markets

	Cojumps	Positive cojumps	Negative cojumps
Average	24%	45%	55%
Chile	56 (18%)	46%	54%
Philippines	61 (20%)	51%	49%
Poland	64 (31%)	53%	47%
Peru	40 (9%)	48%	53%
Malaysia	143 (26%)	45%	55%
Taiwan	186 (30%)	45%	55%
Mexico	170 (30%)	45%	55%
Brazil	170 (28%)	38%	62%
South Africa	199 (28%)	41%	59%
Greece	13 (8%)	46%	54%
China	143 (31%)	45%	55%
Colombia	21 (7%)	62%	38%
Indonesia	93 (34%)	40%	60%
India	120 (33%)	38%	63%
Russia	152 (32%)	39%	61%
Thailand	113 (38%)	40%	60%
Turkey	120 (25%)	38%	63%
Vietnam	28 (8%)	46%	54%

3.4.2 Diffusive and jump betas

The earlier subsection shows us that country jumps are likely to be linked to each other especially within developed markets. This correlation between country jumps is an indicator of a significant systematic jump risk. To assess the exposure of each country fund to market movements, we apply Todorov and Bollerslev (2010)'s methodology which enable us to decompose the systematic market risk (beta) into continuous and jump components. The jump risk can be decomposed into positive (up), negative (down), small and large betas, which respectively measure the sensitivity of each fund to positive, negative, small and large aggregate market jumps.

This subsection summarizes the main proprieties of the estimated continuous and discontinuous (up, down, small and large) and overnight betas. We fix the sampling frequency of intraday returns used in the estimation of these betas at 20 minutes, with returns spanning from 9:35 am to 4:00 pm for each trading day. We calculate the continuous, discontinuous and overnight betas on a monthly basis based on the data from the previous 12 months. Table 3.4 Panel A (respectively B, C and D) provides summary statistics of the distributions of the monthly estimated betas aggregated across all countries (respectively developed, emerging and frontier markets) and time. We find that the mean and the median of the discontinuous beta (respectively 1.14 and 1.08) are higher than the continuous one (respectively 1.00 and 0.95) indicating that country funds are more sensitive to the market jumps than to smooth movements of the market and update faster to unexpected information arrival since jumps are often associated with macroeconomic news announcements. The standard deviation of continuous beta (0.28) is lower than discontinuous one (0.35), suggesting that the continuous beta is less dispersed than the discontinuous beta. We find a similar result for developed, emerging and frontiers markets. The small jump beta is, on average, greater than large jump beta indicating that country funds are more sensitive to small frequent market jumps than large infrequent market jumps. The downside jump beta is, on average, highest among all betas suggesting country funds react to unexpected negative information arrival the most. This

result applies to developed, emerging and frontier markets. Overall, the betas are higher for emerging markets than for developed and frontier markets, implying emerging markets have higher systematic risks than the other markets. The difference between betas observed in developed and emerging markets does not necessarily mean that emerging markets are more linked to aggregate market index than developed ones, but it is simply explained by a higher level of market volatility in emerging markets compared to developed ones.

Table 3.4: Summary statistics of different betas.

Panels A, B, C and D report the mean, median, standard deviation, skewness and kurtosis of monthly estimated continuous, overnight, discontinuous, discontinuous up, down, large and small betas aggregated across all countries (respectively developed, emerging and frontier markets). See Section 3.2 for the description of each beta measure.

Panel A: All countries

	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
Mean	1.00	1.11	1.14	1.13	1.17	1.12	1.07
Median	0.95	1.07	1.08	1.07	1.09	1.04	1.01
St.deviation	0.28	0.35	0.35	0.35	0.39	0.38	0.43
Skewness	0.74	0.70	1.08	0.94	1.06	1.06	0.56
Kurtosis	3.84	3.92	4.79	6.85	6.36	8.96	6.78

Panel B: developed markets

	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
Mean	0.95	1.08	1.07	1.05	1.09	1.07	1.01
Median	0.92	1.06	1.02	1.02	1.04	1.02	0.97
St.deviation	0.22	0.31	0.31	0.27	0.37	0.32	0.42
Skewness	0.62	0.11	1.17	-0.17	1.13	1.32	0.36
Kurtosis	3.34	3.03	5.86	6.87	8.90	9.32	8.45

Panel C: Emerging markets

	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
Mean	1.08	1.17	1.26	1.25	1.28	1.20	1.17
Median	1.07	1.09	1.19	1.20	1.21	1.16	1.11
St.deviation	0.33	0.40	0.38	0.40	0.40	0.44	0.41
Skewness	0.46	0.92	0.87	1.09	0.99	0.70	0.92
Kurtosis	3.13	3.55	3.85	5.16	4.19	8.25	4.44

Panel D: Frontier markets

	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
Mean	0.55	0.60	0.79	0.76	0.88	0.66	0.69
Median	0.53	0.57	0.85	0.82	0.87	0.64	0.73
St.deviation	0.07	0.13	0.14	0.17	0.11	0.17	0.20
Skewness	0.49	0.57	-0.39	-0.52	0.84	0.45	-0.01
Kurtosis	2.09	2.28	2.16	1.79	2.76	2.98	1.77

Figure 3.1 displays the kernel density of the distributions of the monthly estimated continuous and discontinuous betas aggregated across countries and time. The distributions of discontinuous betas are right-skewed (a skewness of 1.08 and 0.74 for respectively discontinuous and continuous betas) and fat-tailed (a kurtosis of 3.84 and 4.97, respectively) compared to the distribution of continuous betas. This result means that large sensitivities of country funds to market movements are more frequent for intraday market jump returns than for continuous ones.

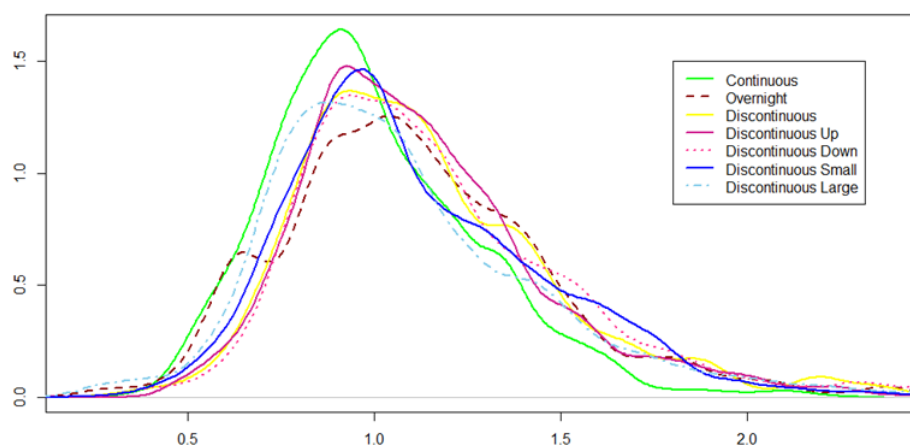


Figure 3.1: Beta distributions.

The graph displays the kernel density of the distributions of the monthly estimated continuous, overnight, discontinuous, discontinuous up, down, small and large betas aggregated across countries and time.

3.4.3 Risk factors and portfolio sorts

This subsection examines the cross-sectional relation between estimated betas and return by forming portfolios ranked on the basis of market betas. At the beginning of each month, we

calculate β^c , β^{own} , β^d , $\beta^{d,up}$, $\beta^{d,down}$, $\beta^{d,small}$ and $\beta^{d,large}$ using 20 minutes intraday returns from the previous 12 months. We then sort funds into quintiles (1-5) according to each beta and form equal-weighted portfolios. The average monthly returns of these sorted portfolios are computed over the same period used to compute different betas (contemporaneous return). We also compute the return of these portfolios over the month that follows the estimation period (post-formation return). Table 3.5 reports the results obtained for the whole period considered in our study (from July 2003 to December 2014). Panel A shows increasing returns of portfolios sorted by continuous betas. The difference between the average contemporaneous returns of the portfolios 1 (high betas) and 5 (low betas) is 0.59% per month. The difference of average returns is clearly higher between these two portfolios over the month following the portfolios formation. The post-formation monthly return is equal to 1.35% for the portfolio 1 and 0.32% for the portfolio 5. The Newey-West (1987) heteroskedastic robust t-statistics of the difference (1.03% per month, 12.35% per annum) is equal to 2.2.¹²

Panel B shows the results from sorting portfolios based on overnight beta. The average returns of sorted portfolios do not exhibit a clear relationship with the estimated overnight beta. Moreover, the difference between the return of the first and last portfolio is not statistically significant at 5% level. This result might be explained by the fact that market news tend to flow during regular trading hours and not after hours, which increases the variability of the market during regular hours.

Panels C, D and E show results from sorting portfolios by respectively discontinuous beta, discontinuous up and down betas. The relation between average returns and market risk factors is more pronounced for discontinuous down beta than for discontinuous up betas. First, the returns of portfolios sorted by discontinuous down beta are monotonically increasing whereas it is not always the case for two others betas. Second, the difference of monthly returns between the first and last portfolios (0.75% and 0.99% for respectively formation and post-formation periods) is largest when portfolios are sorted by discontinuous down beta. The

¹²The Newey-West test is also employed in Ang et al. (2006), Bollerslev et al. (2016) and Alexeev et al. (2017). The Newey-West t-statistic is calculated with 12 lags to adjust for the moving average effects induced by the use of overlapping estimation period (12 months in our case) for the calculation of monthly betas.

difference of monthly returns during the post-formation period is statistically significant at 5% level. These results are consistent with investors disliking downside jump risk and avoiding stocks that co-move strongly with negative market jumps. Stocks with high discontinuous downside beta must carry a positive premium in order to compensate investors from bearing downside jump risk. This result is consistent with Weigert (2016) who find that international stocks with strong sensitivity to extreme market downturns deliver average returns of more than 7% per annum higher than stocks with weak crash sensitivity.

Table 3.5: Contemporaneous and future returns of portfolios sorted by different betas for the period from July 2003 to December 2014.

This table lists the monthly returns and betas for sorted portfolios averaged over the period July 2003 to December 2014. For each month, we calculate β^c , β^{ovn} , β^d , $\beta^{d,up}$, $\beta^{d,down}$, $\beta^{d,small}$ and $\beta^{d,large}$ using 20-min intraday returns from the previous 12 months. We then sort funds into quintiles (1-5) according to each beta and form equal-weighted portfolios. The column labeled "Return" reports the average monthly return of sorted portfolios from the previous 12 months (which is the same period as the period used to compute different betas). The column labeled "Next Return" reports the return of sorted portfolios recorded in the month that follows the estimation period. The row labeled "High-Low" reports the difference between the returns of portfolio 1 and portfolio 5. The Newey-West robust t-statistics with 12 lags is reported in row "test-statistic". See Section 3.2 for the description of each beta measure. ***, **, * imply significance at 0.1%, 1% and 5% levels.

Panel A: Sorted by β^c

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	1.27	1.35	1.40	1.44	1.59	1.58	1.63	1.47	1.55
2	1.10	0.67	1.07	1.19	1.30	1.26	1.32	1.24	1.30
3	1.07	0.83	0.93	1.07	1.07	1.08	1.08	1.00	1.04
4	0.94	0.65	0.80	1.04	0.92	0.92	0.93	0.83	0.91
5-Low	0.68	0.32	0.65	0.79	0.87	0.87	0.87	0.82	0.80
High-Low	0.59	1.03*	0.76	0.65	0.73	0.71	0.76	0.65	0.75
t-statistic	1.82	2.20							

Panel B: Sorted by β^{ovn}

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	1.19	1.17	1.27	1.62	1.54	1.49	1.58	1.45	1.55
2	1.01	0.88	1.02	1.26	1.17	1.21	1.16	1.08	1.17
3	1.00	0.49	0.91	1.06	1.03	1.05	1.03	0.93	1.02
4	1.14	0.89	0.94	0.89	1.16	1.12	1.19	1.13	1.07
5-Low	0.87	0.49	0.76	0.62	0.88	0.88	0.90	0.79	0.81
High-Low	0.32	0.68	0.51	1.00	0.66	0.62	0.67	0.66	0.74

t-statistic	0.90	1.52
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Panel C: sorted by β^d

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	1.44	1.51	1.31	1.42	1.70	1.59	1.76	1.67	1.57
2	0.88	0.47	1.11	1.28	1.31	1.33	1.31	1.20	1.29
3	1.01	0.94	0.93	1.06	1.07	1.10	1.08	0.97	1.10
4	0.97	0.42	0.81	1.01	0.89	0.92	0.88	0.80	0.87
5-Low	0.70	0.49	0.71	0.78	0.74	0.77	0.73	0.61	0.75
High-Low	0.75	1.02*	0.60	0.64	0.96	0.82	1.03	1.06	0.82
t-statistic	1.88	2.45							

Panel D: sorted by $\beta^{d,up}$

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	1.34	1.37	1.34	1.43	1.64	1.64	1.63	1.54	1.54
2	1.00	0.72	1.06	1.24	1.32	1.29	1.34	1.26	1.32
3	1.02	0.81	0.94	1.08	1.10	1.08	1.12	1.06	1.08
4	0.87	0.46	0.82	1.00	0.90	0.91	0.92	0.82	0.88
5-Low	0.82	0.50	0.70	0.77	0.76	0.75	0.80	0.67	0.76
High-Low	0.52	0.87*	0.64	0.66	0.88	0.89	0.83	0.86	0.78
t-statistic	1.35	2.22							

Panel E: sorted by $\beta^{d,down}$

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	1.42	1.36	1.29	1.40	1.68	1.54	1.79	1.67	1.56
2	1.07	0.80	1.12	1.26	1.30	1.32	1.31	1.18	1.28
3	0.92	0.65	0.92	1.07	1.07	1.11	1.07	0.97	1.10
4	0.90	0.61	0.82	1.02	0.89	0.93	0.87	0.80	0.87
5-Low	0.68	0.37	0.72	0.81	0.76	0.82	0.71	0.65	0.76
High-Low	0.75	0.99*	0.58	0.59	0.92	0.72	1.07	1.02	0.81
t-statistic	1.92	2.47							

Panel F: sorted by $\beta^{d,small}$

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	1.30	1.53	1.26	1.36	1.67	1.55	1.73	1.72	1.48
2	1.08	0.42	1.09	1.25	1.29	1.31	1.30	1.20	1.26
3	0.93	0.74	0.98	1.12	1.08	1.14	1.08	0.96	1.14

4	0.90	0.61	0.81	0.99	0.89	0.92	0.88	0.79	0.88
5-Low	0.77	0.48	0.74	0.85	0.77	0.80	0.78	0.58	0.83
High-Low	0.53	1.05**	0.52	0.51	0.90	0.75	0.95	1.14	0.65
t-statistic	1.64	2.86							

Panel G: sorted by $\beta^{d,large}$

Portfolio	Return	Next Return	β^c	β^{own}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	1.12	1.14	1.30	1.47	1.56	1.54	1.59	1.42	1.68
2	1.28	0.90	1.10	1.19	1.35	1.30	1.39	1.30	1.29
3	0.94	1.03	0.95	1.07	1.09	1.11	1.09	1.00	1.05
4	0.96	0.33	0.83	0.99	0.94	0.96	0.94	0.87	0.85
5-Low	0.77	0.54	0.70	0.80	0.80	0.82	0.80	0.75	0.67
High-Low	0.35	0.60	0.60	0.67	0.76	0.72	0.79	0.68	1.01
t-statistic	1.03	1.65							

Panels F and G show results from sorting portfolios by respectively discontinuous small and large betas. The average returns of portfolios sorted by discontinuous small beta are increasing in function of their exposure to the small market jumps while there is no clear relationship between average portfolios returns and their exposure to large market jumps. The difference between the returns of the first and last portfolio sorted by discontinuous large beta is not statistically significant. Table 3.6 reports the results obtained for the pre-crisis period from July 2003 to June 2008.¹³ We notice that the relation between the returns of the sorted portfolios and different factors of risk (except the overnight beta) is more noticeable during the pre-crisis period. The t-statistic of the difference between the returns of the first and last quintile portfolio for contemporaneous return (future return) is 3.56 (3.54), 3.67 (3.11), 3.62 (2.90), 3.59 (2.61) and 3.90 (3.25), 3.18 (1.62) for respectively continuous, discontinuous, discontinuous up, down, small and large betas. These differences are all significant at 5% except for the discontinuous large beta.

¹³We cannot apply the NBER crisis classification due to inadequate number of observations to run Fama-MacBeth regression.

Table 3.6: Contemporaneous and future returns of portfolios sorted by different betas during the pre-crisis period (July 2003- June 2008).

This table lists the monthly returns and betas for sorted portfolios averaged over the period July 2003 to June 2008. For each month, we calculate β^c , β^{ovn} , β^d , $\beta^{d,up}$, $\beta^{d,down}$, $\beta^{d,small}$ and $\beta^{d,large}$ using 20-min intraday returns from the previous 12 months. We then sort funds into quintiles (1-5) according to each beta and form equal-weighted portfolios. The column labeled "Return" reports the average monthly return of sorted portfolios from the previous 12 months (which is the same period as the period used to compute different betas). The column labeled "Next Return" reports the return of sorted portfolios recorded in the month that follows the estimation period. The row labeled "High-Low" reports the difference between the returns of portfolio 1 and portfolio 5. The Newey-West robust t-statistics with 12 lags is reported in row "test-statistic". See Section 3.2 for the description of each beta measure. ***, **, * imply significance at 0.1%, 1% and 5% levels.

Panel A: Sorted by β^c

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	1.62	1.90	1.43	1.48	1.75	1.76	1.78	1.58	1.64
2	1.02	0.80	1.01	1.22	1.43	1.34	1.46	1.39	1.41
3	1.04	0.78	0.89	1.11	1.12	1.14	1.10	1.05	1.04
4	0.53	0.54	0.75	1.09	0.86	0.88	0.85	0.73	0.88
5-Low	0.40	-0.19	0.65	0.79	0.85	0.87	0.84	0.79	0.83
High-Low	1.22***	2.08***	0.78	0.69	0.90	0.89	0.94	0.79	0.81
t-statistic	3.56	3.54							

Panel B: Sorted by β^{ovn}

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	1.40	1.55	1.28	1.73	1.68	1.62	1.72	1.54	1.68
2	0.89	1.15	0.94	1.30	1.16	1.25	1.11	1.04	1.16
3	0.81	0.01	0.82	1.07	0.99	1.04	0.97	0.88	0.97
4	1.16	1.15	1.00	0.88	1.35	1.30	1.39	1.34	1.19
5-Low	0.67	0.22	0.79	0.55	0.88	0.89	0.90	0.75	0.84
High-Low	0.73	1.33	0.49	1.17	0.80	0.72	0.82	0.80	0.84
t-statistic	1.54	1.56							

Panel C: sorted by β^d

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	1.97	2.40	1.32	1.44	1.90	1.73	2.01	1.86	1.71
2	0.79	0.44	1.10	1.38	1.39	1.45	1.38	1.23	1.38
3	0.71	0.81	0.89	1.09	1.08	1.17	1.04	0.92	1.16
4	0.66	-0.13	0.78	1.08	0.84	0.92	0.79	0.73	0.82
5-Low	0.32	0.29	0.68	0.76	0.70	0.74	0.68	0.59	0.70

High-Low	1.65***	2.10**	0.64	0.68	1.19	0.99	1.33	1.27	1.01
t-statistic	3.67	3.11							

Panel D: sorted by $\beta^{d,up}$

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	1.82	2.16	1.38	1.48	1.79	1.81	1.81	1.64	1.65
2	1.05	0.84	1.02	1.29	1.45	1.39	1.49	1.38	1.47
3	0.76	0.72	0.88	1.12	1.14	1.12	1.12	1.11	1.09
4	0.56	-0.11	0.77	1.04	0.87	0.91	0.86	0.77	0.83
5-Low	0.33	0.28	0.67	0.75	0.72	0.74	0.73	0.61	0.73
High-Low	1.49***	1.88**	0.71	0.72	1.07	1.07	1.08	1.02	0.92
t-statistic	3.62	2.90							

Panel E: sorted by $\beta^{d,down}$

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	1.88	2.11	1.26	1.37	1.88	1.67	2.03	1.90	1.67
2	0.90	0.86	1.14	1.40	1.39	1.47	1.37	1.20	1.38
3	0.74	0.45	0.90	1.10	1.08	1.18	1.03	0.91	1.17
4	0.62	0.24	0.78	1.10	0.83	0.89	0.79	0.69	0.84
5-Low	0.31	0.06	0.68	0.79	0.73	0.81	0.67	0.64	0.71
High-Low	1.57***	2.05**	0.58	0.58	1.16	0.87	1.36	1.26	0.96
t-statistic	3.59	2.61							

Panel F: sorted by $\beta^{d,small}$

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	1.80	2.28	1.26	1.36	1.86	1.67	1.99	1.93	1.59
2	1.03	0.28	1.12	1.37	1.39	1.45	1.37	1.21	1.41
3	0.71	0.55	0.92	1.14	1.08	1.20	1.03	0.91	1.16
4	0.44	0.23	0.77	1.01	0.84	0.92	0.80	0.71	0.84
5-Low	0.41	0.41	0.71	0.89	0.74	0.78	0.73	0.56	0.80
High-Low	1.39***	1.87**	0.56	0.48	1.12	0.89	1.26	1.37	0.79
t-statistic	3.90	3.25							

Panel G: sorted by $\beta^{d,large}$

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	1.57	1.51	1.27	1.50	1.70	1.68	1.73	1.53	1.83
2	1.23	1.28	1.08	1.22	1.50	1.42	1.56	1.48	1.38

3	0.71	0.90	0.94	1.12	1.11	1.16	1.09	0.98	1.08
4	0.67	-0.06	0.79	1.06	0.91	0.96	0.88	0.81	0.79
5-Low	0.44	0.42	0.69	0.80	0.77	0.82	0.73	0.69	0.64
High-Low	1.13**	1.09	0.58	0.70	0.94	0.86	1.00	0.84	1.19
t-statistic	3.18	1.62							

Table 3.7: Contemporaneous and future returns of portfolios sorted by different betas during the crisis and post-crisis period (July 2008-December 2014).

This table lists the monthly returns and betas for sorted portfolios averaged over the period July 2008 to December 2014. For each month, we calculate β^c , β^{ovn} , β^d , $\beta^{d,up}$, $\beta^{d,down}$, $\beta^{d,small}$ and $\beta^{d,large}$ using 20-min intraday returns from the previous 12 months. We then sort funds into quintiles (1-5) according to each beta and form equal-weighted portfolios. The column labeled "Return" reports the average monthly return of sorted portfolios from the previous 12 months (which is the same period as the period used to compute different betas). The column labeled "Next Return" reports the return of sorted portfolios recorded in the month that follows the estimation period. The row labeled "High-Low" reports the difference between the returns of portfolio 1 and portfolio 5. The Newey-West robust t-statistics with 12 lags is reported in row "test-statistic". See Section 3.2 for the description of each beta measure. ***, **, * imply significance at 0.1%, 1% and 5% levels.

Panel A: Sorted by β^c

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	0.95	0.85	1.38	1.40	1.45	1.42	1.49	1.38	1.46
2	1.17	0.54	1.12	1.16	1.19	1.18	1.19	1.10	1.20
3	1.10	0.89	0.96	1.04	1.03	1.02	1.05	0.96	1.04
4	1.31	0.75	0.84	0.99	0.98	0.95	1.00	0.92	0.94
5-Low	0.94	0.78	0.64	0.78	0.88	0.87	0.90	0.85	0.77
High-Low	0.02	0.06	0.74	0.62	0.57	0.55	0.59	0.52	0.69
t-statistic	0.04	0.19							

Panel B: Sorted by β^{ovn}

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	1.02	0.81	1.26	1.52	1.41	1.38	1.44	1.35	1.42
2	1.12	0.63	1.10	1.22	1.18	1.18	1.20	1.11	1.18
3	1.20	0.94	1.00	1.04	1.06	1.07	1.07	0.97	1.06
4	1.13	0.66	0.89	0.90	0.98	0.97	1.01	0.95	0.96
5-Low	1.08	0.74	0.73	0.67	0.88	0.86	0.91	0.83	0.78
High-Low	-0.06	0.08	0.53	0.85	0.53	0.51	0.53	0.52	0.64
t-statistic	-0.14	0.20							

Panel C: sorted by β^d

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	0.96	0.69	1.30	1.41	1.52	1.47	1.54	1.50	1.45
2	0.97	0.49	1.11	1.18	1.23	1.22	1.24	1.18	1.19
3	1.29	1.07	0.97	1.04	1.06	1.04	1.11	1.02	1.04
4	1.24	0.93	0.84	0.95	0.93	0.92	0.96	0.87	0.91
5-Low	1.04	0.67	0.74	0.80	0.77	0.79	0.78	0.63	0.80
High-Low	-0.07	0.02	0.56	0.60	0.75	0.68	0.75	0.87	0.65
t-statistic	-0.21	0.08							

Panel D: sorted by $\beta^{d,up}$

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	0.90	0.64	1.30	1.39	1.50	1.49	1.47	1.45	1.44
2	0.95	0.62	1.11	1.20	1.21	1.21	1.21	1.14	1.19
3	1.26	0.90	0.99	1.04	1.07	1.05	1.11	1.01	1.07
4	1.14	0.99	0.85	0.95	0.94	0.92	0.97	0.86	0.93
5-Low	1.26	0.71	0.73	0.79	0.80	0.77	0.87	0.73	0.78
High-Low	-0.36	-0.07	0.58	0.60	0.70	0.73	0.60	0.72	0.66
t-statistic	-1.18	-0.35							

Panel E: sorted by $\beta^{d,down}$

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	1.00	0.66	1.32	1.42	1.49	1.41	1.56	1.45	1.46
2	1.23	0.74	1.09	1.14	1.21	1.19	1.26	1.16	1.19
3	1.08	0.84	0.94	1.04	1.06	1.05	1.10	1.02	1.04
4	1.15	0.95	0.87	0.95	0.96	0.97	0.95	0.90	0.91
5-Low	1.01	0.65	0.74	0.82	0.79	0.83	0.76	0.66	0.80
High-Low	0.00	0.01	0.58	0.60	0.70	0.58	0.81	0.80	0.67
t-statistic	-0.01	0.02							

Panel F: sorted by $\beta^{d,small}$

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	0.85	0.83	1.25	1.36	1.49	1.44	1.49	1.54	1.38
2	1.12	0.56	1.07	1.14	1.20	1.17	1.23	1.19	1.13
3	1.14	0.91	1.04	1.10	1.08	1.08	1.12	1.01	1.12
4	1.32	0.95	0.84	0.96	0.93	0.93	0.97	0.85	0.93
5-Low	1.10	0.55	0.77	0.82	0.80	0.82	0.82	0.60	0.86

High-Low	-0.26	0.28	0.48	0.53	0.69	0.62	0.67	0.94	0.52
t-statistic	-1.31	1.00							

Panel G: sorted by $\beta^{d,large}$

Portfolio	Return	Next Return	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
1-High	0.71	0.80	1.32	1.44	1.43	1.41	1.46	1.33	1.55
2	1.32	0.55	1.12	1.17	1.20	1.18	1.24	1.14	1.21
3	1.16	1.15	0.95	1.03	1.07	1.06	1.09	1.02	1.03
4	1.23	0.70	0.86	0.93	0.97	0.97	0.98	0.93	0.90
5-Low	1.07	0.64	0.71	0.80	0.84	0.83	0.86	0.80	0.70
High-Low	-0.36	0.16	0.61	0.64	0.9	0.58	0.59	0.53	0.84
t-statistic	-1.01	0.65							

Table 3.7 reports the results obtained for the crisis and post-crisis periods from July 2008 to December 2014. We notice that the difference between the contemporaneous returns of the first and last quintile portfolio is negative for overnight, discontinuous, discontinuous up, small and large betas. The return difference is highest in absolute value for discontinuous up and large betas (-0.36). However, contemporaneous and future returns differences are not significant at 5% for all betas. During the crisis and pre-crisis period, we observe an inversion of the patterns of realized returns for portfolios sorted on jump betas (except for discontinuous downside beta). This result is consistent with an increasing investor appetite for equities that positively co-move with large and positive market jumps during periods of market turmoil. These equities will help investors to better hedge against large movements of market and thus would require lower expected returns.

3.4.4 Fama-MacBeth regressions

It is well established in the financial literature that only systematic risk is rewarded by premium. In our four-factor model, the systematic risk is decomposed into four components: the risk of exposure to smooth or continuous fluctuations of the market, the risk of exposure to overnight movements of the market price, the risk of exposure to positive (small) discontinuous

movements of the market and the risk of exposure to negative (large) discontinuous movements of the market.

After estimating the sensitivity of each country fund towards the different risk factors, we follow Fama and MacBeth (1973)'s approach and run the following set of cross-sectional regressions for each month in the sample:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^c \gamma_t^c + \beta_{i,t}^d \gamma_t^d + \beta_{i,t}^{ovn} \gamma_t^{ovn} + \epsilon_{i,t} \quad (\text{I})$$

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^c \gamma_t^c + \beta_{i,t}^{d,up} \gamma_t^{d,up} + \beta_{i,t}^{d,down} \gamma_t^{d,down} + \beta_{i,t}^{ovn} \gamma_t^{ovn} + \epsilon_{i,t} \quad (\text{II})$$

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^c \gamma_t^c + \beta_{i,t}^{d,small} \gamma_t^{d,small} + \beta_{i,t}^{d,large} \gamma_t^{d,large} + \beta_{i,t}^{ovn} \gamma_t^{ovn} + \epsilon_{i,t} \quad (\text{III})$$

where $r_{i,t}$ is the average return of fund i on month t calculated as an arithmetic average of previous 12 monthly returns. Different betas are computed on a monthly basis over the previous 12 months, which is the same period used to calculate the return. γ_t^c , γ_t^d , γ_t^{ovn} , $\gamma_t^{d,up}$, $\gamma_t^{d,down}$, $\gamma_t^{d,small}$ and $\gamma_t^{d,large}$ are the coefficients of the three regressions on month t . Based on the monthly estimates of these coefficients, we estimate the risk premia associated with the different risk factors by taking the mean of the estimates:

$$\hat{\gamma}^k = \frac{1}{N_m} \sum_{t=1}^{N_m} \gamma_t^k, \quad k = (c; d; ovn; d, up; d, down; d, small; d, large)$$

where N_m is the number of months in the sample (126 months in our sample).

Once risk premia are calculated, it is possible to deduce the investor's risk aversion coefficient based on the expected utility theory. To this end, we assume that the representative investor has a power utility function U with a constant relative risk aversion coefficient η and an initial wealth W_0 equal to 1. The market risk premium γ can be seen as the price that the investor is ready to pay to get rid of the zero-mean market risk, $\tilde{r}_0 = r_0 - E(r_0)$:

$$U(W_0 - \gamma) = E(U(W_0 + \tilde{r}_0))$$

Using Taylor series expansions around $\gamma = 0$ and $\tilde{r}_0 = 0$, the risk aversion coefficient can be approximated as follows:¹⁴

$$\eta = \frac{-W_0 U''(W_0)}{U'(W_0)} \approx \frac{2\gamma}{\sigma_0^2}$$

where $\sigma_0^2 = E(r_0^2)$ is the variance of the market return. It should be noted that the previous formula of risk aversion coefficient only holds for a positive risk premium.

Table 3.8 Panels A, B and C report the results of the cross-sectional regressions for respectively the whole period (from July 2003 to December 2014), the pre-crisis period (from July 2003 to June 2008) and the crisis and post-crisis period (from July 2008 to December 2014). The risk premia estimated using all data available from July 2003 to December 2014 are not significant at 5% level, except for the continuous beta in regressions I and III. The reward for continuous risk becomes insignificant when the discontinuous risk is decomposed into downside and upside components (regression II).

If we only restrict our analysis to the pre-crisis period, we find that both continuous and discontinuous betas' premia (respectively 1.4% and 0.7% per month) are statistically significant at 0.1% and 5% level (regression I), respectively. In regression II, only the premium awarded to the downside jump risk (0.79%) is significant at 5% level. In regression III, only the continuous beta premium (1.8%) is significant at 1% level. By averaging continuous and discontinuous risk premia found across three regressions during the pre-crisis period, we get an average market risk premium of 1.56% per month and a risk aversion coefficient of 5.5.

The risk premia during the crisis and post-crisis period are not significant except for the upside and large discontinuous betas in regression II and III. Interestingly, these two betas are associated with a negative premium (-0.9% for upside jump risk and -0.48% for large jump risk). This finding is consistent with common economic theory that investors may seek to hedge themselves against large movements of market, mainly during financial crisis period. In this case, equities that positively co-move with large and positive market jumps are

¹⁴We use a first-order approximation for the first term $U(W_0 - \gamma) = U(W_0) - \gamma U'(W_0)$ and a second-order approximation for the second term $E(U(W_0 + \tilde{r}_0)) = U(W_0) + \frac{\sigma_0^2}{2} U''(W_0)$.

particularly attractive for investors and thus would require lower expected returns.¹⁵ Overall, the reward for bearing continuous and downside discontinuous risks are positively priced in the cross-section of expected stock returns during the pre-crisis period whereas the upside and large jump risks are negatively priced during the crisis and post-crisis period.

Table 3.8: Fama-MacBeth regressions.

This table shows the results of Fama-MacBeth regressions of 12-month average returns on risk characteristics. The Newey-West t-statistics of the estimated parameters are given between parentheses. Panels A, B, and C report the results for respectively the whole period (July 2003-December 2014), the pre-crisis period (July 2003-June 2008) and the crisis and post-crisis period (July 2008-December 2014). See Section 3.2 for the description of each beta measure. ***, **, * imply significance at 0.1%, 1% and 5% levels.

Panel A: Whole period (July 2003-December 2014)

Regression	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
I	0.0093** (2.67)	-0.0013 (-0.38)	0.0006 (0.10)				
II	0.0065 (1.34)	-0.0008 (-0.24)		-0.0027 (-0.71)	0.0060 (1.15)		
III	0.0119** (2.88)	0.0002 (0.07)				-0.0019 (-0.62)	-0.0006 (-0.26)

Panel B: Pre-Crisis period (July 2003-June 2008)

Regression	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
I	0.0144*** (4.63)	-0.0038 (-0.69)	0.0070* (2.09)				
II	0.0092 (1.19)	-0.0025 (-0.46)		0.0042 (0.83)	0.0079* (1.99)		
III	0.0181** (3.08)	-0.0018 (-0.36)				-0.0009 (-0.24)	0.004 (1.65)

Panel C: Crisis and Post-Crisis period (July 2008-December 2014)

Regression	β^c	β^{ovn}	β^d	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
I	0.0047 (0.92)	0.0009 (0.19)	-0.0052 (-0.61)				
II	0.0042 (0.70)	0.0007 (0.16)		-0.009** (-3.06)	0.0042 (0.46)		

¹⁵Cremers et al. (2015) find that both volatility and jump risks are negatively priced in the cross-section of returns but they do not decompose the jump risk into upside/downside or small/large components.

III	0.0062	0.0021	-0.0029	-0.0048**
	(1.36)	(0.42)	(-0.60)	(-2.28)

3.4.5 Currency jump risk premium

This subsection considers another source of jumps and cojumps between international stock markets, the currency jump risk. The exposure of international portfolios to foreign exchange market movements can be explained by at least two factors. First, international portfolios are composed of domestic and foreign assets. The foreign assets that are expressed in domestic currency are exposed to two types of variability: the stock market variability and foreign exchange market variability. The return of international portfolio is thus affected by both stock and exchange markets movements. Second, the exposure of international portfolios to currency risk may come from the correlation between stock and foreign exchange markets.

To assess how country funds react to foreign exchange markets, we consider the number of cojumps of each fund with EUR/USD exchange rate. We choose EUR and USD because they are the two most traded currencies in the world. Also, all considered funds are expressed in USD. As shown in Table 3.9, the cojumps between EUR/USD and the world market portfolio is 22% of all detected jumps. Spain, Switzerland, Germany, and France have the highest proportion of cojumps with respectively 28%, 27%, 26% and 24% of all detected jumps. Countries with the lowest proportion of cojumps with EUR/USD exchange rate include Chile, Peru, Greece, Colombia, Vietnam and frontier markets, where the proportion of cojumps is less than 10% of detected jumps. In general, the proportion of cojumps between European stock markets and EUR/USD exchange rate is higher than other developed and emerging markets.

Table 3.9: Cojumps between stock markets and EUR/USD exchange rate.

The table reports the percentage of cojumps to the total number of detected jumps of all country funds with the EUR/USD exchange rate. The percentage of cojumps with the world market index is also provided. The world market index is an equal-weighted portfolio created by assigning equal weight to all country funds available in the sample. See Appendix 3.A for the cojump measure. Jumps and cojumps are detected for the period going from July 2003 to December 2014.

	Cojumps
World market index	22%
Frontier markets	8%
Chile	9%
New Zealand	11%
Philippines	11%
Poland	16%
Peru	7%
Australia	23%
Canada	16%
Sweden	23%
Germany	26%
Hong Kong	14%
Italy	20%
Japan	16%
Belgium	17%
Switzerland	27%
Malaysia	13%
Netherlands	19%
Austria	15%
Spain	28%
France	24%
Singapore	18%
Taiwan	14%
United Kingdom	23%
Mexico	17%
South Korea	13%
Brazil	14%
South Africa	15%
Greece	5%

China	15%
Colombia	6%
Indonesia	18%
India	19%
Russia	17%
United States	15%
Thailand	18%
Turkey	16%
Vietnam	6%

To evaluate the price of the jump currency risk in the cross-section of stock returns, we consider the three cross-sectional regressions introduced in Section 3.4.4 with an additional factor of risk representing the sensitivity of an asset i to EUR/USD exchange rate jump movements, $\beta_{i,t}^{d,currency}$.

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^c \gamma_t^c + \beta_{i,t}^d \gamma_t^d + \beta_{i,t}^{d,currency} \gamma_t^{d,currency} + \beta_{i,t}^{ovn} \gamma_t^{ovn} + \epsilon_{i,t} \quad (\text{I})$$

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^c \gamma_t^c + \beta_{i,t}^{d,up} \gamma_t^{d,up} + \beta_{i,t}^{d,down} \gamma_t^{d,down} + \beta_{i,t}^{d,currency} \gamma_t^{d,currency} + \beta_{i,t}^{ovn} \gamma_t^{ovn} + \epsilon_{i,t} \quad (\text{II})$$

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^c \gamma_t^c + \beta_{i,t}^{d,small} \gamma_t^{d,small} + \beta_{i,t}^{d,large} \gamma_t^{d,large} + \beta_{i,t}^{d,currency} \gamma_t^{d,currency} + \beta_{i,t}^{ovn} \gamma_t^{ovn} + \epsilon_{i,t} \quad (\text{III})$$

where $\gamma_t^{d,currency}$ is the risk premium associated with the EUR/USD jump risk. $\beta_{i,t}^{d,currency}$ is calculated similarly to the discontinuous beta (formula given in Section 3.2). We only replace the aggregate market index returns by EUR/USD exchange rate returns.

Table 3.10 Panels A, B and C report the results of the cross-sectional regressions for respectively the whole period (from July 2003 to December 2014), the pre-crisis period (from July 2003 to June 2008) and the crisis and post-crisis period (from July 2008 to December 2014). We find that the currency jump risk premium is not significant for the three considered periods. Previous results on continuous and discontinuous equity jump risk premia remain intact. The reward for bearing continuous and downside discontinuous risks are positively priced in the cross-section of expected stock returns during the pre-crisis period whereas the

upside and large jump risks are negatively priced during the crisis and post-crisis period.

Table 3.10: Equity and currency jump risk premia.

This table shows the results of Fama-MacBeth regressions of 12-month average returns on risk characteristics. The Newey-West t-statistics of the estimated parameters are given between parentheses. Panels A, B, and C report the results for respectively the whole period (July 2003-December 2014), the pre-crisis period (July 2003-June 2008) and the crisis and post-crisis period (July 2008-December 2014). See Section 3.2 for the description of each beta measure. ***, **, * imply significance at 0.1%, 1% and 5% levels.

Panel A: Whole period (July 2003-December 2014)

Regression	β^c	β^{ovn}	β^d	$\beta^{d,currency}$	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
I	0.0082** (2.93)	0.0020 (0.60)	-0.0030 (-0.27)	0.0024 (0.38)				
II	0.0057* (2.00)	0.0021 (0.60)		0.0040 (0.65)	-0.0050 (-0.85)	0.0021 (0.32)		
III	0.0088** (3.15)	0.0027 (0.75)		0.0072 (1.52)			0.0035 (0.96)	-0.0112 (-1.90)

Panel B: Pre-Crisis period (July 2003-June 2008)

Regression	β^c	β^{ovn}	β^d	$\beta^{d,currency}$	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
I	0.0116** (3.20)	0.0025 (0.47)	0.0072 (1.95)	0.0032 (0.82)				
II	0.0048 (1.43)	0.0032 (0.57)		0.0036 (0.90)	0.0009 (0.23)	0.0112** (2.44)		
III	0.0106** (3.06)	0.0025 (0.45)		0.0052 (1.14)			0.0061*** (3.82)	0.0016 (0.80)

Panel C: Crisis and Post-Crisis period (July 2008-December 2014)

Regression	β^c	β^{ovn}	β^d	$\beta^{d,currency}$	$\beta^{d,up}$	$\beta^{d,down}$	$\beta^{d,small}$	$\beta^{d,large}$
I	0.0059 (1.54)	0.0017 (0.38)	-0.0104 (-0.60)	0.0019 (0.18)				
II	0.0063 (1.48)	0.0014 (0.30)		0.0043 (0.42)	-0.0092** (-2.13)	-0.0045 (-0.46)		
III	0.0079 (1.87)	0.0029 (0.57)		0.0086 (1.15)			0.0015 (0.25)	-0.0136** (-2.38)

3.4.6 Equity risk premia and the leverage effect

The earlier subsection shows that investors require positive premia for bearing respectively the continuous and downside jump market risks during the pre-crisis period. In this subsection, we examine the potential channels through which the diffusive and discontinuous shocks of the asset price process affect the equity risk premium. We hypothesize that investors are not only compensated for their exposure to continuous and discontinuous price fluctuations, but also for the negative relationship between the return and volatility movements, commonly called the "leverage effect" in the finance literature. Indeed, the burgeoning literature including our paper has shown evidence of asymmetry in the relationship between equity market returns and volatility and different explanations have been proposed.

The first leading explanation for the return-volatility asymmetry is based on time-varying risk premia or "volatility feedback effect" as studied by French et al. (1987) and Campbell and Hentschel (1992). The authors find a strong negative relationship between realized excess holding period returns and the unpredictable component of volatility, which they interpret as indirect evidence of a positive ex ante relationship between return and risk. They argue if volatility is priced, an increase in unexpected volatility would increase the future required rate of return and decrease current stock prices.

Black (1976) and Christie (1982) propose another explanation based on leverage. They suggest that negative returns should raise the firm leverage, leading to higher future volatility whereas positive returns should reduce the firm leverage resulting in a decrease in subsequent volatility. Figlewski and Wang (2000) extend this argument and show the magnitude of the effect of a decline in current price on future volatility is too large to be explained only by changes in financial leverage. That is, the leverage-based explanation states that a fall in stock price should increase subsequent volatility. In theory, a price rise of the same magnitude should induce volatility reduction in the same amount; however, Figlewski and Wang (2000) show that the impact is more pronounced during the down market than during the up time.

In what follows, we examine the role of the return-volatility asymmetry in determining the

equity risk premium. We assume that the log-price process of the aggregate market index $p_{0,t}$ follows a stochastic volatility model with cojumps between the price and volatility processes:

$$dp_{0,t} = \alpha_t dt + \sigma_t dW_t^1 + J_t^r dQ_t^r + J_t^{r,co} dQ_t^{r,v}$$

$$d\log(\sigma_t^2) = \alpha_t^v dt + \sigma_t^v dW_t^2 + J_t^v dQ_t^v + J_t^{v,co} dQ_t^{r,v}$$

where α_t and σ_t are respectively the drift and the volatility of the diffusive component of the price process. α_t^v and σ_t^v are respectively the drift and the volatility of the diffusive part of the volatility process. The jump component of the price process is composed of independent jumps with size J_t^r and a Poisson process Q_t^r with intensity λ_t^r , and common jumps with the volatility process characterized with a size $J_t^{r,co}$ and a Poisson process $Q_t^{r,v}$ with intensity $\lambda_t^{r,v}$. Similarly, the volatility process is characterized by independent jumps with size J_t^v and a Poisson process Q_t^v with intensity λ_t^v , and cojumps with the price process with size $J_t^{v,co}$ and a Poisson process $Q_t^{r,v}$ with intensity $\lambda_t^{r,v}$. The Brownian motions W_t^1 and W_t^2 are negatively correlated with a correlation coefficient ρ_t . The negative covariation between asset returns and volatility changes stems from the negative correlation of diffusive shocks as well as simultaneous and anti-correlated jumps of both processes.

We also assume the existence of a stochastic discount factor M_t defined as follows:¹⁶

$$d\log(M_t) = \delta_t dt + \phi dp_{0,t} + \psi d\log(\sigma_t^2)$$

where δ_t is a function controlling the time preferences. ϕ and ψ are parameters controlling the aversion to respectively the price risk and the variance risk. The stochastic discount factor is decreasing in prices ($\phi < 0$) and increasing in variance ($\psi > 0$).

As shown in Bandi and Reno (2016), the expression of the return risk premium γ is given

¹⁶This pricing kernel has been also employed in Bandi and Reno (2016).

by:¹⁷

$$\gamma = \alpha_t + \frac{\sigma_t^2}{2} - r_f = -\phi\sigma_t^2 - \psi\rho_t\sigma_t\sigma_t^v - \lambda_t^r E[e^{\phi J_t^r}(e^{J_t^r} - 1)] - \lambda_t^{r,v} E[e^{\phi J_t^{r,co} + \psi J_t^{v,co}}(e^{J_t^{r,co}} - 1)]$$

where r_f is the risk-free rate.

The expression of the return risk premium is composed of four terms. The first term is the price of the diffusive return risk. The second term is the reward required to compensate the "leverage effect" induced by the negative correlation between continuous return and volatility changes. The third term represents the reward for bearing the return jump risk whereas the fourth term corresponds to the price of the discontinuous "leverage effect" induced by anti-correlated return and volatility cojumps.

We examine the validity of our hypothesis by estimating both the continuous and discontinuous components of the covariation between the asset returns and the volatility. We follow Ait-Sahalia et al. (2017) who provide consistent estimators for continuous (henceforth CLE) and discontinuous (henceforth DLE) leverage effects using high frequency data:

$$CLE = \sum_{\tau=l_m+1}^{mT-l_m} \Delta p_{0,\tau} \mathbb{1}_{\{|\Delta p_{0,\tau}| \leq \theta_{0,\tau}\}} (\hat{\sigma}_{\tau+}^2 - \hat{\sigma}_{\tau-}^2)$$

$$DLE = \sum_{\tau=l_m+1}^{mT-l_m} \Delta p_{0,\tau} \mathbb{1}_{\{|\Delta p_{0,\tau}| > \theta_{0,\tau}\}} (\hat{\sigma}_{\tau+}^2 - \hat{\sigma}_{\tau-}^2)$$

where $\hat{\sigma}_{\tau+}^2$ and $\hat{\sigma}_{\tau-}^2$ are estimates of the spot variance just before and after time $\frac{\tau}{m}$:

$$\hat{\sigma}_{\tau+}^2 = \frac{m}{l_m} \sum_{\tau'=\tau+1}^{\tau+l_m} (\Delta p_{0,\tau'})^2 \mathbb{1}_{\{|\Delta p_{0,\tau'}| \leq \theta_{0,\tau'}\}}$$

$$\hat{\sigma}_{\tau-}^2 = \frac{m}{l_m} \sum_{\tau'=\tau-l_m}^{\tau-1} (\Delta p_{0,\tau'})^2 \mathbb{1}_{\{|\Delta p_{0,\tau'}| \leq \theta_{0,\tau'}\}}$$

¹⁷This expression can be found by applying Ito's lemma to the martingale processes $M_t e^{r_f t}$ and $M_t e^{p_t}$.

where $\frac{l_m}{m}$ defines the length of the local averaging windows for the estimation of the pre- and post-variances. We also decompose the discontinuous leverage effect into upside and downside components by applying the DLE's formula to respectively positive and negative market returns.

Table 3.11 reports the results of the estimation of the continuous, discontinuous, discontinuous up and discontinuous down leverage effects of the world market index for respectively the whole sample period, the pre-crisis period and the crisis and post-crisis period. The continuous and downside discontinuous covariations between the return and the volatility changes are significantly negative during the pre-crisis period with a value of -0.44 and -0.10, respectively. The negative relationship between continuous parts of the return and the volatility processes means that smooth movements of market prices are associated with smooth opposite variations of the volatility. Similarly, the negative downside discontinuous covariation indicates that negative jumps of the aggregate market index are often associated with contemporaneous positive jumps of market volatility. The contemporaneous negative covariation between return and volatility jumps can be considered as evidence in favor of an almost instantaneous discontinuous volatility feedback effect, meaning that an upward volatility jump is immediately followed by a downward return jump. It also suggests that, like the downside return jump risk, the upside volatility jump risk should also be priced in the cross-section of returns during the pre-crisis period. This finding is consistent with Bollerslev et al. (2006) who also provide evidence of a strong contemporaneous negative correlation between the high frequency returns and the volatility. However, those authors do not decompose the return into continuous and discontinuous components.

Moreover, the results show a significant asymmetry between the upside and downside components of the discontinuous leverage effects during the pre-crisis period, such that the covariation between downside return jumps and upside volatility jumps (downside DLE) is significantly negative (-0.10) whereas the covariation between upside return jumps and downside volatility jumps (upside DLE) is weak, and even positive (0.07). These findings contradict the leverage-based explanation of the negative return-volatility relationship that suggests that

the impact of positive and negative returns on the volatility should be symmetric. Our results are thus consistent with the "down market effect" explanation suggested by Figlewski and Wang (2000) who document that the negative return-volatility dependence is most common during down market periods.

The return-volatility dependence is weak during the crisis and post-crisis period with values lower in absolute value than 0.04 for respectively the CLE, DLE, upside DLE and downside DLE. In contrast, the continuous leverage effect remains strong (-0.26) when the whole sample is considered.

Overall, these findings are consistent with the positive risk premia observed during the pre-crisis period for respectively the continuous and downside jump risks. They also suggest that both continuous and downside discontinuous price and volatility risks share compensations for common underlying risk factors.

Table 3.11: Continuous and discontinuous leverage effects.

The table reports the estimate (the 95% confidence interval is given between brackets) of the continuous (CLE), discontinuous (DLE), discontinuous up and discontinuous down leverage effects of the world market index for the whole period (July 2003-December 2014), the pre-crisis period (July 2003-June 2008) and the crisis and post-crisis period (July 2008-December 2014), respectively. The world market index is an equal-weighted portfolio created by assigning equal weight to all country funds available in the sample. The estimates of the continuous and discontinuous leverage effects are provided in Section 3.4.6. The confidence intervals are calculated using the procedure provided by Ait-Sahalia et al. (2017). An estimate is considered as significantly different from zero if its confidence interval doesn't include zero. See 3.A for the jump measure. Jumps are detected for the period going from July 2003 to December 2014. All figures in the table are multiplied by 10^3 .

	CLE	DLE	Upside DLE	Downside DLE
Whole period	-0.26 [-0.30;-0.21]	-0.07 [-0.06;-0.09]	0.06 [0.05;0.06]	-0.07 [-0.06;-0.08]
Pre-crisis period	-0.44 [-0.55;-0.34]	-0.03 [-0.06;0.008]	0.07 [0.04;0.1]	-0.10 [-0.11;-0.08]
Crisis and post-crisis period	-0.04 [-0.05;-0.03]	-0.02 [-0.024;-0.016]	0.005 [0.002;0.007]	-0.025 [-0.028;-0.023]

3.5 Conclusion

In this paper, we examine continuous and discontinuous systematic risks and their association with equity risk premium across major equity markets. Using the estimation methodology of Todorov and Bollerslev (2010) and intraday data of 37 country exchange-traded funds

covering developed, emerging and frontier markets from July 2003 to December 2014, we estimate the exposure of each country fund returns towards six separate market risks: continuous, overnight, discontinuous up, down, small and large market risks. We find that cojumps are more frequent in developed markets than emerging markets, which is inline with the nature of high market integration in developed markets. We also find that emerging stock markets, particularly non-Asian emerging markets, still offer a good opportunity for investors to reduce their exposure to market risk for the various systematic risks considered in our study.

The results of portfolio sorting approach and the cross-sectional Fama and MacBeth (1973) regressions show that continuous and downside discontinuous risks are positively priced in the cross-section of expected stock returns during the pre-crisis period whereas the upside and large jump risks are negatively priced during the crisis and post-crisis periods, suggesting that investors prefer stocks that help them hedge against large movements of the market during the crisis period. Finally, we provide evidence on the strong negative relationship between market price movements and market volatility changes during the pre-crisis period, which is consistent with the positive continuous and downside jump premia observed during the pre-crisis period.

This work opens interesting perspectives for future research. It would be of interest to develop new methods for computing the portfolio value-at-risk (VAR) based on the market risk decomposition provided in the paper. Studying the underlying mechanisms of the continuous and discontinuous price and volatility covariations should also be of interest.

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Appendix 3.A Jump and cojump identification methodology

LM-ABD jump identification test

The LM test statistic $L_{t,k}$ compares the current asset return with the bipower variation calculated over a moving window with a given number of preceding observations. It tests at time k on day t whether there was a jump from $k-1$ to k and is defined as follows:

$$L_{t,k} = \frac{|r_{t,k}|}{\hat{\sigma}_{t,k}}$$

where

$$\hat{\sigma}_{t,k}^2 = \frac{1}{K-2} \sum_{j=k-K+2}^{k-1} |r_{t,j-1}| |r_{t,j}|$$

$r_{t,k}$ is the intraday return in the interval $[k-1, k]$ of day t . $\hat{\sigma}_{t,k}$ refers to the realized bipower variation calculated for a window of K observations and provides a jump robust estimator of the instantaneous volatility. Lee and Mykland (2008) emphasize that the window size K should be chosen in a way that the effect of jumps on the volatility estimation disappears. They thus suggest to choose the window size K between $\sqrt{252 \times M}$ and $252 \times M$, where M is the number of observations in a day. Under the null hypothesis of absence of jumps at anytime in the interval $[k-1, k]$, the LM statistic is asymptotically distributed as follows:

$$\frac{L_{t,k} - C_M}{S_M} \xrightarrow{M \rightarrow \infty} \xi$$

where ξ has a cumulative distribution function, $P(\xi \leq x) = \exp(e^{-x})$. C_M and S_M are given by:

$$C_M = \frac{\sqrt{2 \log(M)}}{c} - \frac{\sqrt{\log(\pi) + \log(\log(M))}}{2c\sqrt{2 \log(M)}}$$

$$S_M = \frac{1}{c\sqrt{2 \log(M)}} \quad \text{and} \quad c = \sqrt{\frac{2}{\pi}}$$

A jump is detected with LM test on day t in intraday interval k if the following condition

is satisfied:

$$|L_{t,k}| > -\log(-\log(1 - \alpha)) \times S_M + C_M$$

where α is the test significance level.

On the other hand, the ABD test statistic is assumed to be normally distributed in the absence of jumps. A jump is detected with the ABD test on day t in intraday interval k if the following condition is satisfied:

$$\frac{|r_{t,k}|}{\sqrt{\frac{1}{M}BV_t}} > \Phi_{1-\frac{\beta}{2}}^{-1}$$

where BV_t is the bipower variation (Barndorff-Nielsen and Shephard 2004) defined as follows:

$$BV_t = \frac{\pi}{2} \frac{M}{M-1} \sum_{k=2}^M |r_{t,k-1}| |r_{t,k-1}|$$

$\Phi_{1-\frac{\beta}{2}}^{-1}$ represents the inverse of the standard normal cumulative distribution function evaluated at a cumulative probability of $1 - \frac{\beta}{2}$ and $(1 - \beta)^M = 1 - \alpha$, where α represents the daily significance level of the test.

In our study, we identify intraday jumps by relying on the intraday procedure of LM-ABD. A jump is detected with the LM-ABD test on day t in intraday interval k when:

$$\frac{|r_{t,k}|}{\hat{\sigma}_{t,k}} > \theta$$

The threshold value θ is calculated for different significance levels. For a daily significance level of 5% and a sampling frequency of 20 minutes (which corresponds to 19 intraday returns per day in our study), we obtain a threshold value of 4.00 and 4.85 using ABD and LM methods, respectively.

Cojump identification test

Once all intraday jumps are identified using the univariate jump detection test of LM-ABD, we apply the following co-exceedance rule to verify if a cojump occurs between assets i and j at intraday time k on day t (Bae et al., 2003):

$$1\left\{\frac{|r_{i,t,k}|}{\hat{\sigma}_{i,t,k}} > \theta\right\} \times 1\left\{\frac{|r_{j,t,k}|}{\hat{\sigma}_{j,t,k}} > \theta\right\} = \begin{cases} 1 : & \text{a cojump between assets } i \text{ and } j \\ 0 : & \text{no cojump} \end{cases}$$

Thus, a cojump exists when asset returns jump simultaneously. We distinguish between an idiosyncratic jump defined as jump of a single asset or jump that occurs independently of the market movement and cojump defined as jumps of two or more assets that occur simultaneously.

Intraday volatility pattern

It is widely documented (Wood et al. (1985) and Harris (1986)) that intraday returns show a systematic seasonality over the trading day, also called the U-shaped pattern. The intraday volatility is particularly higher at the open and the close of the trading than the rest of the day. To minimize the effects of intraday volatility on our jump detection test, we modify our procedure by rescaling intraday returns with a volatility jump robust corrector introduced by Bollerslev et al. (2008). The k^{th} rescaled intraday return of day t is defined by:

$$\hat{r}_{t,k} = \frac{r_{t,k}}{s_k}$$

where:

$$\begin{aligned}\varsigma_1^2 &= \frac{M \sum_{t=1}^T |r_{t,1}| |r_{t,2}|}{\sum_{t=1}^T |r_{t,1}| |r_{t,2}| + \sum_{t=1}^T \sum_{l=2}^{M-1} |r_{t,l-1}|^{\frac{1}{2}} |r_{t,l}| |r_{t,l+1}|^{\frac{1}{2}} + \sum_{t=1}^T |r_{t,M-1}| |r_{t,M}|} \\ \varsigma_k^2 &= \frac{M \sum_{t=1}^T |r_{t,k-1}|^{\frac{1}{2}} |r_{t,k}| |r_{t,k+1}|^{\frac{1}{2}}}{\sum_{t=1}^T |r_{t,1}| |r_{t,2}| + \sum_{t=1}^T \sum_{l=2}^{M-1} |r_{t,l-1}|^{\frac{1}{2}} |r_{t,l}| |r_{t,l+1}|^{\frac{1}{2}} + \sum_{t=1}^T |r_{t,M-1}| |r_{t,M}|}, \quad k = 2, \dots, M-1 \\ \varsigma_M^2 &= \frac{M \sum_{t=1}^T |r_{t,M-1}| |r_{t,M}|}{\sum_{t=1}^T |r_{t,1}| |r_{t,2}| + \sum_{t=1}^T \sum_{l=2}^{M-1} |r_{t,l-1}|^{\frac{1}{2}} |r_{t,l}| |r_{t,l+1}|^{\frac{1}{2}} + \sum_{t=1}^T |r_{t,M-1}| |r_{t,M}|}\end{aligned}$$

T is the total number of days considered in the study and M is the number of observations in a day.

Chapter 4

Price and Volatility Jump Risks in International Equity Markets

Abstract

This paper examines how international equity markets respond to jumps of an aggregate market factor both at price and volatility levels using a sample covering major developed and emerging markets. We show that both price and volatility jump betas are time-varying and exhibit asymmetric effects across the upside and downside market jumps. We also provide evidence of a significant predictive power that both market price and volatility jumps have on future stock returns, with a stronger degree of predictability obtained with market price jumps.

Keywords: Jump regressions; Price and volatility cojump; Risk premium.

4.1 Introduction

It is well documented in the finance literature that financial asset prices exhibit large discontinuities or jumps in their trajectories. The recent development of nonparametric jump detection techniques (see, among others, Barndorff-Nielsen and Shephard (2004, 2006), Andersen et al. (2007), Lee and Mykland (2008) and Ait-Sahalia and Jacod (2009)) provides strong evidence in favor of the presence of jumps in asset prices.

Financial assets are also characterized by a time-varying volatility that can also exhibit discontinuities in its dynamics. Empirical works (see, among others Broadie et al. (2007), Chernov et al. (2003) and Eraker et al. (2003, 2004)), that use the affine double-jump model (Duffie et al. 2000) to capture the joint dynamics of the asset price and its volatility, provide evidence supporting the presence of jumps in both the price and volatility dynamics. More recently, studies (Bandi and Reno (2016), Jacod and Todorov (2010), Todorov and Tauchen (2011)), that use high frequency data, document that the discontinuous changes in prices are often associated with strongly anti-correlated, contemporaneous, discontinuous changes in volatility, suggesting that both the price and volatility jump risks are derived by common underlying risk factors and thus should be handled jointly by investors.

Our paper contributes to the international asset pricing literature by examining the dependence between international equity markets and aggregate market risks at jump times both in prices and volatility levels. According to the finance theory, investors should be compensated proportionally to their exposure to non-diversifiable risks. Therefore, understanding how international equity markets are linked to the aggregate market jumps is crucial for estimating, managing and pricing jump risks. We choose to study jumps in prices and volatility together because they are strongly linked to each other. Moreover, the recent development of nonparametric jump identification tests as well as jump regressions techniques (Li et al. (2017) and Davies (2016)) and the availability of high frequency data provide new statistical tools to identify and estimate both price and volatility jump risks. Given the importance of factor models in asset pricing theory, we examine the linear relationship between individual assets and the

aggregate market jump risk at price and volatility levels. We mainly assume that individual asset returns (volatility) will respond linearly to a jump of the market price (volatility). The coefficient of the linear price (volatility) jump regression is called price (volatility) jump beta. The price and volatility jump betas are measures of the sensitivity of an individual asset to respectively market price and volatility jumps. In our study, we allow for jump betas to vary over time and we examine if an asymmetric effect exists by decomposing the aggregate price and volatility jump risks into upside and downside components.

Our work is motivated by three strands of the literature. The first examines the role of price jumps on the cross-section of returns. Bollerslev et al. (2016) and Alexeev et al. (2017) document that price jump risk carries a significant positive premium. However, the scope of their empirical works is restricted to the US market. Our study extends the existing literature by exploring if their conclusions hold in an international context. The second strand investigates the pricing of the aggregate volatility risk in the cross-section of returns (Ang et al. (2006), Cremers et al. (2015)). Using option data and by constructing suitable option trading strategies, Cremers et al. (2015) provide evidence that both aggregate jump and volatility are priced risk factors, but both of them carry a negative market price of risk. Our paper extends previous works by focusing particularly on the aggregate volatility jump risk. Our approach is also different from previous studies in that it takes advantage of the availability of high frequency returns and the recent development of new jump regressions techniques (Li et al. (2017) and Davies (2016)).

Our work is also related to international asset pricing literature that investigates the role of tail risks on explaining the cross-section of stock returns worldwide. Using a sample of 40 countries, Weigert (2016) provides evidence of a significant positive premium for holding stocks with a strong sensitivity to extreme market downturns, with a risk premium particularly high in countries with higher income per capita and negative market skewness. In contrast, Oordt and Zhou (2016) find the reward for holding stocks that strongly comove with the market during extreme market crashes is not significant. Their study is, however, limited to the US stock market. Our work enhances previous studies on tail risks in two ways. First,

our approach to estimate jump betas is based on jump regressions, which is novel in the asset pricing theory. Previous works provide measures of tail betas based on extreme value theory. Second, to the best to our knowledge, we are the first study to investigate empirically the aggregate price and volatility jump risks in an international setting.

Our empirical investigations are based on two sets of high frequency data. The first set is composed of ten country exchange-traded funds (ETFs) covering major developed and emerging markets from January 2008 to May 2015. The SPY and EEM, which respectively aim to replicate the performance of S&P 500 and MSCI Emerging Markets indices, are used as proxies for respectively the developed and emerging equity markets. The second set is composed of two volatility indices: The Chicago Board of Options Exchange's (CBOE) Volatility Index (VIX) and CBOE Emerging Markets ETF Volatility Index (VXEEM) serving as proxies for respectively the developed and emerging market volatilities. We apply the techniques proposed by Andersen et al. (2007, henceforth ABD) and Lee and Mykland (2008, henceforth LM) to identify intraday jumps and cojumps of all funds and volatility indices in the sample. We find that simultaneous jumps between individual country funds and two volatility indices have opposite signs, with a higher proportion of positive volatility and negative return cojumps, suggesting a strong anti-correlation between market volatility jumps and asset returns when the market is downward and its volatility is high. We apply the jump regression procedures proposed by Li et al. (2017) and Davies (2016) to estimate the exposure of developed and emerging countries to respectively market price and volatility jumps. We find that both price and volatility jump betas are time-varying over the period of study. When comparing between price (or volatility) jump beta estimates found for respectively SPY and EEM funds, which are used as market proxies, the results show that developed and emerging countries are more linked to their respective aggregate market indices. By examining the reaction of international stock markets to upside and downside market price jumps, we document that international stock markets' response to market price jumps exhibits asymmetric effects between upside and downside components. The results of the volatility jump beta decomposition into upside and downside components, however, are not conclusive. Finally, we examine the ability of

price and volatility market jumps to forecast future returns of international stock markets and find that both price and volatility market jumps have a significant predictive power on future stock market returns, with a greater degree of predictability registered for market price jumps.

The remainder of the paper is organized as follows. Section 4.2 introduces the price and volatility jump betas estimation framework. Section 4.3 describes the data. Section 4.4 discusses our main empirical findings. Section 4.5 concludes.

4.2 Betas estimation framework

This section briefly introduces price and volatility jump regressions and reviews the theoretical framework that we use to estimate price and volatility jump betas.

4.2.1 Price jump regressions

In this subsection, we examine the linear relationship between jumps of individual assets and the aggregate market index. We assume that the log-price of asset i , denoted by $p_{i,t}$, follows a general continuous-time process:

$$dp_{i,t} = \alpha_{i,t}dt + \sigma_{i,t}dW_{i,t} + dJ_{i,t}, \quad 0 \leq t \leq T \quad (4.1)$$

where $\alpha_{i,t}$ represents the drift, $\sigma_{i,t}$ denotes the spot volatility of the asset price, and $W_{i,t}$ is a standard Brownian motion. $J_{i,t}$ is a pure jump process independent of $W_{i,t}$.

The log-price of the aggregate market index $p_{0,t}$ is defined similarly to Eq. 4.1:

$$dp_{0,t} = \alpha_{0,t}dt + \sigma_{0,t}dW_{0,t} + dJ_{0,t}, \quad 0 \leq t \leq T \quad (4.2)$$

Over the time interval $[0, T]$, we suppose that asset prices are observed at discrete time grids $k\Delta$, where $k = 1, \dots, m$ and $m = \lfloor \frac{T}{\Delta} \rfloor$ is the number of discrete observations over $[0, T]$.

$r_{i,k} = p_{i,k\Delta} - p_{i,(k-1)\Delta}$ is the intraday return of asset i over the $[(k-1)\Delta, k\Delta]$ intraday time interval.

We use the linear jump regression model proposed by Li et al. (2017) to examine the relationship between individual assets and the aggregate market index jumps. The linear relationship is given by:

$$r_{i,\tau} = \beta_i r_{0,\tau} + \epsilon_{i,\tau}, \tau \in \Phi \quad (4.3)$$

where Φ is the collection of jump times of the aggregate market index. β_i is a constant parameter measuring the sensitivity of the asset i to large market price movements. $\epsilon_{i,\tau}$ captures asset i 's specific movements. It is important to mention that neither the jump time τ nor jump sizes $(r_{i,\tau}, r_{0,\tau})$ are directly observable from data sampled at discrete times. We also assume that both individual assets and the market index have only a finite number of jumps over $[0, T]$, which means that the price process has a finite jump activity, as opposed to the infinite activity.¹ We denote Ω the set of discrete-time intervals where the market price jumps:²

$$\Omega = \left(k : 1 \leq k \leq m, \frac{|r_{i,k}|}{\tilde{\sigma}_{i,k}} > \theta \right)$$

where $\tilde{\sigma}_{i,k}$ is a jump robust estimator of the instantaneous volatility of asset i at intraday time $k\Delta$. θ is a threshold introduced to disentangle jumps from the diffusive component of asset returns. We refer to Appendix 4.A for the details of the LM-ABD jump identification procedure.

Let $\Omega' = (k \in \Omega : l_m + 1 \leq k \leq m - l_m)$, where the local averaging window length, l_m , is an integer such that $l_m \rightarrow \infty$ and $l_m \Delta \rightarrow 0$ as $m \rightarrow \infty$.

Li et al. (2017) propose a class of weighted estimators of the price jump beta β_i defined as follows:

$$\hat{\beta}_i = \frac{\sum_{k \in \Omega'} \omega_{i,k} r_{i,k} r_{0,k}}{\sum_{k \in \Omega'} \omega_{i,k} r_{0,k}^2}$$

¹This assumption makes sense since we only focus on large jumps with sizes bounded away from zero. Refer to Ait-Sahalia and Jacod (2011) for more details about finite and infinite jump activity.

²The intraday jumps are detected using LM-ABD procedure.

where $\omega_{i,k}$ is a given weight function. The optimal weight function, in the sense of minimizing the asymptotic variance among all weight functions, is given by:

$$\omega_{i,k}^* = \frac{2}{\left(-\tilde{\beta}_i, 1\right) \left(\hat{\varsigma}_{i,k-} + \hat{\varsigma}_{i,k+}\right) \left(-\tilde{\beta}_i, 1\right)}, \quad k \in \Omega'$$

where $\tilde{\beta}_i = \frac{\sum_{k \in \Omega} r_{i,k} r_{0,k}}{\sum_{k \in \Omega} r_{0,k}^2}$ is the unweighted ordinary least square (OLS) estimator of β_i . $\hat{\varsigma}_{i,k-}$ and $\hat{\varsigma}_{i,k+}$ are respectively the approximated pre-jump and post-jump spot covariance matrices:

$$\hat{\varsigma}_{i,k-} = \begin{pmatrix} \hat{\sigma}_{0,k-}^2 & \hat{\sigma}_{0i,k-} \\ \hat{\sigma}_{0i,k-} & \hat{\sigma}_{i,k-}^2 \end{pmatrix} = \frac{1}{l_m \Delta} \sum_{j=0}^{l_m-1} r'_{k-l_m+j} r_{k-l_m+j} \mathbb{1}_{\left\{ \frac{|r_{k-l_m+j}|}{\hat{\sigma}_{k-l_m+j}} \leq \theta \right\}}$$

$$\hat{\varsigma}_{i,k+} = \begin{pmatrix} \hat{\sigma}_{0,k+}^2 & \hat{\sigma}_{0i,k+} \\ \hat{\sigma}_{0i,k+} & \hat{\sigma}_{i,k+}^2 \end{pmatrix} = \frac{1}{l_m \Delta} \sum_{j=1}^{l_m} r'_{k+j} r_{k+j} \mathbb{1}_{\left\{ \frac{|r_{k+j}|}{\hat{\sigma}_{k+j}} \leq \theta \right\}}$$

where $r_k = (r_{0,k}, r_{i,k})$.

We denote $\hat{\beta}_i^*$ the optimal weighted estimator, which is the most efficient estimator of the price jump beta within a class of weighted estimators:

$$\hat{\beta}_i^* = \frac{\sum_{k \in \Omega'} \omega_{i,k}^* r_{i,k} r_{0,k}}{\sum_{k \in \Omega'} \omega_{i,k}^* r_{0,k}^2} \quad (4.4)$$

We follow the methodology proposed by Li et al. (2017) to provide the confidence intervals for the jump beta estimate. In order to take into account potential asymmetry between positive and negative price jumps, we decompose the systematic jump beta into upside and downside components, measuring the sensitivity of an individual asset price to respectively positive and negative market price jumps. The asymmetric price jump betas are as follows:

$$\hat{\beta}_{i,up}^* = \frac{\sum_{k \in \Omega'} \omega_{i,k,up}^* r_{i,k} r_{0,k} \mathbb{1}_{\{r_{0,k} > 0\}}}{\sum_{k \in \Omega'} \omega_{i,k,up}^* r_{0,k}^2 \mathbb{1}_{\{r_{0,k} > 0\}}} \quad (4.5)$$

$$\hat{\beta}_{i,down}^* = \frac{\sum_{k \in \Omega'} \omega_{i,k,down}^* r_{i,k} r_{0,k} \mathbb{1}_{\{r_{0,k} < 0\}}}{\sum_{k \in \Omega'} \omega_{i,k,down}^* r_{0,k}^2 \mathbb{1}_{\{r_{0,k} < 0\}}} \quad (4.6)$$

where the upside and downside weight functions are given by:

$$\omega_{i,k,up}^* = \frac{2}{\left(-\tilde{\beta}_{i,up}, 1\right) \left(\hat{\varsigma}_{i,k-} + \hat{\varsigma}_{i,k+}\right) \left(-\tilde{\beta}_{i,up}, 1\right)'}, \quad k \in \Omega'$$

$$\omega_{i,k,down}^* = \frac{2}{\left(-\tilde{\beta}_{i,down}, 1\right) \left(\hat{\varsigma}_{i,k-} + \hat{\varsigma}_{i,k+}\right) \left(-\tilde{\beta}_{i,down}, 1\right)'}, \quad k \in \Omega'$$

and the unweighted upside and downside estimators are defined as follows:

$$\tilde{\beta}_{i,up} = \frac{\sum_{k \in \Omega} r_{i,k} r_{0,k} \mathbb{1}_{\{r_{0,k} > 0\}}}{\sum_{k \in \Omega} r_{0,k}^2 \mathbb{1}_{\{r_{0,k} > 0\}}}$$

$$\tilde{\beta}_{i,down} = \frac{\sum_{k \in \Omega} r_{i,k} r_{0,k} \mathbb{1}_{\{r_{0,k} < 0\}}}{\sum_{k \in \Omega} r_{0,k}^2 \mathbb{1}_{\{r_{0,k} < 0\}}}$$

4.2.2 Volatility jump regressions

In this subsection, we examine the relationship between the volatility of individual assets and the volatility of an aggregate market index by focusing particularly on jump times of the market volatility. We assume that the relationship between two volatilities is linear at jump times:

$$\vartheta_{i,\tau} = \beta_{vol,i} \vartheta_{0,\tau} + \epsilon_{i,\tau}, \quad \tau \in \Phi_{vol} \quad (4.7)$$

where $\vartheta_{i,\tau} = \log(\sigma_{i,\tau}^2) - \log(\sigma_{i,\tau-}^2)$ measures the variation of the spot variance of asset i at market volatility jump time τ . Φ_{vol} is the collection of jump times of the market volatility. $\beta_{vol,i}$ is a constant parameter measuring the sensitivity of the volatility of asset i to large fluctuations of the market volatility. $\epsilon_{i,\tau}$ captures asset i 's specific volatility movements. Note that neither the jump times nor the spot volatilities are directly observed from the data. However, it is possible to provide estimates of jump times and spot volatilities from discrete data.

We denote Ω_{vol} the set of discrete-time intervals where the market volatility jumps. Let $\Omega'_{vol} = (k \in \Omega_{vol} : l_m + 1 \leq k \leq m - l_m)$, where the local averaging window length, l_m , is an integer such that $l_m \rightarrow \infty$ and $l_m \sqrt{\Delta} \rightarrow 0$ as $m \rightarrow \infty$. The estimates of the spot volatilities can be deduced from the pre-jump and post-jump spot covariance matrices introduced in Section 4.2.1:

$$\hat{\vartheta}_{0,k} = \log(\hat{\sigma}_{0,k+}^2) - \log(\hat{\sigma}_{0,k-}^2), \quad k \in \Omega'_{vol}$$

$$\hat{\vartheta}_{i,k} = \log(\hat{\sigma}_{i,k+}^2) - \log(\hat{\sigma}_{i,k-}^2), \quad k \in \Omega'_{vol}$$

Once the spot volatilities estimated, we need to identify the jump times of the market volatility. As volatilities are latent processes, it is problematic to estimate the jump times of the market volatility. One possible solution, used in practice, is to approximate the jump times of the market volatility process with those of a volatility index traded in the market such as VIX or VXEEM.³ We use LM-ABD method to estimate the jump times of the volatility index.

A first approach to estimate the volatility jump beta $\beta_{vol,i}$ is to use the ordinary least square estimator:

$$\tilde{\beta}_{vol,i} = \frac{\sum_{k \in \Omega_{vol}} \hat{\vartheta}_{i,k} \hat{\vartheta}_{0,k}}{\sum_{k \in \Omega_{vol}} \hat{\vartheta}_{0,k}^2}$$

However, as mentioned in Davies (2016), the OLS estimator is likely to be biased due the error in estimating spot volatilities, especially for small samples. To circumvent this issue, we follow Davies (2016) who proposes an unbiased estimator of the volatility jump beta based on the quasi-maximum likelihood estimation approach:

$$\hat{\beta}_{vol,i} = \arg \max_{b \in R} [\log(L(b|\hat{\varsigma}_{i,k-}, \hat{\varsigma}_{i,k+}, k \in \Omega'_{vol}))] \quad (4.8)$$

³This technique has been used in Todorov and Tauchen (2011) and Davies (2016).

where:

$$\log \left(L \left(b | \hat{\varsigma}_{i,k-}, \hat{\varsigma}_{i,k+}, k \in \Omega'_{vol} \right) \right) = -\frac{1}{2} \sum_{k \in \Omega'_{vol}} \log \left(\frac{8\pi}{l_m} \left(1 + b^2 - b\hat{\lambda}_{i,k} \right) \right) - \sum_{k \in \Omega'_{vol}} \frac{l_m \left(\hat{\vartheta}_{i,k} - b\hat{\vartheta}_{0,k} \right)^2}{8 \left(1 + b^2 - b\hat{\lambda}_{i,k} \right)}$$

$$\hat{\lambda}_{i,k} = \frac{\hat{\sigma}_{0i,k-}^2}{\hat{\sigma}_{0,k-}^2 \hat{\sigma}_{i,k-}^2} + \frac{\hat{\sigma}_{0i,k+}^2}{\hat{\sigma}_{0,k+}^2 \hat{\sigma}_{i,k+}^2}$$

We also follow the methodology proposed by Davies (2016) to provide the confidence intervals for the volatility jump beta estimate. Similarly to price jump beta, we decompose the systematic volatility jump beta into upside and downside components. The quasi-maximum likelihood estimators of the upside and downside volatility jump betas are as follows:

$$\hat{\beta}_{upvol,i} = \arg \max_{b \in R} \left[\log \left(L \left(b | \hat{\varsigma}_{i,k-}, \hat{\varsigma}_{i,k+}, k \in \Omega'_{upvol} \right) \right) \right] \quad (4.9)$$

$$\hat{\beta}_{downvol,i} = \arg \max_{b \in R} \left[\log \left(L \left(b | \hat{\varsigma}_{i,k-}, \hat{\varsigma}_{i,k+}, k \in \Omega'_{downvol} \right) \right) \right] \quad (4.10)$$

where Ω'_{upvol} (respectively $\Omega'_{downvol}$) denotes the set of discrete-time intervals where the market volatility jumps upward (respectively downward).

4.3 Data description

We use two sets of data to conduct our empirical investigation. The first set is composed of ten exchange-traded funds covering major developed and emerging markets: EWG, EWJ, EWQ, EWU and SPY aim to replicate the performance of respectively German, Japanese, French, British and American stock markets whereas EWZ, EZA, GXC and PIN seek to capture the performance of respectively Brazilian, South African, Chinese and Indian stock markets. The EEM fund, which seeks to replicate the performance of the MSCI Emerging Markets index, is used as a proxy for the emerging stock markets whereas SPY is our proxy for the developed stock markets. Each country fund, considered in the study, is constructed

in a way to replicate the performance of its corresponding country index by holding a portfolio of the common stocks that are included in the underlying index, with the weight of each stock in the portfolio substantially corresponding to the weight of such stock in the index. The second set of data consists of two volatility indices: The Chicago Board of Options Exchange's (CBOE) Volatility Index (VIX) and CBOE Emerging Markets ETF Volatility Index (VXEEM) serving as proxies for respectively the developed and emerging market volatilities. Table 4.1 provides the detail of the country ETFs and volatility indices used in our study. Our empirical analysis is based on intraday data from January 2008 to May 2015. Prices and volatility data are sampled every 20 minutes from 9:50 to 15:50 (UTC-4 time zone), resulting in 1865 days with 18 intraday returns per trading day.⁴ The main purpose of using a sampling frequency of 20 minutes is to guard against market microstructure noise.

Table 4.1: Country exchange-traded funds and volatility indices.

The ticker, the name, the inception date and the country (or the market) of each fund (respectively volatility index) in the sample are reported.

Ticker	Fund	Inception Date	Country or Market
EEM	iShares MSCI Emerging Markets ETF	April 7, 2003	Emerging markets
EWG	iShares MSCI Germany ETF	March 12, 1996	Germany
EWJ	iShares MSCI Japan ETF	March 12, 1996	Japan
EWQ	iShares MSCI France ETF	March 12, 1996	France
EWU	iShares MSCI United Kingdom ETF	March 12, 1996	United Kingdom
EWZ	iShares MSCI Brazil Capped ETF	July 10, 2000	Brazil
EZA	iShares MSCI South Africa ETF	February 3, 2003	South Africa
GXC	SPDR S&P China ETF	March 23, 2007	China
PIN	Power Shares India Portfolio ETF	March 5, 2008	India
SPY	SPDR S&P 500	December 30, 2002	United States
VIX	Cboe Volatility Index	January 19, 1993	United States
VXEEM	Cboe Emerging Markets ETF Volatility Index	March 16, 2011	Emerging markets

⁴We also consider different sampling frequencies (10, 30 and 40 minutes) to verify the robustness of our results.

4.4 Empirical Findings

4.4.1 Price and volatility cojumps

This subsection summarizes the results from applying LM-ABD intraday jump detection test. To minimize the effects of the well known intraday volatility pattern on LM-ABD jump identification test, we modify our procedure by rescaling intraday returns with a volatility jump robust corrector introduced by Bollerslev and al. (2008).⁵ Jumps are detected with a threshold value equal to four, which means that the intraday jump return size is at least four times greater than the estimate of the local volatility. We also apply threshold values of three and five to study the robustness of our results.⁶ The jump detection procedure is detailed in Appendix 4.A.

Table 4.2 provides the number of total, positive and negative intraday jumps detected over the sample period. A positive (negative) jump corresponds to an upward (downward) movement of the price. The average yearly number of intraday jumps is the highest for China and India with respectively 78 and 77 intraday jumps per year. The two volatility indices VXEEM and VIX have also an important jump activity with respectively 73 and 68 jumps per year. Brazil and Japan have the lowest jump activity with respectively 39 and 49 jumps per year. The number of negative jumps is higher than positive ones for all country funds, except for Japan. On the other side, the volatility indices have the opposite effect: positive volatility jumps are largely greater than negative ones.

Panels A and B of Table 4.3 provide statistics about the cojumps of country funds with respectively SPY and EEM funds. A cojump is detected when two assets jump simultaneously at the same intraday time interval. We notice that developed markets cojump more frequently with SPY than with EEM. On the opposite, the cojumps of emerging markets with EEM are

⁵It is widely documented (Wood et al. (1985) and Harris (1986)) that intraday returns show a systematic seasonality over the trading day, also called the U-shaped pattern. The intraday volatility is particularly higher at the open and the close of the trading than the rest of the day. This seasonality can lead to spurious detection of jumps.

⁶Detailed results for the threshold values of 3 and 5 can be made available upon request.

higher than those with SPY. This result confirms the fact that emerging markets are more linked to their aggregate market proxy, the EEM fund, whereas the developed markets are more close to the US market. Countries with the lowest proportion of cojumps with SPY include China, South Africa and India, where the proportion of cojumps is less than 37% of detected jumps. Germany registers the highest proportion of cojumps with SPY with around 53% of detected jumps. Countries with the highest proportion of cojumps with EEM include Brazil, South Africa and the United States, where the proportion of cojumps is higher than 47% of detected jumps. Japan has the lowest proportion of cojumps with the EEM with less than 29% of detected jumps. As for positive and negative cojumps, we find that the proportion of negative cojumps of country funds with respectively EEM (or SPY) is greater than positive cojumps. This result is consistent with the high correlation between large down moves in international markets documented by Longin and Solnik (2001) and Ang and Bekaert (2002).

Panels C and D of Table 4.3 provide statistics about the cojumps of country funds with respectively VIX and VXEEM. We find that simultaneous jumps between each of the two volatility indices (VIX and VXEEM) and country funds have an opposite sign for almost all detected cojumps. This means that an upward (downward) jump in the volatility index occurs simultaneously with a downward (upward) jump of the price. We also notice that the proportion of cojumps of country funds with the volatility indices are much fewer than the cojumps with SPY and EEM funds. United Kingdom, Brazil, United States and France have the highest proportion of cojumps with the VIX index with more than 12% of all identified jumps. The proportion is lowest for China, India and South Africa with less than 9% of all identified jumps. The cojumps of country funds with VXEEM are low and their proportions vary between 6% and 10% of all detected jumps. As for positive and negative cojumps, we find that the proportion of cojumps where the volatility index jumps upward and asset prices move downward is greater than negative volatility and positive price cojumps. This finding is consistent with a high correlation between the market volatility and asset returns when the market is downward and its volatility is high.

Panel E of Table 4.3 shows that the volatility indices, the VIX and VXEEM, cojump 83 times over the period going from March 11, 2011 to May 29, 2015, which represents 28% of all detected jumps.⁷ We also find that the proportion of positive cojumps between two volatility indices (60% of all detected cojumps) is greater than negative ones (40% of all detected cojumps), where a positive (negative) volatility cojump is defined as simultaneous positive (negative) jumps of both volatility indices. This finding is consistent with a higher comovement of international stock market volatilities in periods of financial turmoil.

Table 4.2: Summary statistics of jump occurrences.

The percentage of intraday jumps to the number of intraday returns, the percentage of positive jumps and negative jumps to all jumps are reported in columns 3, 5 and 6, respectively. The total number of days available in the sample by fund and the average number of jumps per year are shown in columns 2 and 4. Jumps are detected by LM-ABD procedure. See Appendix 4.A for the details of jump test statistics.

ETF	Days	Intraday jumps	Number of intraday jumps per year	Positive jumps	Negative jumps
EEM	1845	351 (1.06%)	48	156 (44%)	195 (56%)
EWG - Germany	1845	458 (1.38%)	63	200 (44%)	258 (56%)
EWJ - Japan	1845	358 (1.08%)	49	183 (51%)	175 (49%)
EWQ - France	1845	397 (1.20%)	54	172 (43%)	225 (57%)
EWU - UK	1796	328 (1.01%)	46	135 (41%)	193 (59%)
EWZ - Brazil	1845	284 (0.86%)	39	125 (44%)	159 (56%)
EZA - South Africa	1845	457 (1.38%)	62	205 (45%)	252 (55%)
GXC - China	1845	571 (1.72%)	78	272 (48%)	299 (52%)
PIN - India	1802	551 (1.70%)	77	256 (46%)	295 (54%)
SPY - USA	1845	382 (1.15%)	52	150 (39%)	232 (61%)
VIX	1844	499 (1.50%)	68	308 (62%)	191 (38%)
VXEEM	1038	301 (1.61%)	73	166 (55%)	135 (45%)

⁷The Cboe Emerging Markets ETF Volatility Index, VXEEM, was incepted on March 16, 2011.

Table 4.3: Summary statistics of cojump occurrences.

Panel A, B, C, D report the number of cojumps, the percentage of cojumps to the total number of detected jumps, and the percentage of positive and negative cojumps to all cojumps of all country funds with respectively EEM, SPY, VIX and VXEEM. Panel E show the number of cojumps, the percentage of cojumps to the total number of detected jumps, and the percentage of positive and negative cojumps to all cojumps between VIX and VXEEM indices. See Appendix 4.A for the cojump identification procedure.

Panel A: Cojumps of all country funds with EEM

	Cojumps	Positive Cojumps	Negative Cojumps
EWG - Germany	161 (46%)	43%	57%
EWJ - Japan	103 (29%)	49%	51%
EWQ - France	144 (41%)	45%	55%
EWU - UK	152 (46%)	47%	53%
EWZ - Brazil	134 (47%)	42%	58%
EZA- South Africa	167 (48%)	45%	55%
GXC - China	163 (46%)	44%	56%
PIN - India	144 (41%)	49%	51%
SPY - USA	187 (53%)	40%	60%

Panel B: Cojumps of all country funds with SPY

	Cojumps	Positive Cojumps	Negative Cojumps
EWG - Germany	187 (53%)	40%	60%
EWJ - Japan	174 (46%)	37%	63%
EWQ - France	138 (39%)	42%	58%
EWU - UK	154 (40%)	36%	63%
EWZ - Brazil	161 (49%)	41%	58%
EZA- South Africa	97 (34%)	39%	61%
GXC - China	126 (33%)	47%	52%
PIN - India	140 (37%)	42%	57%

Panel C: Cojumps of all country funds with VIX

	Cojumps	Positive (VIX) Cojumps	Negative (VIX) Cojumps
EEM	52 (15%)	56%	21%
EWG - Germany	52 (11%)	62%	13%
EWJ - Japan	33 (9%)	42%	18%
EWQ - France	46 (12%)	52%	22%
EWU - UK	43 (13%)	53%	19%
EWZ - Brazil	36 (13%)	64%	19%

EZA- South Africa	41 (9%)	51%	22%
GXC - China	45 (9%)	58%	20%
PIN - India	36 (7%)	53%	14%
SPY - USA	45 (12%)	62%	16%

Panel D: Cojumps of all country funds with VXEEM

	Cojumps	Positive (VXEEM) Cojumps	Negative (VXEEM) Cojumps
EEM	27 (9%)	48%	33%
EWG - Germany	29 (10%)	55%	34%
EWJ - Japan	19 (6%)	37%	47%
EWQ - France	29 (10%)	48%	38%
EWU - UK	20 (7%)	35%	45%
EWZ - Brazil	19 (7%)	53%	32%
EZA- South Africa	24 (8%)	50%	33%
GXC - China	25 (8%)	56%	32%
PIN - India	23 (8%)	57%	30%
SPY - USA	24 (8%)	63%	25%

Panel E: Cojumps between VIX and VXEEM

	Cojumps	Positive Cojumps	Negative Cojumps
VIX/VXEEM	83 (28%)	60%	40%

4.4.2 Price jump betas

The earlier subsection shows us that jumps in developed markets have tendency to occur simultaneously with the US market whereas jumps in emerging markets are closely linked to the aggregate market index of emerging markets, the EEM fund. These findings suggest that jumps in both developed and emerging markets are rather systematic and are derived by common underlying risk factors. To examine the relationship between the market and individual assets at jump times, we assume that individual asset prices respond linearly to market jumps, which corresponds to the linear factor model introduced in Section 4.2.1.

This subsection summarizes the main results from the estimation of price jump betas. For each individual asset, we ran two regressions using respectively SPY and EEM price jumps

as explanatory market factors. Jumps are detected using LM-ABD method with a threshold value equal to 4. We set the local averaging window l_m to 9, which corresponds to the half of within-day intervals of a trading day. All regressions are performed over the whole study period.

Table 4.4 provides the main results of the weighted price jump beta estimation. We also report the result for the test of a constant jump beta over the full sample. Panel A of Table 4.4 shows the results of the beta estimation using EEM price jumps as a market risk factor. We note that all betas are significantly positive with a relatively narrow confidence interval at 95% level. South Africa, Brazil and India have the highest price jump beta coefficient with the emerging market proxy, the EEM fund, with respectively 1.34, 1.14 and 1.09. The lowest price jump beta coefficient is registered for Japan (0.52), USA (0.66) and UK (0.69). The emerging countries are thus more sensitive to jumps of the aggregate emerging market index than the developed countries considered in the study. The results of the test of constancy show that the null hypothesis of constant price jump beta is rejected for all funds at 1% significance level, except for Brazil and USA. This finding suggests that the price jump beta changes over time, which is consistent with the conditional asset pricing models (Hansen and Richard (1987)).

Panel B of Table 4.4 reports the results of price jump beta estimation using SPY price jumps as a market risk factor. Similarly to the first set of EEM based regressions, all the estimated betas are significantly positive. The developed countries have a higher jump beta coefficients compared to the ones obtained from EEM based regressions. This result suggests that developed markets will react differently to jumps in respectively US and emerging markets. The response of developed markets to a jump occurring in the US market will be more important (in term of size) to a jump happening in emerging markets. As for the test of constancy of the jump price beta over the full sample, we find that the null hypothesis of constant beta cannot be rejected at 1% significance level for Germany, Japan, France, Brazil and China. This result shows that SPY based jump betas are less time-varying than the ones obtained from EEM based regressions.

Table 4.4: Price jump beta estimation and tests for constancy over the full sample. Panels A and B report the results of price jump beta estimation between country funds and respectively EEM and SPY. The columns show the weighted price jump beta estimate, the 95% confidence interval (CI) and the p-value for the test of a constant price jump beta over the period 2008-2015. See Appendix 4.A for the jump identification procedure. See Section 4.2.1 for price jump beta estimation. The confidence interval is calculated using the Monte Carlo procedure proposed by Li et al. (2017). We also follow Li et al. (2017) to perform the test of constancy. ***, **, * imply the rejection of the null hypothesis of constant jump beta respectively at 1%, 5%, and 10% significance levels.

Panel A: EEM price jumps used as a market risk factor

	$\hat{\beta}_i^*$	CI	p-value
EWG - Germany	0.77	[0.74,0.79]	0.04**
EWJ - Japan	0.52	[0.50,0.54]	0.016**
EWQ - France	0.74	[0.71,0.76]	<0.001***
EWU - UK	0.69	[0.67,0.72]	<0.001***
EWZ - Brazil	1.14	[1.10,1.19]	0.999
EZA- South Africa	1.34	[1.30,1.38]	<0.001***
GXC - China	0.75	[0.72,0.77]	0.028**
PIN - India	1.09	[1.06,1.13]	<0.001***
SPY - USA	0.66	[0.63,0.68]	0.999

Panel B: SPY price jumps used as a market risk factor

	$\hat{\beta}_i^*$	CI	p-value
EEM	1.07	[1.03,1.12]	0.999
EWG - Germany	1.04	[1.01,1.08]	0.230
EWJ - Japan	0.70	[0.68,0.73]	0.411
EWQ - France	1.02	[0.99,1.05]	0.014**
EWU - UK	0.92	[0.88,0.96]	<0.001***
EWZ - Brazil	1.22	[1.15,1.28]	0.998
EZA- South Africa	1.37	[1.33,1.42]	<0.001***
GXC - China	0.93	[0.90,0.96]	0.398
PIN - India	1.13	[1.09,1.17]	<0.001***

To check the time-varying nature of price jump betas, we ran price jump beta regressions over years and test the constancy of the yearly estimated price jump beta. Panel A and B Table 4.5 provide the results of the estimated price jump betas over years using respectively EEM and SPY jumps as market risk factors. We first remark that the accuracy of jump

beta estimates given by the 95% confidence level remains high. We also notice that yearly estimated price jump betas seem to be less varying than full period estimates. Indeed, Table 4.6 shows that the rejection rate of the null hypothesis of constant beta over years at 5% significance level represents 27% (39 rejections out of 144 regressions) of all yearly regressions compared to 61% (11 rejections out of 18 regressions) for full sample regressions. In the same way as for the full sample regressions, the rejection rate for SPY based regressions is lower than EEM based regressions. One possible solution to improve the estimation of the remaining time-varying betas is to further shorten the estimation period to six or three months.

Table 4.5: Price jump beta estimation over years.

Panels A and B report the weighted price jump beta estimate (the 95% confidence interval is given between brackets) for every fund and every year in the sample. The results are obtained using respectively EEM and SPY as market proxies. See Appendix 4.A for the jump identification procedure. See Section 4.2.1 for jump beta estimation. We follow Li et al. (2017) to provide confidence interval for the weighted jump beta estimate.

Panel A: EEM price jumps used as a market risk factor				
	2008	2009	2010	2011
EWG	0.53 [0.47,0.58]	0.97 [0.85,1.08]	0.89 [0.82,0.96]	1.03 [0.96,1.11]
EWJ	0.48 [0.43,0.54]	0.54 [0.48,0.61]	0.59 [0.54,0.64]	0.58 [0.53,0.63]
EWQ	0.50 [0.44,0.55]	0.84 [0.74,0.94]	0.79 [0.74,0.84]	1.04 [0.95,1.12]
EWU	0.59 [0.52,0.66]	0.62 [0.54,0.70]	0.88 [0.80,0.95]	0.87 [0.80,0.94]
EWZ	1.29 [1.13,1.45]	1.07 [0.91,1.23]	1.17 [1.05,1.29]	1.13 [1.03,1.22]
EZA	0.78 [0.70,0.87]	1.06 [0.94,1.19]	1.46 [1.23,1.69]	1.08 [0.98,1.17]
GXC	0.81 [0.73,0.89]	0.96 [0.83,1.08]	0.60 [0.56,0.65]	0.95 [0.86,1.03]
PIN	0.60 [0.52,0.69]	0.68 [0.57,0.78]	1.63 [1.33,1.92]	0.66 [0.60,0.71]
SPY	0.67 [0.60,0.75]	0.76 [0.67,0.85]	0.66 [0.60,0.71]	0.80 [0.73,0.87]
	2012	2013	2014	2015
EWG	0.95 [0.84,1.05]	0.58 [0.54,0.62]	0.62 [0.57,0.67]	0.82 [0.75,0.90]
EWJ	0.50 [0.44,0.56]	0.49 [0.44,0.54]	0.42 [0.37,0.46]	0.50 [0.44,0.55]
EWQ	1.01 [0.91,1.11]	0.60 [0.55,0.64]	0.66 [0.61,0.71]	0.82 [0.74,0.90]
EWU	0.79 [0.71,0.86]	0.51 [0.47,0.56]	0.52 [0.47,0.56]	0.64 [0.58,0.71]
EWZ	1.14 [1.01,1.26]	0.97 [0.90,1.03]	1.20 [1.10,1.29]	1.26 [1.15,1.37]
EZA	1.16 [1.03,1.30]	1.17 [1.08,1.26]	1.25 [1.15,1.34]	1.49 [1.36,1.62]
GXC	0.78 [0.70,0.86]	0.75 [0.70,0.80]	0.68 [0.62,0.73]	0.69 [0.62,0.77]

PIN	0.67 [0.60,0.73]	0.77 [0.71,0.83]	0.88 [0.81,0.95]	0.73 [0.67,0.79]
SPY	0.75 [0.68,0.82]	0.48 [0.45,0.51]	0.51 [0.47,0.55]	0.53 [0.48,0.58]

Panel B: SPY price jumps used as a market risk factor

	2008	2009	2010	2011
EEM	1.13 [0.99,1.26]	1.16 [1.01,1.31]	1.25 [1.09,1.40]	1.01 [0.92,1.11]
EWG	0.74 [0.66,0.82]	1.19 [1.03,1.34]	1.20 [1.09,1.30]	1.22 [1.11,1.34]
EWJ	0.72 [0.64,0.79]	0.80 [0.70,0.89]	0.82 [0.75,0.89]	0.70 [0.64,0.76]
EWQ	0.74 [0.67,0.81]	1.10 [0.96,1.25]	1.21 [1.11,1.31]	1.16 [1.06,1.26]
EWU	0.84 [0.74,0.93]	0.77 [0.67,0.87]	1.16 [1.05,1.28]	1.01 [0.90,1.12]
EWZ	1.47 [1.28,1.66]	1.26 [1.05,1.47]	1.30 [1.13,1.46]	1.12 [1.02,1.22]
EZA	1.16 [1.04,1.28]	1.31 [1.17,1.46]	1.61 [1.36,1.86]	1.25 [1.15,1.36]
GXC	0.92 [0.83,1.01]	1.08 [0.95,1.21]	0.89 [0.81,0.96]	0.94 [0.84,1.04]
PIN	0.71 [0.61,0.81]	0.92 [0.81,1.03]	1.63 [1.36,1.90]	0.74 [0.68,0.80]

	2012	2013	2014	2015
EEM	1.04 [0.93,1.15]	0.88 [0.78,0.98]	0.95 [0.84,1.06]	0.93 [0.82,1.03]
EWG	1.14 [1.03,1.25]	0.87 [0.81,0.93]	0.91 [0.82,1.00]	0.92 [0.81,1.04]
EWJ	0.61 [0.56,0.66]	0.64 [0.58,0.70]	0.65 [0.58,0.71]	0.64 [0.58,0.71]
EWQ	1.13 [1.03,1.23]	0.96 [0.88,1.05]	0.90 [0.82,0.99]	0.92 [0.82,1.02]
EWU	0.93 [0.85,1.02]	0.72 [0.65,0.78]	0.76 [0.68,0.85]	0.77 [0.67,0.87]
EWZ	1.21 [1.09,1.33]	0.92 [0.83,1.02]	1.09 [0.96,1.22]	0.99 [0.81,1.17]
EZA	1.16 [1.05,1.27]	0.93 [0.82,1.03]	1.43 [1.31,1.55]	1.32 [1.16,1.48]
GXC	0.94 [0.86,1.02]	0.91 [0.83,0.99]	0.98 [0.89,1.08]	0.81 [0.71,0.91]
PIN	0.71 [0.64,0.78]	0.72 [0.64,0.80]	0.85 [0.76,0.94]	0.81 [0.72,0.91]

Table 4.6: Tests of a constant price jump beta over years.

Panels A and B report the p-values for the test of a constant price jump beta using respectively EEM and SPY as market proxies. The test is performed for every fund and every year in the sample. We follow the methodology provided by Li et al. (2017) to perform the test of constancy. ***, **, * imply the rejection of the null hypothesis of constant jump beta respectively at 1%, 5%, and 10% significance levels.

Panel A: EEM price jumps used as a market risk factor

	2008	2009	2010	2011	2012	2013	2014	2015
EWG	0.948	0.515	0.897	0.61	0.294	<0.001***	<0.001***	0.003***
EWJ	0.085	0.103	0.01**	0.488	0.013**	0.286	0.023**	0.817
EWQ	0.999	0.68	<0.001***	0.619	0.851	<0.001***	0.006***	<0.001***
EWU	0.998	<0.001***	0.078	0.999	0.989	0.081*	0.041**	0.395
EWZ	0.999	0.992	0.974	0.999	0.994	0.314	0.096*	0.008***
EZA	<0.001***	0.959	0.001***	0.036**	0.998	0.982	0.451	0.855
GXC	0.727	0.613	<0.001***	0.8	0.935	0.978	<0.001***	0.632
PIN	<0.001***	0.282	<0.001***	0.993	0.799	0.635	0.479	0.159
SPY	0.999	0.999	0.72	0.999	0.877	<0.001***	0.021**	0.001***

Panel B: SPY price jumps used as a market risk factor

	2008	2009	2010	2011	2012	2013	2014	2015
EWG	0.999	0.999	0.988	0.999	0.999	<0.001***	0.776	0.455
EWJ	0.204	0.528	0.996	0.994	0.759	<0.001***	0.68	0.774
EWQ	0.99	0.917	0.003***	0.098	0.005***	<0.001***	0.236	0.259
EWU	0.995	0.884	<0.001***	0.505	0.851	<0.001***	0.947	0.327
EWZ	0.999	<0.001***	0.649	0.999	0.989	0.07*	0.62	0.366
EZA	0.999	0.997	0.661	0.865	0.471	<0.001***	0.01**	0.079*
GXC	0.337	0.674	<0.001***	0.09	0.343	<0.001***	0.631	0.071*
PIN	0.645	0.99	<0.001***	0.949	0.15	0.029**	0.164	0.864
SPY	0.011*	0.457	<0.001***	0.849	0.526	<0.001***	<0.001***	0.25

4.4.3 Volatility jump betas

We show in Section 4.4.1 that developed and emerging equity markets have tendency to be involved in cojumps with aggregate market volatility indices, the VIX and VXEEM indices. This finding suggests that market volatility jumps could be a potential source of systematic risk in international equity markets. To assess how individual assets are sensitive to market

volatility jumps, we assume that the individual asset volatility jumps are linked linearly to jumps of the market volatility.

Table 4.7: Volatility jump beta estimation and tests for constancy over the full sample.

Panels A and B report the results of volatility jump beta estimation between country funds and respectively EEM and SPY. The columns show the quasi-maximum likelihood volatility jump beta estimate, the 95% confidence interval (CI) and the p-value for the test of a constant volatility jump beta over the period 2008-2015. See Appendix 4.A for the jump identification procedure. See Section 4.2.2 for volatility jump beta estimation. We use the VXEEM and VIX volatility indices to approximate the jump arrival times of respectively EEM and SPY volatilities. The confidence intervals are calculated using the bootstrap procedure provided by Davies (2016). We also follow the methodology provided by Davies (2016) to perform the test of volatility jump beta constancy. ***, **, * imply the rejection of the null hypothesis of constant volatility jump beta respectively at 1%, 5%, and 10% significance levels.

Panel A: EEM volatility jumps used as a market risk factor

	$\hat{\beta}_{vol,i}$	CI	p-value
EWG - Germany	0.58	[0.49,0.74]	0.015**
EWJ - Japan	0.44	[0.35,0.58]	0.562
EWQ - France	0.55	[0.45,0.71]	0.453
EWU - UK	0.56	[0.46,0.74]	0.582
EWZ - Brazil	0.72	[0.59,0.93]	0.996
EZA- South Africa	0.85	[0.49,1.26]	<0.001***
GXC - China	0.42	[0.26,0.71]	<0.001***
PIN - India	0.76	[0.61,0.97]	<0.001***
SPY - USA	0.81	[0.70,0.97]	0.999

Panel B: SPY volatility jumps used as a market risk factor

	$\hat{\beta}_{vol,i}$	CI	p-value
EEM	0.76	[0.72,0.88]	0.999
EWG - Germany	0.60	[0.55,0.70]	0.999
EWJ - Japan	0.46	[0.41,0.58]	0.993
EWQ - France	0.62	[0.57,0.76]	0.999
EWU - UK	0.61	[0.56,0.71]	0.999
EWZ - Brazil	0.52	[0.45,0.66]	0.046**
EZA- South Africa	0.57	[0.51,0.73]	0.003***
GXC - China	0.40	[0.31,0.59]	<0.001***
PIN - India	0.72	[0.60,0.94]	<0.001***

Panel A of Table 4.7 provides the results of volatility jump beta estimation for emerging market volatility jumps. All regressions are performed over the full sample. We find that all volatility jump betas are significantly positive for all countries in the sample. However, the accuracy of the volatility jump beta estimates at 95% confidence level is lower than the price jump beta estimates found in the previous subsection. The countries with highest volatility jump betas with the EEM fund are South Africa (0.85), USA (0.81) and India (0.76). The lowest volatility jump betas are found for China (0.42), Japan (0.44) and France (0.55). The tests of constancy of the volatility jump beta show that the beta estimates are time-varying especially for emerging countries. Panel B of Table 4.7 reports the results of volatility jump beta estimation for all country funds with the SPY volatility jumps used as a market risk factor. Similarly to EEM based regressions, all the SPY based volatility jump beta estimates are significantly positive at 95% confidence level. The null hypothesis of constant volatility jump beta is rejected for all emerging countries. The linear relationship between developed markets and the US market seems to be more stable in time than with emerging markets. When comparing between volatility jump beta estimates found for respectively SPY and EEM, the results show that emerging countries are more sensitive to emerging market volatility jumps than to US market volatility jumps. In contrast, the sensitivity of developed countries to the SPY volatility jumps is higher than to emerging market volatility jumps.

Similarly to price jump beta estimates, we provide the results of volatility jump beta estimation on year-by-year basis to make sure that our estimates are more stable in time for a shorter estimation period. Panel A and B of Table 4.8 report the details of volatility jump beta estimation for respectively EEM and SPY. We notice that the accuracy of estimates is lower than the full sample case. However, the precision remains acceptable at 95% confidence level. Table 4.9 provides the results of the test of volatility jump beta constancy over years. The rejection rates dropped to 22% (10 out of 45 yearly regressions) and 19% (14 out of 72 yearly regressions) for respectively EEM and SPY based regressions compared to full sample regressions where the rejection rate is 44% (4 out of 9 full sample regressions) at 5% significance level.

Table 4.8: Volatility jump beta estimation over years.

Panels A and B report the quasi-maximum likelihood volatility jump beta estimate (the 95% confidence interval is given between brackets) for every fund and every year in the sample. The results are obtained using respectively EEM and SPY as market proxies. See Appendix 4.A for the jump identification procedure. See Section 4.2.2 for volatility jump beta estimation. We follow the bootstrap procedure proposed by Davies (2016) to provide a confidence interval for the volatility jump beta estimate.

Panel A: EEM volatility jumps used as a market risk factor

	2011	2012	2013	2014	2015
EWG	0.67 [0.42,0.91]	0.74 [0.22,1.49]	0.46 [0.34,0.61]	0.60 [0.29,0.92]	1.07 [0.26,2.70]
EWJ	0.51 [0.30,0.73]	0.34 [-0.04,0.81]	0.52 [0.35,0.74]	0.33 [0.15,0.56]	0.30 [-0.50,1.04]
EWQ	0.63 [0.23,0.98]	0.47 [0.20,0.82]	0.54 [0.39,0.73]	0.61 [0.32,0.93]	0.34 [-0.43,1.13]
EWU	0.66 [0.32,0.92]	0.76 [0.47,1.26]	0.37 [0.21,0.57]	0.58 [0.35,0.89]	0.59 [0.04,1.26]
EWZ	0.91 [0.54,1.32]	0.97 [0.54,1.64]	0.91 [0.63,1.20]	0.47 [0.29,0.69]	0.21 [-0.24,0.71]
EZA	0.56 [-0.37,1.04]	1.12 [0.47,2.23]	0.52 [0.11,0.96]	1.06 [0.72,1.40]	0.88 [0.39,1.36]
GXC	0.57 [0.03,1.23]	0.75 [-0.07,1.96]	0.07 [-0.18,0.34]	0.44 [0.18,0.74]	0.83 [0.38,1.81]
PIN	0.92 [0.50,1.29]	1.03 [0.48,1.70]	0.52 [0.27,0.90]	0.87 [0.54,1.21]	0.56 [0.21,0.92]
SPY	0.74 [0.48,0.92]	0.81 [0.63,1.09]	0.86 [0.54,1.19]	0.87 [0.44,1.17]	0.65 [-0.03,1.29]

Panel B: SPY volatility jumps used as a market risk factor

	2008	2009	2010	2011	2012
EEM	0.86 [0.39,1.33]	0.98 [0.70,1.32]	0.71 [0.64,0.83]	0.90 [0.52,1.18]	0.71 [0.32,0.95]
EWG	0.54 [0.33,0.79]	0.58 [0.30,0.83]	0.53 [0.41,0.70]	0.59 [-0.05,0.88]	0.73 [0.31,1.15]
EWJ	0.53 [0.08,0.90]	0.58 [0.42,0.78]	0.52 [0.19,0.77]	0.66 [0.44,0.91]	0.26 [0.02,0.55]
EWQ	0.48 [-0.10,0.95]	0.56 [0.36,0.79]	0.62 [0.45,0.83]	0.78 [0.47,1.31]	0.60 [0.28,0.93]
EWU	0.56 [0.29,0.89]	0.56 [0.42,0.76]	0.64 [0.53,0.81]	0.78 [0.49,1.02]	0.37 [-0.09,0.69]
EWZ	0.65 [0.04,1.04]	0.84 [0.56,1.12]	0.40 [0.27,0.58]	0.92 [0.57,1.54]	0.32 [0.02,0.60]
EZA	0.57 [0.19,1.03]	0.59 [0.18,1.17]	0.54 [0.42,0.70]	0.55 [0.07,0.91]	0.99 [0.52,1.85]
GXC	0.96 [0.36,1.84]	0.69 [0.35,1.21]	0.50 [0.35,0.70]	-0.38 [-1.88,-0.02]	0.59 [-0.07,1.60]
PIN	0.82 [0.44,1.22]	0.75 [0.25,1.28]	0.88 [0.58,1.95]	0.89 [0.38,1.60]	1.12 [0.67,1.68]

	2013	2014	2015
EEM	0.83 [0.60,1.06]	0.54 [0.33,0.75]	0.32 [-0.43,0.77]
EWG	0.55 [0.37,0.79]	0.70 [0.41,0.93]	0.82 [0.44,1.26]
EWJ	0.54 [0.34,0.81]	0.17 [-0.02,0.37]	0.38 [-0.05,0.82]
EWQ	0.64 [0.33,1.01]	0.61 [0.43,0.82]	0.81 [0.48,1.19]
EWU	0.46 [0.26,0.68]	0.66 [0.49,0.85]	0.56 [-0.04,1.15]
EWZ	0.77 [0.51,1.00]	0.13 [-0.04,0.32]	-0.14 [-0.62,0.39]

EZA	0.56 [0.30,1.03]	0.58 [0.38,0.80]	0.16 [-0.86,0.78]
GXC	0.29 [-0.07,0.64]	0.25 [0.07,0.51]	0.45 [0.01,0.95]
PIN	0.46 [0.26,0.72]	0.51 [0.32,0.71]	0.49 [0.16,0.84]

Table 4.9: Tests of a constant volatility jump beta over years.

Panels A and B report the p-values for the test of a constant volatility jump beta using respectively EEM and SPY as market proxies. The test is performed for every fund and every year in the sample. We use the VXEEM and VIX volatility indices to approximate the jump arrival times of respectively EEM and SPY volatilities. See Appendix 4.A for the jump identification procedure. We follow the methodology provided by Davies (2016) to perform the test of volatility jump beta constancy. ***, **, * imply the rejection of the null hypothesis of constant volatility jump beta respectively at 1%, 5%, and 10% significance levels.

Panel A: EEM volatility jumps used as a market risk factor

	2011	2012	2013	2014	2015
EWG	0.999	0.637	0.671	0.004***	<0.001***
EWJ	0.891	0.344	0.603	0.796	0.015**
EWQ	0.975	0.767	0.356	0.121	0.064*
EWU	0.999	0.902	0.24	0.064*	0.464
EWZ	0.999	0.984	0.84	0.983	0.101
EZA	0.609	0.056*	<0.001***	0.099*	0.91
GXC	0.088	<0.001***	<0.001***	0.059*	0.035**
PIN	0.60	0.044**	<0.001***	0.004***	0.987
SPY	0.999	0.999	0.425	0.23	0.661

Panel B: SPY volatility jumps used as a market risk factor

	2008	2009	2010	2011	2012	2013	2014	2015
EEM	0.999	0.999	0.999	0.999	0.999	0.998	0.784	0.51
EWG	0.999	0.977	0.961	0.999	0.99	0.656	0.561	0.867
EWJ	0.932	0.991	0.737	0.999	0.807	0.92	0.093*	0.291
EWQ	0.344	0.999	0.958	0.995	0.984	0.008***	0.712	0.976
EWU	0.803	0.998	0.999	0.999	0.553	0.625	0.988	0.535
EWZ	0.969	0.99	0.747	0.984	0.33	0.38	0.167	0.021**
EZA	0.271	0.026**	0.65	0.958	0.02	<0.001***	0.158	0.021**
GXC	0.084	0.188	0.022**	<0.001***	<0.001***	0.007***	<0.001***	0.637
PIN	0.28	<0.001***	<0.001***	0.311	0.034**	0.027**	0.053*	0.834

4.4.4 Upside and downside jump betas

Several studies have documented that the correlation between international stock markets exhibits asymmetric effects between positive and negative returns. In particular, the correlation is higher for large down moves (see, among others, Longin and Solnik (2001), Ang and Bekaert (2002), Ang and Chen (2002), Hartmann et al. (2004)). We also show in Section 4.4.1 that cojumps between asset returns and market volatilities are more frequent when returns jump downward and volatilities jump upward. This result suggests that volatility jumps are also asymmetric. This subsection examines whether the response of international stock markets to upside and downside market jumps is asymmetric both at price and volatility levels.

Table 4.10 reports the main proprieties of the estimated upside and downside price jump betas. The betas are calculated for each country over the full sample using respectively SPY and EEM funds as market proxies. Looking at the betas of developed and emerging countries with the emerging market fund (EEM), we find that the downside price jump beta is significantly higher than the upside one at 95% confidence level for Germany, France, China and USA. On the opposite, the upside price jump beta is significantly greater than the downside beta only for South Africa. Also, the null hypothesis of constant downside price jump beta is rejected for seven countries at 95% significance level compared to only three countries for the upside price jump beta, suggesting that the upside price jump betas are less varying than downside ones over the sample period. As for the betas of the US market with country funds considered in our study, we find that the difference between the downside and upside price jump betas is significantly positive for Germany and France and significantly negative for South Africa.

Table 4.10: Positive and negative price jump betas estimation and tests for constancy over the full sample.

Panels A, B (respectively C and D) report the results of price jump beta estimation between country funds and respectively positive and negative EEM price jumps (respectively positive and negative SPY price jumps). The columns show the weighted price jump beta estimate, the 95% confidence interval (CI) and the p-value for the test of a constant price jump beta over the period 2008-2015. See Appendix 4.A for the jump identification procedure. See Section 4.2.1 for price jump beta estimation. The confidence interval is calculated using the Monte Carlo procedure proposed by Li et al. (2017). We also follow Li et al (2017) to perform the test of constancy. ***, **, * imply the rejection of the null hypothesis of constant jump beta respectively at 1%, 5%, and 10% significance levels.

Panel A: Positive EEM price jumps used as a market risk factor

	$\hat{\beta}_{i,up}^*$	CI	p-value
EWG - Germany	0.70	[0.67,0.74]	0.447
EWJ - Japan	0.52	[0.49,0.55]	0.105
EWQ - France	0.68	[0.65,0.70]	<0.001***
EWU - UK	0.68	[0.65,0.71]	0.991
EWZ - Brazil	1.09	[1.03,1.16]	0.999
EZA- South Africa	1.40	[1.35,1.45]	<0.001**
GXC - China	0.67	[0.64,0.71]	0.201
PIN - India	1.09	[1.05,1.14]	<0.001***
SPY - USA	0.61	[0.58,0.65]	0.953

Panel B: Negative EEM price jumps are used as a market risk factor

	$\hat{\beta}_{i,down}^*$	CI	p-value
EWG - Germany	0.84	[0.80,0.87]	0.005***
EWJ - Japan	0.52	[0.49,0.54]	0.008***
EWQ - France	0.81	[0.78,0.84]	<0.001***
EWU - UK	0.71	[0.68,0.74]	<0.001***
EWZ - Brazil	1.19	[1.12,1.26]	0.999
EZA- South Africa	1.28	[1.22,1.34]	<0.001***
GXC - China	0.82	[0.79,0.86]	<0.001***
PIN - India	1.11	[1.06,1.15]	<0.001***
SPY - USA	0.70	[0.67,0.74]	0.999

Panel C: Positive SPY price jumps are used as a market risk factor

	$\hat{\beta}_{i,up}^*$	CI	p-value
EEM	1.11	[1.04,1.19]	0.999
EWG - Germany	0.98	[0.93,1.03]	0.152
EWJ - Japan	0.72	[0.68,0.75]	0.602

EWQ - France	0.95	[0.91,0.99]	0.032**
EWU - UK	0.91	[0.86,0.97]	0.999
EWZ - Brazil	1.21	[1.12,1.30]	0.999
EZA- South Africa	1.50	[1.43,1.57]	<0.001***
GXC - China	0.95	[0.90,1.00]	0.362
PIN - India	1.18	[1.13,1.23]	<0.001***

Panel D: Negative SPY price jumps are used as a market risk factor

	$\hat{\beta}_{i,down}^*$	CI	p-value EEM
EEM	1.04	[0.98,1.10]	0.999
EWG - Germany	1.10	[1.05,1.14]	0.578
EWJ - Japan	0.69	[0.66,0.73]	0.122
EWQ - France	1.08	[1.03,1.13]	0.23
EWU - UK	0.93	[0.88,0.97]	<0.001***
EWZ - Brazil	1.23	[1.15,1.30]	0.708
EZA- South Africa	1.27	[1.20,1.34]	<.001***
GXC - China	0.91	[0.87,0.96]	0.422
PIN - India	1.09	[1.04,1.14]	<0.001***

Table 4.11 provides the results of the estimated upside and downside volatility jump betas between country funds and respectively EEM and SPY volatility jumps. By comparing the 95% confidence interval of upside and downside beta estimates, we find that the difference between two betas is not significant for almost all funds. The decomposition of the volatility jump beta into upside and downside components reduces the total number of market volatility jumps considered in the estimation of each beta, yielding to wider confidence levels for the quasi-maximum likelihood estimates, especially for the downside volatility jump beta where negative market volatility jumps are less frequent.

Overall, our findings suggest that international stock markets' response to market price jumps exhibit asymmetric effects between upside and downside components. The results of the volatility jump beta decomposition into positive and negative components, however, are not conclusive.

Table 4.11: Positive and negative volatility jump beta estimation and tests for constancy over the full sample.

Panels A and B (respectively C and D) report the results of volatility jump beta estimation between country funds and respectively positive and negative EEM volatility jumps (respectively positive and negative SPY volatility jumps). The columns show the quasi-maximum likelihood volatility jump beta estimate, the 95% confidence interval (CI) and the p-value for the test of a constant volatility jump beta over the period 2008-2015. See Appendix 4.A for the jump identification procedure. See Section 4.2.2 for volatility jump beta estimation. We use the VXEEM and VIX volatility indices to approximate the jump arrival times of respectively EEM and SPY volatilities. The confidence intervals are calculated using the bootstrap procedure provided by Davies (2016). We also follow the methodology provided by Davies (2016) to perform the test of volatility jump beta constancy. ***, **, * imply the rejection of the null hypothesis of constant volatility jump beta respectively at 1%, 5%, and 10% significance levels.

Panel A: Positive EEM volatility jumps used as a market risk factor

	$\hat{\beta}_{upvol,i}$	CI	p-value
EWG - Germany	0.63	[0.52,0.80]	0.109
EWJ - Japan	0.43	[0.32,0.59]	0.418
EWQ - France	0.61	[0.49,0.77]	0.826
EWU - UK	0.54	[0.41,0.71]	0.819
EWZ - Brazil	0.70	[0.56,0.92]	0.986
EZA- South Africa	0.95	[0.71,1.25]	0.166
GXC - China	0.23	[0.06,0.40]	<0.001***
PIN - India	0.70	[0.58,0.97]	0.001***
SPY - USA	0.77	[0.65,0.91]	0.999

Panel B: Negative EEM volatility jumps used as a market risk factor

	$\hat{\beta}_{downvol,i}$	CI	p-value
EWG - Germany	0.48	[0.33,0.72]	0.041**
EWJ - Japan	0.45	[0.30,0.63]	0.634
EWQ - France	0.41	[0.22,0.63]	0.122
EWU - UK	0.60	[0.44,0.91]	0.185
EWZ - Brazil	0.74	[0.58,0.96]	0.925
EZA- South Africa	0.35	[-0.22,0.69]	<0.001***
GXC - China	0.81	[0.59,1.17]	0.007***
PIN - India	0.87	[0.63,1.18]	0.014**
SPY - USA	0.88	[0.70,1.16]	0.716

Panel C: Positive SPY volatility jumps used as a market risk factor

	$\hat{\beta}_{upvol,i}$	CI	p-value
EEM	0.72	[0.68,0.82]	0.999

EWG - Germany	0.61	[0.55,0.71]	0.999
EWJ - Japan	0.46	[0.41,0.59]	0.748
EWQ - France	0.63	[0.57,0.76]	0.992
EWU - UK	0.60	[0.54,0.71]	0.999
EWZ - Brazil	0.46	[0.38,0.59]	0.001***
EZA- South Africa	0.58	[0.52,0.72]	<0.001***
GXC - China	0.36	[0.27,0.52]	<0.001***
PIN - India	0.71	[0.64,0.92]	<0.001***

Panel D: Negative SPY volatility jumps used as a market risk factor

	$\hat{\beta}_{downvol,i}$	CI	p-value EEM
EEM	0.96	[0.75,1.24]	0.999
EWG - Germany	0.55	[0.41,0.75]	0.999
EWJ - Japan	0.47	[0.30,0.67]	0.999
EWQ - France	0.56	[0.35,0.89]	0.891
EWU - UK	0.64	[0.49,0.85]	0.999
EWZ - Brazil	0.81	[0.56,1.10]	0.999
EZA- South Africa	0.51	[0.29,0.86]	0.371
GXC - China	0.81	[0.47,1.56]	0.008***
PIN - India	0.75	[0.43,1.29]	<0.001***

4.4.5 Predictive jump regressions

The finance theory establishes that investors should be compensated for bearing non-diversifiable risks. Aggregate market price and volatility jumps are a potential source of systematic risk. Therefore, understanding how international stock markets are linked to aggregate market jumps both at price and volatility levels plays a key role on explaining the variation of expected returns in an international setting. This subsection examines the ability of market price and volatility jumps to predict future asset returns by performing the following predictive jump regressions:

$$r_{i,t_k,t_k+h} - r_{f,t_k,t_k+h} = \gamma_{i,0} + \gamma_{i,up} r_{0,k} \mathbb{1}_{\{r_{0,k} > 0\}} + \gamma_{i,down} r_{0,k} \mathbb{1}_{\{r_{0,k} < 0\}} + \epsilon_{i,t_k}, \quad k \in \Omega' \quad (\text{I})$$

$$r_{i,t_k,t_k+h} - r_{f,t_k,t_k+h} = \gamma_{i,0}^{vol} + \gamma_{i,up}^{vol} \hat{\vartheta}_{0,k} \mathbb{1}_{\{\hat{\vartheta}_{0,k} > 0\}} + \gamma_{i,down}^{vol} \hat{\vartheta}_{0,k} \mathbb{1}_{\{\hat{\vartheta}_{0,k} < 0\}} + \epsilon_{i,t_k}, \quad k \in \Omega'_{vol} \quad (\text{II})$$

where t_k is the day on which the k^{th} price (regression I) or volatility (regression II) market jump occurs. r_{i,t_k,t_k+h} and r_{f,t_k,t_k+h} are respectively the returns of asset i and the risk free asset between days t_k and $t_k + h$. $r_{0,k}$ is the k^{th} market jump return. $\hat{v}_{0,k}$ is the estimated k^{th} market volatility jump.

We use the SPY fund as a market proxy for all predictive regressions.⁸ The three-month T-bill rate is used as a proxy for the risk-free rate. The sample covers the period going from January 2008 to May 2015. Figure 4.1 plots the results of the regression of the SPY future excess returns on previous upside and downside market price jumps. The adjusted R-squared gives the percentage of the future excess return variation explained by upside and downside market price jumps. We notice that the degree of predictability that market price jumps have on future market excess returns is high particularly for the 8th and 37th day horizons where the adjusted R-squared reaches 39%. Panel B of Figure 4.1 shows the t-statistics of the upside and downside market price jump estimates for different return horizons. The t-statistics are calculated using the White heteroskedastic-robust procedure (1980). We notice that both upside and downside estimates are significantly different from zero for almost all return horizons between the 8th and 140th days.

Figure 4.2 shows the results of the regression of individual country fund excess returns on upside and downside market price jumps averaged across all, developed and emerging markets. Examining the Panel A, we find that the degree of predictability that market price jumps have on developed market returns is slightly higher than emerging market returns. Similarly to SPY fund, the average adjusted R-squared peaks at the 8th (with respectively 38% and 37%) and 37th (with respectively 37% and 30%) day return horizons for respectively the developed and emerging markets.

Looking at the results of the regression of SPY future excess returns on the upside and downside market volatility jumps in Figure 4.3, we notice that the degree of predictability that the upside and downside market volatility jumps have on future excess returns is significant

⁸We only present the results for SPY fund because it has a greater predictive power than EEM fund. Results for EEM fund can be made available upon request.

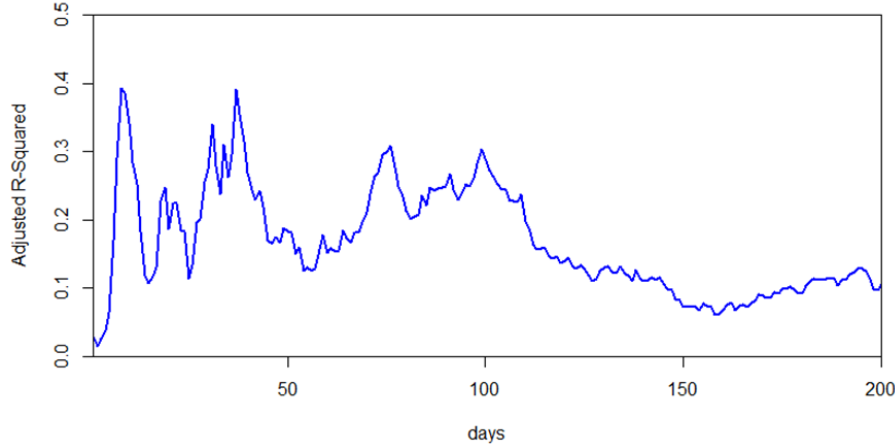
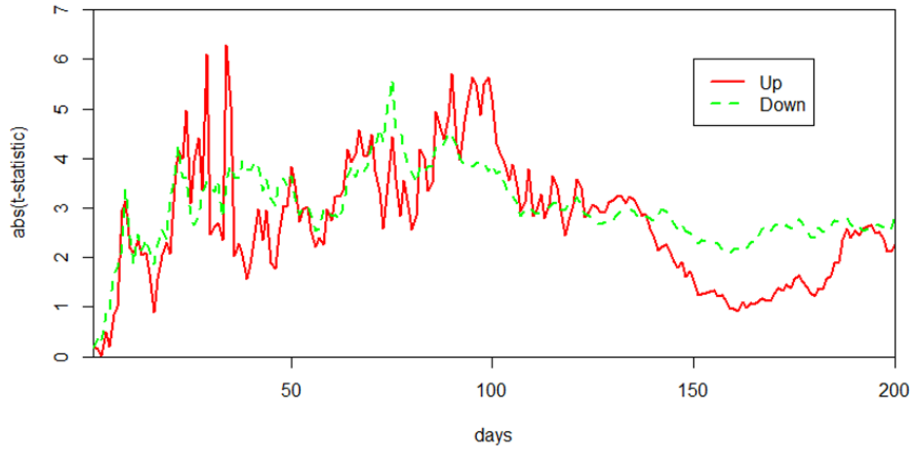
Panel A: Adjusted R-squared**Panel B: Test-statistics of upside and downside market price jump estimates**

Figure 4.1: Positive and negative SPY price jumps and SPY future excess returns.

The figure shows the results of the regression of SPY future excess returns on the upside and downside market price jumps with return horizon varying from one day to one year. SPY fund is used as a market proxy. The three-month T-bill rate is used as a proxy for the risk-free rate. The sample covers the full period (2008-2015). Panel A plots the variation of the adjusted R-squared. Panel B plots the variation of the absolute value of the t-statistics of the upside and downside estimates for different return horizons. The t-statistics are calculated using the White heteroskedastic-robust procedure (1980).

$$r_{0,t_k,t_k+h} - r_{f,t_k,t_k+h} = \gamma_{0,0} + \gamma_{0,up} r_{0,k} \mathbb{1}_{\{r_{0,k} > 0\}} + \gamma_{0,down} r_{0,k} \mathbb{1}_{\{r_{0,k} < 0\}} + \epsilon_{0,t_k}, \quad k \in \Omega'$$

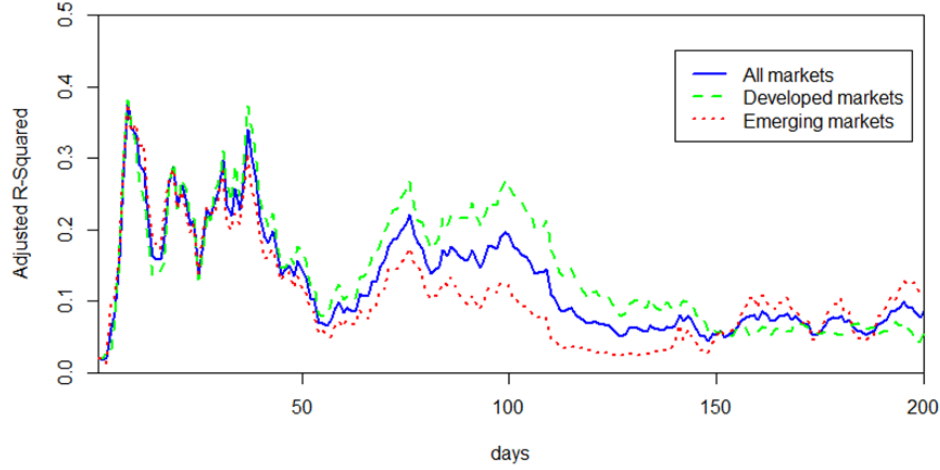
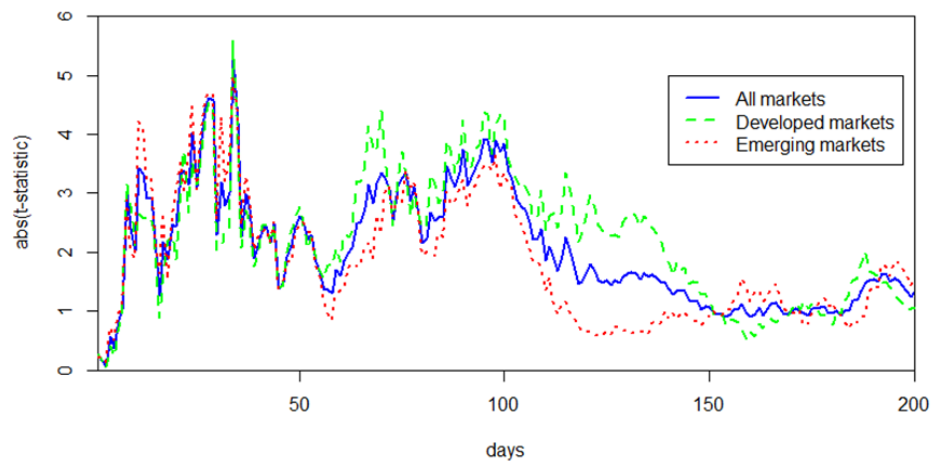
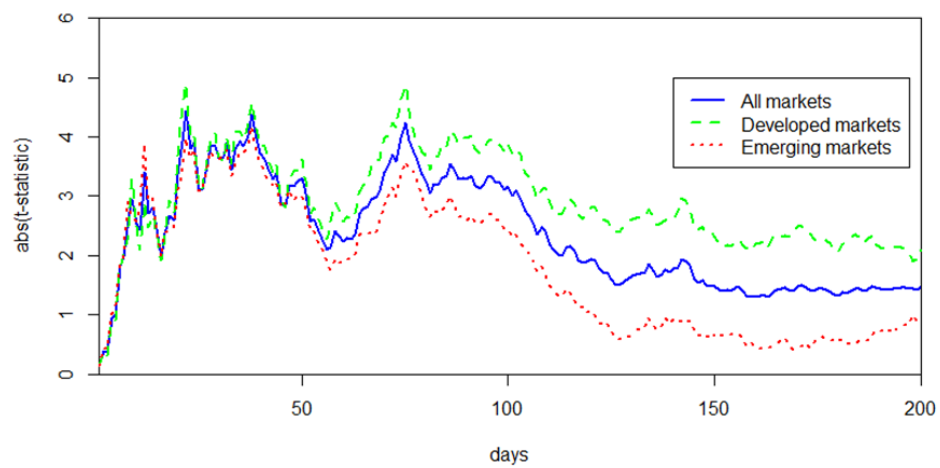
Panel A: Adjusted R-squared

Figure 4.2: Positive and negative SPY price jumps and future individual country fund excess returns. The figure shows the results of the regression of future individual country fund excess returns on the upside and downside market price jumps with return horizon varying from one day to one year. SPY fund is used as a market proxy. The three-month T-bill rate is used as a proxy for the risk-free rate. The sample covers the full period (2008-2015). Panel A plots the variation of the adjusted R-squared averaged respectively across all, developed and emerging funds considered in the study. Panels B and C plot the variation of the absolute value of the t-statistics of the upside and downside estimates averaged respectively across all, developed and emerging funds considered in the study. The t-statistics are calculated using the White heteroskedastic-robust procedure (1980).

$$r_{i,t_k,t_k+h} - r_{f,t_k,t_k+h} = \gamma_{i,0} + \gamma_{i,up} r_{0,k} \mathbb{1}_{\{r_{0,k} > 0\}} + \gamma_{i,down} r_{0,k} \mathbb{1}_{\{r_{0,k} < 0\}} + \epsilon_{i,t_k}, \quad k \in \Omega'$$

between the 6th and 70th day horizons. It peaks at the 28th day horizon with an adjusted R-squared around 6%. Panel B of Figure 4.3 shows that the upside volatility jump estimates are significant for almost all horizons between the 6th and 70th days whereas the downside volatility jump estimates are only significant for a few horizons around the 28th day. Looking at the aggregated results for all, developed and emerging markets in Figure 4.4, we find that the regression estimates are only significant for developed markets, where the adjusted R-squared varies between 2% and 4.5%. This finding shows that the predictive power of market volatility jumps is weak compared to market price jumps.

Overall, the results of the predictive regressions indicate that both price and volatility market jumps have a significant degree of predictability on future excess returns especially at one to four month horizon. However, the proportion of future return variation explained by market price jumps is much greater than that explained by market volatility jumps.

Panel B: Test-statistics of the upside market price jump estimates**Panel C: Test-statistics of the downside market price jump estimates**

(Figure 4.2)

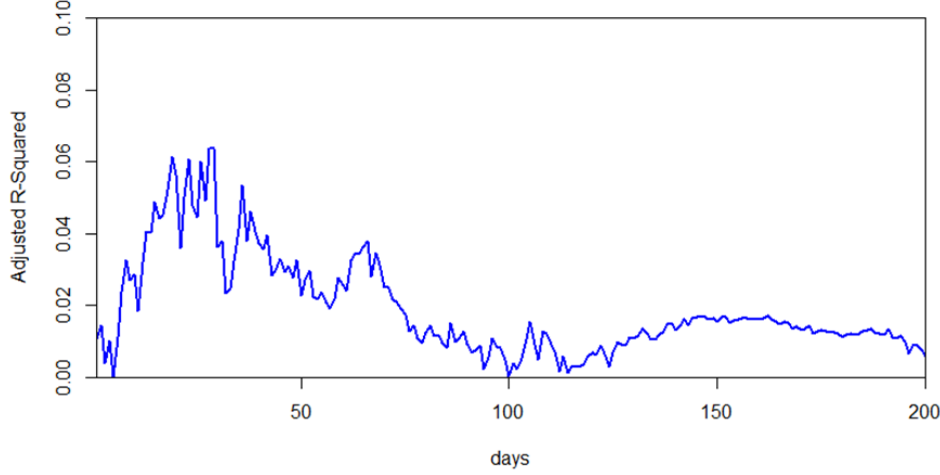
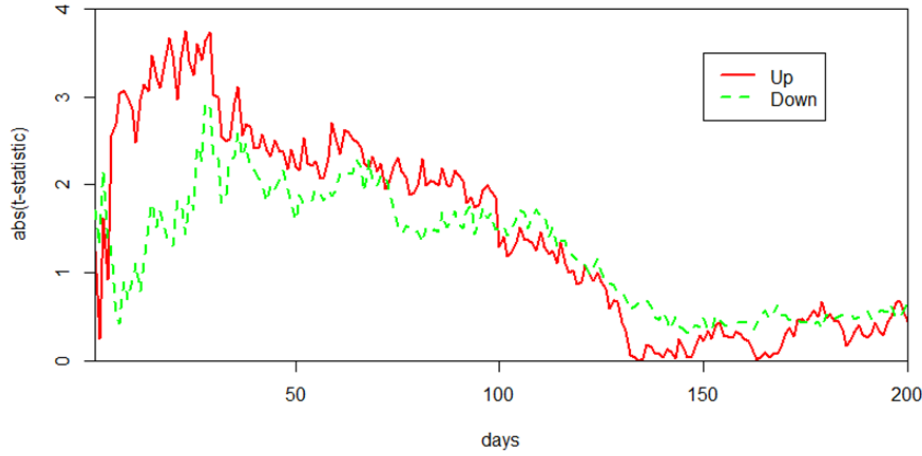
Panel A: Adjusted R-squared**Panel B: Test-statistics of the upside and downside market volatility jump estimates**

Figure 4.3: Positive and negative SPY volatility jumps and SPY future excess returns.

The figure shows the results of the regression of SPY future excess returns on the upside and downside market volatility jumps with return horizon varying from one day to one year. SPY fund is used as a market proxy. The three-month T-bill rate is used as a proxy for the risk-free rate. The sample covers the full period (2008-2015). Panel A plots the variation of the adjusted R-squared. Panel B plots the variation of the absolute value of the t-statistics of the upside and downside estimates for different return horizons. The t-statistics are calculated using the White heteroskedastic-robust procedure (1980).

$$r_{0,t_k,t_k+h} - r_{f,t_k,t_k+h} = \gamma_{0,0}^{vol} + \gamma_{0,up}^{vol} \hat{\vartheta}_{0,k} \mathbb{1}_{\{\hat{\vartheta}_{0,k} > 0\}} + \gamma_{0,down}^{vol} \hat{\vartheta}_{0,k} \mathbb{1}_{\{\hat{\vartheta}_{0,k} < 0\}} + \epsilon_{0,t_k}, \quad k \in \Omega'_{vol}$$

Panel A: Adjusted R-squared

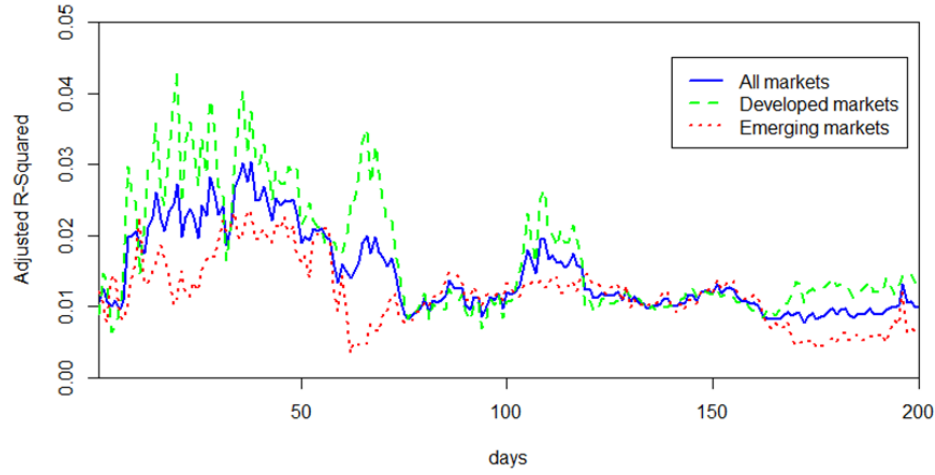
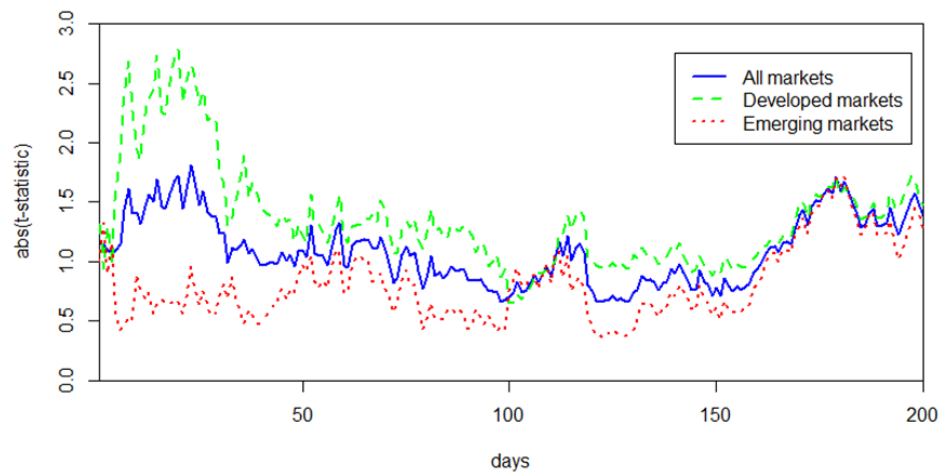
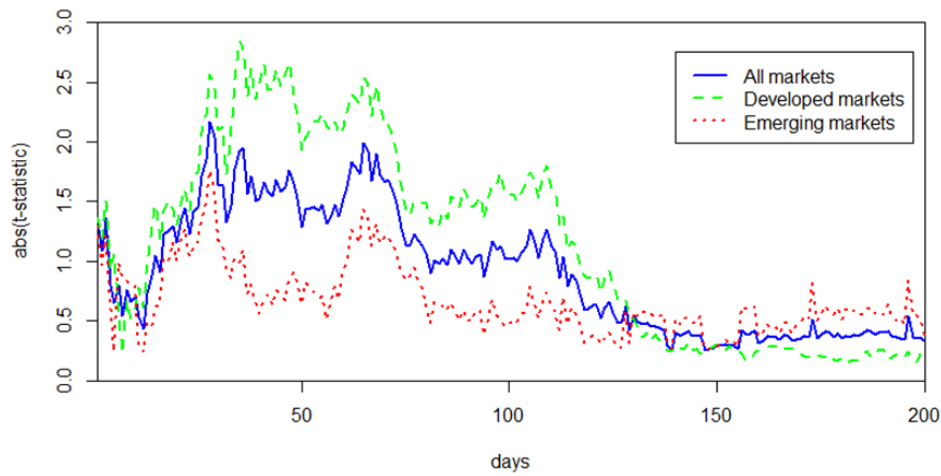


Figure 4.4: Positive and negative SPY volatility jumps and future individual country fund excess returns.

The figure shows the results of the regression of future individual country fund excess returns on the upside and downside market volatility jumps with return horizon varying from one day to one year. SPY fund is used as a market proxy. The three-month T-bill rate is used as a proxy for the risk-free rate. The sample covers the full period (2008-2015). Panel A plots the variation of the adjusted R-squared averaged respectively across all, developed and emerging funds considered in the study. Panels B and C plot the variation of the absolute value of the t-statistics of the upside and downside estimates averaged respectively across all, developed and emerging funds considered in the study. The t-statistics are calculated using the White heteroskedastic-robust procedure (1980).

$$r_{i,t_k,t_k+h} - r_{f,t_k,t_k+h} = \gamma_{i,0}^{vol} + \gamma_{i,up}^{vol} \hat{\vartheta}_{0,k} \mathbb{1}_{\{\hat{\vartheta}_{0,k} > 0\}} + \gamma_{i,down}^{vol} \hat{\vartheta}_{0,k} \mathbb{1}_{\{\hat{\vartheta}_{0,k} < 0\}} + \epsilon_{i,t_k}, \quad k \in \Omega'_{vol}$$

Panel B: Test-statistics of the upside market volatility jump estimates**Panel C: Test-statistics of the downside market volatility jump estimates**

(Figure 4.4)

4.5 Conclusion

In this paper, we examine the relationship between international stock markets and jumps of an aggregate risk factor both at price and volatility levels. By considering a sample covering major developed and emerging stock markets, we measure the sensitivity of each individual stock market to price and volatility jumps of an aggregate market proxy, and document that these betas are time-varying over the sample period and exhibit asymmetric effects across upside and downside market movements. By applying the techniques proposed by Andersen et al. (2007) and Lee and Mykland (2008), we identify all intraday jumps and cojumps of all stock markets and volatility indices (VIX and VXEEM) in the sample and we find that cojumps between individual country funds and two volatility indices have opposite signs, with a higher proportion of positive volatility and negative return cojumps, suggesting a strong anti-correlation between market volatility jumps and asset returns when the market is downward and its volatility is high.

Finally, we consider predictive regressions of future international stock market returns on upside and downside price and volatility market jumps and document that both price and volatility market jumps have a significant predictive power on future stock market returns, with a greater predictability degree found for market price jumps.

The findings of this study show that market price and volatility jump risks are likely to be derived by common underlying risk factors. Given the dependency between two risks, providing suitable hedging strategies for price and volatility jumps is a challenging issue for both practitioners and researchers. Studying the role of systematic price and volatility jumps in forecasting the market volatility is also an interesting topic for future research.

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Appendix 4.A Jump and cojump identification methodology

LM-ABD jump identification test

The LM test statistic $L_{t,k}$ compares the current asset return with the bipower variation calculated over a moving window with a given number of preceding observations. It tests at time k on day t whether there was a jump from $k - 1$ to k and is defined as follows:

$$L_{t,k} = \frac{|r_{t,k}|}{\hat{\sigma}_{t,k}}$$

where

$$\hat{\sigma}_{t,k}^2 = \frac{1}{K-2} \sum_{j=k-K+2}^{k-1} |r_{t,j-1}| |r_{t,j}|$$

$r_{t,k}$ is the intraday return in the interval $[k-1, k]$ of day t . $\hat{\sigma}_{t,k}$ refers to the realized bipower variation calculated for a window of K observations and provides a jump robust estimator of the instantaneous volatility. Lee and Mykland (2008) emphasize that the window size K should be chosen in a way that the effect of jumps on the volatility estimation disappears. They thus suggest to choose the window size K between $\sqrt{252 \times M}$ and $252 \times M$, where M is the number of observations in a day. Under the null hypothesis of absence of jumps at anytime in the interval $[k-1, k]$, the LM statistic is asymptotically distributed as follows:

$$\frac{L_{t,k} - C_M}{S_M} \xrightarrow{M \rightarrow \infty} \xi$$

where ξ has a cumulative distribution function, $P(\xi \leq x) = \exp(e^{-x})$. C_M and S_M are given by:

$$C_M = \frac{\sqrt{2 \log(M)}}{c} - \frac{\sqrt{\log(\pi) + \log(\log(M))}}{2c\sqrt{2 \log(M)}}$$

$$S_M = \frac{1}{c\sqrt{2 \log(M)}} \quad \text{and} \quad c = \sqrt{\frac{2}{\pi}}$$

A jump is detected with LM test on day t in intraday interval k if the following condition

is satisfied:

$$|L_{t,k}| > -\log(-\log(1 - \alpha)) \times S_M + C_M$$

where α is the test significance level.

On the other hand, the ABD test statistic is assumed to be normally distributed in the absence of jumps. A jump is detected with the ABD test on day t in intraday interval k if the following condition is satisfied:

$$\frac{|r_{t,k}|}{\sqrt{\frac{1}{M}BV_t}} > \Phi_{1-\frac{\beta}{2}}^{-1}$$

where BV_t is the bipower variation (Barndorff-Nielsen and Shephard 2004) defined as follows:

$$BV_t = \frac{\pi}{2} \frac{M}{M-1} \sum_{k=2}^M |r_{t,k-1}| |r_{t,k-1}|$$

$\Phi_{1-\frac{\beta}{2}}^{-1}$ represents the inverse of the standard normal cumulative distribution function evaluated at a cumulative probability of $1 - \frac{\beta}{2}$ and $(1 - \beta)^M = 1 - \alpha$, where α represents the daily significance level of the test.

In our study, we identify intraday jumps by relying on the intraday procedure of LM-ABD. A jump is detected with the LM-ABD test on day t in intraday interval k when:

$$\frac{|r_{t,k}|}{\hat{\sigma}_{t,k}} > \theta$$

The threshold value θ is calculated for different significance levels. For a daily significance level of 5% and a sampling frequency of 20 minutes (which corresponds to 19 intraday returns per day in our study), we obtain a threshold value of 4.00 and 4.85 using ABD and LM methods, respectively.

Cojump identification test

Once all intraday jumps are identified using the univariate jump detection test of LM-ABD, we apply the following co-exceedance rule to verify if a cojump occurs between assets i and j at intraday time k on day t (Bae et al., 2003):

$$1\left\{\frac{|r_{i,t,k}|}{\hat{\sigma}_{i,t,k}} > \theta\right\} \times 1\left\{\frac{|r_{j,t,k}|}{\hat{\sigma}_{j,t,k}} > \theta\right\} = \begin{cases} 1 : & \text{a cojump between assets } i \text{ and } j \\ 0 : & \text{no cojump} \end{cases}$$

Thus, a cojump exists when asset returns jump simultaneously. We distinguish between an idiosyncratic jump defined as jump of a single asset or jump that occurs independently of the market movement and cojump defined as jumps of two or more assets that occur simultaneously.

Intraday volatility pattern

It is widely documented (Wood et al. (1985) and Harris (1986)) that intraday returns show a systematic seasonality over the trading day, also called the U-shaped pattern. The intraday volatility is particularly higher at the open and the close of the trading than the rest of the day. To minimize the effects of intraday volatility on our jump detection test, we modify our procedure by rescaling intraday returns with a volatility jump robust corrector introduced by Bollerslev et al. (2008). The k^{th} rescaled intraday return of day t is defined by:

$$\hat{r}_{t,k} = \frac{r_{t,k}}{s_k}$$

where:

$$\begin{aligned}\varsigma_1^2 &= \frac{M \sum_{t=1}^T |r_{t,1}| |r_{t,2}|}{\sum_{t=1}^T |r_{t,1}| |r_{t,2}| + \sum_{t=1}^T \sum_{l=2}^{M-1} |r_{t,l-1}|^{\frac{1}{2}} |r_{t,l}| |r_{t,l+1}|^{\frac{1}{2}} + \sum_{t=1}^T |r_{t,M-1}| |r_{t,M}|} \\ \varsigma_k^2 &= \frac{M \sum_{t=1}^T |r_{t,k-1}|^{\frac{1}{2}} |r_{t,k}| |r_{t,k+1}|^{\frac{1}{2}}}{\sum_{t=1}^T |r_{t,1}| |r_{t,2}| + \sum_{t=1}^T \sum_{l=2}^{M-1} |r_{t,l-1}|^{\frac{1}{2}} |r_{t,l}| |r_{t,l+1}|^{\frac{1}{2}} + \sum_{t=1}^T |r_{t,M-1}| |r_{t,M}|}, \quad k = 2, \dots, M-1 \\ \varsigma_M^2 &= \frac{M \sum_{t=1}^T |r_{t,M-1}| |r_{t,M}|}{\sum_{t=1}^T |r_{t,1}| |r_{t,2}| + \sum_{t=1}^T \sum_{l=2}^{M-1} |r_{t,l-1}|^{\frac{1}{2}} |r_{t,l}| |r_{t,l+1}|^{\frac{1}{2}} + \sum_{t=1}^T |r_{t,M-1}| |r_{t,M}|}\end{aligned}$$

T is the total number of days considered in the study and M is the number of observations in a day.

Chapter 5

General Conclusion

Over the past four decades, the topic of international stock market interdependencies has been extensively studied in the finance literature. The issue has received increasing attention due to the recurrence of financial crises that occurred in both developed and emerging countries during the last decades. Indeed, understanding the nature of cross-market correlations in period of financial and economic turmoil is of great interest for both investors and policy makers who want to guard against the contagion risk. Moreover, the increased market integration that has experienced developed and emerging markets has led the researchers to question whether the benefits of international diversification are disappearing over time.

More recently, more attention has been given to the extreme comovement of international stock markets in the finance literature. The study of the tail dependence structure of international equity market returns was made possible thanks to the availability of high frequency data. It was also boosted by the development of numerous econometrical tools that help researchers to examine the dependence between extreme market variations. This thesis contributes to the existing literature by studying cojumps in international equity markets and assessing their impact on portfolio allocation decisions and asset pricing.

In the second chapter, we empirically investigate the dynamics of cojumps between international equity markets and show their impact on international asset allocation and portfolio diversification benefits. Our empirical work relies on the use of intraday returns for three international exchange-traded funds, SPY, EFA, and EEM, which are used to capture the performance of respectively the US, developed countries (excluding the US and Canada) and emerging equity markets. The data covers the period going from January 2008 to October 2013. We apply the jump identification test of Lee and Mykland (2008) to identify all intraday jumps and cojumps of the three funds over the sample period. We find that the number

of detected intraday jumps is higher in developed markets (US and EFA) than in emerging markets, suggesting a higher degree of asset comovement within developed markets. We also show that cojumps between the US market and other developed markets are higher than cojumps between the US and emerging markets.

We examine the time and space clustering features of jumps across international markets using a bivariate Hawkes model (1971) and provide evidence of an asymmetric jump transmission between markets with a stronger transmission from the US market to other developed and emerging markets. The transmission of jumps in the other way around is also significant but the strength is weaker.

To assess the impact of cojumps on portfolio allocation decisions, we consider a domestic US investor who selects his portfolio composition based on two assets, a domestic risky asset (SPY) and two foreign risky assets (EFA and EEM), in a way to minimize the portfolio's risk. We use the mean-variance and mean-CVaR approaches to determine the optimal portfolio composition and analyze how the demand of foreign assets varies with cojump intensity. We provide strong evidence of a significant negative relationship between the optimal proportion of foreign assets and cojumps between domestic and foreign assets. This result implies that domestic US investors allocate more money towards home assets in the presence of cojumps between US and foreign markets. We also investigate the role of higher-order moments induced by intraday jumps on international diversification. For this purpose, we consider an investor who recognizes idiosyncratic and systematic jumps and assumes a multivariate jump-diffusion process for asset returns and another investor who ignores jumps and assumes a pure multivariate diffusion process for asset returns. Both investors have the same power utility function. Our results show that optimal portfolio weights are almost the same for the pure-diffusion and jump-diffusion investors. The impact of jump higher-order moments on the optimal portfolio composition is thus insignificant.

In the third chapter, we examine the pricing of systematic continuous and jump risks in the cross-section of international stock returns by considering a general pricing framework

involving six separate market risk factors. We first decompose the systematic market risk into intraday and overnight components. The intraday market risk includes both continuous and jump parts. We then consider the asymmetry and size effects of market jumps by separating the systematic jump risk into positive vs. negative and small vs. large components. Our empirical investigation relies on the use of the intraday data of a set of 37 country exchange-traded funds covering developed, emerging and frontier markets from July 2003 to December 2014. By considering the cojumps of individual country markets with an aggregate market index, we find that jumps in developed countries are more linked to the aggregate market index than emerging and frontier markets. We also show that jumps in Asian stock markets are more linked to the aggregate index than other emerging markets in the sample, suggesting that investors investing in non-Asian emerging markets may better minimize their exposure to systematic jump risk.

We apply Todorov and Bollerslev's (2010) methodology to estimate the exposure of each country fund returns towards the systematic market diffusive and jump risks and show that individual country funds are more sensitive to discontinuous market movements than to smooth ones. The small jump beta is, on average, greater than large jump beta indicating that country funds are more sensitive to small frequent market jumps than large infrequent market jumps. We also show that the downside jump beta is, on average, highest among all betas suggesting country funds react to unexpected negative information arrival the most.

The results of portfolio sorting approach and the cross-sectional Fama and MacBeth (1973) regressions show continuous and downside discontinuous risks are positively rewarded in the cross-section of expected stock returns during the pre-crisis period whereas the upside and large jump risks are negatively priced during the crisis and post-crisis periods, suggesting that investors prefer stocks that help them hedge against large movements of the market during the crisis period. By considering the relationship between asset prices and the volatility, we provide evidence of significant continuous and downside jump leverage effects during the pre-crisis period, indicating that both price and volatility risks share compensations for common underlying risk factors during the pre-crisis period.

In the fourth chapter, we tackle the issue of pricing of systematic price and volatility jump risks by examining the response of developed and emerging markets to jumps of an aggregate market index both at price and volatility levels. Our empirical investigation is based on two sets of high frequency data. The first set is composed of ten country exchange-traded funds covering major developed and emerging markets from January 2008 to May 2015. The second set is composed of two volatility indices: The Chicago Board of Options Exchange's (CBOE) Volatility Index (VIX) and CBOE Emerging Markets ETF Volatility Index (VXEEM) serving as proxies for respectively the developed and emerging market volatilities. We apply the method of Lee and Mykland (2008) to identify intraday jumps and cojumps between individual country funds and volatility indices. We show that the discontinuous downside changes in prices are often associated with strongly anti-correlated, contemporaneous, discontinuous upside changes in volatility, suggesting that both the price and volatility jump risks are derived by common underlying risk factors and thus should be handled jointly by investors.

By applying the jump regression procedures proposed by Li et al. (2017) and Davies (2016), we estimate the sensitivity of developed and emerging countries to respectively market price and volatility jumps and document that both price and volatility jump betas are time-varying over the sample period. We also study the exposure of individual country markets to upside and downside price and volatility jumps of the aggregate market index and document that international stock markets' response to market price jumps exhibits asymmetric effects between upside and downside components. In contrast, the results of the volatility jump beta decomposition into upside and downside components are not conclusive. Finally, we examine the role of price and volatility market jumps in forecasting future excess returns of international stock markets and find that both price and volatility market jumps have a significant predictive power on future stock market returns, with a greater degree of predictability obtained with market price jumps.

This dissertation opens interesting avenues for future research. It would be interesting to investigate if the negative relationship between the demand of foreign assets and the intensity of cojumps between domestic and foreign markets could be generalized, in addition to the US

market, to other developed and emerging markets. It would be also of interest to examine the underlying mechanisms of price and volatility cojumps. Future studies could further examine whether exchange-traded funds are a good proxy for their underlying indices. Studying the implications of the pricing frameworks proposed in the second and third essays on the portfolio value-at-risk calculation as well as the simultaneous hedging of price and volatility jump risks are also of great interest for both practitioners and researchers.

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