THIJS MARKWAT

Extreme Dependence in Asset Markets Around the Globe

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Thijs Markwat

Extreme Dependence in Asset Markets Around the Globe

Extreme afhankelijkheid in wereldwijde financiële markten

THESIS

to obtain the degree of Doctor from the
Erasmus University Rotterdam
by command of the
rector magnificus

Prof.dr. H.G. Schmidt

and in accordance with the decision of the Doctorate Board
The public defence shall be held on

Thursday 17 March 2011 at 11.30 hours
by

Thijs Dingeman Markwat
Born in Rotterdam

ERASMUS UNIVERSITEIT ROTTERDAM

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Erasmus Research Institute of Management - ERIM
Rotterdam School of Management (RSM)
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Erasmus University Rotterdam
Internet: `http://www.erim.eur.nl`

ERIM Electronic Series Portal: `http://hdl.handle.net/1765/1`

ERIM Ph.D. Series Research in Management, 227
Reference number ERIM: EPS-2011-227-F&A
ISBN: 978-90-5892-270-0

Design: B&T Ontwerp en advies `www.b-en-t.nl`
Print: Haveka `www.haveka.nl`

This thesis was prepared with $\LaTeX\,2_\varepsilon$.

Voorwoord

Dit proefschrift is het resultaat van vier jaar onderzoek doen naar de afhankelijkheid tussen extreme rendementen in aandelenmarkten. Op 16 november 2006 startte ik als Assistent-in-Opleiding (AiO), niet wetende wat mij exact te wachten stond. En juist dat laatste is waar ik denk dat het om draait als AiO zijnde. Het is een vier jaar durende wetenschappelijke vorming, waar je niet meer voorgekauwd wordt wat je moet leren en doen, maar je juist zelf bepaald wat je wilt leren en doet. Op die manier leer je erg veel. Ik had van te voren niet verwacht dat ik van vier jaar onderzoek doen zoveel zou leren als dat ik gedaan heb.

Het bijzondere van het leertraject tijdens mijn AiO-periode is de diversiteit geweest. In het AiO-programma van ERIM, krijg je in het eerste jaar als AiO verscheidene vakken om je vakkundigheid op je onderzoeksgebied te vergroten. Maar ook vakken als Engels en wetenschapsfilosofie dragen bij aan je ontwikkeling als onderzoeker. Onderwijs verzorgen is een ander aspect van de vorming tijdens je AiO-periode. Het is bijna onbeschrijfbaar hoeveel ik heb geleerd van het verzorgen van practica en sommencolleges Econometrie 2. Ook het begeleiden van werkcolleges en scripties heeft mijn kwaliteiten als onderzoeker vergroot. Presentaties en seminars verzorgen, waarbij je anderen duidelijk moet maken wat je doet en waarom het belangrijk is, is een leerzame opgave. Tot slot, maar veruit het belangrijkste, is het onderzoek doen zelf. Ik denk dat er maar weinig gebieden zijn waarop het gezegde ‘vallen en opstaan’ zo toepasselijk is als op het onderzoek doen tijdens een AiO-periode. Maar echt onderzoek doen leer je alleen zo.

Ik kan zonder reserves zeggen dat ik genoten heb van mijn AiO-tijd. Er zijn maar weinig andere banen, als die er überhaubt al zijn, waar je zoveel vrijheid hebt. Een dagje thuis werken was een van mijn specialiteiten. Verder is het erg bijzonder om vier maanden naar Sydney, Australië te gaan voor onderzoek. Ook de conferenties in het

buitenland droegen in grote mate bij aan het plezier dat ik tijdens mijn AiO-periode heb beleefd. Dublin, Parijs, Florence, Singapore, Washington en Perth vormen een mooi lijstje.

Erg veel dank gaat uit naar mijn promotor Dick van Dijk en copromotor Erik Kole, die tevens mijn co-auteurs zijn bij drie van de vier hoofdstukken in dit proefschrift. Ik heb ontzettend veel van jullie geleerd en ben vaak weer gemotiveerd als ik het tijdens een hoofdstuk even niet meer zag zitten. Hoewel jullie op een verschillende manier de dagelijkse begeleiding vorm gaven, hebben jullie allebei in grote mate bijgedragen aan mijn proefschrift en mijn verworven capaciteiten als onderzoeker. Een van mijn lastigste momenten in mijn AiO-periode was dan ook aan jullie te vertellen dat ik toch in de praktijk ging werken. Al met al hoop ik van harte in de toekomst nog onderzoek met jullie te kunnen blijven doen. Dick, Erik, bedankt!

Verder wil ik nog een aantal mensen bedanken voor de bijdrage aan dit proefschrift. Gerben en Laurens, met jullie heb ik mijn eerste wetenschappelijke publicatie binnengehaald. Verder hebben jullie mij tijdens mijn stage bij Robeco geadviseerd om AiO te worden. Beste Mathijs, behalve dat je in mijn kleine commissie zit, hebben de door jou georganiseerde PhD-lunchseminars mij veel opgebracht. Het heeft zowel mijn artikelen als mijn presentatievaardigheden zonder meer verbeterd. Beste Richard, voor technische vragen kon ik altijd bij je terecht. Ook wil ik mijn kamergenoot Tim bedanken. Je was een prettige kamergenoot. Graag wil ik ook alle overige collega's bedanken, waarvan ik er een aantal bij naam wil noemen. Arco, Anne, Dennis, Eelco, Hans, Kar Yin, Kees, Lennart, Simon, Sjoerd, bedankt. Verder wil ik mijn teamgenoten en de overige mensen binnen de HCB, waarmee ik gedurende de afgelopen vier jaar veel plezier mee heb gehad, bedanken.

Uiteraard bedank ik ook mijn vrienden met wie ik erg veel plezier heb gehad de afgelopen vier jaar. Tijdens mijn AiO-periode heb ik ook wel lastige momenten gekend, en dan is samenzijn met vrienden een goede manier om weer motivatie op te doen. Hierdoor kon ik na een tegenslag iedere keer weer met frisse moed aan de slag. Ewout, Wouter, Martin, Auke, Floris, Karim, Annet, bedankt!

Tenslotte wil ik mijn familie bedanken. Floris en Marieke jullie zijn als broer en zus zeer dierbaar voor mij, ik geniet er dan ook altijd van als we bij elkaar zijn. Pa en ma, jullie hebben toch wel de belangrijkste bijdrage voor dit proefschrift geleverd. Van jullie heb ik de benodigde eigenschappen meegekregen om dit proefschrift te schrijven, maar, vele malen belangrijker, de waarden van het leven.

Thijs Markwat,
Rotterdam, 28 December 2010

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Chapter 1

Introduction

In times of financial crises the dependence between asset prices increases to levels exceeding those observed during tranquil periods. Because of this increased dependence, it is difficult to avoid the large and negative returns that occur during these crisis periods. Put differently, the benefits of diversification to reduce the risk of investing seem to disappear during these crisis periods, when in fact they are needed most. When investors and risk managers would have a better knowledge of the dependence during crises periods, they are able to make better allocation decisions and they can get a clearer view of the risks they are bearing.

In this thesis we perform empirical analyses of extreme dependence between stock markets around the globe. Small and moderate stock returns tend to be less dependent than large returns. Extreme dependence is defined as the dependence between extremely large returns. Investigating stock markets is relevant, because institutional investors such as pension funds often allocate more than 50% of their portfolios to stocks. Furthermore, stock markets show clear signs of extreme dependence, and severe crises periods occur relatively frequently, once every few years. In the last two decades several major financial crises occurred, including the 1994 Peso crisis, the 1997-1998 Asian crisis, the burst of the internet bubble in 2001-2002, and more recently the 2008-2009 credit crisis.

The main element of this thesis is time-variation in extreme dependence. This dependence generally emerges during turmoil periods, which are characterized by crashes in stock markets around the globe. A crash is an extremely large negative return. The implications of a crash for investors are profound. When an investor is exposed to a single asset, a crash of this asset will dramatically reduce the investor's wealth. However, if the investor holds a diversified portfolio of several assets (or asset classes) and extreme dependence between the assets (asset classes) is low, the impact on the investor's wealth of a crash of one of these assets is much lower. On the other hand, if extreme dependence is high, all assets (asset classes) tend to crash simultaneously, and the investor's wealth will decrease by a large amount.

During turmoil periods, crashes in one market contagiously propagate to other markets. Dornbusch et al. (2000) defined contagion as the propagation of a (negative) shock in asset prices from one market to other markets. Because of contagion, markets will show a strong tendency to crash together, indicating the presence of extreme dependence. Contagion appears to be present, for example, in emerging markets. Although crashes initially may occur in a single emerging market, spill-over effects can transmit these crashes to other emerging markets (either in the same region or not). Finally, even developed markets can become infected. This happened, for instance, during the 1997 Asian crisis. Contagion does not necessarily start in emerging markets, but can start in developed markets as well. For instance, during the recent credit crisis, crashes were transmitted from the US market to other markets around the globe.

1.1 Motivation

Our motivation to perform a comprehensive study on extreme dependence in international stock markets is the ongoing process of financial globalization, which in recent decades has strengthened stock market comovement and gives rise to stock market contagion during turmoil periods. Due to the presence of extreme dependence, it has become more and more difficult to build a well-diversified portfolio that is not dramatically hit during times of stock market crashes.

We distinguish between two types of financial globalization. First, inter-market dependence has increased for both developed stock markets (e.g. US, Western Europe, and Japan) and smaller, emerging markets. These emerging stock markets were relatively closed to investors from developed markets. The liberalization of most emerging markets during the 1990s decreased their segmentation (see Bekaert et al., 2003; Bekaert and Harvey, 2003, 1995), creating an opportunity for investors from developed markets to invest in these very markets. However, this market integration has resulted in increased dependence with developed markets and fewer investment diversification opportunities in emerging markets. Opportunities emerge, however, when the extreme dependence between emerging markets and developed markets is lower than that among the developed markets. In chapters 2, 3, and 4 of this thesis we consider both developed and emerging markets, and investigate how the time-variation in extreme dependence behaves between these markets.

Second, the financial sector in general has become more globalized, increasing the complexity of the entire financial system and the degree of vulnerability to economic shocks. Not only have stock markets of different geographical regions become more integrated, such as the liberalization of emerging markets, the stock markets themselves have also become more integrated with other financial markets. Examples of these other markets are bond markets, currency markets, and even mortgage markets, shown by the current credit crisis. Therefore, if extreme returns in another asset market propagate to stock markets, this can constitute a higher level of extreme dependence in stock markets. This dimension of financial integration has increased the interdependence of exposures to the different asset classes of a well-diversified investor or risk manager. To summarize, with the growing integration of the global financial system, stock markets are more vulnerable to shocks from other markets, increasing the occurrence of extreme dependence.

1.2 Methodological aspects

Due to extreme dependence, markets tend to crash together. The probability of markets crashing together can be measured in terms of tail dependence, which is the conditional probability that an extremely negative (positive) return experienced by one market will lead another market to experience the same. Consequently, tail dependence is used as a more formal notion of the probability of markets crashing together. If tail dependence is high, markets tend to crash together. The methods and approaches we use in this thesis to model extreme dependence are able to model tail dependence between multivariate returns. Next, we discuss some methodological aspects that are important in modelling extreme dependence, asymmetric dependence and tail dependence.

First, the multivariate Gaussian distribution, which is widely used for risk management and asset allocation purposes, is not appropriate for modelling asset returns in general, and stock returns in particular. From a univariate point of view, Mandelbrot (1963) and Fama (1965) already showed that the Gaussian distribution cannot properly model the 'tail behavior' of financial returns, as substantial returns occur considerably more often than expected under normality. The multivariate Gaussian distribution is also inadequate, as the dependence between stock returns appears to be asymmetric and shows tail dependence (see Embrechts et al., 2002, 2003), which is not well captured by the linear correlation coefficient. Longin and Solnik (2001) examine the validity of the assumption of multivariate normality for the tail behavior of multivariate stock returns, using extreme value theory (EVT) (see Embrechts et al., 1997). They concluded that normality is consistently rejected for the joint lower tail, but not for the joint upper tail. This rejection of multivariate normality in the negative tail is caused by the fact that the normal distribution imposes no tail dependence, while stock returns do show tail dependence. Therefore, diversification gains, based on the Gaussian multivariate distribution, are not accurate and will overestimate the true diversification gains.

Second, there are hardly any suitable standard parametric distributions that can capture the asymmetric dependence and tail dependence of multivariate stock returns. The multivariate Student's t distribution can model the thickness of the negative tail properly, but being a symmetric distribution, it also implies the same thickness for the positive tail. The lack of suitable multivariate distributions has led to the introduction of copulas in finance (see Patton, 2009). Copulas can be used to separate the marginal distributions of stock returns from their dependence structure. Given that different marginal distributions may be used in combination with different copulas, a wide variety of multivariate distributions can be constructed. Regarding asymmetric dependence, several copulas that can capture this feature are available, including the Clayton and Gumbel copula. Furthermore, different copulas can be mixed to obtain even more flexible dependence structures. The use of copulas and mixtures of copulas is relatively new in finance(see Patton, 2009). It is for this reason that we investigate in greater detail the use of copulas when modeling extreme dependence.

Third, as the overall dependence between stock returns varies over time (see Longin and Solnik, 1995; Ramchand and Susmel, 1998; Campbell et al., 2002), the extreme dependence between stock returns may vary over time as well. The dependence during turmoil periods can be characterized as strong and asymmetric, but considerably weaker and much closer to symmetric during tranquil periods (such that it in fact resembles the dependence implied by a Gaussian distribution (see Rodriguez, 2007; Okimoto, 2008)). Several models have been developed to capture this time-variation in dependence, such as multivariate GARCH models and Markov switching models. Patton (2006b) introduced time-varying (or conditional) copula models, which are able to capture time-variation in dependence and asymmetric dependence. In this thesis we examine time-varying extreme dependence by using copula models, GARCH type models and logistic regressions.

1.3 General outline

In the different chapters of this thesis we examine time-varying extreme dependence in stock markets around the globe. Each chapter takes a different perspective. First, we investigate how crashes contagiously spread between international stock markets, and how this propagation can be explained. Next, we examine to what extent the probabilities of stock markets around the globe crashing together has changed over the past decades. Then, we develop a framework, to accurately model and distinguish between changes in different characteristics of dependence. Finally, we look at time-varying dependence from a more practical view, and evaluate forecasts of extreme dependence using different modelling approaches.

Chapter 2 looks at time-variation in extreme dependence in a contagion framework, and extends the framework to measure financial contagion as developed by Bae et al. (2003). Their approach links the number of stock market crashes to financial variables using multinomial logit regressions. However, Bae et al. (2003) treat different types of crashes as equal, while we make a distinction between different types of crashes. Specifically, we distinguish between local emerging market crashes, regional crashes where several markets in a region are hit by a crash, and global crashes. Using a novel framework based on ordered logit regressions we model the occurrence of local, regional and global crashes as a function of their past occurrences and financial variables. We consider daily stock market returns of emerging and developed markets. We find significant evidence that global crashes do not occur abruptly but are preceded by local and regional crashes. This happened, for example, during the 1997 Asian crisis. This crisis originated in Thailand, then infected other developing Asian countries, and finally financial markets in the United States and Western Europe were affected as well. Besides this form of contagion, we also find evidence for interdependence, which is defined as increased dependence that can be linked to economic or financial variables. Interdependence shows up by the effect of interest rates, bond returns and stock market volatility on crash probabilities. When it comes to forecasting global crashes, our model outperforms a binomial model for global crashes only.

Because of financial globalization, the dependence between stock markets around the world has increased (see Bekaert and Harvey, 1995; Longin and Solnik, 1995; Bekaert and Harvey, 2003; Berben and Jansen, 2005). In Chapter 3 we examine the effects of this increased interdependence between international stock markets on the probability of global crashes. Using weekly regional stock returns, we find that the probability of global crashes has increased dramatically, from around 0.1 percent in 1992 to 1.5 percent in 2010. The Asian crisis and particularly the credit crisis contributed to substantially higher global crash probabilities. We use different copulas with different dependence characteristics to allow for possibly non-linear features in the dependence between stock markets. We use Gaussian, Student's t, Gumbel and Clayton copulas to infer which dependence structure is most suitable for weekly regional stock returns. Except for small periods of lower tail dependence only, the dependence structure is symmetric, with lower as well as upper tail dependence.

We distinguish between two different features of dependence between asset returns, namely the strength and the structure of dependence. Strength refers to the degree of dependence (i.e. higher of lower), while structure refers to dependence as symmetric or asymmetric, tail-dependent or tail-independent, and linear or non-linear. Both these features are typically found to be time-varying, due to financial globalization as well as to the state of the economy. Most obviously this holds for the strength of dependence as measured by correlations, for example. Typically, correlations tend to be higher when returns are negative or when financial markets are more volatile. It also applies however to the structure of dependence, which may be characterized as being symmetric or asymmetric, or as displaying tail dependence or not. Such structural characteristics may also be subject to change, for example due to increasing financial integration, macroeconomic conditions and market liquidity.

In chapter 4 we develop a new modeling framework that can capture changes in both strength and structure of the dependence of asset returns. Specifically, we put forward a mixture copula, with time-varying mixture weights and time-varying copula parameters. Changes in the strength of dependence are accounted for by changes in the parameters of the copulas. Changes in structural characteristics of the dependence such as asymmetry and tail dependence are represented by time-variation in the mixture weights. Both types of change are assumed to occur through a latent Markov-Switching process. Existing models only allow for switches in either strength or structure. Obviously, missing out on one of these can have severe consequences for risk management and portfolio selection. We apply our model to daily returns in international equity markets. We use a mixture of a Gaussian copula and a survival Gumbel copula, both with time-varying parameters, to accommodate a variety of dependence structures. We find a clear distinction between periods with weak and strong dependence and between periods of symmetric and asymmetric dependence. Furthermore, ignoring changes in either the strength or structure of dependence leads to biases in one-day Value-at-Risk estimates.

Chapter 5 takes a more practical view of time-variation in extreme dependence. This chapter investigates the accuracy of Value-at-Risk forecasts obtained from different modeling approaches. More specifically, we examine different modelling approaches to forecast ten-day Value-at-Risk for a portfolio consisting of stocks and bonds. We distinguish between forecasting Value-at-Risk under temporal and portfolio aggregation. Temporal aggregation is used when the data is modelled at a frequency lower than the highest available frequency, for which an asset price is observed. Direct forecasts are constructed by setting the modeling frequency equal to the forecast horizon. If a frequency higher than the forecast horizon is used, we use either scaling or iterating to extrapolate one-period forecasts to multi-period forecasts. Scaled multi-period forecasts are obtained by simply multiplying a one-period forecast with a constant proportional to time. Iterated multi-period forecasts also take into account shocks that could occur between the end of the one-period forecast and the end of the forecast horizon. Regarding portfolio aggregation there are two choices. First, the portfolio returns are calculated and with these portfolio returns a model is estimated from which a forecast is made. Second, the returns are modelled bivariately, and forecasts are made from this bivariate model and the portfolio weights. We find that for the 1% VaR, the bivariate modelling approach outperforms the univariate approach. For the 5% VaR this is the other way around. Regarding temporal aggregation, direct and scaled forecasts perform worse than iterated forecasts, particularly regarding the 1% VaR forecasts.

Overall, this thesis contributes to the literature by shedding more light on the behavior of extreme dependence. Due to the financial globalization risk-managers, investors and financial regulators are more and more exposed to this extreme dependence. The thorough investigation of extreme dependence in this thesis, adds to our knowledge and understanding of extreme dependence. The main contributions are the following. First, we add to the ongoing debate on contagion and interdependence, as discussed in Dornbusch et al. (2000), by using a novel framework in which we allow for both types of transmission mechanisms, and where the contagion mechanism evolves according to a domino effect. Second, we contribute to the relatively new literature on the use copulas in finance (see Patton, 2009). Our first contribution in this field is to show the practical use of multivariate copulas on stock return data. Most other studies using copulas to examine changes in dependence only consider bivariate pairs. In this application, we show in a novel way, by using multivariate copulas, how the integration of the financial system has increased the probability on the occurrence of global crashes. Our second contribution regards the use of mixture copulas, where both the dependence parameters as well as the mixture weights can independently vary over time. Other studies consider only one type of time-variation in the mixture copula. We show that those models describe the time-varying dependence between stock returns less accurate than our model does. Finally, to the best of our knowledge we are the first to investigate the effects of both temporal and portfolio aggregation, and the interaction between these, on Value-at-Risk forecasts. Other studies only consider either temporal or portfolio aggregation. Additionally, they examine the effect of aggregation on volatility forecasts, which could lead to different conclusions than for extreme return forecasts, such as Value-at-Risk.

Chapter 2

Contagion as a Domino Effect in Global Stock Markets*

2.1 Introduction

Stock market crashes are one of the major risks that investors face. Although such crashes occur infrequently, their impact on the value of asset portfolios can be substantial. The October 1987 crash, for example, reduced stock prices by over 20 percent in most developed markets. In emerging stock markets, crashes can be even more severe. Asian markets lost over 30 percent in October 1997 during the Asian crisis. As emerging countries are commonly quite susceptible to macroeconomic shocks, crashes occur more often in their stock markets. While many of these crashes are "local" and remain confined to individual countries, some spread to neighboring emerging markets, resulting in regional stock market crashes. Some may even evolve into global crashes, where developed markets are also affected. The 1997 Asian crisis, for instance, originated in Thailand, then infected other developing Asian countries, and finally financial markets in the United States and Western Europe were affected as well.

For investors as well as policy makers it is important to know whether crashes remain local, or a "domino pattern" occurs, with local crashes evolving via regional crashes into global crashes. If crashes remain local, investors can hedge relatively easy. However, hedging is more difficult, and diversification opportunities diminish rapidly, when local crashes spread regionally or even globally (see Ibragimov and Walden, 2007). In this case, the domino effect may destabilize several markets and

*This chapter is based on the article by Markwat, Kole, and Van Dijk (2009a).

even the entire financial system, calling regulators into action. On the other hand, if markets tumble like domino tiles, a local or regional crash can be interpreted as an early warning signal of more turmoil to follow. Kole et al. (2006) show that the gain of including the possibility of global crashes in asset allocation decisions can become rather large if the crash probabilities increase.

This study empirically examines the transmission mechanism of stock market crashes around the globe, using daily data for the US, Europe and several emerging markets in Latin America and Asia for the period from July 1996 to July 2007. In particular, we investigate whether the evolution of crashes exhibits a domino effect. We first identify periods with local, regional and global crashes (and periods without any crash at all). We then use an ordered logit model for the probabilities of occurrence of the different crash types. An ordered logit model is precisely able to capture the natural ordering of crashes by severity. This setup enables the inclusion of both domino-style contagion and normal interdependence between financial markets. A domino effect is present when one-period lagged occurrences of local, regional or global crashes significantly increase the probability of more severe crashes. We capture interdependence by including variables that represent information from the currency market, the bond market, and short-term interest rates.

As our main result we find strong evidence in favor of a domino effect. A crash occurring today significantly increases the probability of a more severe crash tomorrow. This result holds for all different types of crashes. The domino pattern indicates that global crashes, which can hardly be diversified, do not occur abruptly but rather evolve out of prior local or regional crashes. Our results confirm that in times of financial distress panic spreads contagiously, as described in Dornbusch et al. (2000). A local crash is a good predictor of more financial turmoil ahead. Additionally, we find that bond market returns, interest rate levels and stock market volatility significantly influence local, regional and global crash probabilities, though currency changes do not. Higher interest rates and higher stock market volatility lead to higher probabilities of more severe crashes, while higher bond returns in emerging markets lead to lower crash probabilities. We do not find that the relation between the financial variables and crash likelihood depends on the type of crash that occurred the day before. Finally, we find that our model, allowing for different types of crashes including local and regional ones, is more successful in detecting and forecasting global crashes than a binomial model for global stock market crashes only.

We contribute to the literature in various ways. First, our explicit distinction between local, regional and global crashes, and our model of the evolution of these crashes as a domino effect sheds new light on the propagation of large negative stock market returns. This adds to the approach of Bae et al. (2003) and (to a lesser extent) of Cumperayot et al. (2006). Bae et al. (2003) consider the number of simultaneous extreme returns in different stock markets. In a multinomial logistic regression model they find significant effects of interest rates, changes in exchange rates and conditional stock market volatility on this number. However, they analyze only one region at a time, and do not investigate which part of the dependence between crashes in different countries can be attributed to reactions on crashes in other financial markets and which part to shocks in other financial variables. We extend their study by explicitly including global crashes in our analysis. These global crashes are most important for investors and regulators, because diversification opportunities evaporate in this case.

Second, we add to the ongoing debate on contagion and interdependence, as discussed in Dornbusch et al. (2000) (see also Pericoli and Sbracia, 2003), by using a framework in which we allow for both types of transmission mechanisms. Interdependence means spillovers of shocks resulting from the normal dependence between markets, due to trade links and geographical position, among others. So, interdependence refers to the dependence that exists in all states of the world. Contagion, on the other hand, constitutes a form of dependence that does not exist in tranquil periods but only occurs for large or extreme shocks to financial markets. Contrary to interdependence, this dependence cannot be linked to observed changes in macroeconomic or financial variables. Dornbusch et al. (2000) argue that this type of dependence is a result of "irrational" phenomena, such as financial panic, herd behavior and loss of confidence. We define contagion as the dependence that still exists after correcting for interdependence. Contrary to the common approach, our logistic framework does not measure contagion as correlation between residuals, but instead we construct contagion variables based on past extreme events. This enables us to distinguish between contagion and interdependence in the occurrence and evolution of local, regional and global crashes.

Most other studies concerning interdependence and contagion are based on bivariate analyses, and do not investigate dependence at the global level. The most popular approach is based on correlations between returns in different markets.[1] Kleimeier et al. (2008) show that these correlation based tests may lead to wrong conclusions due to different trading hours. Using time-aligned data they find contagion during the Asian crisis, contrary to Forbes and Rigobon (2002). Other authors attempt to model the volatility transmission mechanism by means of multivariate GARCH models[2] or use extreme value theory[3] to avoid the problem that increased correlations in

[1] See King and Wadhwani (1990); Lee and Kim (1993); Loretan and English (2000) and Forbes and Rigobon (2002).

[2] See Hamao et al. (1990), Longin and Solnik (1995), and Ng (2000).

[3] See Kaminsky and Schmukler (1999), Longin and Solnik (2001), and Hartmann et al. (2004).

periods of turmoil may be mostly a result of increased volatility.[4] Rodriguez (2007) uses copulas to measure contagion and finds evidence for contagion based on changes in dependence of extreme returns. Other studies making the distinction between interdependence and contagion are Connolly and Wang (2003) and Fazio (2007), where the latter concludes that interdependence exists between regions and contagion only within regions, and the former reject interdependence between regions while finding contagion between regions. Recently, Boyer et al. (2006) investigate the spread of crises through asset holdings of international investors, and find that this is an additional channel through which crises can spread. Our research is complementary to these studies.

A small number of previous studies consider crises and contagion in a multicountry environment. For instance, Dungey and Martin (2007) use factor models with world, regional and country factors and define contagion as the correlation between the residuals. This approach, however, is not specifically suited for measuring dependence among extreme shocks. The logistic approach, as pointed out by Bae et al. (2003), is more suitable to deal with extreme values, for the reason that it is closely related with extreme value theory. Christiansen and Ranaldo (2009) apply the methodology of Bae et al. (2003) to the stock markets of the EU and its new members and find evidence of an increased dependence of new EU stock markets to those in Western Europe. Other studies that use a multicountry environment are Favero and Giavazzi (2002) on exchange rate contagion, and Kose et al. (1990) who use a Bayesian framework to model output, consumption and investment. However, these two approaches are also not specifically suited for analyzing crashes. Kamin (1999) and more recently Dungey et al. (2008) empirically analyze whether the role of economic fundamentals (linkages) and contagion varies across financial crises. Although some differences are found, generally all crises seem to have much in common. Using information from the business cycle, Candelon et al. (2008) find a significant increase in the cross-country comovements of five Asian stock markets during the Asian crisis. For a comprehensive overview on recent developments in the contagion literature we refer to Dungey et al. (2005).

This chapter proceeds as follows. In Section 2.2 we describe the data set, and provide our definition of stock market crashes as well as the classification into local, regional and global crashes. In Section 2.3 we put forth the methodology for analyzing the domino effect based on the ordered logit model. In Section 2.4 we discuss the empirical results concerning the patterns in the different types of crashes, including several sensitivity tests. Section 2.5 explores the economic relevance of our model

[4]See Boyer et al. (1999), Loretan and English (2000), Forbes and Rigobon (2002).

compared to a binomial crash model for global crashes only. We conclude in Section 2.6.

2.2 The dynamics of stock market crashes

In this section we first discuss our data and definitions of local, regional and global stock market crashes. We then document the dynamic properties of the different crash types, to examine the appropriateness of modelling contagion as a domino effect.

2.2.1 Data

We investigate the transmission of stock market crashes for emerging markets in Latin America and Asia, and developed markets in the US and Europe. We include six countries from Latin America: Argentina, Brazil, Chile, Colombia, Mexico and Venezuela, as well as six countries from Asia: India, Korea, Malaysia, Philippines, Taiwan and Thailand. We obtain country and regional indices from the IFC emerging market database (EMDB), currently maintained by Standard & Poors. For the US and Europe we use MSCI equity indices. Although Europe exist of more countries rather than one, we do not consider local crashes in Europe for two reasons. First, the stocks markets in Western Europe are highly integrated. Second, regarding Europe as a region leads to a symmetric treatment of the US and Europe. We base our analysis on daily returns in US dollars for the period from July 1, 1996 until July 30, 2007, giving a total of 2839 observations. All data are taken from Datastream.

Table 2.1 provides summary statistics of the log daily stock returns for the full sample period. The regional indices show that emerging markets are riskier than developed markets, while the average returns are perhaps not as high as might be expected to compensate for this higher risk. This can be explained by the 1997 Asian crisis and the 1998 Russian debt crisis, which considerably depressed emerging market returns.[5] Across the emerging market countries the annualized average returns vary widely, ranging from a minimum of −7% in Thailand to a maximum of 16% in Mexico. The volatilities also show large variation across countries. For example, the Chilean stock market has a volatility of only 17% per year, while volatility in Korea is much higher and equal to 42%. Volatility generally exceeds 25%, indicating the high investment risk typical for emerging markets. Kurtosis is also substantially higher

[5] Average yearly returns computed over the period 1999 – 2007 are equal to 21, 13, 2 and 5 % for Latin America, Asia, the US and Europe, respectively, which are more in line with their respective volatilities.

Table 2.1: Descriptive statistics of daily log returns of national and regional stock market indices.

	ARG	BRA	CHI	COL	MEX	VEN	IND	KOR	MAL	PHI	TWN	THA	LA	ASIA	US	EUR
Mean	0.07	0.14	0.08	0.10	0.16	0.01	0.12	0.08	-0.02	-0.04	0.00	-0.07	0.14	0.03	0.07	0.09
Volatility	0.35	0.35	0.17	0.23	0.26	0.40	0.25	0.42	0.30	0.26	0.28	0.37	0.23	0.18	0.18	0.17
Min	-0.34	-0.15	-0.06	-0.14	-0.15	-0.46	-0.12	-0.22	-0.24	-0.10	-0.11	-0.17	-0.12	-0.07	-0.07	-0.06
Max	0.15	0.14	0.07	0.16	0.14	0.21	0.09	0.27	0.23	0.20	0.08	0.17	0.12	0.07	0.06	0.05
Skewness	-1.90	-0.35	-0.27	-0.22	-0.16	-2.25	-0.39	0.24	0.75	0.91	0.01	0.36	-0.61	-0.23	-0.11	-0.25
Kurtosis	33.61	8.45	6.46	19.08	9.82	56.19	7.17	14.29	34.84	19.47	5.51	10.23	10.22	5.75	6.43	5.39
5th quantile	-0.032	-0.035	-0.016	-0.021	-0.025	-0.035	-0.025	-0.038	-0.025	-0.025	-0.028	-0.034	-0.023	-0.018	-0.018	-0.018
Mean Crash	-0.051	-0.052	-0.024	-0.034	-0.037	-0.057	-0.038	-0.061	-0.045	-0.039	-0.039	-0.052	-0.036	-0.027	-0.025	-0.025
Vol. Crash	0.035	0.021	0.009	0.018	0.016	0.043	0.013	0.027	0.025	0.014	0.012	0.020	0.015	0.009	0.009	0.008
Argentina		0.37	0.27	0.17	0.38	0.14	0.10	0.12	0.09	0.09	0.12	0.11	0.44	0.14	0.23	0.22
Brasil	0.51		0.38	0.21	0.46	0.22	0.13	0.17	0.13	0.13	0.15	0.12	0.76	0.21	0.25	0.28
Chile	0.37	0.51		0.21	0.37	0.20	0.13	0.15	0.15	0.13	0.16	0.16	0.46	0.23	0.22	0.24
Colombia	0.16	0.19	0.23		0.22	0.18	0.12	0.10	0.14	0.12	0.10	0.10	0.24	0.15	0.05	0.13
Mexico	0.45	0.59	0.48	0.19		0.19	0.15	0.16	0.15	0.14	0.13	0.16	0.66	0.18	0.35	0.29
Venezuela	0.12	0.17	0.14	0.07	0.18		0.09	0.08	0.11	0.15	0.08	0.10	0.24	0.13	0.11	0.14
India	0.08	0.14	0.14	0.10	0.15	0.04		0.17	0.14	0.17	0.15	0.20	0.16	0.29	0.10	0.15
Korea	0.10	0.18	0.18	0.08	0.20	0.06	0.22		0.20	0.19	0.28	0.29	0.19	0.50	0.13	0.15
Malaysia	0.08	0.08	0.14	0.06	0.14	0.07	0.14	0.24		0.33	0.16	0.33	0.15	0.33	0.06	0.13
Philippines	0.08	0.12	0.16	0.11	0.13	0.07	0.16	0.23	0.29		0.12	0.32	0.15	0.28	0.08	0.16
Taiwan	0.07	0.12	0.18	0.08	0.11	0.04	0.19	0.30	0.20	0.19		0.18	0.17	0.47	0.11	0.14
Thailand	0.11	0.15	0.22	0.09	0.16	0.09	0.18	0.31	0.37	0.35	0.24		0.18	0.33	0.06	0.11
Latin America	0.59	0.91	0.63	0.26	0.84	0.22	0.17	0.22	0.13	0.15	0.15	0.19		0.24	0.33	0.33
Asia	0.13	0.22	0.28	0.15	0.23	0.09	0.44	0.67	0.50	0.40	0.75	0.50	0.27		0.11	0.23
US	0.36	0.43	0.36	0.10	0.55	0.07	0.06	0.09	0.01	0.05	0.06	0.05	0.55	0.09		0.32
Europe	0.30	0.39	0.42	0.18	0.47	0.12	0.18	0.20	0.14	0.14	0.16	0.19	0.49	0.27	0.43	

The upper panel of the table shows summary statistics of the daily log returns on the country and regional stock indices, including the annualized mean, annualized volatility, minimum, maximum, skewness, kurtosis, and the 5th quantile, which is used to identify the occurrence of crashes. The rows labeled 'Mean Crash' and 'Vol. Crash' show the mean and standard deviation of the returns below this 5th quantile. The entries below the main diagonal in the lower panel of the table are the linear correlations between the stock index returns; entries above the main diagonal are the conditional probabilities of observing a crash in a given (row) country conditional on the occurrence of a crash in another (column) country. The sample period runs from July 1, 1996 to July 30, 2007 (2839 observations).

than for the developed markets, pointing out that extremely large returns occur more often in emerging markets. Interestingly, skewness is negative for the Latin American countries, while it is positive for the Asian markets (except India). The biggest crash in the sample was observed on 29 November 2002, when the Venezuelan index lost 46% of its value. Maximum returns also vary from moderate (Chile, India, Taiwan) to very high (Venezuela, Korea, Malaysia, Philippines).

The last three rows of the upper part of Table 2.1 report the 5% quantile of the empirical return distribution together with the mean and volatility of returns in the left tail below this quantile. The extreme returns have the lowest mean and highest volatility for Argentina, Korea and Venezuela, indicating that in these countries the extreme returns introduce more risk and vary more than in the other countries. For the regional indices, we observe that the 5% quantile, and the mean and volatility of returns in the left tail are approximately equal for Asia, US and Europe, while they are substantially larger (in absolute value) for Latin America. From this perspective Latin America would be the most risky region to invest in.

The entries below the main diagonal in the bottom part of Table 2.1 are linear correlation coefficients between contemporaneous daily returns. For the regional indices, we observe that the correlations between the US, Europe and Latin America are of the same order of magnitude around 0.50. The correlations between Asia and the other regions are lower, especially the correlation between the US and Asia (0.09). This lower correlation is mainly a result of different trading hours of stock markets around the globe. As trading on a given calendar day starts in Asia, then moves to Europe, and ends in the US, information from the European and (especially) the US stock markets cannot affect the Asian market on the same day, such that these correlations (mostly) measure the effect of the Asian market on Europe and the US. The correlations between current returns in Asia and one-day lagged returns in Europe and the US (0.29 and 0.38, respectively), are more in line with the other regional correlations.

The correlations between individual emerging markets are somewhat lower on average. The average correlations between countries within Latin America and Asia are equal to 0.29 and 0.24, respectively, while the average cross-correlation (the correlation between the countries in Asia and Latin America) is only 0.12. We note, though, that the correlations between the four largest Latin American markets (Argentina, Brazil, Chile, Mexico) are considerably higher at around 0.50, comparable to the correlation between developed markets.

2.2.2 Crash definition and classification

Following Bae et al. (2003), a stock market crash in a given country occurs when the daily return lies below the 5% quantile of the empirical return distribution over the complete sample period. A local crash occurs when one to three individual emerging markets experience a crash, while the respective regional indices do not.[6] A regional crash in Latin America, Asia, the US or Europe occurs when the respective regional index has a daily return below the 5% quantile of the empirical return distribution. In addition, for Latin America and Asia a regional crash occurs when four or more countries in the region experience a crash. This additional definition enables us to observe a regional crash in emerging markets when only small countries crash. Otherwise, results could be driven by large countries such as Brazil, Mexico, Korea and Thailand, as the IFC indices are value-weighted. We define a global crash as the simultaneous occurrence of two or more regional crashes, of which at least one is in a developed region. Because of the differences in stock market trading hours, we also define a global crash when the US or Europe encounters a crash on day t, followed by a crash in Asia on day $t + 1$.[7] As stock markets rapidly, possibly instantaneously, adjust to shocks (Kleimeier et al., 2008), we use the highest possible sampling frequency available, which is daily.[8]

Based on the definitions given above, no crash occurs on 1810 days, out of a total of 2839 days in the full sample period. Local, regional, and global crashes occur on 616, 271, and 142 days, respectively. Hence, regional crashes occur slightly more often than once every two weeks and global crashes about once a month. Although this may seem quite frequent, it should be noted that crashes are clustered. Typically, several global crashes occur in short time-periods, alternated by long periods with hardly any global crashes. To examine whether these numbers are high or low we compute the expected numbers of crashes assuming all markets are independent. Since the crash probability equals 5% for all indices by construction, these can be computed analytically. This results in an expected number of 1228 days without any type of crash, and 1066, 497, 48 days with a local, regional and global crash, respectively. Comparing these numbers to the actual numbers of crashes shows that the crash risk involved with investing in equity markets is indeed rather large. While the numbers of days with a local or regional crash in our sample are lower than expected

[6] Results hardly change when we vary this number between three to six markets.

[7] We note that differences in trading hours are crucially important when analyzing relations between daily stock market returns, see Kleimeier et al. (2008), but to a much lesser extent when counting extreme events, as we do here.

[8] We also perform our analysis with 2-day returns, which gives qualitatively similar results. Details are available upon request.

under independence, global stock market crashes, which are the most troublesome for investors, occur three times more often.

The entries above the main diagonal in the lower part of Table 2.1 are conditional probabilities of observing a crash in a specific stock market, given the occurrence of a crash in another market. These probabilities give insight into the dependence of extreme stock market returns. By construction, the same number of crashes occur for all individual markets, and therefore these probabilities are also symmetric. For the regional indices we find that the probability of observing a crash given that another region encounters a crash is around 0.30 on average. For the individual markets in both Latin America and Asia we find substantial variation in these conditional probabilities, although most are between 0.10 and 0.20. To put these numbers into perspective, note that if all markets were independent these conditional probabilities would be equal to 0.05. Hence, the empirical conditional probabilities show that there is substantial dependence in the occurrence of crashes across countries and regions.

2.2.3 Crash dynamics

We continue by documenting some stylized facts on the dynamic properties of the different types of crashes. Specifically, we introduce a diagnostic measure which sheds light on how local, regional and global crashes evolve. This measure, which we call the crash transition matrix, is useful in particular to assess whether modelling contagion as a domino effect is appropriate. The ij-th entry of this transition matrix is equal to the probability of observing the state in column j, given that on the previous day the state in row i occurred. The states correspond with the different types of crashes.

Table 2.2A shows the empirical crash transition matrix. Several interesting observations emerge. First, the probabilities of observing a crash (no matter what type) on the next day increases from 0.28 when no crash occurs today to 0.43 when a local crash occurs today. This even increases further to 0.55 for a regional crash and 0.73 for a global crash occurring today. For both regional and global crashes we find increasing probabilities of occurrence, conditional on the occurrence of a crash on the previous day. The probabilities of observing a global crash, for example, increase from 0.03 when no crash occurred on the previous day, via 0.06 to 0.11 following the occurrence of a local or regional crash, respectively. Most global crashes do not occur abruptly but rather evolve out of prior local or regional crashes, which suggests that modelling contagion as a domino effect makes sense. Second, crashes of a given type are persistent. The probability that a certain crash continues is much higher than the probability of occurrence of the same type of crash on two consec-

Table 2.2: Crash transition probabilities

A: Raw returns

	N	L	R	G
N	0.72	0.19	0.07	0.03
L	0.57	0.27	0.10	0.06
R	0.45	0.27	0.17	0.11
G	0.27	0.23	0.29	0.20

B: Standardized returns

	N	L	R	G
N	0.71	0.19	0.08	0.02
L	0.56	0.29	0.10	0.05
R	0.51	0.24	0.16	0.09
G	0.23	0.24	0.30	0.22

C: Bootstrapped raw returns

	N	L	R	G
N	0.68	0.20	0.08	0.04
L	0.61	0.24	0.10	0.05
R	0.55	0.25	0.13	0.07
G	0.44	0.22	0.21	0.13

D: Bootstrapped standardized returns

	N	L	R	G
N	0.68	0.20	0.09	0.03
L	0.60	0.25	0.10	0.05
R	0.58	0.23	0.13	0.06
G	0.41	0.23	0.23	0.13

The four panels in this table contain crash transition probabilities, where the ij-th element is the probability of observing the state in column j, given that on the previous day the state in row i occurred. The row and column labels N, L, R, and G correspond to no crash, local, regional and global crash, respectively. Panels A and B are based on the crashes identified in the series of raw and standardized returns, respectively, of the twelve emerging market country indices and four regional indices over the sample period July 1, 1996 – July 30, 2007 (T = 2839 observations), using the classification rules explained in Section 2.2.2. Panels C and D show the average transition matrices computed from 10,000 bootstrap samples of length T obtained by the stationary bootstrap for the raw and standardized returns, respectively.

utive days if these were independent. For example, the empirical probability that a global crash continues is 20%, which is more than 80 times as large as the probability of $(\frac{142}{2839})^2$ =0.25% of observing two consecutive days with a global crash if these occurrences were independent. The same holds for local and regional crashes. Third, crashes die out gradually as indicated by the relatively high probabilities of a regional crash following a global one, or a local crash following a regional one.

Boyer et al. (1999), Loretan and English (2000), and Forbes and Rigobon (2002) argue that increased correlations between stock market returns in times of extreme downturns can be attributed to increased volatility during these periods. To examine whether our results for the crash dynamics are driven by this volatility effect, we compute the crash transition matrix using crash definitions based on standardized returns.[9] Table 2.2B shows that the transition probabilities are approximately equal to those found for the crashes based on raw returns. We conclude that the dynamic dependence between crashes is not affected by time-varying levels of volatility.

Finally, we examine whether the crash dynamics are mainly driven by linear autocorrelation or higher-order or non-linear effects are at work. For this purpose we

[9]We use the sample volatility over the past year to standardize the returns. For the standardized returns, we find 1801, 621, 289 and 128 days with no, local, regional and global crash, respectively.

employ the stationary bootstrap of Politis and Romano (1994). Contrary to the standard i.i.d. bootstrap, this bootstrap method can take autocorrelation into account. Instead of drawing subsequent observations in the bootstrap sample completely at random, they are drawn in the natural ordering with a specific probability p. The optimal value of p can be determined using the method of Politis and White (2004).[10] For our data this turns out to be $p = 0.50$.[11] Using the stationary bootstrap, we obtain a bootstrapped sample of 2839 observations, corresponding with the length of the empirical return series, and compute its crash transition matrix. If the transmission mechanism of crashes is mainly driven by linear autocorrelation, the bootstrapped matrix should be approximately equal to the empirical crash transition matrix.

Table 2.2C shows the average transition matrix based on 10,000 bootstrapped samples. Again we observe higher probabilities for regional and global crashes when a crash occurred on the previous day. However, the pattern is less clear than for the original data. For the transitions between regional and global crashes the differences between the original and the bootstrapped crash transition matrix become particularly large. For instance, the probability of observing a regional crash today and a global crash tomorrow decreases from 0.11 to 0.07. The probability that a global crash continues is 0.11, much less than the 0.20 in panel A. This indicates that there are indeed higher-order dependencies in the dynamic patterns of crashes, especially concerning the more severe crashes. Again, using standardized returns hardly has any influence on the results (see Table 2.2D).

2.3 Methodological framework

The increasing probabilities of occurrence of regional and global crashes following a crash on the previous day clearly indicate that stock market crashes gradually disseminate and evolve into more severe crashes. However, it remains to be seen whether this is due to domino-style contagion or due to normal interdependence between financial markets. We analyze this formally by modelling the evolution of local, regional and global crashes by an ordered logit model. Given that the different crash types have a natural ordering by severity, the ordered logit model is appropriate for our modelling purposes.

We denote the observed crash on day t as y_t, taking the values 0, 1, 2 or 3 when no crash, or a local, regional or global crash occurs, respectively. The observation y_t

[10] This method minimizes the mean squared errors of the variances and autocovariances of the stationary bootstrapped data, given that the first draw is random.

[11] We computed the optimal values of p for the four regional indices and then took the average. The individual values of p for the sample returns are 0.73, 0.83, 0 and 0.42, for Latin America, Asia, USA and Europe respectively. For the standardized returns these are 0.71, 0.82, 0 and 0.46.

is assumed to be related with the latent continuous variable y_t^* by

$$y_t = j \quad \text{if } \alpha_j < y_t^* < \alpha_{j+1}, \quad \text{for } j = 0, \ldots, m-1, \tag{2.1}$$

where in our case $m = 4$. The α_j for $j = 0, \ldots, m$ are thresholds separating the different crash categories, where $\alpha_0 \equiv -\infty$ and $\alpha_m \equiv \infty$. In the ordered logit model the latent variable y_t^* is linearly related to a vector of covariates $\boldsymbol{x}_t$, that is $y_t^* = \boldsymbol{x}_t'\boldsymbol{\beta} + \varepsilon_t$, with ε_t assumed to follow a standardized logistic distribution. The choice of variables entering $\boldsymbol{x}_t$, discussed below, will enable us to distinguish between a domino contagion effect and interdependence as the underlying cause for the propagation of stock market crashes. Using the link between y_t and y_t^* as specified above, the probability of observing a crash of type j at time t is given by

$$p_{jt} = Pr[y_t = j] = \Lambda(\alpha_{j+1} - \boldsymbol{x}_t'\boldsymbol{\beta}) - \Lambda(\alpha_j - \boldsymbol{x}_t'\boldsymbol{\beta}), \quad \text{for } j = 0, \ldots, m-1, \tag{2.2}$$

where Λ is a logistic function, and $\Lambda(\alpha_0 - \boldsymbol{x}_t'\boldsymbol{\beta}) \equiv 0$ and $\Lambda(\alpha_m - \boldsymbol{x}_t'\boldsymbol{\beta}) \equiv 1$.

The coefficients $\boldsymbol{\beta}$ and the thresholds α_j, $j = 1, \ldots, m-1$, in the ordered logit model can be estimated straightforwardly by maximum likelihood. The log likelihood for a sample of T observations is given by

$$\ell(\boldsymbol{\beta}, \alpha_1, \alpha_2, \alpha_3) = \sum_{t=1}^{T} \sum_{j=0}^{m-1} I[y_t = j] \log(p_{jt}), \tag{2.3}$$

where $I[y_t = j] = 1$ if observation t was of type j and zero otherwise. We use White misspecification robust standard errors. In line with other studies using models with limited dependent variables, we use the pseudo-R^2 of McFadden (1974) as a measure of fit of the model. If the loglikelihood of the full, unrestricted model is denoted by ℓ_1 and the log-likelihood of a restricted model which only includes the threshold parameters by ℓ_0, the pseudo-R^2 is given by

$$R^2 = 1 - \frac{\ell_1}{\ell_0} \tag{2.4}$$

We perform likelihood ratio tests on the individual and joint significance of the coefficients in our model.

Though the coefficient estimates in ordered logit regressions can be interpreted based on their significance and signs, they cannot be used to assess the marginal effects of the covariates on the crash probabilities as the model is nonlinear. Hence, we examine these marginal effects by means of probability response curves, as in Bae et al. (2003). These curves show the probabilities of observing a crash of type j at time t as a function of a specific covariate x_{it}. Varying the value of this variable from its minimum to maximum, we compute the average probabilities of observing the different types of crashes across all T observations of the remaining variables $\boldsymbol{x}_{t/i}$. This also allows us to assess the economic significance of our ordered logit regressions, in the sense that the probability response curves provide an indication of the magnitude of the changes in the crash probabilities due to variation in the regressors.

2.3.1 Covariates

We choose the covariates in order to discriminate between a contagious domino effect and interdependence as the underlying reason for the observed dynamics of local, regional and global stock market crashes. To allow for the presence of a domino effect in the evolution of crashes, we include dummy variables for local, regional and global crashes on the previous day. Positive effects of these dummies induce higher probabilities of observing a crash today, if a certain type of crash has occurred in the previous period.

Interdependence effects are incorporated by including several variables that represent information from the currency market, the fixed income market, and short-term interest rates. In our choice of variables, we follow the existing literature, and select to a large extent the same variables as Bae et al. (2003). For the currency markets we use the insight of Cumperayot et al. (2006) that extremes in currency markets and equity markets are related. While the inclusion of economic fundamentals could be useful as shown by Kaminsky and Reinhart (1999) and more recently Chen (2009), the frequency of macroeconomic data does not correspond with the frequency of our observations, and we cannot use them.

For the currency market we follow Bae et al. (2003) and take the average exchange rate returns in Latin America and in Asia. These variables are constructed by taking the equally weighted average of the daily log changes in the currencies of all six countries in the region against the US Dollar. We expect a positive effect on the probability of more severe crashes as depreciations lead to a lower value of the stock index. Moreover, depreciations signal net capital outflow, potentially due to a loss of confidence in the emerging markets. The Asian crises serves as a typical example, where the Asian currencies depreciated first, followed by tumbling stock markets.

To investigate whether shocks in the bond market lead to increased crash likelihood we include daily returns (in US dollars) on well-diversified regional bond portfolios. These portfolios consist of bonds with long and short maturities, issued by sovereign and quasi-sovereign entities. We expect a negative effect of emerging market bond returns on crash probabilities. A fall in the prices of government bonds issued by an emerging country may point at a decrease in its creditworthiness and an increase in its default probability. Higher financing costs for the national government will harm economic growth, and a fall of the stock market can be expected. The default of Argentina in 2001 is an example of such a pattern. The US government bond market (and to a lesser extent the European bond market) serves as an international safe haven. So, positive returns on a US government bond portfolio may indicate a flight to quality due to international distress. Therefore, we expect a positive relation between US government bond returns and crash likelihood.

We also include two variables associated with extreme events in the currency and bond markets. Extreme currency depreciations are defined as those depreciations above the 95% quantile of the empirical distribution of currency returns. For the bond market the extreme observations are those below the 5% quantile. The variables are constructed by counting the number of extreme events in the past five days and over the regions. We add these two variables to capture possible overreaction to bad news, not captured by the other currency and bond variables.

The third group of variables consist of three-month interbank interest rates.[12] Interest rates are on average negatively correlated with stock market returns, as they imply higher costs of capital. For emerging markets, higher interest rates can also be a sign of exchange rate pressure. Higher interest rates are therefore expected to increase crash probabilities.

Finally we include volatility of the stock market itself. We follow the RiskMetrics approach and compute volatility for day t as $\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1-\lambda)u_{t-1}^2$, where u_{t-1} is the demeaned stock market return on the previous day and the decay parameter $\lambda = 0.94$, (see JPMorgan and Reuters, 1994). We compute the daily volatility on each of the four regional stock market indices. Higher volatility increases the probability of extreme negative returns, and therefore we expect a positive relation between volatility and the crash probabilities.

The data is provided by JP Morgan for the fixed income related variables, and by Reuters for the currencies. All the data are obtained from Datastream. All variables are included in the ordered logit model with a lag of one day, such that our models are predictive in nature.

Table 2.3 shows that the correlations between the different groups of covariates are low and often insignificant.[13] This indicates that the various types of variables provide different and complementary information. Within the different groups some

[12]For some emerging market countries we use the one-month interbank interest rate, as the three month interbank interest was not available.

[13]The 5 percent critical values for significance of the correlation coefficients based on a sample of $N = 2839$, are -0.04 and 0.04.

Table 2.3: Cross-correlations of covariates

FX change LA	1															
FX change Asia	0.07	1														
Bond LA	−0.24	−0.11	1													
Bond Asia	−0.13	−0.18	0.52	1												
Bond US	0.00	0.05	0.07	0.39	1											
Bond Europe	0.00	−0.07	0.00	0.15	0.31	1										
Interest LA	0.08	0.03	−0.01	0.02	0.01	0.01	1									
Interest Asia	0.01	0.09	0.00	−0.02	0.02	0.00	0.27	1								
Interest US	0.02	0.05	−0.02	0.01	0.04	0.00	0.20	0.36	1							
Interest Europe	−0.02	0.05	0.00	−0.01	0.01	−0.04	0.02	0.61	0.60	1						
Volatility LA	0.01	0.05	0.04	0.07	0.01	−0.01	0.12	0.13	0.19	0.20	1					
Volatility Asia	0.02	0.05	0.00	0.00	0.02	0.02	0.23	0.26	0.33	0.09	0.61	1				
Volatility US	0.03	0.03	0.02	0.04	0.02	0.01	0.23	0.08	0.38	−0.03	0.53	0.54	1			
Volatility Europe	0.01	0.02	0.00	0.04	0.02	0.01	0.17	−0.07	0.28	−0.16	0.58	0.58	0.82	1		
Extreme FX	0.04	0.07	−0.02	−0.06	0.02	0.02	0.09	0.27	0.05	0.02	0.29	0.31	0.11	0.14	1	
Extreme bond	0.04	0.00	−0.04	−0.08	0.00	0.00	0.14	−0.03	0.01	−0.16	0.27	0.23	0.34	0.33	0.20	1

The table reports the cross-correlations of the covariates that are used in the ordered logit model, over the sample period July 1, 1996 – July 30, 2007.

correlations are higher, for instance among the interest rates and stock market volatilities.

2.4 Empirical results

2.4.1 Base model

Table 2.4 reports the estimation results of the ordered logit model for local, regional and global stock market crashes. Panel a shows the coefficient estimates, the log-likelihood and the pseudo-R^2 of the regression. Panel b provides results on likelihood ratio tests for the joint significance of specific groups of covariates.

The first and most important result is that we find strong evidence for the presence of a domino effect. The positive and highly significant coefficients of the previous crash dummies show that crises spread according to a domino effect. This supports our hypothesis that local crashes have a tendency to evolve into more severe crashes by contagion.

To gauge the economic relevance of the domino effect, Table 2.5 reports the crash transition matrix implied by the estimated model. For each combination of current crash type j and previous crash type i, we calculate the transition probabilities for all observed values of the other explanatory variables. Table 2.5 gives the corresponding sample averages. The probabilities in the columns for local, regional and global crashes show the increase in crash likelihood when more severe crashes have occurred. For instance, given that no crash occurred on the previous day, the crash probabilities are equal to 0.21 for a local crash, 0.09 for a regional crash and 0.05 for a global crash. If a local crash occurred on the previous day, crash probabilities become 0.25, 0.12 and 0.06, respectively. So, a crash in a single emerging market provides an important signal of an overall increase in crash risk. A domino of crashing markets may well hit even well-diversified global investors.

The domino effect is more pronounced for regional crashes. In this case the regional and global crash probabilities almost double to 0.13 and 0.08, respectively. After a global crash the probability of a consecutive global crash even triples to 0.13. Regional and local crash probabilities also increase substantially to 0.19 and 0.30, respectively. The domino effect in the ordered logit model is less prevalent than in the transition matrix in Table 2.2A. This may be due to the inclusion of the other financial variables in the model to control for interdependence. However, it is clear that the other financial variables do not subsume the domino effect. Consequently, investors and policy makers should take domino-style contagion into account, as only monitoring financial linkages is not enough.

Table 2.4: Estimation results ordered logit model

A: Coefficient estimates	Coefficient	St. error	t-stat.	p-value
Currency change LA	−4.08	8.07	−0.51	0.61
Currency change Asia	6.55	7.68	0.85	0.39
Bond returns LA	−24.48	6.40	−3.82	0.00
Bond returns Asia	−13.81	15.44	−0.89	0.37
Bond returns US	35.40	15.92	2.22	0.03
Bond Returns Europe	−10.33	6.80	−1.52	0.13
Interest level LA	0.00	0.00	0.44	0.66
Interest level Asia	0.04	0.02	2.40	0.02
Interest level US	0.05	0.08	0.61	0.54
Interest level Europe	0.04	0.04	0.89	0.37
Volatility LA	0.52	0.72	0.72	0.47
Volatility Asia	1.88	0.85	2.20	0.03
Volatility US	1.42	1.07	1.33	0.18
Volatility Europe	2.44	1.24	1.97	0.05
Extreme FX count	0.15	0.05	2.90	0.00
Extreme bond count	0.03	0.03	0.85	0.39
Local crash dummy	0.40	0.10	4.06	0.00
Regional crash dummy	0.62	0.14	4.30	0.00
Global crash dummy	1.21	0.21	5.83	0.00
α_1	2.53	0.19		
α_2	3.90	0.19		
α_3	5.19	0.20		
Log likelihood	−2613.26			
R^2	0.07			

B: Joint significance tests on groups of variables	Log likelihood	d. f.	p-value
Currencies	−2613.61	2	0.70
Bonds	−2628.64	4	0.00
Interest	−2623.23	4	0.00
Volatilities	−2640.72	4	0.00
Extreme events	−2618.41	2	0.01
Past crashes	−2637.23	3	0.00

The table reports estimation results for the ordered logistic regression model for the four different crash categories (no, local, regional, global), with covariates as shown in the table. The variables ‘Local’, ‘Regional’ and ‘Global’ are dummy variables taking the value one if this type of crash occurred on the previous day. The sample period runs from July 1, 1996 to July 30, 2007 (2839 observations). Panel B reports likelihood ratio tests on the joint significance of the coefficients for different groups of covariates.

The significance of the past crash dummies is particularly noteworthy in light of the fact that we include stock market volatility measures in the model. By definition there are more crashes in times of high volatility. As volatilities are persistent and highly correlated across regions, regional and global crashes will occur more

Table 2.5: Marginal effects of prior crashes

	N	L	R	G
N	0.65	0.21	0.09	0.05
L	0.57	0.25	0.12	0.06
R	0.52	0.27	0.13	0.08
G	0.38	0.30	0.19	0.13

The table contains the crash transition matrix as implied by the estimates of the ordered logit regression model in Table 2.4. The ij-th element is the probability of observing the state in column j, given that on the previous day the state in row i occurred. The row and column labels N, L, R, and G correspond to no crash, local, regional and global crash, respectively. The reported probabilities are averages of the probabilities computed over all the possible values of the other covariates in the model.

frequently when volatilities are high. The patterns in the crash transition matrix in Table 2.2 could therefore result from global comovement in volatilities. The significance of the crash dummies in the ordered logit model clearly demonstrates the presence of a domino effect.

Second, we detect interdependence by the significant coefficients on the different groups of explanatory variables in Table 2.4. Part of the occurrence of crashes can be attributed to dependencies with other financial variables that hold in all states of the markets. Interdependence occurs by different channels, since the variables within the group of bond returns, interest rate levels and volatilities are all jointly significant at the 5 percent significance level.[14] The positive coefficient estimates of the interest rate level and volatility variables are in line with our expectations. Higher interest rates significantly increase the probabilities of stock market crashes. Increased stock market volatilities also make extreme returns, and thus crashes, more probable. The coefficient estimates for the variables in these two groups all show the same sign, confirming our hypotheses about these variables. For the bond portfolio returns, we also find the expected signs, negative for Latin America and, Asia and positive for the US. Contrary to the US, the European bond market does not show up as a safe haven. The insignificance may reflect the changing role of the European bond market after the monetary unification. Extreme events in bond markets do not influence crash probabilities significantly.

The currency variables are both insignificant, and a relation between crash probabilities and normal exchange rate movements in the emerging market seems absent. This finding is in contrast to other studies, such as Bae et al. (2003) and Dungey and Martin (2007). Contrary to Bae et al. (2003) we use lagged values for the explanatory

[14]We also considered two relative interest rates: the day-on-day change between two interest rate levels and the difference of the current interest rate level from its three month moving average. For both these variables we do not find significant coefficient estimates. The same holds for extreme changes in interest rates. Results are not shown here to save space, but are available upon request.

variables because our aim is to predict crashes.[15] Moreover, we want to measure the effect of currency changes on local, regional and global crashes simultaneously, while Bae et al. (2003) examine Asia and Latin America separately. Possibly the extreme currency indicator subsumes all effects of exchange rates on stock market crashes, as its coefficient estimate is highly significant. When we exclude this variable, however, the estimated coefficients for average currency changes remain insignificant. This implies that stock markets only react to substantial depreciations of emerging market currencies. We interpret this finding as another form of contagion, from the currency market to stock markets. As this relation only occurs during crisis periods it cannot qualify as interdependence.

We construct probability response curves to examine the marginal effects of the different regressors in the ordered logit model and to assess their economic significance for the crash probabilities. Figure 2.1 reports the probability response curves for all individual variables. Additionally, it shows a selected number of joint effects for the interest rate and equity volatility variables. The graphs show that the effects of the different variables on the crash probabilities are economically important. The effects seem larger for the bond market and equity volatility variables than for the currency and interest rate related variables. For the bond market, except for the US, lower returns lead to higher probabilities of regional and global crashes. For the lowest return on the Latin American bond market this even results in a probability of a global crash equal to 0.25. The interest rate variables seem to have less influence on stock markets, although the effects are not negligible. The volatilities show a slightly stronger effect than the interest rate variables.

Interest rate levels as well as stock market volatilities are persistent and tend to move together across the different regions (see also the correlations within groups in Table 2.3). That is, we would expect the US and European equity volatility to move together, for instance. Because the coefficient estimates for these variables also have the same sign, it may be more realistic to assess their effect on the crash probabilities by taking these cross-correlations into account. We therefore show "joint" probability response curves for these variables in Figure 2.1. The joint volatility response curve is computed by varying the volatilities of the four regions simultaneously between their respective minima and maxima. For the joint interest response curve we do the same. Here the economic relevance of interest rates and stock market volatilities becomes clear. When all volatilities are high the probability of observing no crash is equal to 0.23, while there is a probability of 0.44 that a regional or global crash occurs. The joint interest rate curve also shows substantial probabilities of crashes

[15] Using contemporaneous currency changes results in highly significant correctly signed estimates. Results are not reported here but are available upon request.

Figure 2.1: Probability response curves

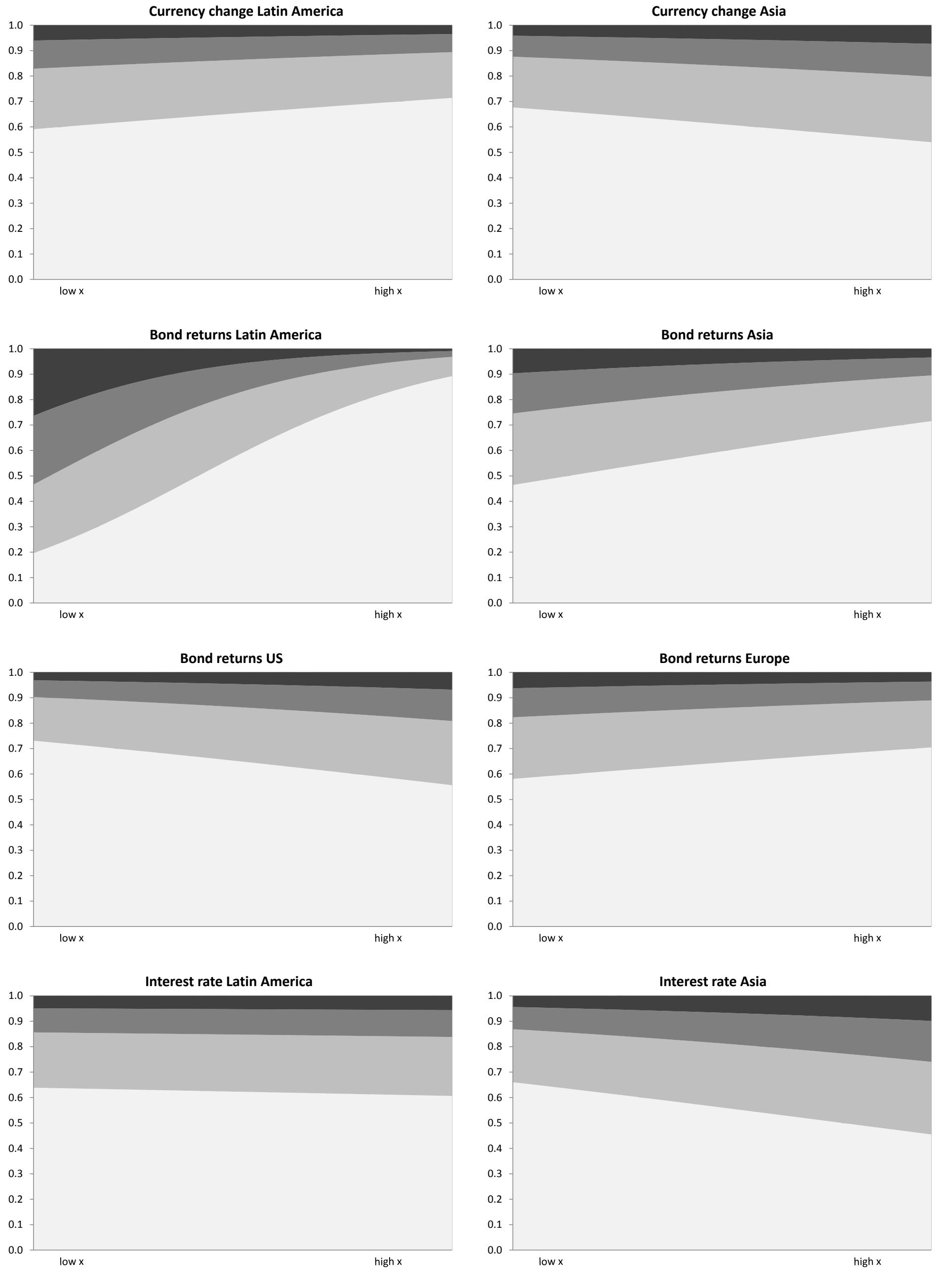


Figure 2.1: Probability response curves, *continued*

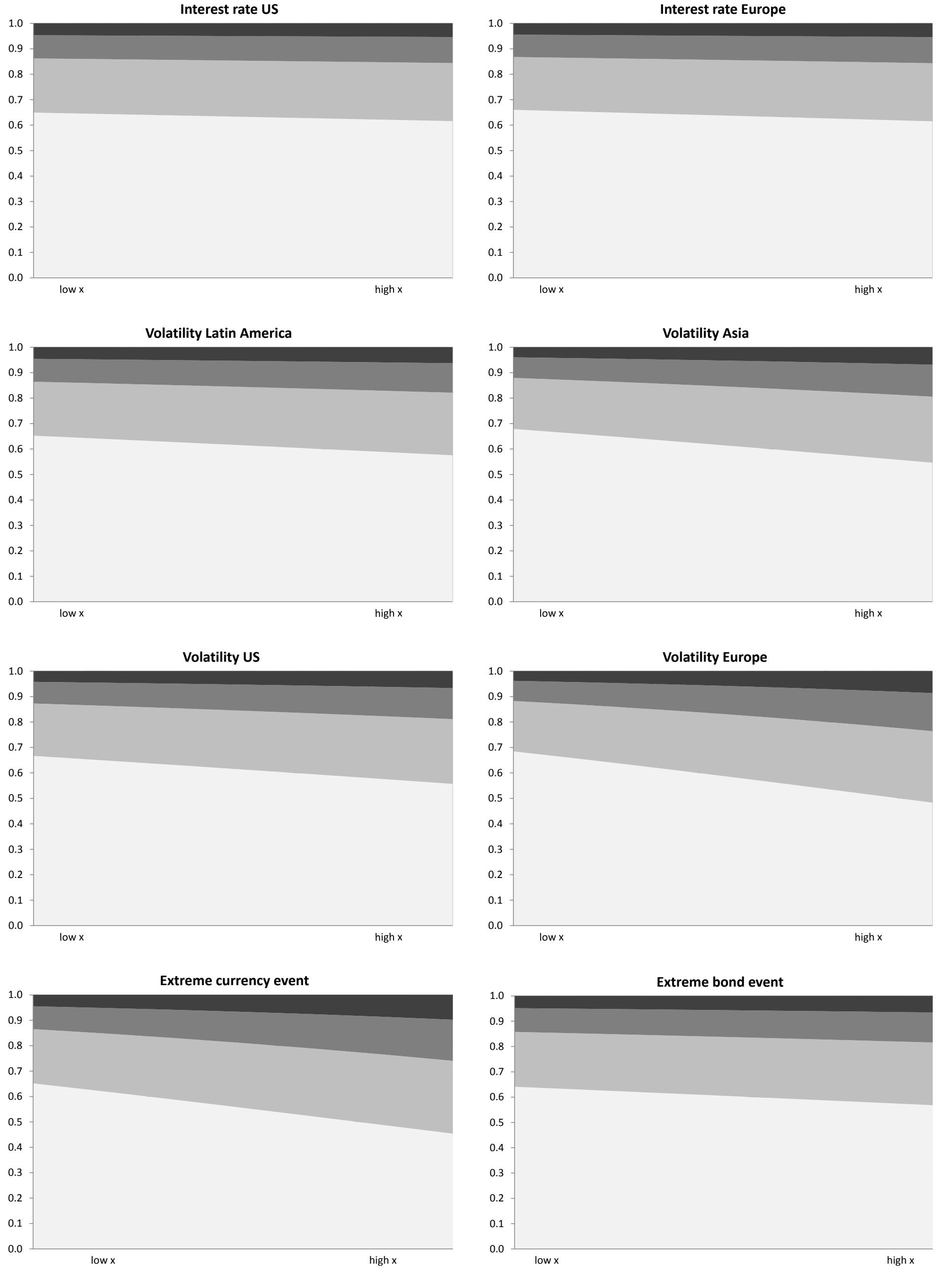
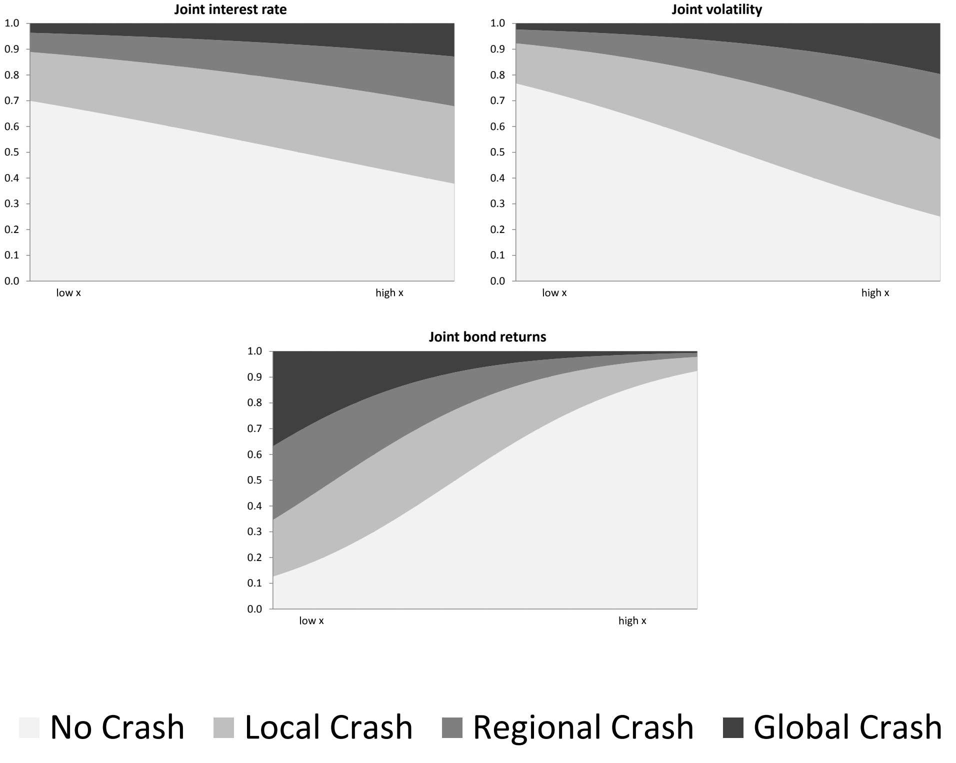


Figure 2.1: Probability response curves, *continued*



The graphs show the probability response curves in the ordered logit regression model reported in Table 2.4. The areas are the probabilities of observing a specific type of crash. The probabilities are computed by varying one specific variable x_{it}, over the x-axis, from its minimum (most left) to its maximum (most right). Then for each point on the probability response curve, we compute the probabilities of observing a type of crash for all T observations of the remaining variables $x_{t/i}$. The joint response graphs for interest rates and equity volatility are computed by varying all four variables between their respective minimum and maximum simultaneously.

when the interest rates are at a high level simultaneously, as opposed to the marginal effects of individual interest rates.

Knowing to which extent financial variables contribute to severe crashes is important for policy makers as well as investors, as both types of economic agents can benefit from anticipating crashes before they occur. Although this is not directly related to contagion in the sense of crashes spreading from local to regional and even global, our results suggest that instability of exchange rates and bond markets as well as high levels of interest rates and stock market volatility provide important "early warning signals" that may be used to avoid more severe crashes.

The extreme currency and bond market graphs indicate the presence of contagion from other markets to the stock market. For the extreme currency depreciations this effect is stronger than for the bond market. The probability of a global crash increases from 0.03 to 0.08 as the number of extreme depreciations increase from 0 to 6, indicating the influence of emerging currencies on global stock markets.

Finally, for the estimates of the threshold parameters α_j we use a Wald test to determine whether each α_j is significantly different from its adjacent thresholds α_{j-1} and α_{j+1}. We find that this is indeed the case and therefore the distinction between the four crash types seems appropriate. The pseudo-R^2 is equal to 0.07, which is comparable to other studies that consider forecasting models for crashes. This indicates that the explanatory variables have some predictive power with respect to crashes. We also examine whether there is autocorrelation in the residuals and we find that there is hardly any left, which is important as the estimation of the ordered logit model assumes conditional independence.

2.4.2 Conditional effects

Our base model provides evidence for both interdependence and contagion. In this section we explore whether the effects of the financial variables on the crash probabilities are dependent on the occurrence of a particular type of crash on the previous day. If, for example, the relations between the financial variables and the crash probabilities are found to be stronger in times of turmoil, this can be interpreted as excessive dependence in financial markets. This may be then be considered as a mixed form of contagion and interdependence.

From the results of this analysis (discussed in Appendix A) we conclude that there is no evidence for such conditional effects. The relations between the financial variables and the crash probabilities are stable, in the sense that they do not depend on the prior occurrence of crashes. There is, however, one exception: average currency depreciations in Latin American, which are insignificant in the base model, have a significant positive effect on crash likelihood when a global crash occurred on the previous day.

2.4.3 Robustness checks

We perform several checks to assess the robustness of the substantial role that the domino effect plays in the transmission of stock market crashes.

Multinomial logit

We check the appropriateness of using an ordered logit model by formally testing it against a multinomial logit model. We perform the likelihood ratio test for non-nested model selection of Vuong (1989) as well as an alternative distribution-free test introduced by Clarke (2007). Both tests are based on the Kullback-Leibler information criterion (KLIC), which measures the distance from the true, unknown specification. The difference in KLIC is the expected value of the (log) likelihood ratio,

$$E_0\left[\log \frac{f_{\mathrm{o}}(y_t|\boldsymbol{x}_t;\boldsymbol{\theta}_{\mathrm{o}})}{f_{\mathrm{m}}(y_t|\boldsymbol{x}_t;\boldsymbol{\theta}_{\mathrm{m}})}\right],$$

taken with respect to the true distribution, where $f_{\mathrm{o}}(y_t|\boldsymbol{x}_t;\boldsymbol{\theta}_{\mathrm{o}})$ and $f_{\mathrm{m}}(y_t|\boldsymbol{x}_t;\boldsymbol{\theta}_{\mathrm{m}})$ denote the likelihood functions of the ordered and multinomial models, respectively, and $\boldsymbol{\theta}_{\mathrm{o}}$ and $\boldsymbol{\theta}_{\mathrm{m}}$ their respective parameter vectors. The Vuong test for the null hypothesis $H_0 : E_0\left[\log\bigl(f_{\mathrm{o}}(y_t|\boldsymbol{x}_t;\boldsymbol{\theta}_{\mathrm{o}})/f_{\mathrm{m}}(y_t|\boldsymbol{x}_t;\boldsymbol{\theta}_{\mathrm{m}})\bigr)\right] = 0$ is given by

$$\frac{LR_T(\hat{\boldsymbol{\theta}}_{\mathrm{o}},\hat{\boldsymbol{\theta}}_{\mathrm{m}}) - \frac{1}{2}(k_{\mathrm{o}} - k_{\mathrm{m}})\ln T}{\sqrt{T\hat{\omega}^2}}, \tag{2.5}$$

where $LR_T(\hat{\boldsymbol{\theta}}_{\mathrm{o}},\hat{\boldsymbol{\theta}}_{\mathrm{m}})$ is the summed log-likehood ratio for the sample of T observations based on parameter estimates $\hat{\boldsymbol{\theta}}_{\mathrm{o}}$ and $\hat{\boldsymbol{\theta}}_{\mathrm{m}}$, $\hat{\omega}^2$ is an estimate of the variance given by

$$\hat{\omega}^2 = \frac{1}{T}\sum_{t=1}^{T}\left[\log \frac{f_{\mathrm{o}}(y_t|\boldsymbol{x}_t;\hat{\boldsymbol{\theta}}_{\mathrm{o}})}{f_{\mathrm{m}}(y_t|\boldsymbol{x}_t;\hat{\boldsymbol{\theta}}_{\mathrm{m}})}\right]^2 - \left[\frac{1}{T}\sum_{t=1}^{T}\log \frac{f_{\mathrm{o}}(y_t|\boldsymbol{x}_t;\hat{\boldsymbol{\theta}}_{\mathrm{o}})}{f_{\mathrm{m}}(y_t|\boldsymbol{x}_t;\hat{\boldsymbol{\theta}}_{\mathrm{m}})}\right]^2.$$

The second term in the denominator in (2.5) is a correction term for the different numbers of parameters in the in the ordered and multinomial models, where in our case $k_{\mathrm{o}} = 22$ and $k_{\mathrm{m}} = 60$. The Vuong statistic converges in distribution to $N(0,1)$.

Clarke (2007)'s distribution-free test is based on the null hypothesis that

$$\Pr\left[\log \frac{f_{\mathrm{o}}(y_t|\boldsymbol{x}_t;\boldsymbol{\theta}_{\mathrm{o}})}{f_{\mathrm{m}}(y_t|\boldsymbol{x}_t;\boldsymbol{\theta}_{\mathrm{m}})} > 0\right] = 0.5, \tag{2.6}$$

which reflects the fact that if both models are equally close to the true specification, the likelihood function of the ordered logit model should exceed that of the multinomial model for half of the observations. The corresponding test statistic is given by

$$B = \sum_{t=1}^{T} I\left[\log \frac{f_{\mathrm{o}}(y_t|\boldsymbol{x}_t;\boldsymbol{\theta}_{\mathrm{o}})}{f_{\mathrm{m}}(y_t|\boldsymbol{x}_t;\boldsymbol{\theta}_{\mathrm{m}})} - \frac{1}{2}(k_{\mathrm{o}} - k_{\mathrm{m}}) \ln T > 0\right],$$

where $I[]$ is an indicator function taking the value one if its argument is true. Asymptotically, the B-statistic has a binomial distribution with parameters T and $p = 0.5$.

We calculate both statistics for comparing the ordered logit model discussed in the previous section to a multinomial model with the same covariates $\boldsymbol{x}_t$. The Vuong test statistic attains a value of 10.55 with a p-value of 0.00, which means that the multinomial logit model is strongly rejected. The distribution free test statistic equals 0.73 (meaning that for 73 percent of the observations the likelihood for the ordered model is larger than that of the multinomial model), with a p-value of 0.00. Based on these test results we conclude that our ordered model is better able to describe the occurrence of stock market crashes than the multinomial model.

Alternative ordered regression specifications

To test the robustness of our specification we implement four alternative regressions. First, our results may be influenced by time-varying volatility, as we work with raw daily returns. We redo the crash classification and then estimate the ordered logit model using standardized returns. Table 2.6 shows that, except for the volatility coefficients, the results do not change substantially. This is in line with the preliminary results from the crash transition matrices in Table 2.2. In particular, the coefficients of the previous day crash dummies remain highly significant. We conclude that the domino effect is not driven by time-varying volatility in the stock market.

As a second robustness check we use the 2.5% quantile instead of the 5% quantile to define crashes. Obviously, this leads to less crashes for each individual market and, consequently, also less local, regional and global crashes. Table 2.6 shows that the ordered logit results are not sensitive to this alternative crash definition. For the domino effect, we find that the coefficients of the dummies for local and global crashes on the previous day remain virtually the same as in the base model. The coefficient for regional crashes declines from 0.62 to 0.33 while its p-value increases from 0.00 to 0.08.

Our final two robustness checks are based on variations in the definitions of regional and global crashes as explained in Section 2.2.2. In the first alternative classification we do not identify a global crash in case a regional crash occurs in Asia on

Table 2.6: Robustness checks

	Check 1		Check 2		Check 3		Check 4	
	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value	Coeff.	p-value
Currency change LA	−4.70	0.58	0.28	0.98	−2.27	0.79	−5.13	0.55
Currency change Asia	−3.02	0.77	17.48	0.13	1.85	0.85	8.38	0.39
Bond returns LA	−15.22	0.01	−14.22	0.03	−28.89	0.00	−25.40	0.00
Bond returns Asia	−22.02	0.15	−21.44	0.18	−16.62	0.26	−15.81	0.29
Bond returns US	34.46	0.03	51.37	0.00	40.97	0.01	40.87	0.01
Bond Returns Europe	−8.12	0.22	−1.92	0.81	−7.04	0.29	−8.38	0.21
Interest level LA	0.00	0.80	0.01	0.24	0.00	0.43	0.00	0.35
Interest level Asia	0.06	0.00	0.03	0.12	0.04	0.03	0.04	0.02
Interest level US	0.01	0.88	0.13	0.18	0.07	0.36	0.05	0.52
Interest level Europe	0.01	0.74	0.03	0.56	0.03	0.50	0.03	0.38
Volatility LA	0.16	0.81	0.73	0.33	0.95	0.16	0.68	0.31
Volatility Asia	−0.93	0.29	1.75	0.09	1.19	0.17	1.59	0.07
Volatility US	−0.19	0.86	0.65	0.60	1.48	0.16	1.50	0.15
Volatility Europe	1.68	0.16	3.75	0.00	2.54	0.03	2.39	0.04
Extreme FX count	0.16	0.00	0.26	0.00	0.15	0.00	0.15	0.00
Extreme bond count	0.02	0.41	0.04	0.29	0.03	0.26	0.04	0.18
Local crash dummy	0.54	0.00	0.42	0.00	0.40	0.00	0.40	0.00
Regional crash dummy	0.71	0.00	0.33	0.08	0.74	0.00	0.70	0.00
Global crash dummy	1.77	0.00	1.29	0.00	0.85	0.00	1.64	0.00
α_1	1.50		3.62		2.49		2.49	
α_2	2.82		4.88		3.90		3.85	
α_3	4.21		6.44		5.30		6.38	
Log likelihood		-2677.35		-1868.91		-2664.57		-2555.44
R^2		0.05		0.09		0.07		0.08

The table reports estimation results for different variations of the ordered logistic regression model for the four crash categories (no, local, regional, global), with covariates as shown in the table. The variables ‘Local’, ‘Regional’ and ‘Global’ are dummy variables taking the value one if this type of crash occurred on the previous day. The sample period runs from July 1, 1996 to July 30, 2007 (2839 observations). In check 1, crashes are defined using standardized returns. In check 2, the 2.5th quantile of the empirical distribution of the raw returns is used as the threshold to identify a crash. In check 3, a regional crash on day $t+1$ in Asia does not induce a global crash if the US or Europe encountered a crash on day t, while regional emerging market crashes are not said to occur when four or more individual emerging market countries in the region experience a crash. In check 4, global crashes only occur when three or more regions crash simultaneously.

day $t+1$ following a regional crash in the US or Europe on day t. Furthermore, we also abandon the occurrence of regional emerging market crashes when four or more individual emerging markets in a particular region crash. In the second alternative classification a global crash occurs when three or four regions crash instead of two (from which one has to be developed). Though both settings are stricter, the estimation results using these alternative classifications hardly differ from the original one, see Table 2.6. In both cases, the coefficients of the previous day crash dummies remain highly significant, with magnitudes comparable to the base model. Hence, our conclusions regarding the domino effect are not affected.

In sum, the various robustness checks in this section demonstrate that our results are not due to the effects of time-varying volatility, and are not driven by arbitrary choices for the crash definitions and crash classifications.

2.5 Comparison with binomial global crash model

In this section we assess the economic relevance of the domino effect and our modelling approach. If relevant, including local and regional crashes should help forecasting global crashes. We address this issue by comparing our ordered logit model with a binomial logit model for global crashes only. For the latter model we combine the days with no crash, local crash or regional crash into a single "no global crash" state. Redefining the variable y_t to be equal to one when a global crash occurs and zero otherwise, the probability of a global crash in the binomial logit model is given by

$$p_t = \Pr(y_t = 1) = \frac{e^{\tilde{\boldsymbol{x}}_t' \boldsymbol{\beta}_b}}{1 + e^{\tilde{\boldsymbol{x}}_t' \boldsymbol{\beta}_b}}, \tag{2.7}$$

where the vector $\tilde{\boldsymbol{x}}_t$ includes the same financial variables as used in the ordered logit model plus a constant, but not the dummy variables for local and regional crashes occurring on the previous day.

2.5.1 In-sample comparison

The estimation results for the binomial model in Table 2.7 reveal several advantages of using the refined crash classification instead of a binomial approach. First, the coefficients in the ordered logit model as shown in Table 2.4 are estimated with considerably more precision, with standard errors being only half as large on average. For instance, the standard errors of the two extreme event coefficient estimates are 0.05 and 0.03 for the ordered model against 0.10 and 0.06 for the binomial model. Second, the ordered model shows more consistency concerning the signs of the coefficient estimates across different regions. For the interest rate and the equity volatility variables, we find that the estimated coefficients have the same sign for all four regions in the ordered model, while in the binomial model signs differ within these groups of variables. Including separate states for local and regional crashes thus increases the precision and the interpretability of the coefficient estimates for the explanatory variables.

Table 2.7: Estimation results binomial logit model

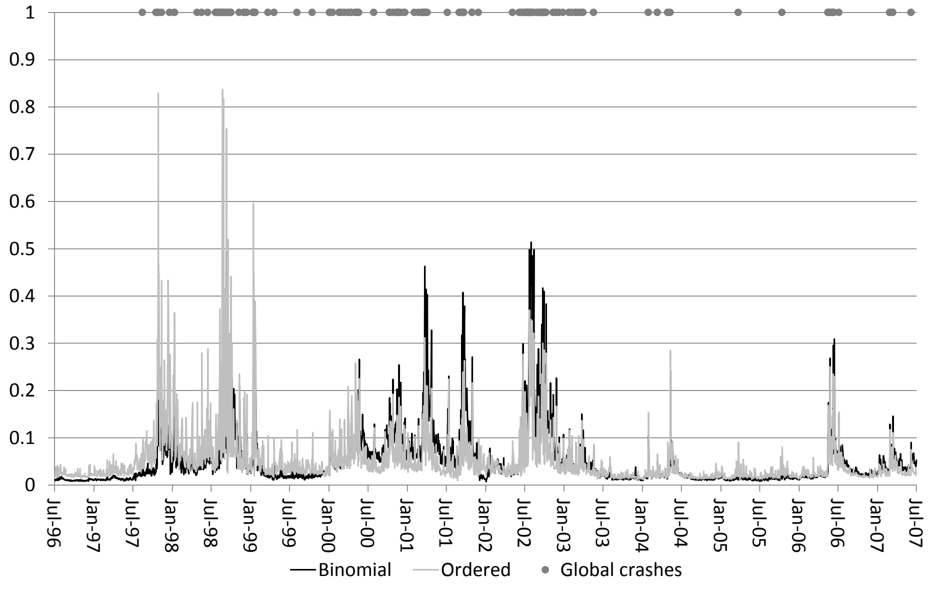
	Coeff.	St. error	t-stat.	p-value
Currency change LA	9.96	18.58	0.54	0.59
Currency change Asia	−20.21	23.31	−0.87	0.39
Bond returns LA	−19.35	10.52	−1.84	0.07
Bond returns Asia	12.89	26.49	0.49	0.63
Bond returns US	35.43	32.68	1.08	0.28
Bond Returns Europe	−6.56	13.92	−0.47	0.64
Interest level LA	−0.02	0.01	−1.15	0.25
Interest level Asia	−0.02	0.05	−0.34	0.73
Interest level US	0.60	0.18	3.29	0.00
Interest level Europe	−0.06	0.09	−0.62	0.54
Volatility LA	1.20	1.28	0.94	0.35
Volatility Asia	2.02	2.02	1.00	0.32
Volatility US	−1.30	2.22	−0.59	0.56
Volatility Europe	7.03	2.21	3.19	0.00
Extreme FX count	0.21	0.10	2.15	0.03
Extreme bond count	0.03	0.06	0.44	0.66
Global crash dummy	0.74	0.27	2.73	0.01
Constant	−6.40	0.51	−12.42	0.00
Log likelihood	−491.83			
R^2	0.13			

The table reports estimation results for the binomial logistic regression model for global crashes, with covariates as shown in the table. The variable 'Global' is a dummy variable taking the value one if a global crash occurred on the previous day. The sample period runs from July 1, 1996 to July 30, 2007 (2839 observations).

The ordered logit model explicitly uses the local and regional crashes in the parameter estimation, which obviously increases the total number of observed crashes. In this way it avoids a weakness of binomial crash models, namely that crashes occur too infrequently to estimate contagion and interdependence effects with sufficient precision. On the other hand the results in Section 2.4 show that the ordered model is still capable of distinguishing global crashes from less severe crashes.

Figure 2.2 shows the implied probabilities of observing a global crash obtained from the binomial model and the ordered logit model, as well as the actually observed global crashes. The ordered model for local, regional and global crashes leads to a better performance in detecting global crashes than only accounting for global crashes in the model. Especially periods in which global crashes are clustered are better detected, see for example the effects of the 1997 Asian crisis and the 1998 Russian debt crisis. Furthermore, around the burst of the internet bubble (March, 2000) the ordered model clearly shows increased global crash probabilities, while the binomial model hardly indicates any turmoil in financial markets. During the turbulent period between 2001 and 2003 the binomial model produces somewhat higher global crash

Figure 2.2: Global crash probability estimates in the ordered and binomial logit models.



The graph shows the estimated probabilities of a global crash for the ordered and binomial logit models. The actual occurrences of global crashes are indicated with bullets. The sample period runs from July 1, 1996 to July 30, 2007 (2839 observations).

probabilities than the ordered model. However, in those periods the ordered model's crash probabilities are also relatively high. After 2003 less global crashes occurred, but for the crashes that did occur, the ordered model is more successful in detecting them than the binomial model. This holds in particular for the period between December 2003 and December 2005.

2.5.2 Out-of-sample comparison

Next we examine the out-of-sample predictive accuracy of the ordered logit model, relative to the binomial model. We use the period July 1996 till December 2001 for specifying and estimating both models, and leave the period January 2002 till July 2007 for forecast evaluation.[16] Based on the conventional wisdom that large models

[16]We avoid using information from the out-of-sample period in the specification and estimation of the models by recomputing our dependent variable based on the 5th quantile of the empirical return distribution over the period till December 2001. The same applies to the regressors representing extreme events in the currency and bond markets.

with many insignificant parameters often lead to bad forecasting performance, we apply a variable selection procedure to reduce the number of covariates.[17] For both the ordered and binomial models we start with the full model and eliminate the least significant variable. Then the model is re-estimated and again the least significant variable is removed. This process is continued until the coefficients for all remaining variables are significant at the 10% level.[18]

Table 2.8 reports the results from this general-to-specific model selection procedure for both models. We observe that for both models the number of regressors is drastically reduced, though the ordered model contains somewhat more variables. Besides the previous crash dummies, which are all significant in both models, the ordered model contains six financial variables, while in the binomial model only four variables are included. This could be expected as the ordered model's estimates are more precise, as discussed in the previous section.

Forecasts of the probability of a global crash for the period January 2002 - July 2007 are displayed in Figure 2.3. The ordered model is clearly more successful than the binomial model in forecasting global crashes. The period May 2002 till June 2003 contains many global crashes. At the beginning of this period our ordered model already correctly warns for the occurrence of global crashes, while the binomial model's crash probabilities hardly increase. Then, during the period between July and October 2002, for both models the global crash probability forecasts strongly increase, taking values above 0.4. In this period both models are able to forecast the global crashes that occurred. After October 2002 the turmoil in the global financial markets continues, as indicated by the substantial number of global crashes that occur. During this period, the ordered model again forecasts the global crashes better than the binomial model. Finally, after 2003 some shorter periods with global crashes occurred and in all these cases the ordered model indicates this correctly, contrary to the binomial model.

To further analyze the differences in forecasting performance we compute the quadratic probability score (QPS), hit rates, false alarm rates and the Kuipers score, (see for example Granger and Pesaran, 2000). The QPS is defined as

$$\text{QPS} = \frac{1}{P} \sum_{t=R+1}^{T} (f_t - y_t)^2, \tag{2.8}$$

[17]Coefficient estimates in the full model over the sample July 1996 till December 2001 are comparable to Table 2.4, but standard errors are substantially larger. These results are available on request.

[18]Stricter significance levels would result in models with too few explanatory variables to make a fair comparison between the ordered and binary models.

Table 2.8: Estimation results from the general-to-specific model selection.

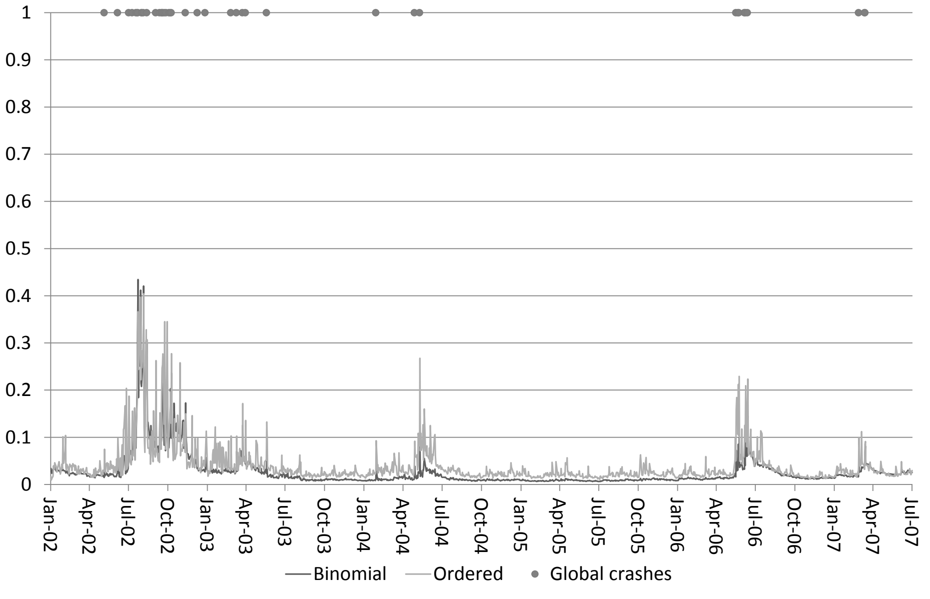
A: Ordered logit model	Coeff.	St. error	t-stat.	p-value
Bond returns LA	−23.98	5.91	−4.06	0.00
Bond returns US	43.93	19.70	2.23	0.03
Interest level Latin America	−0.01	0.01	−1.87	0.06
Volatility Asia	4.23	0.99	4.28	0.00
Volatility Europe	4.15	1.08	3.84	0.00
Extreme FX count	0.16	0.06	2.55	0.01
Local crash dummy	0.27	0.14	1.91	0.06
Regional crash dummy	0.68	0.18	3.76	0.00
Global crash dummy	0.92	0.28	3.27	0.00
α_1	2.19	0.22		
α_2	3.46	0.23		
α_3	4.92	0.26		
Log likelihood	−1290.05			
R^2	0.07			

B: Binomial model	Coeff.	St. error	t-stat.	p-value
Bond returns LA	−25.04	9.93	−2.52	0.01
Interest level US	0.39	0.21	1.88	0.06
Volatility Asia	3.74	2.20	1.70	0.09
Volatility Europe	7.17	2.11	3.41	0.00
Global	0.72	0.43	1.67	0.09
constant	−6.76	0.92	−7.36	0.00
Log likelihood	−229.69			
R^2	0.13			

The table reports the estimation results for the ordered and binomial logistic regressions, after the removal of insignificant coefficients. An iterative general-to-specific procedure is used where in each iteration the variable with the least significant coefficient estimate is removed, until all remaining coefficients are significant at the 10% level results. The remaining covariates in the final models are as shown in the table. The variables 'Local', 'Regional' and 'Global' are dummy variables taking the value one if this type of crash occurred on the previous day. The sample period runs from July 1, 1996 to December 31, 2001 (1421 observations).

where f_t is the probability forecast for time t and $y_t \in \{0, 1\}$ is the corresponding realization, R and P are the number of observations in the in-sample and out-of-sample periods, with $R + P = T$. The QPS varies between zero and one, indicating perfect and no forecasting performance, respectively. For the binomial and ordered models, the QPS attains the value 0.0262 and 0.0260, indicating a slightly better forecast performance for the ordered logit model, although the difference seems negligible. Since global crashes are rare, the QPS is dominated by the frequent observations of no global crash.

Figure 2.3: Global crash probability forecasts in the ordered and binomial logit models.



The graph shows the probability forecasts of a global crash for the ordered and binomial logit models. The actual occurrences of global crashes are indicated with bullets. The sample period runs from January 1, 2002 to July 30, 2007 (1417 observations).

To focus on the ability of the models to forecast global crashes, we examine their hit rates and false alarm rates. The hit rate is defined as the fraction of crashes that were correctly predicted, while the false alarm rate is defined as the fraction of days without a global crash for which a crash was predicted to occur. Obviously, computing the hit rate and false alarm rate requires a cut-off level w, such that probability forecasts larger than w are taken to be predictions of a crash. We vary w between 0 and 0.20 with increments of 0.01, to examine the sensitivity of the forecast performance to this cut-off level.

Table 2.9 shows the hit rates and false alarm rates for the different values of w. Also shown is the Kuipers score, defined as the difference between the hit rate and the false alarm rate. Both models attain the highest Kuipers score for $w = 0.03$, with values equal to 0.546 for the ordered model and 0.535 for the binomial model. Again, the ordered model has slightly better predictive accuracy. It is useful to note that the underlying hit rates and false alarm rates differ substantially though, and are equal to 0.732 and 0.197 for the binomial model, and 0.927 and 0.381 for the ordered

Table 2.9: Forecast performance evaluation

	Ordered				Binomial			
w	H	F	KS	c s.e.	H	F	KS	s.e.
0.00	1.000	1.000	0.000	0.000	1.000	1.000	0.000	0.000
0.01	1.000	0.999	0.001	0.001	1.000	0.727	0.273	0.012
0.02	1.000	0.715	0.285	0.012	0.878	0.360	0.518	0.053
0.03	0.927	0.381	0.546	0.043	0.732	0.197	0.535	0.070
0.04	0.756	0.230	0.526	0.068	0.634	0.120	0.514	0.076
0.05	0.683	0.151	0.532	0.073	0.561	0.097	0.464	0.078
0.06	0.634	0.120	0.514	0.076	0.488	0.076	0.412	0.078
0.07	0.585	0.092	0.493	0.077	0.439	0.062	0.377	0.078
0.08	0.585	0.072	0.514	0.077	0.366	0.053	0.313	0.075
0.09	0.512	0.064	0.448	0.078	0.293	0.044	0.248	0.071
0.10	0.488	0.051	0.437	0.078	0.244	0.036	0.208	0.067
0.11	0.366	0.041	0.325	0.075	0.244	0.031	0.213	0.067
0.12	0.342	0.035	0.307	0.074	0.220	0.025	0.194	0.065
0.13	0.268	0.029	0.239	0.069	0.220	0.020	0.199	0.065
0.14	0.244	0.026	0.218	0.067	0.220	0.016	0.204	0.065
0.15	0.244	0.024	0.220	0.067	0.220	0.014	0.206	0.065
0.16	0.244	0.020	0.224	0.067	0.195	0.013	0.182	0.062
0.17	0.220	0.019	0.201	0.065	0.195	0.013	0.182	0.062
0.18	0.195	0.018	0.177	0.062	0.195	0.012	0.184	0.062
0.19	0.171	0.017	0.154	0.059	0.195	0.011	0.184	0.062
0.20	0.171	0.015	0.155	0.059	0.171	0.010	0.161	0.059

The table reports the hit rate (H), the false alarm rate (F), and the Kuipers score ($KS = H - F$) and its standard error, for probability forecasts of global crashes obtained from the ordered and the binomial logit models, for the period January 1, 2002 - July 30, 2007 (1417 observations). Probability forecasts exceeding the cut-off level w are taken to be predictions of a global crash.

model. This means that for the optimal Kuipers score the ordered model predicts almost all global crashes (93 percent) correctly, which comes at the expense of a substantial number of false alarms (38 percent). The binomial model predicts only 73 percent of the crashes correctly, with 20 percent false alarms. If missing a global crash is more costly than a false alarm, which is likely to be the case in practice, the ordered logit approach is clearly to be preferred. This conclusion actually also holds if false alarm rates were relatively expensive. In that case, we could choose, for instance, a cutoff level of 0.08 for the ordered logit model, giving a false alarm rate of only 7.2 percent and a hit rate of 59 percent. To compare this with the binomial model we might take $w = 0.06$, which results in a comparable false alarm rate (7.6 percent), at the cost of a 10 percent (58.5-48.8) lower hit rate.

2.6 Conclusions

In this chapter we have investigated whether stock market crashes propagate from local to regional and global levels as a domino effect. Using daily returns for a sample of emerging and developed stock markets for the period July 1996 - July 2007, we classified crashes as local, regional or global. This classification was used in an ordered logit regression framework to examine the propagation of stock market crashes, and the relevance of interdependence and contagion effects. Our approach differs from other studies by explicitly defining different types of crashes, and modelling their transmission mechanism as a domino effect.

We report evidence that less severe crashes tend to be followed by more severe crashes. The probabilities of a regional or global crash occurring tomorrow increase significantly and substantially when a local (or regional) crash occurs today. In explaining the occurrence and evolution of crashes we also find evidence for interdependence between stock markets and other asset markets. Information from the currency, stock and bond markets are important determinants of the probabilities of local, regional or global crash occurrences. Our out-of-sample analysis confirms the superiority of the ordered model that includes local and regional crashes in forecasting global crashes to a standard binomial model.

The domino effect that we report holds an important lesson for investors and regulators. On the one hand, it stresses again the danger of contagion in financial markets, as it exists beyond dependencies and linear autocorrelation that dominate normal periods. On the other hand, the domino effect can be used to improve early-warning systems. Besides the statistical evidence for incorporating the domino effect, we also document its economic relevance. If failing to forecast global crashes is more costly than giving a false alarm, the ordered model with the domino effect outperforms the binomial model without it. If the false alarm rate should be kept at reasonable levels, to limit reputational damage for example, the ordered model does a better job as well. Concluding, because of their susceptibility to macroeconomic shocks, emerging markets can be the point of origin of an eventually global crash. Therefore, all investors and regulators should keep an eye on what happens in these markets, whether they are directly exposed to it or not.

2.A Conditional effects

In this appendix we discuss the results obtained from the ordered logit model with conditional effects, that is, the effects of financial variables on the crash probabilities are allowed to be dependent on past crashes. To test for the presence of this mixed type of interdependence and contagion, we proceed as follows. We interact one of the financial variables x_{it} in the model with the different past crash dummy variables. Thus we obtain four state dependent variables $x_{it}D_{jt} \equiv x_{it|j}$, where D_{jt} is a dummy variable taking the value one if crash type j occurs at time $t-1$ and zero otherwise. We estimate an ordered logit model including these four new conditional variables and the other variables in their original form. We repeat this procedure for each of the financial variables included in the model, resulting in sixteen separate ordered logit regressions. The reason for not estimating a model which has coefficients varying with the crash type for all financial variables simultaneously is the large number $(16 \times 4 + 3 + 3 + 1 = 71)$ of coefficients.

If this intermediate form of interdependence and contagion were relevant, we would expect to find clear patterns in the estimates of the state-dependent coefficients. For instance, for the average currency change variables we expect the coefficients to become more negative conditional on more severe crashes, as this implies that the higher the turmoil, the stronger the relation between stock market crashes and currency changes.

To formally examine whether this extension of the model leads to better description of the observed crashes, we perform likelihood ratio (LR) tests for the null hypothesis that the coefficients $\beta_{i|j}$, $j = 0, 1, 2, 3$, of the state-dependent variables are equal. This test statistic is χ^2 distributed with three degrees of freedom, corresponding to three parameter restrictions $\beta_{i|0} = \beta_{i|1} = \beta_{i|2} = \beta_{i|3}$.

Table 2.10 reports the estimates of the state-dependent parameters for the sixteen estimated regression models together with the p-value of the LR test for their equality. To save space we do not report the estimates of the other coefficients in these models.[19] In general we do not observe clear patterns in the estimates of the state-dependent coefficients. In fact, for almost all variables the conditional estimates fluctuate around the coefficient estimate in the base model in a seemingly random fashion. In addition, except for the bond returns and the volatility variable in Asia, the LR tests do not reject the null of equality of the conditional coefficients, confirming that the relations between crashes and the financial variables are not dependent on past crashes. Put differently, the effects of the financial variables on the crash

[19] The estimates of the other coefficients hardly change compared to the base model in Table 2.4.

Table 2.10: Regression results with crash dependent effects

	Coefficient	St. error	t-statistic	p-value
Currency change LA (N)	0.08	14.78	0.01	1.00
Currency change LA (L)	5.06	11.70	0.43	0.67
Currency change LA (R)	−6.48	28.25	−0.23	0.82
Currency change LA (G)	−62.20	27.00	−2.30	0.02
Local	0.38	0.10	3.72	0.00
Regional	0.60	0.15	4.05	0.00
Global	1.37	0.20	6.77	0.00
Log likelihood	−2610.48			
$\chi(3)$	0.13			
Currency change Asia (N)	8.21	14.14	0.58	0.56
Currency change Asia (L)	26.37	20.22	1.30	0.19
Currency change Asia (R)	−5.93	19.13	−0.31	0.76
Currency change Asia (G)	−44.27	46.35	−0.96	0.34
Local	0.38	0.10	3.74	0.00
Regional	0.64	0.14	4.46	0.00
Global	1.28	0.20	6.44	0.00
Log likelihood	−2611.92			
$\chi(3)$	0.44			
Bond returns LA (N)	−38.56	10.11	−3.81	0.00
Bond returns LA (L)	−34.50	11.06	−3.12	0.00
Bond returns LA (R)	−20.37	11.74	−1.73	0.08
Bond returns LA (G)	1.79	10.61	0.17	0.87
Local	0.37	0.10	3.66	0.00
Regional	0.58	0.14	4.10	0.00
Global	1.37	0.20	6.90	0.00
Log likelihood	−2608.59			
$\chi^2(3)$	0.07			
Bond returns Asia (N)	−54.95	23.96	−2.29	0.02
Bond returns Asia (L)	−26.92	21.50	−1.25	0.21
Bond returns Asia (R)	−7.49	29.42	−0.25	0.80
Bond returns Asia (G)	41.90	23.49	1.78	0.07
Local	0.37	0.10	3.61	0.00
Regional	0.57	0.14	4.03	0.00
Global	1.23	0.19	6.48	0.00
Log likelihood	−2608.41			
$\chi^2(3)$	0.02			
Bond returns US (N)	28.90	19.93	1.45	0.15
Bond returns US (L)	53.31	29.58	1.80	0.07
Bond returns US (R)	32.28	38.47	0.84	0.40
Bond returns US (G)	33.10	57.41	0.58	0.56
Local	0.40	0.10	4.04	0.00
Regional	0.62	0.14	4.43	0.00
Global	1.22	0.21	5.91	0.00
Log likelihood	−2613.00			
$\chi^2(3)$	0.91			
Bond returns Europe (N)	−20.64	9.43	−2.19	0.03
Bond returns Europe (L)	16.12	13.06	1.23	0.22
Bond returns Europe (R)	−30.28	16.38	−1.85	0.06
Bond returns Europe (G)	4.00	19.12	0.21	0.83
Local	0.40	0.10	3.98	0.00
Regional	0.63	0.14	4.55	0.00
Global	1.19	0.19	6.23	0.00
Log likelihood	−2609.50			
$\chi^2(3)$	0.06			

Table 2.10: Regression results with crash dependent effects, *continued*

	Coefficient	St. error	t-statistic	p-value
Interest level LA (N)	0.00	0.01	0.55	0.58
Interest level LA (L)	0.01	0.01	0.97	0.33
Interest level LA (R)	−0.01	0.01	−1.07	0.28
Interest level LA (G)	−0.03	0.03	−1.05	0.30
Local	0.33	0.16	2.07	0.04
Regional	0.85	0.24	3.57	0.00
Global	1.70	0.47	3.58	0.00
Log likelihood	−2611.53			
$\chi^2(3)$	0.32			
Interest level Asia (N)	0.03	0.02	1.23	0.22
Interest level Asia (L)	0.05	0.02	2.24	0.03
Interest level Asia (R)	0.06	0.04	1.53	0.13
Interest level Asia (G)	−0.05	0.07	−0.78	0.44
Local	0.23	0.22	1.07	0.29
Regional	0.42	0.30	1.40	0.16
Global	1.69	0.44	3.81	0.00
Log likelihood	−2611.748			
$\chi^2(3)$	0.39			
Interest level US (N)	0.05	0.09	0.53	0.60
Interest level US (L)	0.13	0.12	1.03	0.30
Interest level US (R)	−0.14	0.17	−0.79	0.43
Interest level US (G)	0.13	0.23	0.55	0.58
Local	0.14	0.42	0.35	0.73
Regional	1.23	0.60	2.06	0.04
Global	0.93	0.84	1.11	0.27
Log likelihood	−2612.28			
$\chi^2(3)$	0.58			
Interest level Europe (N)	0.03	0.04	0.77	0.44
Interest level Europe (L)	0.04	0.06	0.72	0.47
Interest level Europe (R)	0.07	0.07	0.91	0.36
Interest level Europe (G)	0.00	0.09	0.00	1.00
Local	0.37	0.27	1.39	0.16
Regional	0.47	0.34	1.38	0.17
Global	1.35	0.42	3.21	0.00
Log likelihood	−2613.04			
$\chi^2(3)$	0.93			
Volatility LA (N)	1.04	0.85	1.22	0.22
Volatility LA (L)	0.32	1.02	0.31	0.75
Volatility LA (R)	1.26	1.17	1.08	0.28
Volatility LA (G)	−1.62	1.45	−1.11	0.27
Local	0.55	0.26	2.16	0.03
Regional	0.53	0.34	1.55	0.12
Global	1.93	0.46	4.15	0.00
Log likelihood	−2611.58			
$\chi^2(3)$	0.34			
Volatility Asia (N)	2.74	1.05	2.60	0.01
Volatility Asia (L)	1.86	1.32	1.41	0.16
Volatility Asia (R)	1.26	1.82	0.69	0.49
Volatility Asia (G)	−6.99	3.10	−2.26	0.02
Local	0.54	0.28	1.94	0.05
Regional	0.88	0.42	2.11	0.04
Global	3.25	0.69	4.69	0.00
Log likelihood	−2608.58			
$\chi^2(3)$	0.02			

Table 2.10: Regression results with crash dependent effects, *continued*

	Coefficient	St. error	t-statistic	p-value
Volatility US (N)	2.42	1.21	1.99	0.05
Volatility US (L)	0.84	1.54	0.55	0.58
Volatility US (R)	0.10	1.80	0.06	0.95
Volatility US (G)	−0.23	2.29	−0.10	0.92
Local	0.66	0.27	2.44	0.01
Regional	1.05	0.37	2.82	0.00
Global	1.75	0.54	3.24	0.00
Log likelihood	−2611.83			
$\chi^2(3)$	0.41			
Volatility Europe (N)	2.97	1.30	2.29	0.02
Volatility Europe (L)	3.38	1.70	1.99	0.05
Volatility Europe (R)	0.57	1.93	0.29	0.77
Volatility Europe (G)	0.62	2.34	0.26	0.79
Local	0.34	0.27	1.23	0.22
Regional	1.06	0.37	2.86	0.00
Global	1.71	0.54	3.15	0.00
Log likelihood	−2611.88			
$\chi^2(3)$	0.43			
Extreme FX (N)	0.13	0.08	1.70	0.09
Extreme FX (L)	0.19	0.09	2.21	0.03
Extreme FX (R)	0.17	0.10	1.72	0.09
Extreme FX (G)	0.09	0.14	0.67	0.50
Local	0.37	0.12	3.10	0.00
Regional	0.59	0.16	3.58	0.00
Global	1.26	0.23	5.51	0.00
Log likelihood	−2613.00			
$\chi^2(3)$	0.91			
Extreme bond (N)	0.08	0.04	1.81	0.07
Extreme bond (L)	0.02	0.05	0.46	0.64
Extreme bond (R)	0.00	0.07	−0.03	0.97
Extreme bond (G)	−0.15	0.09	−1.79	0.07
Local	0.44	0.12	3.71	0.00
Regional	0.69	0.17	3.94	0.00
Global	1.53	0.23	6.59	0.00
Log likelihood	−2610.18			
$\chi^2(3)$	0.10			

The table reports estimation results for the ordered logistic regression model for the four different crash categories (no, local, regional, global), with covariates as shown in Table 5.6., but in each regression one original variable is conditioned on the occurrence of a crash on the previous day. Thus, in each case we multiply the variable under consideration with the past crash dummies (including a no crash dummy), which gives rise to four variables. For convenience we only report coefficient estimates for the crash dummies and for the crash conditioned variable, where the labels (N), (L), (R) and (G) refer to no crash, and local, regional and global crash, respectively. The $\chi^2(3)$-statistic tests whether conditioning a variable significantly improves the model. The sample period runs from July 1, 1996 to July 30, 2007 (2839 observations).

probabilities do not depend on the degree of turmoil in the financial markets. Thus we find no evidence of this intermediate type of contagion and interdependence.

However, there are some interesting but also counterintuitive results in Table 2.10. First, while the average currency depreciation in Latin America was not significant in the base model, this relation becomes significant when a global crash has occurred on the previous day. For the average currency depreciation in Asia we observe the same pattern, but here the coefficients are not significant. It seems that normal currency depreciations increase the crash probabilities only if a global crash occurred on the previous day. Thus, in times of high turmoil investors also seem to take into account normal depreciations.

In the conditional regressions for the interest rates some past crash dummies become insignificant, while the interest rate variables remain insignificant. To a lesser extent this occurs for equity volatility too. This has a more statistical than economic cause: as the interest rates and volatilities are strictly positive, the dummy variables and their respective conditional variables attain the value zero or a value larger than zero simultaneously. This results in very high correlations of around 0.95 between the past crash dummies and the conditional variables.

Chapter 3

The Rise of Global Stock Market Crash Probabilities: 1992-2010

3.1 Introduction

During the last decades the dependence between global stock markets has increased as a result of financial globalization. Ample empirical evidence for this increased dependence exists. Longin and Solnik (1995), Berben and Jansen (2005) and Baele and Inghelbrecht (2009) show that the dependence between developed markets has increased significantly over past decades. In addition, emerging markets have become more financially integrated (see Bekaert and Harvey, 1995, 2003; De Roon, 2005; Bekaert et al., 2003). For investors this means that diversification opportunities for investing in global stock markets have decreased, while risk managers are exposed to higher risks holding a globally diversified portfolio.

Thus, the developed and the emerging markets have become more integrated, and their respective stock markets have become more dependent Beine et al. (see 2010, for instance). This increased dependence might also result in a higher tendency for these markets to crash together. Therefore, we hypothesize that the probability of global stock market crashes has increased over the past two decades. It is exactly these global crashes that investors fear the most, because during such crashes diversification possibilities evaporate. This shows the necessity of having a good understanding of how likely global crashes are to occur, and how severe these are likely to be.

This chapter investigates whether global stock market crashes are likely to occur more frequently these days as a consequence of increased financial globalization. For instance, if the integration of emerging markets has not resulted in emerging and developed stock markets having a higher tendency to crash together, then an investor still has the opportunity to diversify his exposures by investing in emerging stock markets.

To make any inference on global crash probabilities, and consequently test our hypothesis, we need to specify a return distribution. Longin and Solnik (2001), Ang and Chen (2002), Poon et al. (2004) and Hartmann et al. (2004) show that for multivariate returns, the dependence in the tails (especially the negative tail) is higher than the dependence implied by a multivariate normal distribution. The linear correlation coefficient, the natural dependence measure if variables are normally distributed, is therefore not suitable for measuring the dependence between stock returns, because it is a symmetric measure and it cannot capture tail dependence and asymmetry. In this context this would imply that the global crash probabilities are underestimated when the linear correlation coefficient is used as a dependence measure, if the returns are not generated by a Gaussian distribution.

Therefore, copulas are more frequently used to model dependence between financial variables (see Patton, 2009, and the references therein). With copulas we can separate the dependence structure from the marginal distributions. In other words, we can build a multivariate distribution, by choosing marginal distributions and the copula, which completely describes the dependence, separately. As the dependence structure can vary over time, and different copulas lead to different dependence structures, copulas are an appropriate tool to put our hypothesis under scrutiny.

We test our hypothesis by looking at the changes in global crash probabilities since 1992, using a rolling copula approach. We consider weekly stock market returns from four regions, the emerging markets in Latin America and Asia and developed markets in the United States and Europe. For every four year window in our rolling copula approach we estimate five different copulas, all with different dependence structure, resulting in time series of the dependence measures. Then, we define a global crash as a week in which all the four regions have a return belonging to the lower 5% quantile of the return distribution. These global crash probabilities are computed with the use of the parameter estimates for the different copulas.

Our results show that global crash probabilities have significantly and dramatically increased from 0.1 % in December 1992 to around 1.5% in February 2010. When we consider the sample running from December 1992 until December 2007, with the exclusion of the credit crisis, which possibly blurs the results, the increase in global crash probabilities is still significant. We find that only during the Asian and credit crisis the rotated Gumbel copula, an asymmetric copula with strong lower tail dependence, is most suitable to model the return distribution. During other periods this is either the symmetric tail independent Gaussian or symmetric tail dependent Student's t copula. Additionally, due to the Asian crisis the global crash probabilities increased by a large amount, and never returned to the levels before this crisis. These results are robust for the length of the rolling window and for different quantiles used to define crashes. When global crashes are defined as three regions instead of four regions crashing together, the results remain comparable as well.

We contribute to the existing literature in three ways. First, we show in a novel way, by using multivariate copulas, how the integration of the financial system has changed the dependencies between stock markets of different regions. Most other studies using copulas to examine changes in dependence only consider bivariate pairs, (see Jondeau and Rockinger, 2006; Patton, 2006b; Rodriguez, 2007; Dias and Ebrechts, 2009; Guegan and J.Zhang, 2009). The importance of using higher dimensional copulas, particularly when concerning the tails of the multivariate distribution, can be illustrated with the following example. If we use a bivariate Gaussian copula with correlation 0.25 and the correlation doubles, then the 5% percent joint crash probability approximately doubles as well. However, if we use a four-dimensional Gaussian copula with pair-wise correlations of 0.25 and the correlations double, then the 5% percent joint crash probability increases 7.5 times. This effect becomes even more pronounced, when larger differences in dimensions are used. This shows the importance of using higher dimensional copulas when analyzing crash probabilities.

Second, we use a rolling copula approach, which makes our time-variation with regards to dependence more robust than other studies, which is particularly important for studying phenomena such as crashes. For instance, Jondeau and Rockinger (2006) and Patton (2006b) use GARCH type evolutions of the copula parameters. It is not straightforward on how these evolutions should modeled, and logistic transformations have to be imposed to keep the parameter in its feasible range. Jondeau and Rockinger (2006) and Rodriguez (2007) use Markov switching in the dependence parameters. Although these models can accommodate abrupt changes, and can model persistence in dependence well, these only allow for different levels of dependence equal to the number of states. Our rolling window approach does not suffer from these problems, because no specific evolution process has to be assumed and dependence measures can attain continuous different levels.

Finally, we explicitly compute probabilities of these geographic regions crashing together. These can function as important inputs in investment strategies and risk management. To the best of our knowledge, such quantification on global crash probabilities has not been done before.

Another possibility to calculate global crash probabilities is to use multivariate Extreme Value Theory (EVT) as in Hartmann et al. (2004), which is an easy and theoretically well-founded technique to compute (conditional) probabilities of more markets jointly crashing together. The idea behind this technique is based on counting exceedances over or below a certain threshold. For example, suppose a risk-manager needs to calculate the probability that two assets jointly have a return below -10%. The risk-manager often faces the problem that the data set only (if at all) contains a few return observations below -10%. However, probabilities of exceedances below a lower (in absolute terms) threshold, say -5% or -2.5%, can often be properly calculated. Then, according to EVT, these probabilities can be extrapolated to probabilities of exceedances below higher thresholds. However, we have several reasons to use the parametrical copula approach instead. Firstly, EVT suffers from the curse of dimensionality, while this copula approach can be used in larger dimensions. Secondly, the copula setup can be easily extended to incorporate time-variation in the dependence. For intance, we can let the copula parameters evolve according to a GARCH-type process, or according to a Markov switching model to distinguish between bull and bear markets. Such dynamics are much less straightforwardly incorporated using EVT. Finally, no optimal threshold exists for which data can be used for tail-estimation. See Embrechts et al. (1997) for an overview for other weaknesses of EVT.[1]

The Chapter proceeds as follows. In Section 3.2 we describe the methodology used in the chapter. Section 3.3 discusses the data. We report the estimation results in Section 3.4. Sensitivity tests are performed in Section 3.5. We draw conclusions in Section 3.6.

3.2 Methodology

3.2.1 The model

To model the stock market dependence between different regions and to compute the probabilities of global crashes, we have to specify the joint density of these regions' stock markets, say $f(\mathbf{x})$, where f is the density function of the n-dimensional stock market return vector $\mathbf{x}$. However, given the empirical evidence of nonlinear dependence of stock market returns (see Poon et al., 2004, among others), we use a copula approach to model the dependence between the returns. Copulas are used as an

[1] Embrechts (2000) concludes that EVT is a useful technique for risk-management on a complementary basis. However, it should only play a small, though important, role. From that perspective, it would be an interesting extension of this research to compare our results with results obtained with EVT.

intuitive way to link univariate distributions with a dependence structure, resulting in a multivariate distribution. Sklar (1959)'s theorem provides this mapping:

$$\mathbf{F}(x_1, \ldots, x_n) = \mathbf{C}(F_1(x_1), \ldots, F_N(x_n)). \tag{3.1}$$

This theorem states that we can split any cumulative multivariate distribution $\mathbf{F}$ into marginals distributions F_i and a copula $\mathbf{C}$. The reverse means that we can combine different margins into a multivariate distribution by using a copula. This approach enables us to model the dependence among stock markets irrespective of the marginal behavior of the components of $f(\mathbf{x})$. For a comprehensive overview of copulas see Joe (1997).

We briefly describe the marginal models after which we look at the dependence model in much more detail. To prevent misspecification of the margins we will use the empirical distribution function as marginal models. Using the empirical distribution function leads to consistent estimates, although these are not as efficient as in the case where the correct margins are specified (see Chen and Fan; Genest and Rivest, 1993; Genest et al., 1995). On the other hand, using wrongly specified margins can lead to biased estimates for the copula parameters (see Fermanian and Scaillet, 2005). As our main purpose is modeling the dependencies among the regions and the empirical distribution function leads to consistent estimates, we use the empirical distribution function for the margins.[2]

Regarding the dependence model, one of the most important dependence characteristics of stock markets is the existence of asymmetric dependence and tail dependence. Asymmetric dependence means that the dependence is higher during crashes than during booms. To explain tail dependence, we first introduce quantile dependence. In the bivariate case, lower (upper) quantile dependence is defined as the probability that a return is below (above) a given quantile q, given the other return was also below (above) a quantile q. The mathematical expression for lower quantile dependence is

$$\tau_L(q) = P(F_1(x_1) < q | F_2(x_1) < q) = \frac{C(q,q)}{q}, \tag{3.2}$$

and for upper quantile dependence it is

$$\tau_U(q) = P(F_1(x_1) > q | F_2(x_1) > q) = \frac{1 - 2q - C(q,q)}{1-q}. \tag{3.3}$$

[2] We redid the analysis with asymmetric GARCH(1,1,1) marginal models. Although quite frequently the standardized residuals did not pass the empirical distribution tests for normality, the copula estimates were quite comparable.

Lower and upper tail dependence coefficients are defined as the limits of the quantile dependence measures, that is

$$\lambda_L = \lim_{v \downarrow 0} \frac{C(v,v)}{v} \quad \text{and} \quad \lambda_U = \lim_{v \uparrow 1} \frac{1-2v+C(v,v)}{1-v}.$$

This means that for copulas with relatively high lower tail dependence crashes are more likely than for copulas with relatively low lower tail dependence. To examine changing dependencies and changes in global crash probabilities over time, we will use three different dependence structures: a symmetric structure without any tail dependence; a symmetric structure with both upper and lower tail dependence; and an asymmetric structure with only lower tail dependence and no upper tail dependence. We do not consider copulas with only upper tail dependence, or copulas with non-zero, but different lower and upper tail dependence, because the purpose of this study is to examine crash probabilities. Moreover, other studies (see Hu, 2006, for instance) do not find upper tail dependence, while there is no lower tail dependence, between stock market returns.

For the tail-independent and tail-dependent symmetric dependence structures two suitable candidates are the Gaussian and the Student's t copula. The tail-independent (see Embrechts et al., 2002) Gaussian copula is defined by the cumulative distribution function (cdf)

$$C^{\Phi}(u_1 \dots u_n; \Omega^{\Phi}) = \Phi_n(\Phi^{-1}(u_1) \dots \Phi^{-1}(u_n); \Omega^{\Phi}), \tag{3.4}$$

where Φ_n is the n-variate normal cdf with correlation matrix $\mathbf{\Omega^{\Phi}}$, and Φ^{-1} is the inverse of the univariate normal cdf.

The Student's t copula is defined by the cdf

$$C^{\Psi}(u_1 \dots u_n; \Omega^{\Psi}, \nu^{\Psi}) = \Psi_n(\Psi^{-1}(u_1; \nu^{\Psi}) \dots \Psi^{-1}(u_n; \nu^{\Psi}); \Omega^{\Psi}, \nu^{\Psi}), \tag{3.5}$$

where Ψ_n is the n-variate Student's t cdf with correlation matrix $\mathbf{\Omega^{\Psi}}$ and d.f. ν^{Ψ} and Ψ^{-1} is the inverse of the univariate Student's t cdf. The symmetric Student's t copula exhibits equal upper and lower tail-dependence, given by $\lambda = t_{\nu+1}\left(\sqrt{(\nu+1)\frac{\rho-1}{\rho+1}}\right)$. The Student's t copula has the disadvantage that the degrees of freedom between the pairs is the same for all pairs. Shortly below we describe how we deal with this problem.

For the asymmetric dependence structure, i.e. copulas with only lower tail dependence, the choice is a bit more difficult, as there are in this case no parametric multivariate copulas with different dependence between different pairs. Two commonly used asymmetric copulas are the Clayton and the Gumbel copula. The Clayton copula is defined by the cdf

$$C^{cl}(u_1 \ldots u_n; \gamma) = \left(u_1^{-\gamma} + \ldots + u_1^{-\gamma} - d + 1\right)^{\frac{-1}{\gamma}}, \tag{3.6}$$

with $\gamma > 0$. This copula is asymmetric and it puts more weight on events in the negative tail. Lower tail dependence is equal to $\lambda^L = 2^{\frac{-1}{\gamma}}$, and upper tail dependence is equal to zero. The Gumbel copula is defined by the cdf

$$C^{Gum}(u_1 \ldots u_n; \delta) = \exp\left(-\left((-\ln u_1)^{\delta} + \ldots + (-\ln u_n)^{\delta}\right)^{1/\delta}\right). \tag{3.7}$$

This copula is asymmetric and it puts more weight on events in the positive tail. Therefore, we use the rotated (or survival) version of it (see Joe, 1997). This rotated version has lower tail dependence equal to $\lambda^L = 2 - 2^{\frac{1}{\delta}}$ and no upper tail dependence.

For dimensions larger than 2, the Clayton copula and the (survival) Gumbel copula have only one dependence parameter for all pairs. This is rather restrictive as it, for instance, would imply an equal dependence between the US-Europe and US-Asia stock market pair. However, there are different extensions for increasing the dimensionality of these copulas. We use the method described in Aas et al. (2009) to construct higher-dimensional copulas out of two-dimensional copulas. These pair copulas are not constrained by the restriction that the dependence is same between different pairs.

This methodology also allows us to estimate a multivariate Student's t copula where the degrees of freedom (d.f.) can differ between pairs. The resulting Student's t copula is a natural, more flexible, extension to the "standard" Student's t copula. To summarize: we use two "standard" four dimensional copulas (Gaussian and Student's t) and we use three pair constructed copulas (Clayton, Gumbel and Student's t with different d.f.).

3.2.2 Densities and likelihoods pair construction

This section summarizes the methodology of Aas et al. (2009) and shows how it is applicable in this research. The main idea is that not only copulas but all multivariate distributions can be decomposed as a function of bivariate distributions, of which some are conditional distributions on other variables. This idea was introduced by Joe (1996). Aas et al. (2009) were the first to apply this methodology on copulas.

Multivariate distribution can be decomposed into $n(n-1)/2$ bivariate distributions. However, there are many possible orderings of conditional bivariate densities that lead to the same multivariate distribution. Bedford and Cooke (2001, 2002) elaborated on this topic and used vines to model the conditional densities. By far the most used vines are the canonical vine and the D-vine. In this research a canonical vine is most applicable because the US stock market, being the largest and leading stock market, can serve as a pivotal variable.

Figure 3.1 illustrates how a canonical vine copula is constructed. We first model the dependence between the pivotal variable US, indexed by 1, and the other variables Europe, Latin America and Asia, indexed by 2, 3 and 4. With these dependencies (**12**, **13** and **14**) we construct new variables, conditioned on variable 1. For instance, the new pivotal variable Europe, given the US, is denoted 2|1. Next, we model the dependence between the new constructed variables, where the dependence **23|1** represents the dependence between Europe and Latin America, conditioned on the US. In the last step we model the dependence **34|12** between Latin America (3|12) and Asia (4|12), all conditioned on the US and Europe.

In appendix A we show in more detail how the multivariate distributions can be constructed out of pair copulas. The probability density function (pdf) for the four-dimensional canonical vine in general becomes

$$\begin{aligned} c(u_1, u_2, u_3, u_4) &= c_{12}(F_1(u_1), F_2(u_2)) \cdot c_{13}(F_1(u_1), F_3(u_3)) \\ &\cdot \; c_{14}(F_1(u_1), F_4(u_4)) \cdot c_{23|1}(F(u_2|u_1), F(u_3|u_1)) \\ &\cdot \; c_{24|1}(F(u_2|u_1), F(u_4|u_1)) \cdot c_{34|12}(F(u_3|u_1, u_2), F(u_4|u_1, u_2)), \end{aligned} \tag{3.8}$$

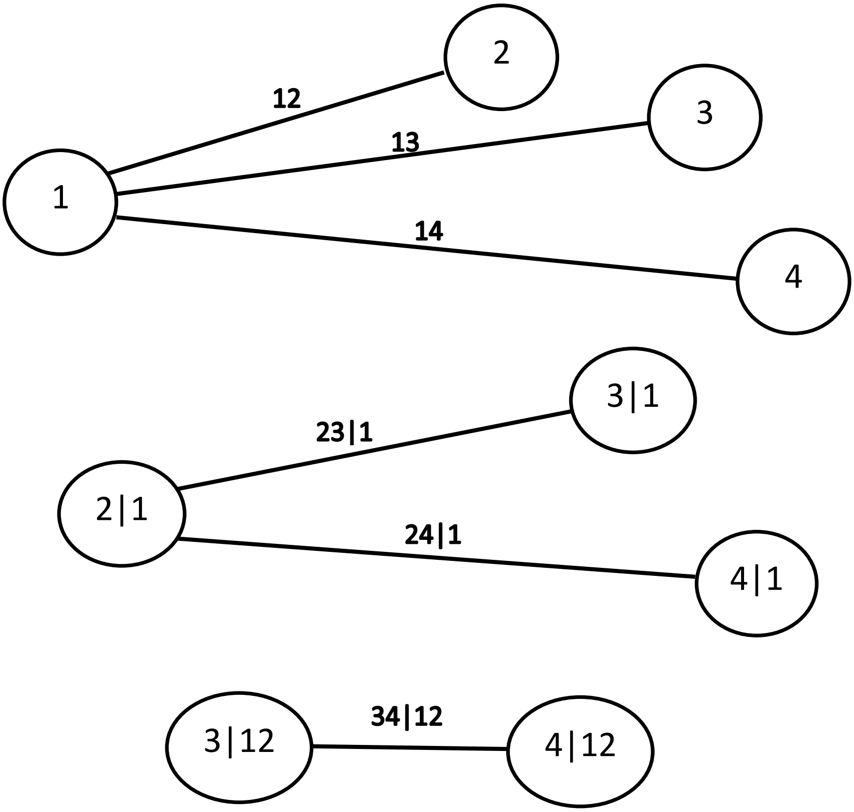
with u_1, u_2, u_3, u_4 being the US, European, Latin American and Asian marginal distributions respectively, this expression shows that the copula is a product of three bivariate copulas joining the US market with the other markets. Then there are two bivariate conditional copulas that join the European with the Latin American and Asian market, with the US market as conditioning variable. Finally there is another bivariate conditional copula to model the dependence between the Latin American and Asian stock market, where the conditioning is on the US and European market. The bivariate copulas in this setting can be of different copula families with different characteristics.

3.2.3 Estimation

We apply maximum likelihood to estimate the parameters for the Gaussian, Student's t, canonical vine Student's t, canonical vine Clayton and canonical vine survival Gumbel copulas. The maximum likelihood estimator is

$$\hat{\theta}_{ML} = \max_{\theta} \ell(\theta), \tag{3.9}$$

Figure 3.1: canonical vine representation



This figure shows the canonical vine representation in case of four variables.

where

$$\ell(\theta) = \sum_{t=1}^{T} \log(c(u_1, u_2, u_3, u_4; \theta)).$$

For the Gaussian and standard Student's t copula $c(u_1, u_2, u_3, u_4; \theta)$ is the corresponding pdf of (3.4) and (3.5), for the canonical vine copulas $c(u_1, u_2, u_3, u_4; \theta)$ is equal to (3.8). Note that for the Gaussian copula, θ comprises the six correlations, for the Student's t it has an additional d.f. parameter, for the canonical vine Student's t it comprises six correlations and six d.f. parameters, and for the canonical vine Clayton and Gumbel it comprises six $\gamma' s$ and six δ's. Note that in equation (3.9) the densities of the margins are not included because we use the empirical cdf as nonparametric estimator of the margins. Standard errors are obtained as in Genest et al. (1995), where a correction for the nonparametric estimates of the margins is taken into account. Estimation of pair-copulas, can become difficult and time-consuming, particularly when the dimensionality increases. Haff et al. (2009) propose a simplification for the construction of pair-copulas. However, for the four dimensions we use, we found no difficulties in estimating the original, more correct, pair-copulas of Aas et al. (2009).

Because we estimate four-dimensional copulas, we have to make sure that the correlation matrix stays positive definite during the optimization process. It turned out that all the estimated correlation matrices were positive definite using the following procedure: for all the four different copulas we firstly estimated six possible bivariate copulas of which the estimates are used as starting values for the optimization of the four-dimensional copula. In addition, these starting values were found to be already close to the final four-dimensional ML estimates.

3.2.4 Crashes

The main purpose of this chapter is to investigate whether the dependence among the four regions has increased, and whether this has resulted in more global crashes. In this section we describe how probabilities on global crashes are defined and how we test whether these probabilities have increased. Following Bae et al. (2003), we define a global crash when all the four returns of the regional markets belong to the lower quantile q. For all the copulas, this is computed by

$$P_{gb} \equiv P[\text{Global crash}] = C(q, q, q, q; \hat{\theta}), \tag{3.10}$$

where $\hat{\theta}$ is the estimated parameter vector. For the Gaussian and standard Student's t copula P_{gb} can be computed analytically. For the canonical vine copulas there is no explicit expression for the cdf. Aas et al. (2009) uses simulation of the vine copulas, to compute different quantiles of vine copulas. However, numerical integration of the density (3.8) costs less computing time than simulation of the vine copula. Therefore, we use numerical integration, with Gaussian quadrature integration scheme, in these cases to compute P_{gb}.

To make inferences on the global crash probabilities, we use a simulation study. Using the fact that maximum likelihood estimators are normally distributed, we generate 5000 random drawings of the parameters. With these simulated parameter values, we compute the simulated global crash probabilities. Given these simulated global crash probabilities, we compute for each point in time the $(1-\alpha)\%$ highest density region (HDR) (see Hyndman, 1996). The parameters could be estimated on their boundaries. In those cases we truncate the simulated parameter values on the boundary. This means that, the estimated parameters are then distributed not normally but truncated-normally. One consequence of this approach is that the estimated global crash probabilities are not equal to the means of the simulated crash probabilities, but they are equal to the modes. To formally test whether the global crash probabilities have increased between periods, we examine whether the lower bound of the $(1-\alpha)\%$ HDR region at time $t=\tau$ is larger than the upper bound of the HDR region at time $t=\tau-\zeta$, where ζ should be large enough so that the two corresponding estimation windows are non-overlapping.

We illustrate the importance of using higher dimensional copulas on the estimation of crash probabilities, instead of only using bivariate pairs, in more detail, with the example of the introduction . Suppose only two regions exist, and consider a bivariate Gaussian copula with correlation 0.25. The global crash probability $P_{gb} = C(0.05, 0.05; 0.25) = 0.006$, for threshold $q = 0.05$. If the correlation doubles, we get $P_{gb} = C(0.05, 0.05; 0.5) = 0.012$. Thus a doubling of the correlation results in a doubling of the global crash probabilities. Now consider the four regions, with equal correlation of 0.25 between all 6 pairs. This results in $P_{gb} = C(0.05, 0.05, 0.05, 0.05; c_{0.25}) = 0.0003$, with $c^4_{0.25}$ is a four dimensional correlation matrix with off-diagonal elements 0.25. If correlations double to 0.5, then $P_{gb} = C(0.05, 0.05, 0.05, 0.05; c^4_{0.5}) = 0.0026$. This is a 7.5 times increase in global crash probability[3]. Thus, examining bivariate pairs can lead to misleading results, and therefore, if possible, higher dimensional copulas should be used.

3.3 Data

We use the weekly regional MSCI stock market indices, covering the period from January 1989, when the weekly emerging market data became available, until February 2010, for the following markets: Latin America (LA), Asia (AS), United States (US) and Europe (EU). This provides us with a sample size of T = 1115 weekly observations. All data is obtained from DataStream. We use weekly data because a monthly frequency would be too low and daily data only became available on 31 June 1995. Additionally, using daily data, we would encounter the problem of non-overlapping trading hours. Table 3.1 shows the descriptive statistics for the data.

The mean returns vary substantially between different regions, from 2 percent per year for Asia to 12 percent per year for Latin America. The performance of the developed regions' stock markets is around 5 percent per year. The high return on the Latin American market is justified by the high volatility of this market. The other regions' markets show lower volatility. The minimum returns are comparable

[3]For a Student's t copula with 4 d.f. this increase is almost 3.5 times

Table 3.1: Data Analysis

	LA	AS	US	EU
mean	0.12	0.02	0.06	0.05
std	0.31	0.24	0.16	0.18
min	−0.40	−0.19	−0.17	−0.16
max	0.14	0.20	0.10	0.10
skewness	−1.60	−0.58	−0.68	−0.86
kurtosis	13.48	7.01	8.36	7.38
LA	1			
AS	0.46	1		
US	0.55	0.46	1	
EU	0.56	0.55	0.70	1

Descriptive statistics for the regional indices over the sample Jan 1989 - February 2010. Descriptive statistics include annualized mean and volatility, the maximum and minimum return, the skewness and kurtosis of the returns. The correlation matrix is also reported.

for Asia, US and Europe, while the Latin American minimum return is much larger. The maximum return in the Asian market is considerably larger than the maximum returns of the other markets. The skewness shows that large negative returns are more likely than large positive returns in all regions.

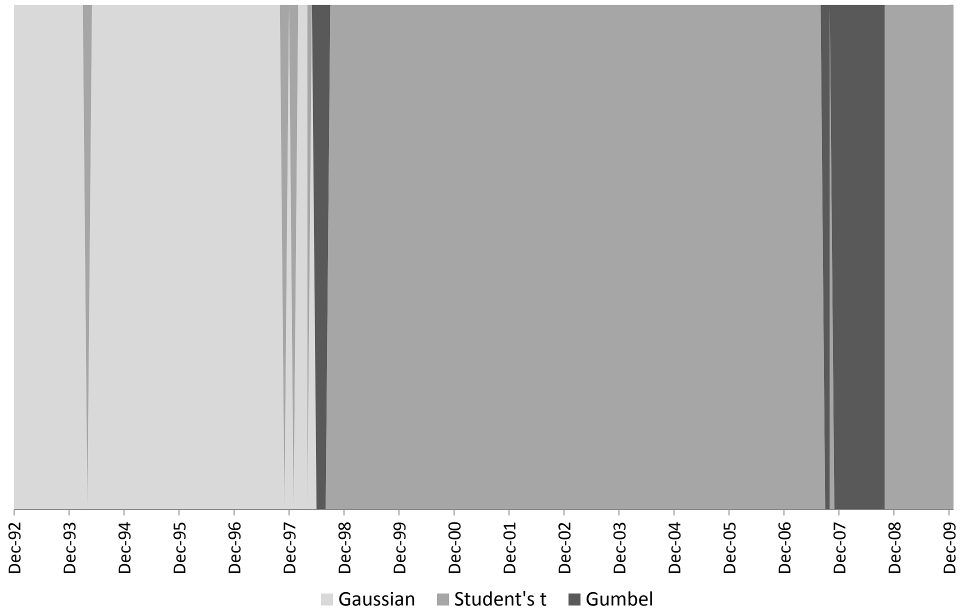
The correlation matrix shows that correlation between the US and European markets, is the highest of all possible correlations with a value of 0.70. The emerging markets are less correlated than the developed markets. Asia is overall the least correlated market. These statistics suggests that during the January 1989 - December 2010 period emerging stock markets were a useful addition to a portfolio consisting only of assets from developed markets. However, if the data are not normally distributed, diversification gains based on the linear correlation coefficient can be misleading.

3.4 Empirical results

The rolling window estimations are performed on weekly data, but after each estimation we move four weeks forwards in time, approximately one month.[4] This results in a time-series of dependence measures. Thereafter we compute at each point in time the probabilities that all regions crash together, where we define a crash using $q = 0.05$. Remember, we estimate five four-dimensional copulas: the Gaussian, the standard Student's t, and using Aas et al. (2009) method also the Student's t, the

[4]This is purely from a computing time perspective, because the estimation takes a long time. Particularly for the canonical vine Student's t copula.

Figure 3.2: Lowest AIC Copulas



This figure reports the copulas which attained the lowest AIC value (Akaike information criterion) for the four estimated copulas at each point $t = \tau$.

Clayton and the survival Gumbel copula, to measure the dependence between the regions.

As not all copulas are nested we compute the small sample adjusted Akaike Information Criterion (AIC) values for all estimations and copulas.[5] Figure 3.2 shows for all weeks which copula attains the lowest AIC value. For all the 224 estimation periods the Gaussian copula renders the lowest AIC 68 times, the Student's t 139 times and the Gumbel 17 times. The canonical vine Student's t or Clayton copula never results in the lowest AIC. This result shows that for weekly stock returns the dependence structure is mostly symmetric, except during the Asian and credit crisis. In addition, since the Asian crisis lower tail dependence between stock returns is present, which has reduced diversification opportunities.

Regarding the Student's t, the different d.f. between different pairs are probably not that important. If this would have been important, the Student's t with different d.f. would probably have outperformed the standard Student's t. To test this more formally, we perform a likelihood ratio test between the canonical Student's t and the

[5]The small sample AIC is defined as $AIC = 2k - 2\ell + \frac{2k(k+1)}{n-k-1}$.

standard Student's t copula. The test statistic is computed as $LR = 2\ell_{canonical\,t} - 2\ell_t$, distributed as a χ^2 distribution with 5 d.f., because there are 5 restrictions that make the canonical vine Student's t copula equal to the standard Student's t copula, (see Aas et al., 2009). The standard Student's t copula is never rejected in favor of the canonical vine copula. In 5 of the 224 estimations the p-value of the LR test is between 0.05 and 0.10, but in general larger than 0.40. Therefore we will not use the canonical vine Student's t copula. For the Clayton copula, these findings are in line with Okimoto (2008), who finds that the Clayton copula is too asymmetric and too tail dependent, to fit these types of financial data well. As these two copulas are inferior to the others in describing the dependence, we will not use these anymore and we focus on the other three copulas.

3.4.1 Dependence measures

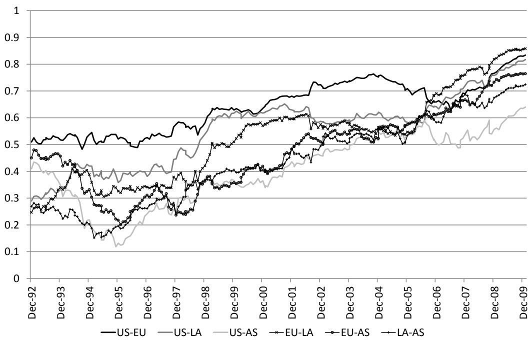
Figure 3.2 shows that until the Asian crisis the Gaussian copula was most suitable to describe the dependence between the stock markets. During this crisis there was a short lived asymmetric dependence regime, as the Gumbel copula attains the lowest AIC value. After Asian crisis the Gaussian copula is never the most suitable copula again, indicating some structural change in the dependence between global stock markets. During the credit crisis there is a prolonged period, of almost a year, with asymmetric dependence, modelled by the Gumbel copula.

In Figure 3.3 we show the parameter estimates for the Gaussian, Student's t and canonical vine Gumbel copula. Irrespective of the copula choice, we see that the dependence between the US and Europe is the highest for most of the sample period. The second largest dependence is between the US and Latin America. Additionally all the dependencies are increasing over the sample period, which could reflect financial globalization.

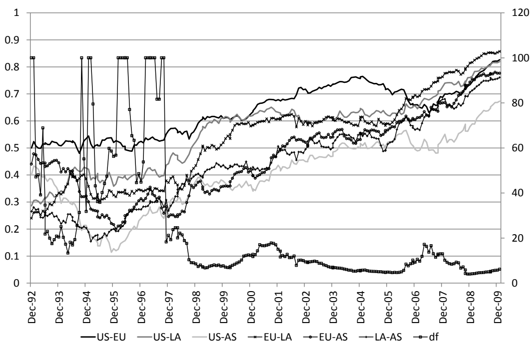
More specifically for the Gaussian we find that the correlation between US and Europe increases from 0.51 (first estimation) to 0.83 (last estimation). The correlation between the two emerging regions Asia and Latin America increased from 0.27 to 0.72, indicating the integration of emerging markets. The correlation between pairs involving the Asian market show the same general movements over the sample. Between 1992 and 1995 these correlations were decreasing by almost 0.3, whereafter the correlations gradually increased, with values higher than 0.6 in 2010. All correlations show a sudden increase during the Asian crisis. Since 2006 the correlations increased by 0.2, which is quite large for a four year time period.

For the Student's t copula the correlation estimates are almost equal to the Gaussian copula correlation estimates. Therefore we only focus on the d.f. estimates.

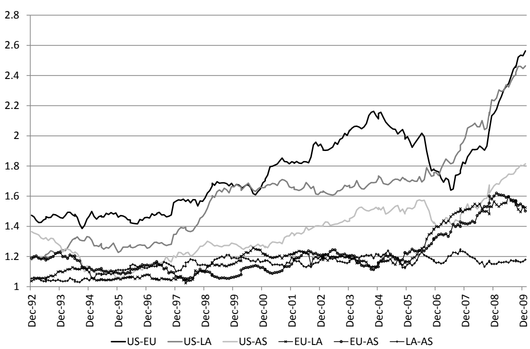
Figure 3.3: Parameter estimates



(a) Gaussian



(b) Students t



(c) Gumbel

This figure shows the parameter estimates for the Gaussian copula (a), Student's t copula (b) and Gumbel copula (c). For the Student's t copula the estimated degrees of freedom are plotted against a secondary axis. The first estimation runs from December 1988 - December 1992, the last estimation from February 2005 - February 2010.

Until the Asian crisis the degrees of freedom estimates are quite high, where the d.f. parameter sometimes reaches the boundary of 100. These large d.f. values are consistent with the fact that the Gaussian copula attains the lowest AIC values over this period. Only in 1994 the d.f. were estimated around 20, but not low enough for the Student's t copula to attain a lower AIC than the Gaussian copula. Due to the Asian crisis, the d.f. were estimated around 10 and became even lower with the estimate 3.9 in the estimation window ending November 2008, when the stock markets crashed during the credit crisis. Thus after the Asian crisis the global stock markets have become more tail-dependent indicating more risk.

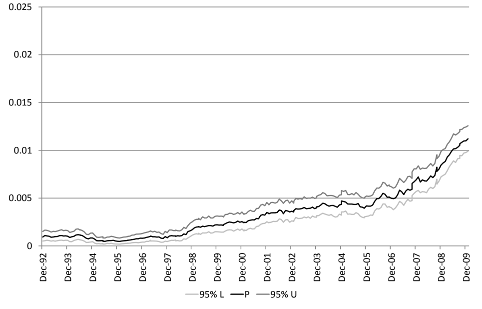
The estimate of the Gumbel parameters between the two developed markets implies the highest dependence followed by the US-Latin America pair. In 2007 and 2008, for the latter pair the dependence was even estimated a bit higher. For the other markets pairs the Gumbel copula estimation implies that the pairs are much less dependent until 2006. After 2006 and during the credit crisis the dependence increased for all pairs, except Latin America and Asia. This implies that lower tail-dependence went up, which makes the likelihood of crashes higher.

Thus for all the three copulas the dependence between US and Europe is almost always the highest. The dependence between the Latin American and Asian markets was mostly quite low in the beginning of the sample, but it has increased to a large degree as time goes by. At the end of the sample this dependence is almost as high as dependence between US and Europe. Most of the time, pairs involving Latin America showed a higher dependence than the pairs involving Asia. To summarize, the global dependencies have increased and in the next section we investigate what this means for global crashes.

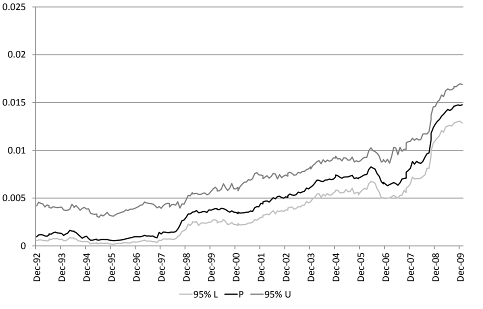
3.4.2 Crashes

In Figure 3.4 we show the implied 5% global crash probabilities from the copula models, together with the corresponding 95% HDR's. Irrespective of the copula model used, the global crash probabilities have been steadily increasing over the last fifteen years as a result of increased dependence between financial markets. Although this is not a direct proof of stock market integration, this result suggests financial globalization of stock markets. Particularly the Asian crisis and the credit crisis resulted in higher global crash probabilities. Overall, the increased dependence, which we concluded from the increased parameter estimates during the sample, results in highly increasing global crash probabilities. The implications for investors in global stock markets are obvious. Diversification strategies have become less successful over the past decades.

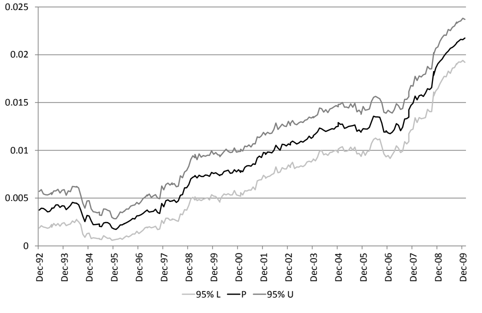
Figure 3.4: Global crash probabilities



(a) Gaussian



(b) Student's t



(c) Gumbel

This figure shows the estimated 5% global crash probabilities for the Gaussian copula (a), Student's t copula (b), Gumbel copula (c). In all graphs the 95% highest density region is also reported. The first estimation runs from December 1988 - December 1992, the last estimation from February 2005 - February 2010.

Looking at the individual copulas in Figure 3.4, leads to some interesting conclusions. First, for the Gaussian copula the occurrence of global crashes increases from once every 1111 weeks to once every 89 weeks. The 95% HDR shows that the global crash probabilities are estimated very precisely.

For the Student's t copula we see the large increase in global crash probabilities as a result of the credit crisis. Around July 2008 the global crash probability was 0.8 percent, which almost doubled to 1.5 percent during the crisis. Compared to the Gaussian copula the HDR region is somewhat wider, which is a result of the large standard errors when estimating degrees of freedom. In the period 1992 to 1998 the estimated probability is almost equal to the lower bound of the 95% HDR. Figure 3.3 shows that this coincides with the period when the d.f. are rather large. When simulating the global crash probabilities to obtain the 95% HDR, the degrees of freedom was often set at the lower bound of 2, indicating larger global crash probabilities. On the other hand, when the simulated d.f. were higher than the estimated d.f., then global crash probabilities hardly changed. This is because there is little difference between Student's t copulas which for instance have 200 or 800 degrees of freedom. This confirms the asymmetry displayed in the graph.

Finally, the Gumbel copula shows the highest global crash probabilities. In the most parts of the sample it is around two times the probabilities of the Student's t copula. The Gumbel copula implies a global crash probability of 1.6 percent in July 2008 just before the credit crisis. The credit crisis raises this probability to even 2.2 percent, which is equal to once every 45 weeks. Note also the asymmetry for this copula. In the beginning of the sample for some pairs the Gumbel parameter was estimated at 1, which corresponds to independence. During the simulation for the HDR region, some simulations resulted in higher dependence, but lower dependence is never possible, because 1 is the lower bound for the Gumbel copula parameter.

In Table 3.2 we show the global crash probabilities for 5 different months. We start at the beginning of the sample (December 1992) and then skip 4 years each time until December 2008. Moreover, we also report the end of the sample (February 2010). This table shows the estimated probabilities, as well as the corresponding 95% highest density regions.

Since the estimated global crash probabilities and corresponding HDRs are reported with a 4 year interval and the estimation window is four years, we regard the estimated probabilities as independent estimates. This assumption eases the formal testing on whether the global crash probabilities have increased. For all copula models we see that the lower bound of the 95% HDR in February 2010 is *higher* than the upperbound of the 95% HDR in December 1992. Thus we can state with a high level of certainty that global crash probabilities have thus significantly increased over the past two decades. This conclusion also holds when we look at the increment from December 1992 to December 2004, which does not include the credit crisis. The credit crisis is thus not the reason that we find a significant increase in global crash probabilities. There are also some sub-periods in which an significant increase is found. For instance, for the Gaussian copula between December 1996 and December 2000 or between December 2000 and December 2004. But also for the Student's t and Gumbel copula there are significant increases in subsamples.

3.5 Sensitivity analysis

Our first sensitivity analysis relates to the threshold chosen to compute the global crash probabilities. In Figure 3.5 we show the 1, 2.5, 10, 25 percent global crash

Table 3.2: Global crash probabilities and HDRs

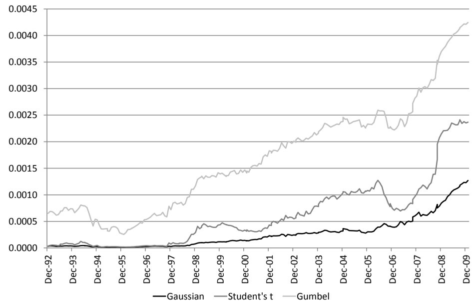
Panel A	95%L	P	95%U
Dec-92	0.0005	0.0009	0.0015
Dec-96	0.0004	0.0008	0.0013
Dec-00	0.0018	0.0025	0.0035
Dec-04	0.0036	0.0047	0.0058
Dec-08	0.0072	0.0085	0.0099
Feb-10	0.0099	0.0112	0.0126
Panel B	**95%L**	**P**	**95%U**
Dec-92	0.0006	0.0009	0.0042
Dec-96	0.0004	0.0010	0.0040
Dec-00	0.0022	0.0035	0.0060
Dec-04	0.0058	0.0074	0.0094
Dec-08	0.0110	0.0127	0.0146
Feb-10	0.0128	0.0148	0.0169
Panel C	**95%L**	**P**	**95%U**
Dec-92	0.0019	0.0038	0.0057
Dec-96	0.0013	0.0032	0.0044
Dec-00	0.0052	0.0077	0.0098
Dec-04	0.0101	0.0129	0.0148
Dec-08	0.0165	0.0191	0.0208
Feb-10	0.0192	0.0217	0.0237

This table reports the global crash probabilities for six different dates. The first date is the beginning of the sample, the next four dates are four years ahead each time and the last date is the end of the corresponding estimation sample (which started four years earlier). The lower bound of the 95% HDR, the global crash probability upper bound of 95% HDR are reported in column two to four respectively. Panels A, B and C show the results for the Gaussian, Student's t and Gumbel copulas respectively.

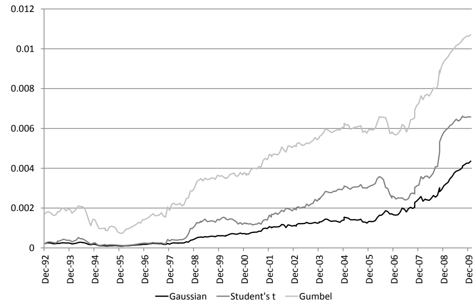
probabilities. The larger the quantile used as definition for global crashes, the less important is the copula used. For instance, 1 percent global crash probabilities are very different for the normal, Student's t and Gumbel copula. While this probability is almost zero for the Gaussian copula, for the other two copulas this probability becomes rather large during the sample period. For the 25% global crash probability, which is in fact the probability that all four regions have a return belonging to the lowest quartile of the regions returns, the different copulas show approximately the same results. This makes sense as tail-dependence, one of the main differences between the copulas, is not relevant in the center of the distribution. The consequences of the Asian crisis and credit crisis are visible for all different quantiles used. After these crises the global crash probabilities have not returned to the levels that existed before these crises.

Our second sensitivity test regards the length of the rolling window, which is a nuisance parameter in our model. Therefore we examine whether the main results do not change too much when we use window lengths shorter and longer than four

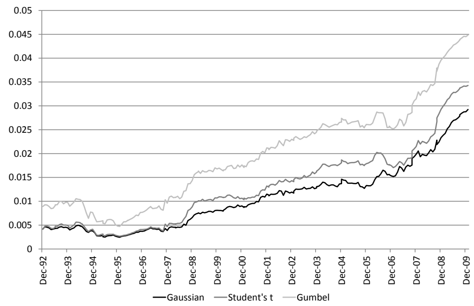
Figure 3.5: Global crash probabilities for different thresholds



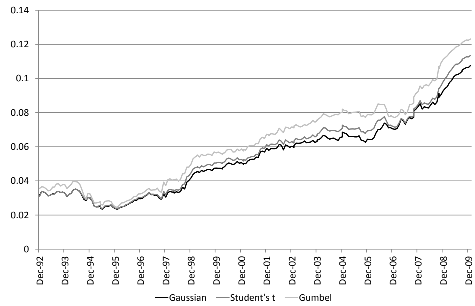
(a) 1%



(b) 2.5%



(c) 10%

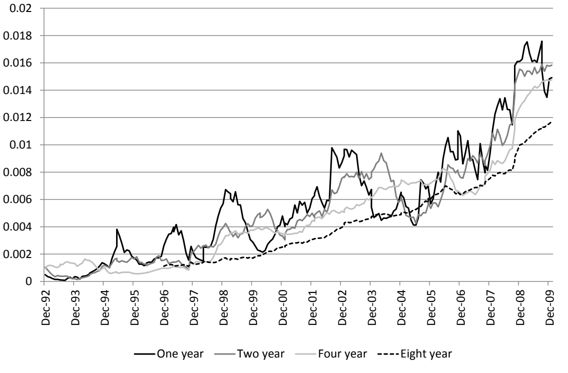


(d) 25%

This figure shows the estimates 1,2.5,10,25% global crash probabilities for the Normal, Student's t and Gumbel copula. The first estimation runs from December 1988 - December 1992, the last estimation from February 2005 - February 2010.

years. For this additional analysis Figure 3.6 shows the 5% global crash probabilities for length one, two and eight years, where the eight year global crash probabilities are only available from 1996 on. The original four year window probabilities are added for comparison. We only show the results of new global crash probabilities of the Student's t copula, as the Gaussian and Gumbel copulas show comparable results. It is interesting to note that the different window lengths lead to approximately the same pattern for the global crash probabilities. Shorter windows lead to more fluctuating probabilities, but the general steep increasing pattern remains for all windows. The one year window probabilities clearly increase during the peso crisis, Asian crisis, dotcom crisis and the credit crisis. As the observations during specific crisis periods get relatively less influential for longer windows, the effects of specific crisis are less visible for longer windows. However, even for the eight year window, the influence of the credit crisis is clearly visible.

Figure 3.6: Other window lengths



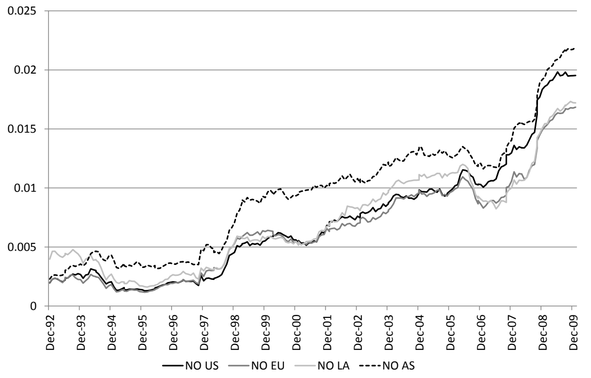
This figure shows the 5% global crash probabilities for the Student's t copula for different lengths of the rolling window.

Lastly, we define global crashes as an observation where three regions crash simultaneously instead of four. These new global crash probabilities are computed using (3.10), where each time one region is not taken into consideration. For instance, if the second variable in (3.10) is the Europe observation, then the probability for a global crash that comprises US, Latin America and Asia is computed by $P_{gb} = C(q, 1, q, q; \hat{\theta})$. Because each time we leave out one region, this results in four new global crash probabilities. Again only the Student's t results are reported. Figure 3.7 shows the 5% global crash probabilities when only three regions are concerned. For instance, the line named NO AS is the probability that the US, Europe and Latin America crash together. This probability is substantially higher than the other three probabilities, indicating that Asia was a good investment regarding diversification. The general pattern in these global crash probabilities is approximately the same as when four regions are considered, so the results are not sensitive to excluding one region. Since 2006 the global crash probability excluding the US becomes almost as large as the probability excluding Asia. This is justified by the relatively low correlation between the US and Asia since 2006 (see Figure 3.3, panel b).

3.6 Conclusion

We have examined the dependence among the US, European, Latin American and Asian stock markets with a rolling window estimation approach, with a window of

Figure 3.7: Three region definition



This figure shows the 5% global crash probabilities for the Student's t copula with 3-region 5% global crashes. The first estimation runs from December 1988 - December 1992, the last estimation from February 2005 - February 2010.

four years. Based on Gaussian, Student's t and survival Gumbel copulas, we computed the probability of the occurrence of global crashes. The main conclusion is that, irrespective of the copula used, the global crash probabilities have increased dramatically and significantly over the period from December 1992 until February 2010. This results is also robust for the threshold probability, the size of the rolling window, and the number of regions that need to crash jointly to be classified as a global crash. Moreover, the increase in global crash probabilities as a result of the Asian and credit crisis is rather large. Additionally, there are also multiple subsamples within these crises, where the global crash probabilities increased significantly. Thus over the period from December 1992 until February 2010, as a result of financial globalization of the four regions under consideration, diversification opportunities have substantially decreased.

For academics this research provides some interesting topics for further research, which includes an investigation of whether global crashes have also become more severe. In addition, it would also be of interest to link the level of global crash probabilities to measures of financial globalization. The main conclusion for risk-managers reads that geographical diversification opportunities are almost monotonically decreasing, as the global crash probabilities keep rising. To keep the risk of portfolios at acceptable levels, risk-managers should think of other ways, besides geographical diversifications, to diversify their exposures.

3.A Canonical vine copulas

In this section we explain the use of canonical vine copulas in more detail. The main idea of multivariate vine-copulas is imposing a hierarchical structure on the variables. Further it makes use of the fact that a n-dimensional density in general can be decomposed as

$$f(x_1, \ldots, x_n) = f(x_1)f(x_2|x_1)f(x_3|x_1, x_2)\ldots f(x_n|x_1 \ldots x_{n-1}), \tag{3.A.1}$$

which is, except for relabeling of the variables, a unique decomposition. From equation (3.1) it follows that

$$C(u_1, \ldots, u_n) = F(F_1^{-1}(u_1), \ldots, F_n^{-1}(u_n)) \tag{3.A.2}$$

where $F_i^{-1}(u_i) = x_i$. Applying the chain rule on (3.A.2) gives

$$f(x_1, \ldots, x_n) = c_{1\ldots n}(F_1(x_1), \ldots, F_n(x_n))f_1(x_1)\cdots f_n(x_n) \tag{3.A.3}$$

In the bivariate case this would reduce to

$$f(x_1, x_2) = c_{12}(F_1(x_1), F_2(x_2))f_1(x_1)f_2(x_2) \tag{3.A.4}$$

where c_{12} is the copula joining $F_1(x_1)$ and $F_2(x_2)$. From the last equation one can easily see that,

$$f(x_2|x_1) = \frac{f(x_1, x_2)}{f(x_1)} = c_{12}(F_1(x_1), F_2(x_2))f_2(x_2) \tag{3.A.5}$$

All the factors in (3.A.1) can be written in such a way. For three random variables Joe (1996) show that,

$$f(x_3|x_1, x_2) = c_{13|2}(F(x_1|x_2), F(x_3|x_2))f(x_3|x_2) \tag{3.A.6}$$

where $c_{13|2}$ is a bivariate copula operating on $F(x_1|x_2)$ and $F(x_3|x_2)$ which are calculated by,

$$F(x_i|x_j) = \frac{\partial C_{x_i x_j}(F(x_i), F(x_j))}{\partial F(x_j)}. \tag{3.A.7}$$

The term $f(x_3|x_2)$ in (3.A.6) can be further decomposed in

$$f(x_3|x_2) = \frac{f(x_2, x_3)}{f_2(x_2)} = c_{23}(F_2(x_2), F_3(x_3))f_3(x_3), \tag{3.A.8}$$

so that, by inserting (3.A.5), (3.A.6), (3.A.8) in (3.A.1), a complete trivariate density $f(x_1, x_2, x_3)$ is expressed as

$$f(x_1, x_2, x_3) = f_1(x_1)f_2(x_2)f_3(x_3)c_{12}(F_1(x_1), F_2(x_2))c_{23}(F_2(x_2), F_3(x_3)) \cdot c_{13|2}(F(x_1|x_2), F(x_3|x_2)). \quad (3.A.9)$$

Dividing both sides by the marginal densities $f_1(x_1), f_2(x_2), f_3(x_3)$ results in the copula expression. The only non-trivial part using higher dimension is the calculation of the marginal conditional distributions on which the copulas operate. For more conditioning variables, i.e. lower in the hierarchy, Joe (1996) showed that for every j,

$$F(x_i|\mathbf{v}) = \frac{\partial C_{x,v_j|\mathbf{v}_{-j}}(F(x|\mathbf{v}_{-j}), F(v_j|\mathbf{v}_{-j}))}{\partial F(v_j|\mathbf{v}_{-j})}, \quad (3.A.10)$$

where v is a vector of conditioning variables, and v_{-j} the same vector excluding the jth element. When continuing this, all terms in 3.A.1 can be decomposed as,

$$f(x|\mathbf{v}) = c_{x,v_j|\mathbf{v}_{-j}}(F(x|\mathbf{v}_{-j}), F(v_j|\mathbf{v}_{-j}))f(x|\mathbf{v}_{-j}) \quad (3.A.11)$$

Thus, each conditional density can be represented as a bivariate copula and a marginal density.

Chapter 4

Time Variation in Asset Return Dependence: Strength or Structure?*

4.1 Introduction

The dependence between asset returns typically has pronounced nonlinear and time-varying features. In particular, the comovement of asset prices tends to be stronger when returns are negative or when financial markets are more volatile (see Longin and Solnik, 2001; Ang and Chen, 2002; Ang and Bekaert, 2002; Cappiello et al., 2006, among others). Also, the dependence does not disappear when returns take extreme (negative) values (see Longin and Solnik, 2001; Butler and Joaquin, 2002; Hartmann et al., 2004, among others). These properties of asymmetric dependence and (lower) tail dependence invalidate the use of the (Pearson) correlation coefficient as a measure of dependence. For the same reason the multivariate normal distribution is inappropriate for asset returns, as it implies symmetric dependence and tail independence (see Embrechts et al., 2002, 2003).

In recent years, copula functions have become a popular tool for describing nonlinear dependence between asset returns.[1] Copulas separate the dependence structure from the marginal distributions, and thus allow for a great deal of flexibility in the construction of an appropriate multivariate distribution for returns. Copulas with

*This chapter is based on the article by Markwat, Kole, and Van Dijk (2009b).

[1] See Joe (1997) and Nelsen (2006) for general introductions to copula theory and Cherubini et al. (2004) for applications in finance.

asymmetric dependence and non-zero lower tail dependence have been found useful in various applications, including risk management, derivative pricing and portfolio construction (see Patton, 2009, for a recent survey).

Empirical evidence suggests that the dependence between asset returns varies over time also for a variety of reasons other than the alternation of bear and bull markets or of volatile and quiet markets. For example, the dependence between international stock markets can change because of increasing economic and financial integration (see Bekaert and Harvey, 1995; Longin and Solnik, 1995; Goetzmann et al., 2005; Cappiello et al., 2006; Patton, 2006b; Bekaert et al., 2009, for example), macroeconomic conditions (Bracker and Koch, 1999) and market liquidity (Baele and Inghelbrecht, 2009). Within the copula framework, two approaches have been pursued to capture such changes in dependence. First, conditional copulas as introduced by Patton (2006b) have been considered, which allow the parameters in a given copula function to vary over time, typically in the form of an autoregressive or Markov switching process (see Jondeau and Rockinger, 2006; Bartram et al., 2007; Hafner and Manner, 2008, among others). If the copula function itself is kept the same, structural characteristics such as (a)symmetric dependence and tail (in)dependence do not change. We therefore refer to this approach as changing *strength* of dependence. Second, instead of the copula parameters the copula function itself may be allowed to vary over time (see Rodriguez, 2007; Chollete et al., 2009; Okimoto, 2008, among others). This means that the structural form of the dependence can change, for instance, from symmetric to asymmetric. We label this as variation in the *structure* of dependence.

Our main contribution in this chapter is to integrate changes in the *strength* and *structure* of dependence in one general copula framework. Specifically, we put forward a mixture copula, with time-varying mixture weights and time-varying copula parameters. The mixture weights can vary over time to produce changes in the dependence structure. Changes in the parameters of the copulas produce time-variation in the dependence strength.

Both types of changes are assumed to occur through a Markov-Switching mechanism. The Markov-Switching framework is suitable for modelling both recurrent changes between a limited set of dependence configurations (due to the alternation of bull and bear markets or changing macroeconomic conditions, for example) and non-recurrent, permanent changes in dependence (due to increased financial integration, for example). Importantly, the regime switches for the strength and those for the structure are assumed to be governed by separate latent Markov processes. This approach enables us to formally test whether both types of time-variation are present. More generally, it allows us to assess the relative importance of changes in the dependence strength and dependence structure. We can examine whether the two types of change occur independently or coincide.

So far, time-variation in the strength and the structure of dependence have only been considered in isolation, though they are fundamentally different. Changes in the strength of dependence do not alter its basic characteristics, like asymmetry and tail dependence, but changes in the structure do. In fact, only allowing for either changes in the dependence strength or the structure could easily give rise to misleading conclusions.

We use a time-varying mixture copula to study the changes in dependence between daily returns on a number of international stock markets. We mix a Gaussian copula and a survival Gumbel copula, both with time-varying parameters, to accommodate a variety of dependence structures. As our main finding we show a clear distinction between periods with weak and strong dependence and between periods of symmetric and asymmetric dependence. The strength of dependence is characterized as weak (strong) about 50 (50) percent of the time, while the dependence structure is characterized as symmetric (asymmetric) about 70 (30) percent of the time, on average.

To illustrate the importance of the distinction between the two kinds of changes, suppose that a risk manager models the correlation coefficient in a Gaussian copula to be time-varying, but ignores the possibility of changes in the dependence structure. If the dependence characteristics change, say, to a structure with lower tail dependence, the correlation dynamics will be misspecified. The Gaussian copula implies tail independence unless the correlation is equal to one (see Embrechts et al., 2003). So, the correlation estimate will be biased towards one, resulting in "near"-tail dependence, in order to match the tail dependence in the data. On the other hand, if the risk manager assumes that only changes in the dependence structure matter, he would mistake a change in strength for a change in structure. Both mistakes could lead to wrong calculations of risk measures like Value-at-Risk and Expected Shortfall. More specifically, we find that not including both types of changes in dependence leads to biases in Value-at-Risk estimates of up to 15%.

This chapter proceeds as follows. In Section 4.2 we outline the time-varying mixture copula approach. In Section 4.3 we describe the international stock market returns data and the specific modeling choices for the empirical application . We discuss the empirical results in Sections 4.4 and 4.5. We conclude in Section 4.6.

4.2 Methodology

In this section we describe the general set-up of the copula framework that comprises time-variation in both the strength and structure of dependence. For ease of exposition the model is described for the bivariate case, but the generalization to more than two variables is straightforward. We also show how tests for time-variation in dependence strength and structure can be implemented, and provide details on the estimation procedure for our model.

4.2.1 General framework

We consider two random variables X and Y, with realizations denoted as x and y. In our empirical application, X and Y represent daily returns on different stock markets. The dependence between X and Y is completely characterized by their joint distribution $F_{XY}(x, y)$. Sklar (1959)'s theorem states that we can express any joint distribution in terms of the marginal distributions F_X and F_Y and a copula function C, that is

$$F_{XY}(x, y; \theta) = C(F_X(x; \theta_X), F_Y(y; \theta_Y); \theta_C), \tag{4.1}$$

where θ_X and θ_Y denote parameter vectors for the marginals, θ_C is a vector of copula parameters, and $\theta = (\theta'_X, \theta'_Y, \theta'_C)'$. In addition, if the marginal distributions F_X and F_Y are continuous, the copula function C is unique. The decomposition in (4.1) immediately shows the attractiveness of the copula approach for flexibly modeling dependence. Since the marginal distributions F_X and F_Y only contain information on the individual variables, the dependence between X and Y is governed completely by the copula C. As the choice of marginal distributions does not restrict the choice of the copula or vice versa, a wide range of joint distributions can be obtained by combining different marginals with different copulas. We assume that the marginal distributions F_X and F_Y are continuous and specified parametrically up to vectors of unknown coefficients θ_X and θ_Y. In this article, we concentrate on possible specifications of the copula function C to accommodate time-varying features in the dependence.

A key property of a copula is its so-called 'quantile dependence' and the limiting case of tail dependence. Quantile dependence is the conditional probability that both variables lie above or below a given quantile q of their marginal distributions, given one marginal is below or above this quantile q. It is defined as $\tau(q) = C(q, q)/q$ for $q \leq 0.5$ and $\tau(q) = (1-2q+C(q, q))/(1-q)$ for $q > 0.5$. Lower and upper tail dependence coefficients are defined as the limits of the quantile dependence measures, that is,

$\tau_L = \lim_{q\downarrow 0} \tau(q)$ and $\tau_U = \lim_{q\uparrow 1} \tau(q)$. Different copula specifications (also referred to as copula 'families') have different quantile and tail dependence characteristics. The Gaussian copula for instance is symmetric, i.e. $\tau(q) = \tau(1-q)$ for $0 \leq q \leq 0.5$, and has no tail dependence, i.e. $\tau_L = \tau_U = 0$. On the other hand, the Gumbel copula is asymmetric with $\tau(q) < \tau(1-q)$ for $0 \leq q < 0.5$, and has no lower tail dependence but upper tail dependence (i.e. $\tau_L = 0$ and $\tau_U > 0$), while the reverse properties holds for the Clayton copula.

Recent applications of copulas to asset returns frequently conclude that a single copula is not sufficient to describe the dependence between these series adequately (see Hu, 2006; Rodriguez, 2007; Okimoto, 2008; Chollete et al., 2009). A mixture of copulas enables more flexibility and a wider range of dependence patterns. Two copulas C_a and C_b can produce the mixture copula

$$C(u, v; \theta_C) = \omega C_a(u, v; \theta_{C_a}) + (1-\omega) C_b(u, v; \theta_{C_b}), \tag{4.2}$$

where $0 \leq \omega \leq 1$ is the weight that determines the relative importance of the two copulas and u and v denote the probability integral transforms, i.e. $u \equiv F_X(x)$ and $v \equiv F_Y(y)$. C_a and C_b may be copulas from the same family, though with different weights, but they can also be from different families with different properties.

There is also ample empirical evidence suggesting that the dependence between asset returns is subject to change, which a time-invariant copula such as (4.2) can not capture. Assuming that the functional forms of the copulas C_a and C_b do not change, we can incorporate time-variation in two ways. First, the copula parameters θ_{C_a} and θ_{C_b} can change over time, as considered by Jondeau and Rockinger (2006) and Patton (2006b), among others. This leads to a time-varying *strength* (or degree) of dependence. Second, the mixture weights ω can vary over time, as in Rodriguez (2007), Okimoto (2008) and Chollete et al. (2009). Assuming that the constituents C_a and C_b are copulas from different families, such changes result in a time varying *structure* of dependence.[2]

We propose a time-varying mixture copula for changes in the strength of dependence via the mixture weight ω and in strength of dependence via the copula parameters θ_{C_a} and θ_{C_b}. Thus, the time-varying mixture copula is given by

$$C(u, v; \theta_C) = \omega_t C_a(u, v; \theta_{C_a t}) + (1-\omega_t) C_b(u, v; \theta_{C_b t}). \tag{4.3}$$

Changes in the strength of dependence can have rather different implications than changes in the structure of dependence, though it is likely that the two can be mis-

[2]In case C_a and C_b are copulas from the same family, a time-varying mixture weight ω is observationally equivalent to time-varying copula parameters θ_{C_a} and θ_{C_b}.

taken for each other. Hence, it is useful to distinguishing between the two types of time-variation. It is also possible that strength and structure change simultaneously. Both reasons suggest the need for a model accommodating both types of time-variation in dependence jointly.

To work with the flexible mixture copula in (4.3) we have to specify how the parameters $\theta_{C_a t}$ and $\theta_{C_b t}$ and the weight ω_t evolve over time. We opt for a regime-switching approach (cf. Jondeau and Rockinger, 2006) and assume that the parameter vectors $\theta_{C_j t}$, $j = a, b$ can switch between two different values $\theta_{C_j^{(1)}}$ and $\theta_{C_j^{(2)}}$. The switching between these two states is governed by a first order Markov process $S_{\theta,t} \in \{1, 2\}$ with transition probabilities $p_{\theta,ii} \equiv P[S_{\theta,t} = i | S_{\theta,t-1} = i]$ for $i = 1, 2$. For the dependence structure we adopt a similar idea, (cf. Rodriguez, 2007; Okimoto, 2008; Chollete et al., 2009), and assume that the mixture weight ω_t can take two different values $\omega^{(1)}$ and $\omega^{(2)}$, depending on the value of another two-state Markov process $S_{\omega,t} \in \{1, 2\}$ with transition probabilities $p_{\omega,ii} \equiv P[S_{\omega,t} = i | S_{\omega,t-1} = i]$ for $i = 1, 2$.

Other possibilities for the evolution are available. For the copula parameters $\theta_{C_a t}$ and $\theta_{C_b t}$ autoregressive specifications have been considered by Jondeau and Rockinger (2006), and Patton (2006b), among others. These kinds of models often show a very strong persistence. The volatility literature argues that strong persistence suggests the presence of large infrequent breaks or regime switches (see Diebold and Inoue, 2001; Gouriéroux and Jasiak, 2001; Lamoureux and Lastrapes, 1990, among others).[3] This justifies our choice to use a Markov processes.

We assume that the Markov processes $S_{\theta,t}$ and $S_{\omega,t}$ are independent of each other (and independent of x and y). In other words, we assume that changes in the strength of dependence and in the structure of dependence occur independently. This assumption allows straightforward testing for the presence of either type of change in dependence, while allowing for the other type. For example, we can test for the absence of changes in the dependence strength by testing the null hypothesis $\theta_{C_j^{(1)}} = \theta_{C_j^{(2)}}$, while allowing for regime-switching in the weight ω_t. Conversely, we can test for the absence of changes in the dependence structure by testing the null hypothesis $\omega^{(1)} = \omega^{(2)}$, while allowing for regime-switching in the parameters $\theta_{C_a t}$ and $\theta_{C_b t}$. These (likelihood ratio) tests suffer from the usual complications involved in specification tests in Markov Switching models due to the presence of unidentified nuisance parameters under the null hypothesis, such that simulation is needed to obtain the distribution under the null hypothesis and appropriate critical values (see Hansen, 1992; Garcia).

[3] Dias and Ebrechts (2009) provide direct evidence in the context of copulas for the presence of infrequent structural changes in the dependence between exchange rates.

It is straightforward to allow for more than two different values of the copula parameters θ_{C_j} and the mixture weight ω_t by increasing the states of the Markov processes. This extension may be particularly useful when the framework of Markov processes is used for modelling non-recurrent, permanent structural changes. As demonstrated by Chib (1998) this may be achieved by restricting the transition probabilities such that the regimes occur in a non-reversible sequence Pástor and Stambaugh (see 2001); Pesaran et al. (see 2006); Pettenuzzo and Timmermann (see 2009, for applications of this approach).

4.2.2 Estimation

Several different methods are available for estimating the parameter vector $\theta_C = (\theta_{C_a}^{(1)\prime}, \theta_{C_a}^{(2)\prime}, \theta_{C_b}^{(1)\prime}, \theta_{C_b}^{(2)\prime}, p_{\theta,11},\ p_{\theta,22}, \omega^{(1)}, \omega^{(2)}, p_{\omega,11}, p_{\omega,22})'$ in the time-varying mixture copula (4.3) with Markov-Switching specifications for ω_t and $\theta_{C_j t},\ j = a, b$. As the marginal distributions F_X and F_Y are specified parametrically up to unknown parameter vectors θ_X and θ_Y, Maximum Likelihood (ML) is the obvious approach. From the general specification in (4.1), the log likelihood function for the observation at time t is given by

$$\ell_t(\theta) = \log c(F_X(x_t; \theta_X), F_Y(y_t; \theta_Y); \theta_C) + \log f_X(x_t; \theta_X) + \log f_Y(y_t; \theta_Y), \quad (4.4)$$

where f_X and f_Y are the densities corresponding with the marginals F_X and F_Y, and c is the density of the copula C.

In typical empirical applications, the number of parameters in θ quickly grows large. For example, even though we consider fairly simple specifications for the margins and constituent copulas for our data set of daily stock returns, our most general time-varying mixture copula contains 26 parameters. In such cases, numerical optimization of the log-likelihood becomes a daunting task. An alternative two-stage estimation method, which we also adopt here, is the Inference Function for Margins (IFM) procedure described in Joe (1997). The IFM method uses the natural decomposition of the complete log likelihood in (4.4) into the log likelihoods for the margins and for the copula:

$$\ell_t(\theta) = \ell_{c,t}(\theta_X, \theta_Y, \theta_C) + \ell_{X,t}(\theta_X) + \ell_{Y,t}(\theta_Y).$$

with $\ell_{c,t}(\theta_X, \theta_Y, \theta_C) = \log c(F_X(x_t; \theta_X), F_Y(y_t; \theta_Y); \theta_C)$, $\ell_{X,t}(\theta_X) = \log f_X(x_t; \theta_X)$ and $\ell_{Y,t}(\theta_Y) = \log f_Y(y_t; \theta_Y)$. The IFM method boils down to estimating the parameters θ_X and θ_Y in the margins first by univariate ML, that is,

$$\hat{\theta}_X = \underset{\theta_X}{\operatorname{argmax}}\ \ell_X(\theta_X) \quad \text{and} \quad \hat{\theta}_y = \underset{\theta_Y}{\operatorname{argmax}}\ \ell_Y(\theta_Y), \tag{4.5}$$

where $\ell_X(\theta_X) = \sum_{t=1}^{T} \ell_{X,t}(\theta_X)$ and $\ell_Y(\theta_Y) = \sum_{t=1}^{T} \ell_{Y,t}(\theta_Y)$ with T denoting the sample size. In a second step, the parameters in the copula are estimated conditional on the estimated parameters for the margins, by solving

$$\hat{\theta}_C = \underset{\theta_C}{\operatorname{argmax}}\ \ell_c(\hat{\theta}_X, \hat{\theta}_Y, \theta_C) \tag{4.6}$$

where $\ell_c(\hat{\theta}_X, \hat{\theta}_Y, \theta_C) = \sum_{t=1}^{T} \ell_{c,t}(\hat{\theta}_X, \hat{\theta}_Y, \theta_C)$, with $\ell_{c,t}(\hat{\theta}_X, \hat{\theta}_Y, \theta_C) = \log c(\hat{u}, \hat{v}; \theta_C)$, $\hat{u} = F_X(x_t; \hat{\theta}_X)$ and $\hat{v} = F_Y(y_t; \hat{\theta}_Y)$. In both steps of the IMF method we use numerical optimization to maximize the loglikelihood. This two-step estimation procedure leads to consistent and asymptotically efficient estimators, see Joe (2005) and Patton (2006a). We compute appropriate standard errors for $\hat{\theta}_C$, which take into account the additional uncertainty due to the use of estimated parameters for the margins. For the parameter vector $\hat{\theta} = (\hat{\theta}'_X, \hat{\theta}'_Y, \hat{\theta}'_C)'$ it holds that (see Patton, 2006a),

$$\sqrt{T}(\hat{\theta} - \theta_0) \sim^A N(0, \hat{H}^{-1}\widehat{OPG}\hat{H}^{-1}), \tag{4.7}$$

where H and OPG are the Hessian and outer product of the gradients respectively. Robust standard errors can be obtained by taking the square-root of the diagonal elements of $\hat{H}^{-1}\widehat{OPG}\hat{H}^{-1}$.

Because the time-varying mixture copula (4.3) depends on the latent Markov processes $S_{\theta,t}$ and $S_{\omega,t}$, we have to estimate the transition probabilities too. We follow the conventional approach of the EM algorithm as described in Hamilton (1989) to estimate the parameters in θ_C. Applying the IFM approach requires that the parameters of the marginal models, θ_X and θ_Y can strictly be separated from the copula parameters θ_C. In our case, this means that the marginals F_X and F_Y can not be subject to regime-switching induced by $S_{\theta,t}$ and $S_{\omega,t}$.

4.3 Data and model specification

We apply the time-varying mixture copula approach to a number of international stock market returns. In this section we describe the data set and specify the details of the time-varying mixture copula for this empirical application, in particular the choice of constituent copulas C_a and C_b in (4.3) and the marginal distributions F_X and F_Y.

4.3.1 Data

We examine the dependence and changes therein between nine major stock markets. We consider the following countries: United States (US), Canada (CA), Mexico (MX), United Kingdom (UK), Germany (GE), France (FR), Japan (JP), Hong Kong (HK) and Korea (KO). We implement the time-varying mixture copula for six pairs of stock markets: US-CA, US-MX, UK-GE, UK-FR, JP-HK, and JP-KO. We choose these specific combinations because the two markets in each of these pairs do not suffer from non-synchronous trading. If we were to combine Asian, European and American markets, their non-overlapping trading hours would seriously distort the dependence patterns, in daily returns. Another option to deal with the non-synchronous trading hours would be to lower the data frequency. However, using a lower frequency might lead to estimation difficulties, because estimating two Markov processes in combination with mixture copulas requires many observations.

We use daily market index returns over the period from July 3, 1995, when the emerging market data came available, to November 7, 2008. We use MSCI indices for all countries except Mexico and Korea, for which we use IFC-S&P indices. To avoid any spurious correlation caused by holidays or other non-trading days we remove days on which at least one of the markets was closed. This leaves us with a sample size of $T = 3250$ observations.

Table 4.1: Descriptive statistics

	Mean	St.dev	Skew	Kurt
US	0.04	0.20	−0.16	11.19
Canada (CA)	0.09	0.22	−0.72	12.12
Mexico (MX)	0.10	0.30	0.09	13.85
UK	0.02	0.20	−0.23	13.83
Germany (GE)	0.04	0.25	−0.14	8.00
France (FR)	0.05	0.23	−0.22	9.83
Japan (JP)	−0.03	0.25	0.17	8.09
Hong Kong (HK)	0.01	0.27	−0.19	11.07
Korea (KO)	0.00	0.44	0.26	18.28

The table reports the annualized mean, annualized volatility, skewness and kurtosis of daily stock market returns over the period from July 3, 1995 to November 7, 2008 ($T = 3250$ observations).

Table 4.1 reports summary statistics of the daily returns. Canada and Mexico render the highest annualized returns, while Japan is the only market with a negative mean return. Standard deviations are all in the range 20 - 25 percent on an annualized basis, except for Mexico and Korea, which show substantially higher volatility, reflecting the higher level of risk of these emerging markets. Skewness is negative for all countries except Mexico, Japan and Korea, suggesting that in most markets large negative returns occur more frequently than large positive returns. Kurtosis ranges from 8.00 to 18.28, indicating much fatter tails than for the normal distribution.

The unconditional correlations between the stock markets pairs US-CA, US-MX, UK-GE, UK-FR, JP-HK, and JP-KO are 0.64, 0.60, 0.73, 0.81, 0.41, and 0.35, respectively. These correlations clearly show that European markets have the highest degree of comovement in terms of correlation, followed by American and Asian markets. To get a first indication of the dependence structure for different quantiles of the return distributions, Figure 4.1 displays the exceedance correlations as used in Longin and Solnik (2001), Ang and Chen (2002) and Patton (2006b), among others. We compute the correlations given that both returns lie above or below a given quantile q of their empirical marginal distributions. For most country pairs, correlations in the left tail are higher than correlations in the right tail of the return distributions. The difference is most pronounced for the Asian countries, which have the lowest unconditional correlation. The UK and France have a higher correlation conditional on a positive return in both markets than conditional on two negative returns. They also have the highest unconditional correlation. The kink at zero, indicates that for all country pairs the correlation conditional on negative returns is higher than the correlation conditional on positive returns. This shows the importance of allowing for asymmetry when modelling dependence.

4.3.2 The marginal distributions

For the marginal distributions of the daily stock index returns we employ an AR(1)-Threshold GARCH(1,1) [TGARCH] model with a (standardized) skewed Student's t distribution for the innovations, (cf. Jondeau and Rockinger, 2006; Chollete et al., 2009, among others).

For a daily return series X_t the model reads

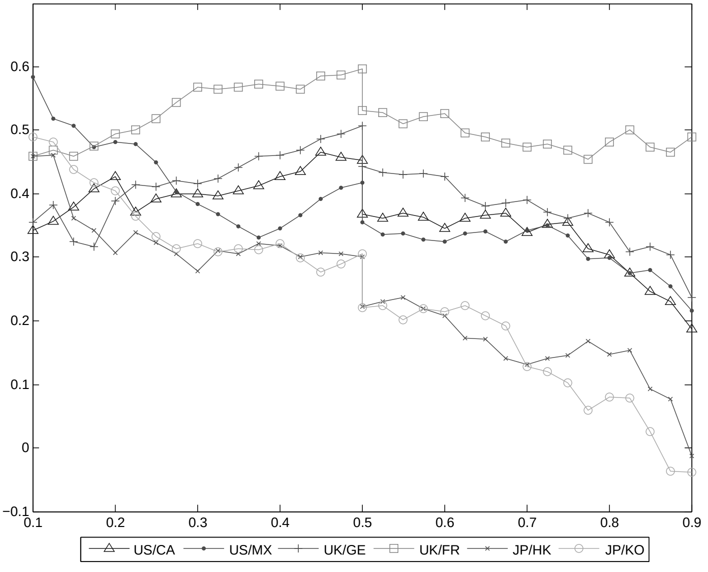
$$X_t = \phi_0 + \phi_1 X_{t-1} + \varepsilon_t \tag{4.8}$$

$$\varepsilon_t = \sigma_t z_t \tag{4.9}$$

$$\sigma_t^2 = \alpha + \beta^+ (\varepsilon_{t-1}^+)^2 + \beta^- (\varepsilon_{t-1}^-)^2 + \gamma \sigma_{t-1}^2 \tag{4.10}$$

$$z_t \sim st(\nu, \lambda) \tag{4.11}$$

Figure 4.1: Exceedance correlations



The graph shows the exceedance correlations of Ang and Chen (2002) for the different pairs of stock indices. The sample covers the period from July 3, 1995 to November 7, 2008. The horizontal axis shows the quantiles for which the exceedance correlation is computed.

where $\varepsilon_t^+ = \max(\varepsilon_t, 0)$, and $\varepsilon_t^- = \min(\varepsilon_t, 0)$. The skewed Student's t density is given by

$$st(z;\nu,\lambda) = \begin{cases} bc\left(1 + \frac{1}{\nu-2}\left(\frac{bz+a}{1-\lambda}\right)^2\right)^{-(\nu+1)/2} & \text{if } z < -a/b \\ bc\left(1 + \frac{1}{\nu-2}\left(\frac{bz+a}{1+\lambda}\right)^2\right)^{-(\nu+1)/2} & \text{if } z \geq -a/b \end{cases} \tag{4.12}$$

with

$$a = 4\lambda c\frac{\nu-2}{\nu-1}, \quad b^2 = 1 + 3\lambda^2 - a^2, \quad \text{and} \quad c = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\pi(\nu-2)}\Gamma\left(\frac{\nu}{2}\right)}.$$

The skewness (and kurtosis) of X_t are nonlinear functions of the parameters ν and λ. A negative value of the parameter λ corresponds with a left-skewed density, which is commonly observed for stock index returns, see also Table 4.1. To ensure positivity and stationarity of the conditional variance σ_t^2 we impose the restrictions $\alpha > 0$ and $\beta^+, \beta^-, \gamma \geq 0$, and $(\beta^+ + \beta^-)/2 + \gamma \leq 1$ in (4.10).

We do not allow for regime-switching in the marginal distribution (cf Jondeau and Rockinger, 2006; Chollete et al., 2009). It is of course possible to include regime switching in, for example, the conditional volatility σ_t, as in Okimoto (2008) (either induced by $S_{\theta,t}$ and $S_{\omega,t}$ or by a separate Markov process). However, this would preclude the use of the IFM method for parameter estimation. Instead we would have to resort to one-step ML estimation of all parameters in the margins and the copula jointly. Other possible extensions of the model for the marginal distribution include time-variation in the parameters ν and λ, as considered by Jondeau and Rockinger (2006, 2009).

4.3.3 The constituent copulas

For the copulas C_a and C_b in (4.3) we choose the Gaussian copula and the survival Gumbel copula. Consequently, the resulting mixture can accommodate a variety of different dependence structures. The underlying idea is that stock returns may have (presumably tranquil) periods with symmetric return dependence, which a Gaussian copula can describe, but also (turmoil) periods with asymmetric dependence and lower tail-dependence, for which a survival Gumbel copula is suitable. The specific choice for the survival Gumbel copula is motivated by Okimoto (2008), who finds that other copulas with lower tail-dependence (Joe and Clayton copulas, for instance) are too asymmetric to capture the dependence structure of equity returns adequately. Hu (2006) also uses these copulas to examine the dependence structure of returns in developed equity markets (albeit in a mixture copula with constant weights).

The Gaussian copula has cdf

$$C_{Gau}(u, v; \rho) = \Phi_\rho(\Phi^{-1}(u), \Phi^{-1}(v); \rho) \tag{4.13}$$

where $u = F_X(x)$ and $v = F_Y(y)$ as defined before, Φ_ρ is the bivariate normal cdf with correlation ρ, and Φ^{-1} is the inverse of the univariate standard normal cdf. The corresponding density is given by

$$c_{Gau}(u, v; \rho) = \frac{1}{\sqrt{1-\rho^2}} \exp\left(\frac{-(r^2 - 2\rho rs + s^2)}{2(1-\rho^2)} + \frac{r^2 + s^2}{2}\right), \tag{4.14}$$

where $r = \Phi^{-1}(u)$ and $s = \Phi^{-1}(v)$. The normal copula exhibits independence in both the lower and upper tail unless $|\rho| = 1$ (see Embrechts et al., 2003).

The survival Gumbel copula has cdf

$$C_{Gum}(u, v; \delta) = u + v - 1 + \exp\left(-[(-\ln(1-u))^\delta + (-\ln(1-v))^\delta]^{\frac{1}{\delta}}\right) \tag{4.15}$$

and the corresponding density

$$c_{Gum}(u,v;\delta) = \frac{(\ln(1-u)\ln(1-v))^{\delta-1}C^{Gum}(1-u,1-v;\delta)}{(1-u)(1-v)((-\ln(1-u))^{\delta}+(-\ln(1-v))^{\delta})^{2-\frac{1}{\delta}}}\times$$
$$(\delta-1-\ln C_{Gum}(1-u,1-v;\delta)) \quad (4.16)$$

where the parameter $\delta \in [1,\infty)$. The strength of dependence is increasing in δ, with $\delta = 1$ and $\delta = \infty$ corresponding to independence and perfect dependence. The survival Gumbel copula exhibits upper tail independence, but lower tail dependence with coefficient $\tau_L = 2 - 2^{\frac{1}{\delta}}$.

When using the Gaussian and survival Gumbel copulas in (4.3), the parameters ρ and δ are vary according to the value of $S_{\theta,t}$. For identification of the regimes with different strength of dependence, we impose the restriction $\rho^{(1)} < \rho^{(2)}$. No restrictions are put on the parameters of the Gumbel copula, but it turns out that for all country pairs the estimates are such that $\delta^{(1)} < \delta^{(2)}$. Hence, we can characterize the regimes $S_{\theta,t} = 1$ and 2 by (relatively) weak and by strong dependence. Similarly, for identification purposes we impose the restriction $\omega_2 < \omega_1$, so that the weight on the Gaussian copula in the first regime $S_{\omega,t} = 1$ is larger than in the second regime $S_{\omega,t} = 2$. For this reason we label these regimes by (relatively) symmetric and asymmetric dependence.

In addition to the general time-varying mixture copula (4.3) we estimate several nested, restricted versions of the model. By examining the loss in the likelihood due to the imposed restrictions we can asses which characteristics are most important in modelling the dependence in the equity returns. As discussed in the previous section, we conduct a likelihood ratio test of the null hypothesis $\omega^{(1)} = \omega^{(2)}$ to test for the presence of a time-varying dependence structure. The restricted model with switching copula parameters but constant mixture weight is given by

$$C(u,v;\theta_C) = \omega C_{Gau}(u,v;\rho_t) + (1-\omega)C_{Gum}(u,v;\delta_t). \quad (4.17)$$

Similarly, we conduct a likelihood ratio test of the null hypothesis $\rho^{(1)} = \rho^{(2)}$ and $\delta^{(1)} = \delta^{(2)}$ to test for the presence of time-varying strength in the dependence. We estimate a model where the copula parameters are constant, but the mixture weight can switch according to the value of $S_{\omega,t}$,

$$C(u,v;\theta_C) = \omega_t C_{Gau}(u,v;\rho) + (1-\omega_t)C_{Gum}(u,v;\delta). \quad (4.18)$$

We examine two other restricted copula specifications that have been considered previously. We implement the model proposed by Okimoto (2008), which assumes constant copula parameters, while the mixture weights in the two regimes are set equal to $\omega^{(1)} = 1$ and $\omega^{(2)} = 0$, such that the dependence structure switches between a Gaussian copula and a survival Gumbel copula, that is

$$C(u, v; \theta_C) = \begin{cases} C_{Gau}(u, v; \rho) & \text{if } S_{\omega,t} = 1, \\ C_{Gum}(u, v; \delta) & \text{if } S_{\omega,t} = 2. \end{cases} \tag{4.19}$$

Hu (2006) considers a specification with constant copula parameters and constant mixture weight, that is,

$$C(u, v; \theta_C) = \omega C_{Gau}(u, v; \rho) + (1 - \omega) C_{Gum}(u, v; \delta). \tag{4.20}$$

4.4 Results

4.4.1 Results for the margins

Table 4.2 reports the estimation results for the marginal AR(1)-TGARCH(1,1) models with skewed Student's t innovations. The parameter estimates largely reflect well-known stylized facts of univariate daily stock return distributions. First, for all countries volatility is highly persistent as the sum of $(\beta^+ + \beta^-)/2 + \gamma$ is estimated to be close to 1. This persistence allows for longer periods of relatively high and low volatility. Second, for all countries the estimate of β^- substantially exceeds the estimate of β^+, reflecting the property that negative return shocks have a larger impact on conditional volatility than positive shocks. Third, the degrees of freedom ν vary from 6.6 for Korea to 18.5 for the UK, indicating fatter tails than for Gaussian distribution. Fourth, the skewness parameter λ is negative for all countries, and significant at the 1% level for all countries but Japan and Mexico. Fifth, the AR(1) parameter ϕ_1 is small and significantly only for half of the countries, corresponding with the small first-order autocorrelation in daily stock returns.

For the IFM method it is of crucial importance that the marginal models are correctly specified, as otherwise the estimates of the copula parameters in the second step can be severely biased (see Fermanian and Scaillet, 2005). We apply the Kolmogorov-Smirnov, Cramer-Von Mises and Anderson-Darling tests to examine the goodness-of-fit. For all markets except Hong Kong these tests, reported in the final three columns of Table 4.2, cannot reject the null hypothesis of correct specification of the skewed Student's t distribution for the innovations. For Hong Kong we re-estimated the AR(1)-TGARCH(1,1,1) model with generalized error distribution for

Table 4.2: Estimation results margins

	ϕ_1	$\alpha \cdot 10^4$	β^+	β^-	γ	ν	λ	$\ell \cdot 10^{-3}$	K-S	C-M	A-D
US	−0.047	0.013	0.000	0.139	0.922	9.478	−0.123	10.38	0.639	0.711	0.058
	(0.018)	(0.003)	(0.015)	(0.017)	(0.012)	(1.448)	(0.023)				
CA	0.074	0.025	0.032	0.120	0.910	7.549	−0.115	10.01	0.776	0.812	0.649
	(0.018)	(0.007)	(0.010)	(0.018)	(0.012)	(0.905)	(0.024)				
MX	0.103	0.098	0.014	0.179	0.874	7.115	−0.030	8.95	0.697	0.781	0.846
	(0.018)	(0.020)	(0.009)	(0.024)	(0.016)	(0.814)	(0.021)				
UK	−0.024	0.021	0.011	0.128	0.915	18.487	−0.094	10.28	0.943	0.904	0.902
	(0.018)	(0.004)	(0.007)	(0.015)	(0.011)	(5.106)	(0.026)				
GE	−0.006	0.025	0.028	0.135	0.909	12.638	−0.097	9.58	0.831	0.846	0.710
	(0.018)	(0.006)	(0.010)	(0.016)	(0.010)	(2.463)	(0.025)				
FR	0.002	0.026	0.018	0.123	0.916	11.792	−0.088	9.78	0.981	0.892	0.749
	(0.018)	(0.006)	(0.009)	(0.015)	(0.010)	(2.177)	(0.025)				
JP	−0.021	0.032	0.040	0.099	0.918	10.415	−0.021	9.31	0.715	0.591	0.450
	(0.018)	(0.010)	(0.010)	(0.014)	(0.012)	(1.662)	(0.027)				
HK	0.016	0.024	0.038	0.081	0.915		1.204	9.42	0.394	0.386	0.115
	(0.018)	(0.006)	(0.012)	(0.015)	(0.011)		0.035				
KO	0.097	0.047	0.042	0.115	0.916	6.632	−0.061	8.07	0.167	0.252	0.215
	(0.018)	(0.013)	(0.010)	(0.017)	(0.011)	(0.777)	(0.022)				

The table reports estimation results of the AR(1)-TGARCH(1,1,1) model with skewed Student's t innovations, as in equations (4.8) to (4.12). For the Hong Kong stock market a generalized error distribution (GED) is used for the innovations. The parameter of the GED distribution is given in the column headed λ. The sample period runs from July 3, 1995 till November 7, 2008 ($T = 3250$ observations). The table reports the estimates for the autoregressive component (column 2), the parameters in the TGARCH specification (columns 3- 6) and the degrees of freedom and skewness parameters (column 7 and 8), with standard errors given in parentheses, as well as the log likelihood value ℓ (column 9) and p-values for the the Kolmogorov-Smirnov (K-S), Cramer-Von Mises (C-M) and Anderson-Darling (A-D) tests for uniformity of the standardized residuals in columns 10-12.

the innovations. As this distribution can not be rejected, we use the generalized error distribution for the Hong Kong stock return innovations.

As a robustness check we consider two alternatives for the marginal distributions. First, we adopt the semi-parametric approach of Chen and Fan (2006). We estimate the AR(1)-TGARCH(1,1) model with quasi-ML with a normal distribution for the innovations z_t. Then we use the empirical CDF of the standardized residuals $\hat{z}_t$ to obtain the required input for the copula estimation. Second, we use the empirical CDF's of the returns themselves as marginals. The first alternative gives results that are almost identical to those obtained with the fully parametric marginal specification in (4.8)-(4.11). For the second alternative the general patterns in the copula estimates remain similar, but for some specific parameters the differences with the fully parametric model are somewhat larger.[4]

[4]Details are available upon request.

4.4.2 Results for the US and Canada

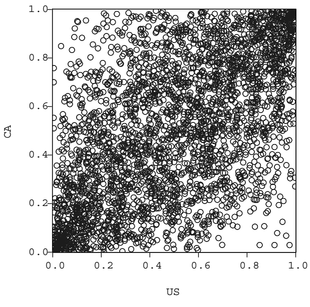
Column two in Table 4.3 reports the parameter estimates of the copula in (4.3) for the daily returns in the US and Canada. The estimation results provide evidence for the presence of different regimes for both the strength and the structure of dependence between returns in these stock markets. First, the weights on the Gaussian copula takes the values $\omega^{(1)} = 1$ and $\omega^{(2)} = 0$. So regime $S_{\omega,t} = 1$ corresponds with symmetric and no tail dependence. Regime $S_{\omega,t} = 2$ implies asymmetric and lower tail dependence. [5] Second, regimes with relatively weak and strong dependence are also well defined. For identification purposes we imposed the restriction $\rho^{(1)} < \rho^{(2)}$ for the Gaussian copula. We find in addition that $\delta^{(1)} < \delta^{(2)}$ for the survival Gumbel copula. Both copulas have weaker dependence in the regime $S_{\theta,t} = 1$. Standard errors of the copula parameters are fairly small, indicating good accuracy of the estimates.

Taken together, there are periods with symmetric and no tail dependence and periods with asymmetric and tail dependence, and within both we find regimes with relatively weak and with strong dependence. The scatterplots of the probability integral transforms (PIT) from the estimated margins F_{US} and F_{CA} in Figure 4.2 visualize our conclusion. Panel (a) shows the PITs for all observations. Panels (b)-(e) show them separately for the four different regimes, where each observation is allocated to a certain regime depending on the smoothed inference probabilities of the two Markov processes. Panels (b) and (d) concern the regimes with symmetric dependence (as $P(S_{\omega,t} = 2) < 0.5$), with the dependence being relatively weak (b) or strong (d) (as determined by the value of $P(S_{\theta,t} = 2)$). Although the difference between the estimates of the correlation parameters $\rho^{(1)} = 0.52$ and $\rho^{(2)} = 0.70$ may not seem large, the scatters clearly show that dependence in returns is considerably stronger in the second regime. The same applies to the scatters for the asymmetric dependence regimes in panels (c) and (e) (where $P(S_{\omega,t} = 2) > 0.5$). The asymmetry and lower tail dependence are more pronounced in panel (e). To some extent this is caused by the small number of observations in panel (c), but it is also present in the implied estimates for $\tau_L^{(1)}$ and $\tau_L^{(2)}$, which are equal to 0.23 and 0.78. An important assumption in our time-varying mixture copula is that changes in the strength and structure of dependence occur independently. We test the validity of this assumption by estimating the same copula specification, but with the switches among the four regimes driven by a single Markov process with unrestricted transition probabilities. A likelihood ratio test can then be conducted straightforwardly to test

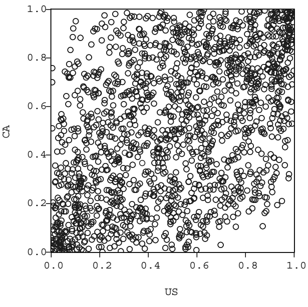
[5] Whenever a parameter estimate reaches a boundary, we impose this value and only compute standard errors for the remaining parameters.

the null hypothesis that the transition probabilities can be restricted in accordance with the independence of the Markov processes $S_{\theta,t}$ and $S_{\omega,t}$. The test statistic renders a p-value of 0.77, such that we cannot reject the independence of changes in the strength and structure of dependence.

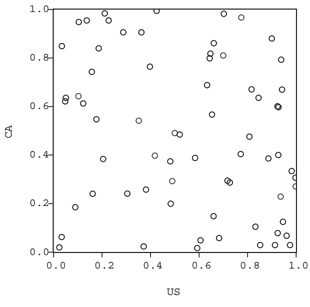
Figure 4.2: Scatterplots of u_t's for US-CA.



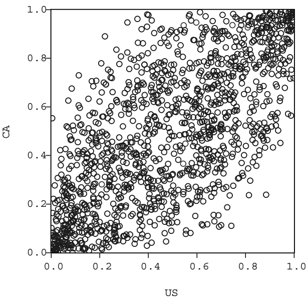
(a) All



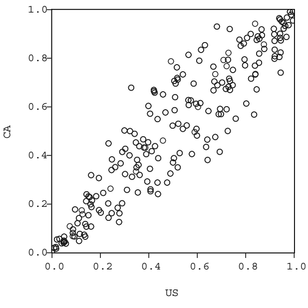
(b) Weak, symmetric



(c) Weak, asymmetric



(d) Strong, symmetric



(e) Strong, asymmetric

The transition probabilities for strength $p_{\theta,11} = 0.990$ and $p_{\theta,22} = 0.988$ indicate high persistence of the regimes. The unconditional probabilities of being in the weak or strong dependence regimes are 0.54 and 0.46.[6] So the process $S_{\theta,t}$ spends approximately half of the time in each of the regimes, irrespective of the structure of dependence. For the dependence structure the transition probabilities $p_{\omega,11} = 0.971$ and $p_{\omega,22} = 0.877$ imply that the symmetric regime is more persistent and therefore occurs more often than the asymmetric regime. The unconditional probabilities of being in the symmetric and in the asymmetric regimes are equal to 0.81 and 0.19.

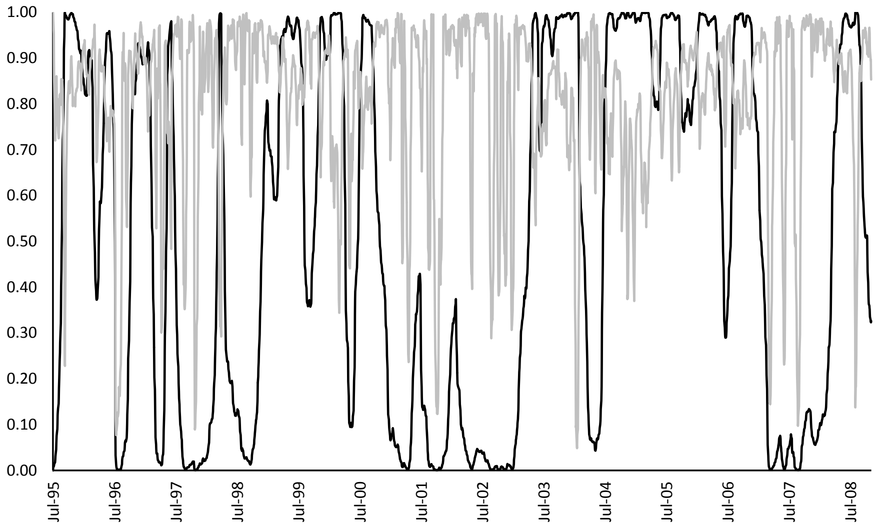
[6]The unconditional probabilities are given by $P(S_{\theta,t} = 1) = \frac{1-p_{\theta,22}}{2-p_{\theta,11}-p_{\theta,22}}$ and $P(S_{\theta,t} = 2) = \frac{1-p_{\theta,11}}{2-p_{\theta,11}-p_{\theta,22}}$.

Table 4.3: Estimation results for US-CA

	[1]	[2]	[3]	[4]	[5]
$\rho^{(1)}$	0.519	0.473	0.724	0.723	0.596
	(0.073)	(0.054)	(0.017)	(0.013)	(0.011)
$\rho^{(2)}$	0.703	0.731			
	(0.016)	(0.019)			
$\delta^{(1)}$	1.215	1.297	1.320	1.346	ND
	(0.087)	(0.115)	(0.060)	(0.038)	
$\delta^{(2)}$	3.533	2.375			
	(0.299)	(0.567)			
$\omega^{(1)}$	1	0.833	1		1
	(–)	(0.087)	(–)		(–)
$\omega^{(2)}$	0		0.094		
	(–)		(0.148)		
$p_{\theta,11}$	0.990	0.987			
	(0.006)	(0.005)			
$p_{\theta,22}$	0.988	0.987			
	(0.004)	(0.004)			
$p_{\omega,11}$	0.971		0.988	0.987	
	(0.012)		(0.004)	(0.003)	
$p_{\omega,22}$	0.877		0.984	0.982	
	(0.030)		(0.007)	(0.006)	
ℓ_C	786.574	775.611	768.387	768.104	711.034
LR test		21.927	36.375	36.940	151.081
p-value		0.014	0.000	0.000	0.000

The table reports estimation results for the mixture copula specifications for daily stock index returns for the US and Canada over the period from July 3, 1995 to November 7, 2008. Model [1] is the general time-varying mixture copula in (4.3), allowing for changes in both the strength and structure of dependence. Model [2] is the specification in (4.17), which restricts the mixture weight to be constant but allows for changes in the copula parameters (thus allowing for changes in the strength of dependence but not in the structure). Model [3] is the specification in (4.18), which restricts the copula parameters to be constant but allows for changes in the mixture weight (thus allowing for changes in the structure of dependence but not in the strength). Model [4] is the specification in (4.19), which assumes that the copula parameters are constant while allowing for changes in the mixture weight but restricted such that $\omega_1 = 1$ and $\omega_2 = 0$. Model [5] is the specification in (4.19), which restricts the copula parameters and the mixture weight to be constant. Numbers in parentheses below the parameter estimates are asymptotic standard errors. For the restricted models the parameters that are assumed constant are reported in the respective 'regime 1' row of the table. When a boundary is reached during the estimation the boundary value is imposed for this parameter. In those cases a (-) appears instead of a standard error. Unidentified parameters are indicated with ND. The last three rows report the log likelihoods of the copula models (ℓ_C), the likelihood ratio statistic of model [j] against model [1], for j = 2, 3, 4 or 5, and the corresponding p-values.

Figure 4.3: Smoothed probabilities for US-CA



The graph shows the smoothed probabilities of being in the regime with relatively weak strength of dependence ($S_{\theta,t} = 1$, black line) and the smoothed probabilities of being in the regime with relatively symmetric dependence structure ($S_{\omega,t} = 1$, grey line) in model (4.3) for the US and Canada. The sample covers the period from July 3, 1995 to November 7, 2008.

Figure 4.3 shows the smoothed inference probabilities of being in the weak dependence regime ($S_{\theta,t} = 1$) and of being in the symmetric dependence regime ($S_{\omega,t} = 1$). The regime with strong dependence seems mostly to occur in bear markets and turmoil periods with high volatility. Switches from the weak to strong dependence regime frequently coincide with the occurrence of a financial crisis, e.g. the Asian crisis (July 1997), the Russian crisis (August 1998), the crash of the dot-com bubble (March 2001) and the start of the current crisis (January 2007). The dynamics of the dependence structure regimes are less easy to relate to macroeconomic or financial circumstances, although the probability of being in the regime with asymmetric and lower tail dependence is typically higher during the crises periods mentioned above.

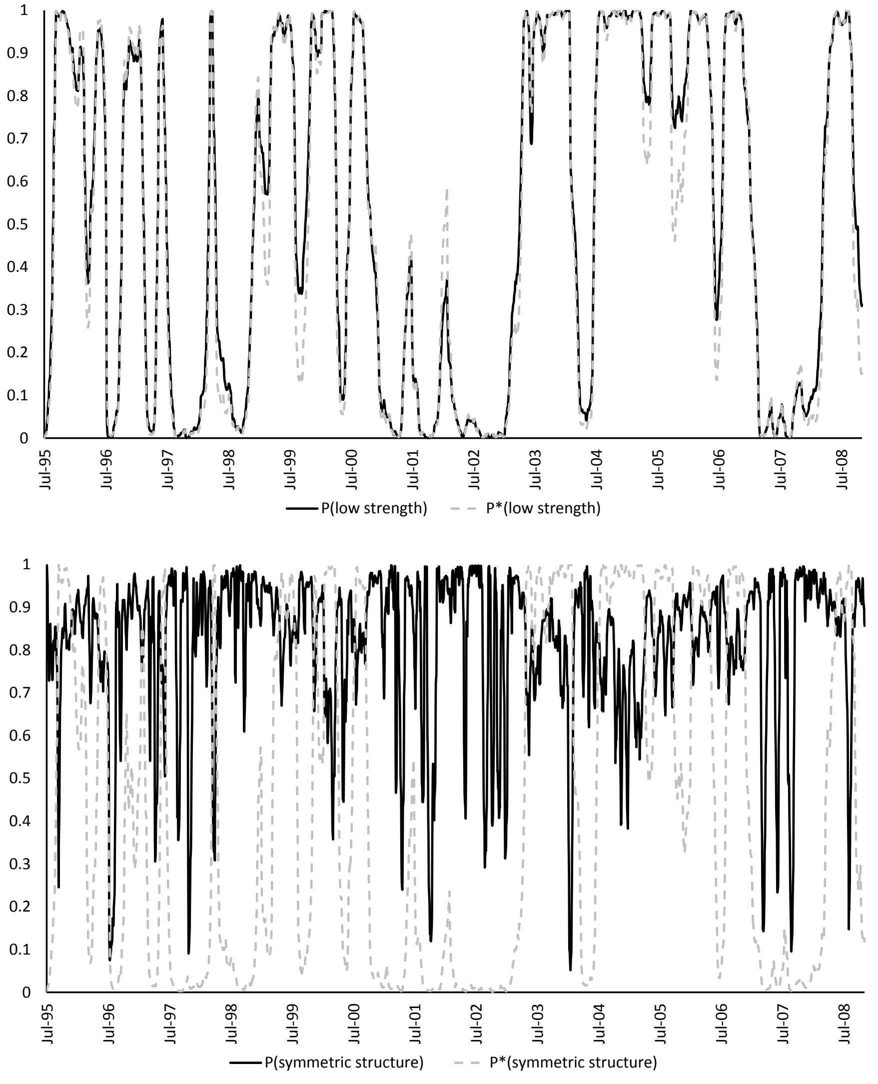
Columns 3 to 6 of Table 4.3 report the estimation results for the restricted models as given in (4.17), (4.18), (4.19) and (4.20), respectively. From the results for model [2], where the dependence strength can change but the dependence structure is constant, we see that this restriction hardly affects the estimates of the copula parameters ($\rho^{(1)}, \rho^{(2)}, \delta^{(1)}, \delta^{(2)}$). In the upper graph of Figure 4.4 we show the smoothed inference probabilities of being in the weak dependence regime for the restricted model (solid line). A dashed line shows the smoothed inference probabilities of being in the weak dependence regime obtained from the general model. Because these two sets of probabilities are almost identical, the changes in the strength of dependence can be estimated fairly accurately without taking into account possible changes in the dependence structure. The constant weight on the Gaussian copula is estimated at 0.83, which is approximately equal to the unconditional probability of being in the symmetric dependence regime in the general model. The likelihood ratio (LR) statistic of this restricted model against the general model equals 21.93. Due to the presence of unidentified nuisance parameters $p_{\omega,11}$ and $p_{\omega,22}$, the LR statistic is not distributed as $\chi^2(1)$. Simulating the null distribution of the LR statistic as in Hansen (1992) leads to a p-value of 0.014. This test rejects the restricted model, and indicates the relevance of changes in the dependence structure.

Model [3] allows for a changing dependence structure, but imposes constant dependence strength, see (4.18). In this case, the correlation estimate in the Gaussian copula is even higher than in the strong dependence regime of the general model (0.72 versus 0.70), while the estimate of the parameter in the Gumbel copula is 1.35, slightly larger than the estimate in the weak dependence regime of the general model (1.22). The weight on the Gaussian copula is 1 in the more symmetric regime and 0.094 in the asymmetric regime. We thus have regimes with weak asymmetric dependence and with strong symmetric dependence. The estimates of this model are therefore almost equal to model [4], where the weights $\omega^{(1)}$ and $\omega^{(2)}$ are restricted to be 1 and 0, respectively (see (4.19)). The LR statistic between model (4.18) and the general model equals 36.38, and the difference in the numbers of parameters is four. Again we simulate the LR statistic, and this leads to a rejection of the model without possible changes in dependence strength with a p-value of 0.00.

The lower graph of Figure 4.4 shows the smoothed probability of being in the regime where the dependence structure is more symmetric in model [3]. Interestingly, these probabilities do not at all resemble the *dependence structure* probabilities in the general model. Actually, they are almost the mirror image of the smoothed probabilities for being in the weak *dependence strength* of our model. Thus, while changes in the dependence strength are not allowed for in (4.18), they are in fact captured by the changes in dependence structure. Indeed, the Gaussian copula with $\rho = 0.72$ has an *overall* stronger dependence than the Gumbel copula with parameter $\delta = 1.32$.

The final restricted model [5] in (4.20) does not allow for any regime-switches in the dependence strength or structure. The estimation results in Table 4.3 show that the obtained copula is fully Gaussian with correlation coefficient equal to 0.596. The difference in the log likelihood compared with the other models becomes very large in this case. Therefore, at least some time variation is required for modelling the dependence between these stock market returns.

Figure 4.4: Smoothed probabilities for US-CA - restricted models



The upper graph shows the smoothed probabilities of being in the weak dependence regime from the restricted model (4.17) (solid) and from the general model (4.3) (dashed). The lower graph shows the smoothed probabilities of being in the more symmetric regime from the restricted model (4.18) (solid) and from the general model (4.3) (dashed). The sample covers the period from July 3, 1995 to November 7, 2008.

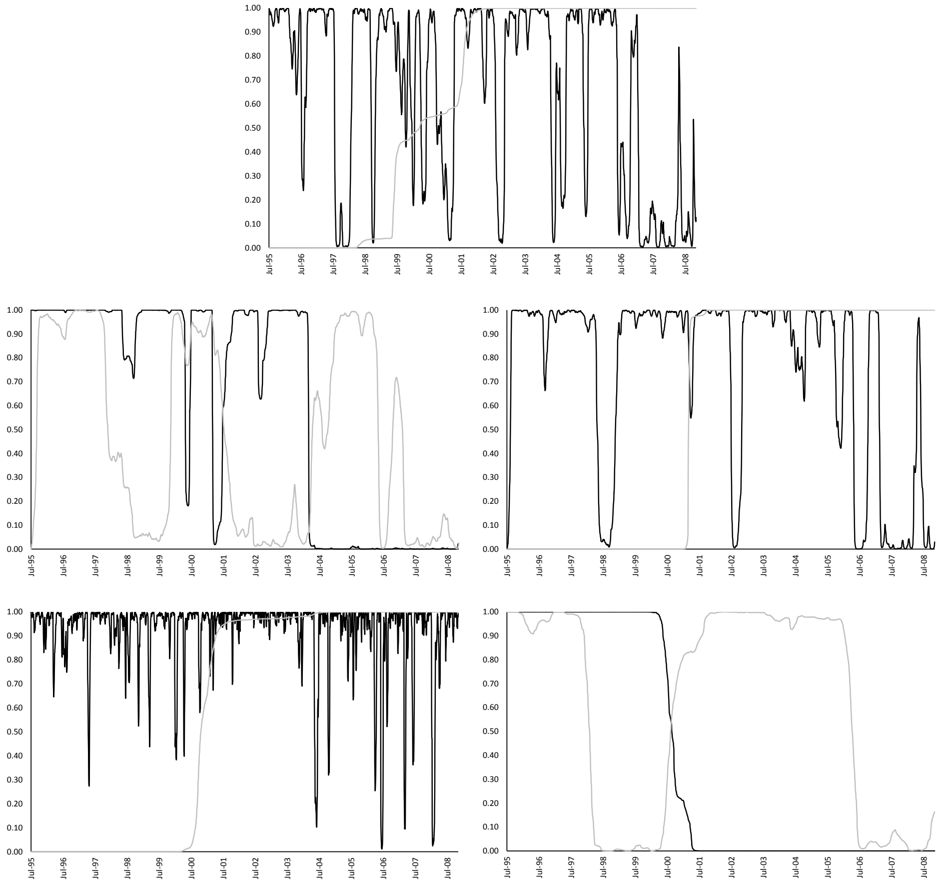
4.4.3 Results for other country pairs

We repeat our analysis for the other country pairs. Tables 4.4-4.8 repeat the estimation results for the other stock market pairs. Figure 4.5 shows the smoothed probabilities of being in the weak dependence regime and in the (more) symmetric dependence regime for each of these pairs. In general, the results are comparable to those obtained for the US and Canada. For all country pairs, we find evidence for changes in both strength and structure of dependence, although the characteristics and timing of the various regimes vary considerably. For all countries, we reject the hypothesis of no changes in strength with p-values equal to 0.00. We reject the hypothesis of absence of changes in structure with p-values smaller than 0.05. We conclude that accounting for either only time-varying structure of dependence, as in Rodriguez (2007), Okimoto (2008) and Chollete et al. (2009), or only time-varying strength of dependence, as in Jondeau and Rockinger (2006), Bartram et al. (2007) and Hafner and Manner (2008), does not model the dependence between international stock markets adequately.

For the US/CA pair we found that $\omega^{(1)} = 1$ and that $\omega^{(2)} = 0$, which means that the dependence structure is either fully symmetric and Gaussian or asymmetric and Gumbel. For the other country-pairs for all estimates, but $\omega^{(1)}$ for UK/GE, it holds that $\omega^{(1)} \neq 1$ and $\omega^{(2)} \neq 0$. Therefore we perform a test whether the more parsimonious model, with the restrictions $\omega^{(1)} = 1$ and that of $\omega^{(2)} = 0$ is also suitable for the other country pairs. For all countries this more parsimonious model is rejected with p values ranging from 0.00 for UK/FR to 0.03 for UK/GE. Thus, a mix of a symmetric and asymmetric copula is needed to model the dependence adequately.

For the US and Mexico we find a clear difference between the weak and strong dependence regimes as both $\rho_1 < \rho_2$ and $\delta_1 < \delta_2$, although the difference between the Gumbel parameters is not as large as for the US and Canada. The Gaussian copula is most important in the more symmetric regime, although the Gumbel copula still receives a non-negligible weight of 0.136. In the asymmetric regime the copula is a weighted average of the Gaussian and Gumbel copulas with weights 0.353 and 0.647. The smoothed inference probabilities in Figure 4.5 show that the dependence structure switches only once during the summer of 2001, from the lower tail dependent regime to the more symmetric regime. Here the Markov-Switching framework accommodates a non-recurrent, permanent change in dependence. The strength of dependence regime is persistent with probabilities 0.990 and 0.980. The strong dependence regime occurs during most periods of financial crises and since 2006.

Figure 4.5: Smoothed probabilities



The graph shows the smoothed probabilities of being in the regime with relatively weak dependence ($S_{\theta,t} = 1$, black line) and the smoothed probabilities of being in the regime with relatively symmetric dependence ($S_{\omega,t} = 1$, grey line) in model (4.3). The sample covers the period from July 3, 1995 to November 7, 2008.

The estimation results of Germany and the UK in Table 4.5 show that the asymmetric part of the mixture copula always implies a strong dependence, with $\delta^{(1)}$ and $\delta^{(2)}$ both exceeding 2. The correlations in the Gaussian copula differ substantially, with $\rho^{(1)} = 0.48$ and $\rho^{(2)} = 0.82$. The regime $S_{\omega,t} = 1$ is strictly symmetric. Since $\omega^{(1)} = 1$ only the Gaussian copula matters. In the asymmetric regime $S_{\omega,t} = 2$ the mixture copula is approximately an equally-weighted average of the Gaussian and Gumbel copulas. The smoothed probabilities for the weak dependence strength regime in Figure 4.5 are close to one until December 2003, and then drop to zero for the remaining part of the sample period, indicating a permanent increase in the

Table 4.4: Estimation results for US-MX

	[1]	[2]	[3]	[4]	[5]
$\rho^{(1)}$	0.578	0.512	0.758	0.729	ND
	(0.048)	(0.051)	(0.073)	(0.017)	
$\rho^{(2)}$	0.825	0.837			
	(0.029)	(0.033)			
$\delta^{(1)}$	1.140	1.148	1.238	1.262	1.559
	(0.048)	(0.094)	(0.082)	(0.038)	(0.092)
$\delta^{(2)}$	1.832	1.543			
	(0.534)	(0.189)			
$\omega^{(1)}$	0.864	0.744	0.929		0.000
	(0.138)	(0.121)	(0.056)		(–)
$\omega^{(2)}$	0.353		0.126		
	(0.317)		(0.130)		
$p_{\theta,11}$	0.990	0.992			
	(0.006)	(0.005)			
$p_{\theta,22}$	0.980	0.987			
	(0.012)	(0.008)			
$p_{\omega,11}$	1.000		0.987	0.983	
	(–)		(0.006)	(0.004)	
$p_{\omega,22}$	0.999		0.986	0.977	
	(0.002)		(0.014)	(0.007)	
ℓ_C	712.815	702.044	688.809	685.101	593.412
LR test		21.541	26.470	55.428	238.805
p-value		0.011	0.000	0.000	0.000

Estimation results for the mixture copula specifications for US-MX. For further details see Table 4.3.

dependence strength around that time. The dependence structure also switches relatively infrequently. It changes to being tail dependent following the Asian crisis, and becomes symmetric again at the end of 1999, until another regime-switch occurs around the time of the dot-com crisis. After this date the dependence structure is symmetric for around 3 years, and ends in the asymmetric regime in 2007 and 2008.

For France and the UK, we observe a one-time change from an almost symmetric dependence structure to a much more asymmetric structure at the burst of the dot-com bubble in April 2001, when the mixture weight for the Gaussian copula drops from 0.96 to 0.35. For the Gaussian copula, the correlation is high in both regimes ($\rho^{(1)} = 0.82$ and $\rho^{(2)} = 0.93$, indicating strong co-movement or even "near" tail-

Table 4.5: Estimation results for UK-GE

	[1]	[2]	[3]	[4]	[5]
$\rho^{(1)}$	0.480	0.638	0.855	0.844	0.677
	(0.042)	(0.033)	(0.076)	(0.008)	(0.006)
$\rho^{(2)}$	0.818	0.823			
	(0.028)	(0.023)			
$\delta^{(1)}$	2.120	1.314	1.439	1.541	ND
	(0.209)	(0.108)	(0.254)	(0.035)	
$\delta^{(2)}$	3.761	3.953			
	(0.381)	(0.740)			
$\omega^{(1)}$	1.000	0.707	0.962		1.000
	(–)	(0.091)	(0.175)		(–)
$\omega^{(2)}$	0.405		0.191		
	(0.232)		(0.289)		
$p_{\theta,11}$	0.998	0.997			
	(0.002)	(0.002)			
$p_{\theta,22}$	0.998	0.996			
	(0.002)	(0.003)			
$p_{\omega,11}$	0.996		0.997	0.995	
	(0.006)		(0.003)	(0.003)	
$p_{\omega,22}$	0.996		0.997	0.996	
	(0.007)		(0.003)	(0.002)	
ℓ_C	1196.071	1187.708	1161.306	1153.922	991.302
LR test		16.726	69.529	84.298	409.538
p-value		0.032	0.000	0.000	0.000

Estimation results for the mixture copula specifications for UK-GE. For further details see Table 4.3.

dependence between these markets. The difference in Gumbel parameters is more pronounced, with $\delta^{(2)} = 1.99$ exceeding $\delta^{(1)} = 1.33 =$. This difference indicates much stronger (tail) dependence in the regime $S_{\theta,t} = 2$, with $\tau_L^{(1)} = 0.32$ and $\tau_L^{(2)} = 0.58$. Again we find that the strong dependence regime is relevant for financial crises and the subsequent bear markets (Asian crises, July 1997; April 2001; September 2002, and the recent financial crisis).

Japan and Hong Kong also experienced a single change from symmetric dependence structure to asymmetric structure ($\omega^{(1)} = 0.868$ compared to $\omega^{(2)} = 0.273$), which occurred around the burst of the dotcom bubble. The Gumbel parameter estimates in Table 4.7 are fairly small though, suggesting that the lower tail depen-

Table 4.6: Estimation results for UK-FR

	[1]	[2]	[3]	[4]	[5]
$\rho^{(1)}$	0.823	0.722	0.873	0.577	ND
	(0.014)	(0.078)	(0.010)	(0.021)	
$\rho^{(2)}$	0.931	0.890			
	(0.007)	(0.021)			
$\delta^{(1)}$	1.334	1.188	1.443	2.829	2.090
	(0.061)	(0.125)	(0.067)	(0.084)	(0.041)
$\delta^{(2)}$	1.986	2.545			
	(0.194)	(1.472)			
$\omega^{(1)}$	0.958	0.723	0.969		0.000
	(0.018)	(0.079)	(0.027)		(–)
$\omega^{(2)}$	0.348		0.250		
	(0.071)		(0.070)		
$p_{\theta,11}$	0.996	0.994			
	(0.003)	(0.004)			
$p_{\theta,22}$	0.988	0.995			
	(0.006)	(0.008)			
$p_{\omega,11}$	1.000		0.997	0.993	
	(–)		(0.003)	(0.003)	
$p_{\omega,22}$	0.999		0.996	0.994	
	(0.001)		(0.002)	(0.002)	
ℓ_C	1542.942	1503.111	1494.663	1433.328	1280.737
LR test		79.662	96.558	219.227	524.410
p-value		0.000	0.000	0.000	0.000

Estimation results for the mixture copula specifications for UK-FR. For further details see Table 4.3.

dence between these markets is not particularly strong. The transition probability $p_{\theta,22} = 0.87$ is relatively low, showing that most of the time the dependence strength is in the weak regime. Figure 4.5 confirms that the strength is mostly strong , although we observe that the strong strength regime starts to occur more and more often after March 2004.

Japan and Korea is the only pair that shows independence in the weak and symmetric regime, as shown in Table 4.8. Note that the dependence structure changes from the tail independent symmetric regime to a tail dependent regime after the crash of the dot-com bubble. The dependence strength switches only a few times, while ending, as all other countries, in the strong dependence regime.

Table 4.7: Estimation results for JP-HK

	[1]	[2]	[3]	[4]	[5]
$\rho^{(1)}$	0.435	0.387	0.585	0.337	0.379
	(0.057)	(0.039)	(0.062)	(0.019)	(0.005)
$\rho^{(2)}$	0.893	0.883			
	(0.032)	(0.043)			
$\delta^{(1)}$	1.128	1.192	1.164	2.591	ND
	(0.050)	(0.052)	(0.039)	(0.276)	
$\delta^{(2)}$	1.899	2.559			
	(0.608)	(0.957)			
$\omega^{(1)}$	0.868	0.645	0.749		1.000
	(0.184)	(0.145)	(0.130)		(–)
$\omega^{(2)}$	0.273		0.228		
	(0.253)		(0.139)		
$p_{\theta,11}$	0.989	0.990			
	(0.005)	(0.005)			
$p_{\theta,22}$	0.871	0.872			
	(0.030)	(0.035)			
$p_{\omega,11}$	1.000		1.000	0.988	
	(–)		(–)	(0.007)	
$p_{\omega,22}$	0.999		0.999	0.875	
	(0.001)		(0.001)	(0.029)	
ℓ_C	289.007	281.209	276.660	273.339	251.001
LR test		15.595	24.694	31.337	76.011
p-value		0.022	0.000	0.000	0.000

Estimation results for the mixture copula specifications for JP-HK. For further details see Table 4.3.

4.5 Economic significance

4.5.1 Exceedance correlation and quantile dependence

We examine the economic significance of a model with both changes in the dependence strength and structure by looking at quantile dependence and exceedance correlation (see Chollete et al., 2009). These measures shed light on the dependence of extreme returns, and are therefore important for investors and risk-managers assessing their downside risk.

For all combinations of $S_{\theta,t}$ and $S_{\omega,t}$, panel A of Table 4.9 reports the lower tail dependence coefficients τ_L. When the dependence structure is in the (relatively)

Table 4.8: Estimation results for JP-KO

	[1]	[2]	[3]	[4]	[5]
$\rho^{(1)}$	0.003	−0.045	−0.079	0.010	0.371
	(0.103)	(0.063)	(0.140)	(0.049)	(0.008)
$\rho^{(2)}$	0.473	0.552			
	(0.035)	(0.041)			
$\delta^{(1)}$	1.425	1.730	1.420	1.411	ND
	(0.112)	(0.335)	(0.075)	(0.031)	
$\delta^{(2)}$	1.959	1.260			
	(0.239)	(0.153)			
$\omega^{(1)}$	0.992	0.792	0.770		1.000
	(0.115)	(0.082)	(0.192)		(–)
$\omega^{(2)}$	0.453		0.000		
	(0.172)		(–)		
$p_{\theta,11}$	0.999	0.998			
	(0.001)	(0.002)			
$p_{\theta,22}$	1.000	0.999			
	(–)	(0.001)			
$p_{\omega,11}$	0.999		0.997	0.997	
	(0.001)		(0.003)	(0.002)	
$p_{\omega,22}$	0.999		0.999	0.999	
	(0.002)		(0.001)	(0.001)	
ℓ_C	336.522	327.309	297.917	296.163	239.572
LR test		18.427	77.209	80.719	193.900
p-value		0.011	0.000	0.000	0.000

Estimation results for the mixture copula specifications for JP-KO. For further details see Table 4.3.

symmetric regime $S_{\omega,t} = 1$, the lower tail dependence coefficient is equal to zero for those country pairs for which $\omega^{(1)} = 1$ (US-CA and UK-GE) and the Gaussian distribution receives all weight in the mixture. The Gaussian copula implies tail independence (unless $|\rho| = 1$). For the other country pairs, the Gumbel copula receives some weight in this regime, but as it is fairly small, the tail dependence coefficient remains close to zero. For US-MX, for example, the weight on the Gumbel copula is 0.14 in regime $S_{\omega,t} = 1$, and the lower tail dependence coefficient is 0.02 (0.07) in the weak (strong) dependence regime. As the mixture weight for the Gumbel copula is larger when $S_{\omega,t} = 2$, the lower tail dependence coefficient in this regime is larger. For some country pairs, the lower tail dependence becomes rather large.

Table 4.9: Tail dependence

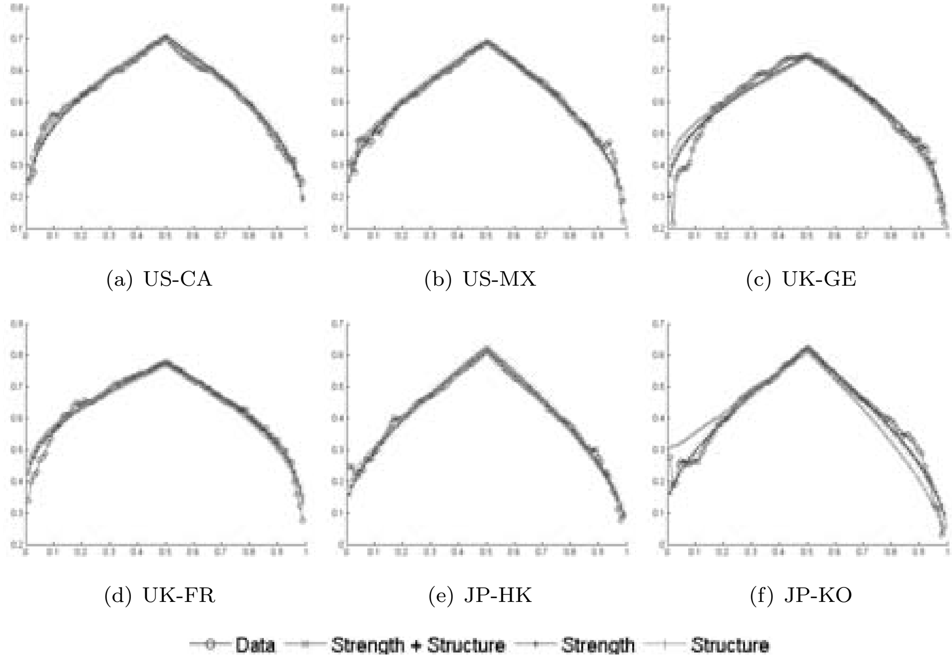
	US-CA	US-MX	UK-GE	UK-FR	JP-HK	JP-KO
Panel A: lower tail dependence coefficients						
Weak, symmetric dependence	0.00	0.02	0.00	0.01	0.02	0.00
Weak, asymmetric dependence	0.23	0.11	0.36	0.21	0.12	0.21
Strong, symmetric dependence	0.00	0.07	0.00	0.02	0.07	0.00
Strong, asymmetric dependence	0.78	0.35	0.47	0.38	0.43	0.31
Panel B: exceedance probabilities						
Weak, symmetric dependence	0.26	0.28	0.23	0.52	0.20	0.05
Weak, asymmetric dependence	0.27	0.23	0.47	0.41	0.20	0.24
Strong, symmetric dependence	0.40	0.53	0.52	0.69	0.62	0.23
Strong, asymmetric dependence	0.79	0.55	0.69	0.63	0.59	0.43

Panel A of the table reports the tail dependence for different combinations of the regimes of the strength and structure of dependence, implied by the estimation results of the dependence model. The tail dependence is $\tau_L = (1 - \omega_{s_\omega})(2 - 2^{\frac{1}{\delta_{s_\theta}}})$. Panel B report the probability of observing one return in the lower 5%-percentile given that the other return belongs to this percentile. This is computed by $C(0.05, 0.05)/0.05 = p_{c5\%} = \omega_{s_\omega} C_{Gau}(0.05, 0.05; \rho_{s_\theta})/0.05 + (1 - \omega_{s_\omega}) C_{Gum}(0.05, 0.05; \delta_{s_\theta})/0.05$.

For the US-CA pair, where the Gumbel copula receives all weight in the asymmetric regime, τ_L is equal to 0.23 (0.78) in the weak (strong) dependence regimes.

Though these lower tail dependence coefficients suggest large differences in the dependence between extreme returns across the different regimes, they do not tell a complete story. The Gaussian and Gumbel copulas differ fundamentally as the one implies lower tail independence but the other tail dependence, This property is not informative about the dependence between returns below small quantiles q. Therefore, Panel B shows the exceedance probabilities $\tau(q)$ for $q = 0.05$, i.e., the probability of observing a return below the 5th quantile given that the other return is below this quantile. For all country pairs, we find a higher value of $\tau(q)$ in the strong dependence regime ($S_{\theta,t} = 2$) compared to the weak dependence regime ($S_{\theta,t} = 1$), for a given dependence structure regime (keeping $S_{\omega,t}$ fixed). For US-CA, UK-GE, and JP-KO, the exceedance probabilities also increase when going from the symmetric dependence regime ($S_{\omega,t} = 1$) to the asymmetric regime ($S_{\omega,t} = 2$), for a given strength of dependence regime (keeping $S_{\theta,t}$ fixed). For US-MX and JP-HK the exceedance probabilities stay approximately the same in this case, while for UK-FR these actually decline. A decline in exceedance probability, when going from

Figure 4.6: Simulated quantile dependence



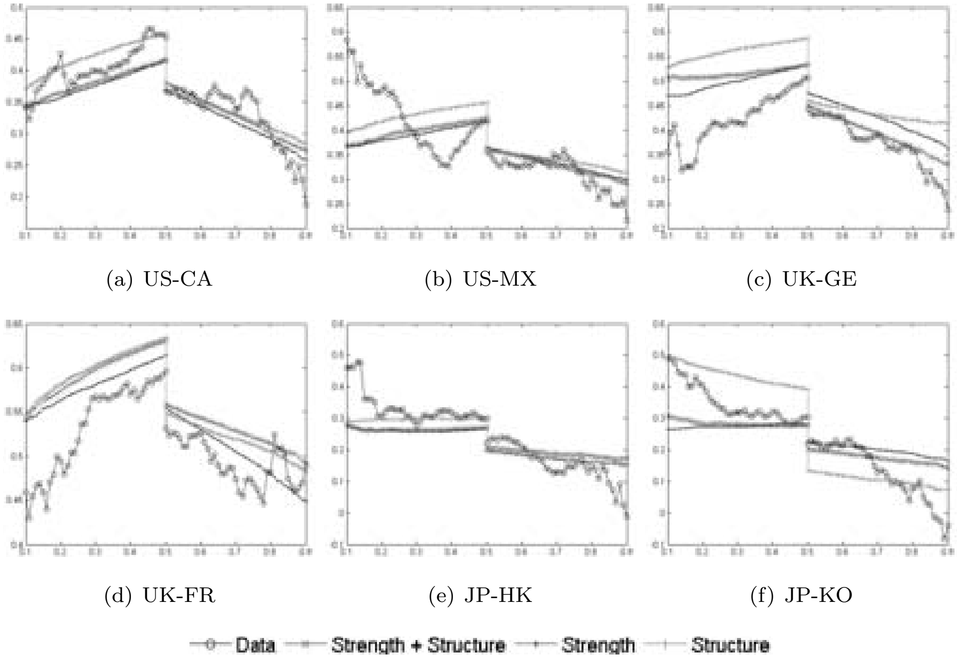
(a) US-CA (b) US-MX (c) UK-GE

(d) UK-FR (e) JP-HK (f) JP-KO

For all country pairs, this figure shows the quantile dependence implied by the different models as well as the empirical quantile dependence. In all graphs we show the quantile dependence from the model where the strength and structure can vary (4.2) and the models where either the strength or the structure can vary, (4.17) and (4.18). We used 10,000*3249 simulations and computed the exceedance correlation of the inverse standard normal of the marginals, and computed exceedance correlations implied by the models, for the following thresholds: from 0.01 to 0.99 by increments of 0.01.

the symmetric to the asymmetric regime can happen because a strong dependent Gaussian copula implies a higher $\tau(q)$ than a weak dependent Gumbel copula. For the UK and France $\tau(q)$ declines from 0.52 to 0.41 when going from $S_{\omega,t} = 1$ to $S_{\omega,t} = 2$ in case of the weak dependence regime ($S_{\theta,t} = 1$). The Gaussian copula with $\rho^{(1)} = 0.83$ gives a higher exceedance probability than a Gumbel copula with $\delta^{(1)} = 1.33$. When the dependence is strong ($S_{\theta,t} = 2$), $\tau(q)$takes the values 0.69 and 0.63 in the two dependence structure regimes, as a Gaussian copula with $\rho^{(2)} = 0.93$ implies a higher a exceedance probability at $q = 0.05$ than the Gumbel copula with $\delta^{(2)} = 1.986$. Next we asses how well our model replicates the dependence observed in the empirical data. Therefore, we compare the quantile dependence of the empirical data, with simulated data from the mixture model with time-varying strength and structure. In addition, we perform the same analysis for the two restricted models in which only one dependence characteristic is allowed to vary. We simulate 10,000 samples

Figure 4.7: Simulated exceedance correlations



(a) US-CA (b) US-MX (c) UK-GE

(d) UK-FR (e) JP-HK (f) JP-KO

For all country pairs, this figure shows the exceedance correlations implied by the different models as well as the empirical exceedance correlations. In all graphs we show the exceedance correlation from the model where the strength and structure can vary (4.2) and the models where either the strength or the structure can vary, (4.17) and (4.18). We used 10,000*3249 simulations and computed the exceedance correlation of the inverse standard normal of the marginals, and computed exceedance correlations implied by the models, for the following thresholds: from 0.1 to 0.9 by increments of 0.01.

of the same length as the empirical time series (N=3249). For each of the simulated series, we compute the quantile dependence of the standard normal PIT for different thresholds q varying from 0.01 to 0.99 with increments 0.01.

Figure 4.6 shows the empirical quantile dependence and the quantile dependence implied by the three different models. For most countries, all models replicate the quantile dependence of the empirical data quite well. The models perform less when replicating the left tail of the UK-GE pair and both tails of the JP-KO pair. For these tails the model with time-varying strength and structure of dependence is somewhat more accurate than the model with only time-varying strength, and substantially better than the model where only the structure of dependence can vary over time. Altogether, quantile dependence is modeled quite accurate by the models. Using the same simulation, we compute the exceedance correlations for different thresholds ranging from 0.1 to 0.9 with increments 0.01.[7] These are shown in Figure 4.7. For most countries, the time-varying mixture copula allowing for changes in both strength and structure replicates the empirical pattern. Especially for the pairs US-CA and JP-KO the model is able to replicate the exceedance correlation accurately. For the other pairs, the model performs less, as both restricted model do. As for the quantile dependence, the results for our model and the model with only time-varying strength are comparable, while only time-variation in the structure leads to somewhat worse results. In summary, to match exceedance correlations and quantile dependencies well, we need at least time-varying strength of dependence.

4.5.2 Value at Risk and Expected shortfall

To assess the economic relevance of changes in the strength of dependence as well as the structure of dependence we investigate Value at Risk (VaR) and Expected Shortfall (ES) for equally-weighted portfolios of the two countries in a pair.[8] These two measures are commonly used in practice by risk-managers. For instance, due to the Basel accord, each day banks have to report their VaR.

For a threshold q, $\text{VaR}(q)$ corresponds with the q-th quantile of the portfolio loss distribution. Expected shortfall is the expected loss of a portfolio given that the loss is larger than $\text{VaR}(q)$. If we denote the portfolio return by Z then VaR and ES can be expressed by,

$$\text{VaR}(q) = \text{argmax}\{z : P(Z \leq z) \leq q\}$$

and

$$\text{ES}(q) = E[Z|z \leq \text{VaR}(q)]$$

To compare the VaR and ES estimates obtained from the general time-varying mixture copula with the models with only either time-varying strength or structure of dependence we perform a simulation study. We vary the probability of the weak dependence regime and the symmetric dependence regime between 0 and 1 with steps of 0.05. This results in 441 combination of regime probabilities in the strength-structure plane. For each of those, we simulate 1,000,000 random drawings from each of the three copula models. Following Chollete et al. (2009), we convert these random drawings to the real line by using the standard normal PIT. We form equally-weighted portfolios from the simulated returns and compute $\text{VaR}(q)$ by taking the q-th quan-

[7] Exceedance correlations based on quantiles between 0.01-0.1 and 0.9-0.99, behave very badly, in contrast with quantile dependencies. Therefore we consider only the exceedance correlations between 0.1 and 0.9

[8] It is also possible to calculate the portfolio returns, and directly compute VaR estimates from these returns. However, Markwat et al. (2010) show that multivariate return dynamics contain important information for calculating VaR.

tile of the simulated data, and ES(q) by the average of the values below the q-th quantile of the simulated data.

Note that Okimoto (2008) and Chollete et al. (2009) compute *unconditional* VaR and ES estimates, by averaging across the regimes with different structure of dependence. This means they ignoring the time-variation in the structure of dependence. For instance, Okimoto (2008) concludes that a copula specification with symmetric dependence overestimates (underestimates) VaR(q) for high (low) values of q relative to a semi-symmetric dependence model. This result may hold unconditionally, but as a result of the time-varying nature of the dependence it is not necessarily true for different time periods. To shed light on this issue, we consider VaR and ES estimates *conditional* on specific probabilities of being in the different dependence regimes.

To compare the VaR estimates across copulas we follow Okimoto (2008) and Chollete et al. (2009). We compute the VaR(q) ratios of the general time-varying mixture copula and both restricted specifications ($=\frac{\mathrm{VaR}(q)}{\mathrm{VaR}_{\mathrm{restricted}}(q)}$). If this ratio is positive the restricted models underestimate VaR(q) compared to our model, and the restricted models overestimate VaR(q) when the ratio is negative. In the comparison we assume that the model with both time-varying strength and structure of dependence is the true model. We have the following motivation for making this assumption. The strong rejections of the restricted models in Section 4.4 suggest that the model with time-varying strength and structure of dependence comes much closer to the actual dependence in the data than the restricted models. To save space in the following, we only describe the results based on VaR(q) as the results on ES lead to the exact same conclusions.[9]

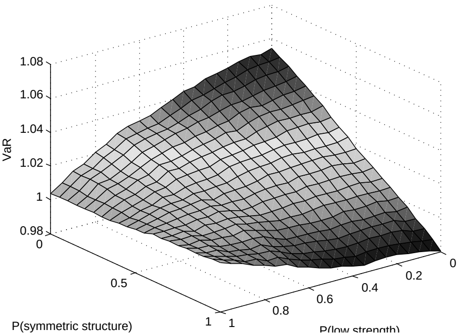
Figure 4.8 shows the VaR(q) ratios for $q = 0.01$. The panels on the left show VaR ratios relative to the "strength only" copula, while the panels on the right show VaR ratios relative to the "structure only" copula. The graphs demonstrate that ignoring either the strength or the structure of dependence leads to substantially different VaR estimates. In line with the statistical analysis, the difference in VaR estimates is more pronounced for the structure only model, than for the strength only model, for all country pairs.

The US-CA pair (a) shows that not including changes in the structure of dependence leads to a relative overestimation of VaR by 2% when the dependence is symmetric and strong, while it leads to a relative underestimation by about 6% when the dependence is asymmetric and strong. Not including changes in the strength of dependence leads to an even higher overestimation of 6% (symmetric and weak dependence) and underestimation by 10% (asymmetric and strong dependence). For the US-MX pair (c) keeping the dependence structure constant does not have a large

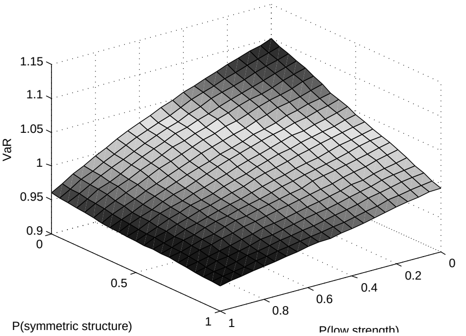
[9]The results based on ES are available upon request.

effect on the VaR(q) estimates. Keeping the dependence strength constant (d) again leads to a large VaR overestimation (9%) when the dependence is asymmetric and strong. The pairs involving the European countries (e,f,g,h) show similar results. For UK-GE overestimation of VaR using the restricted models is a bigger problem than underestimation. The JP-HK pair (i) shows hardly any difference in VaR estimates when the strength only model is considered. For the structure only model (j), the underestimation ranges from 14% to 10%, when the actual dependence is strong and the probability of the symmetric structure increases from 0 to 1. JP-KO (k) is the only pair for which the strength only model leads to substantially different VaR estimates, with VaR being underestimated by 10% in the asymmetric and weak dependence regime. The largest underestimation for the structure only model for this pair (l) is even 15%, in the strong and symmetric dependence regime. Figure 4.9 shows the results for VaR(5%) as a robustness-check. The results and conclusions are the same as for the VaR(1%). Thus, ignoring different dependence characteristics can lead to biases in VaR estimates up to 15%.

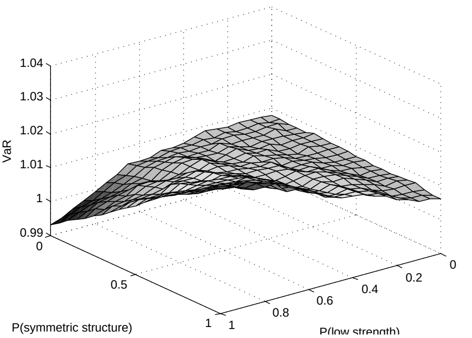
Figure 4.8: 1% VaR Ratios



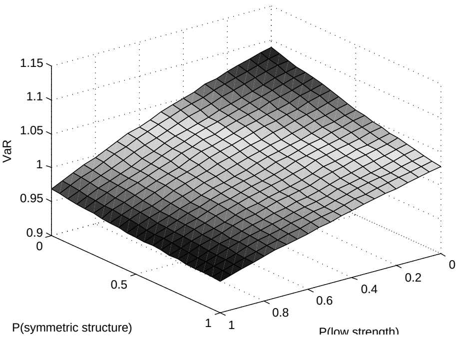
(a) US/CA - Strength only



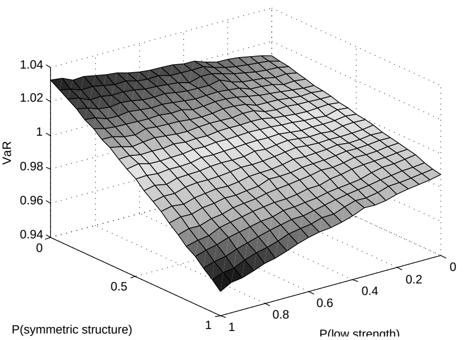
(b) US/CA - Structure only



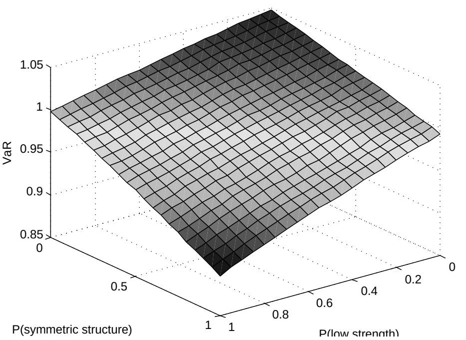
(c) US/MX - Strength only



(d) US/MX - Structure only



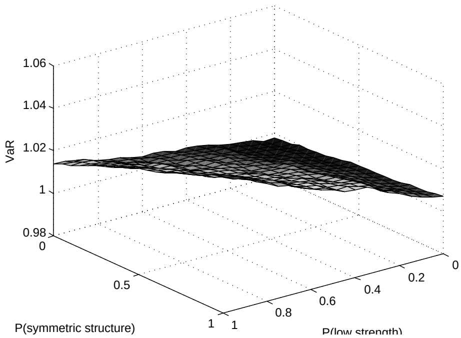
(e) UK/GE - Strength only



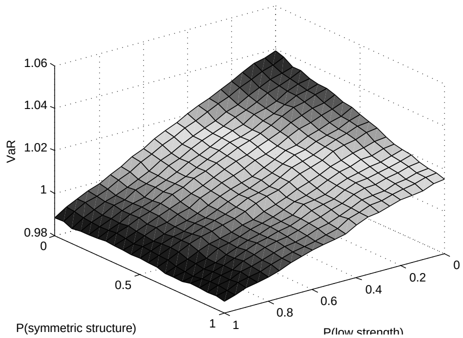
(f) UK/GE - Structure only

The figure shows the VaR(1%) ratios of the general time-varying mixture copula and both restricted specifications ($=\frac{\mathrm{VaR}(q)}{\mathrm{VaR}_{\mathrm{restricted}}(q)}$). The figures on the left show the ratio of our model against the strength only model. The figures on the right show the ratio for our model against the structure only model.

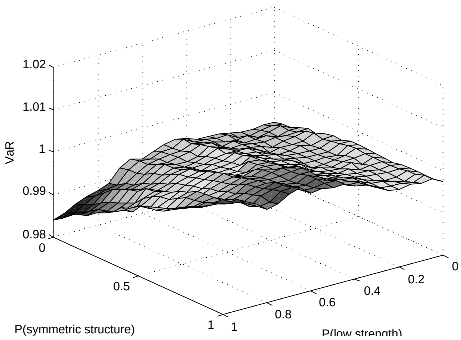
Figure 4.8: continued



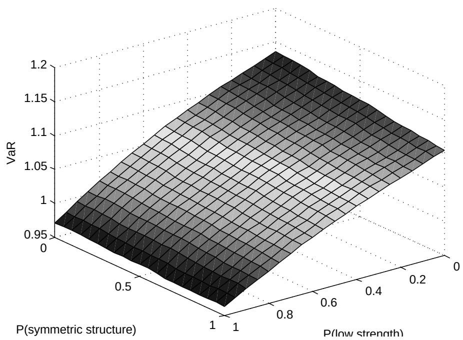
(g) UK/FR - Strength only



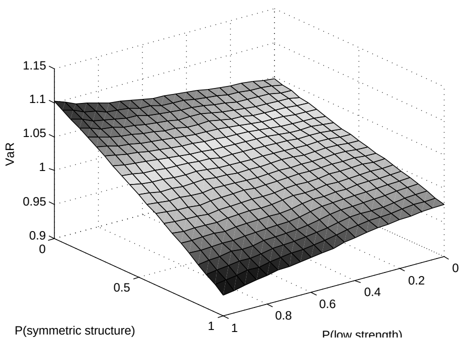
(h) UK/FR - Structure only



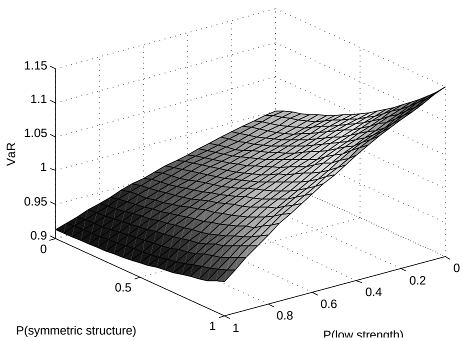
(i) JP/HK - Strength only



(j) JP/HK - Structure only

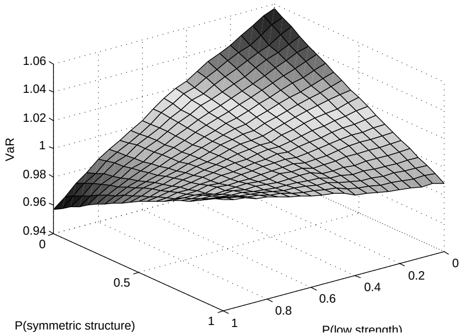


(k) JP/KO - Strength only

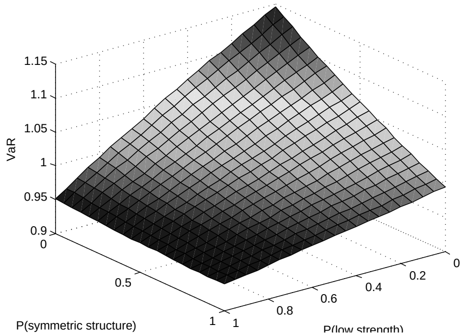


(l) JP/KO - Structure only

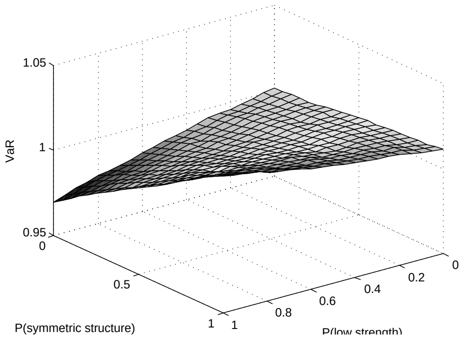
Figure 4.9: 5% VaR Ratios



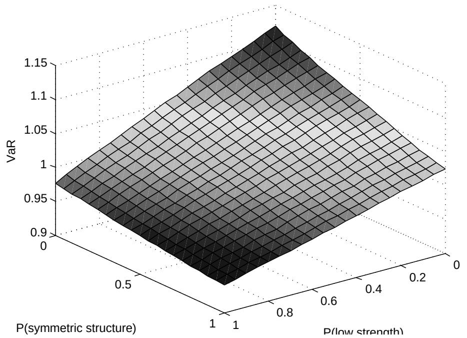
(a) US/CA - Strength only



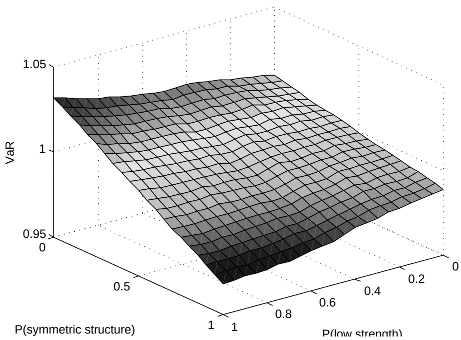
(b) US/CA - Structure only



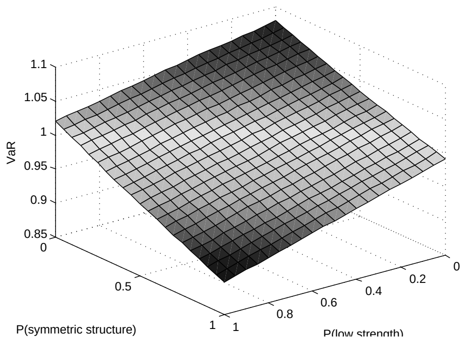
(c) US/MX - Strength only



(d) US/MX - Structure only



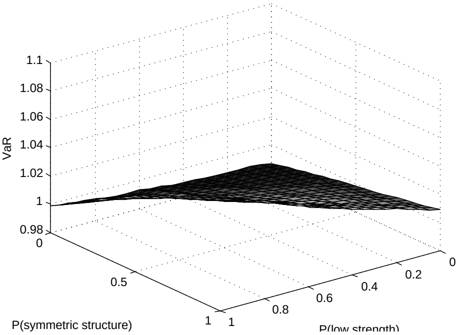
(e) UK/GE - Strength only



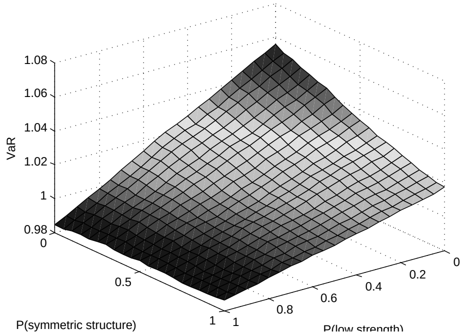
(f) UK/GE - Structure only

See notes Figure 4.8, but now for VaR(5%)

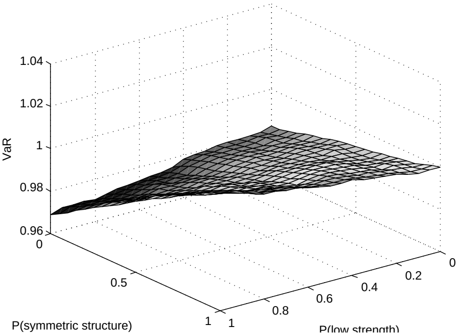
Figure 4.9: continued



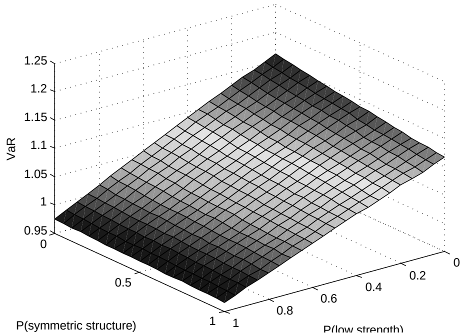
(g) UK/FR - Strength only



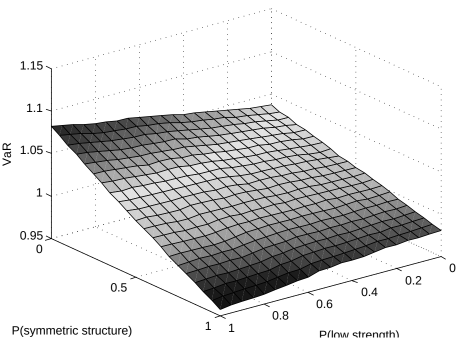
(h) UK/FR - Structure only



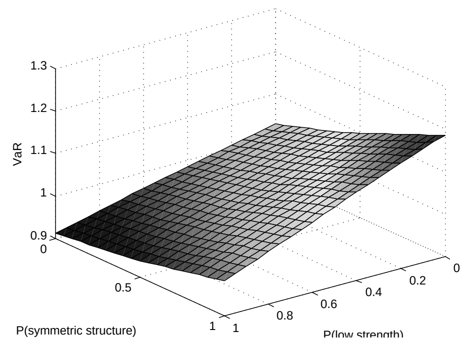
(i) JP/HK - Strength only



(j) JP/HK - Structure only



(k) JP/KO - Strength only



(l) JP/KO - Structure only

4.6 Conclusion

We have proposed a mixture copula that allows for flexible time-variation in both the strength of dependence and in the dependence structure. The two types of change in dependence are captured by Markov regime-switching in the mixture weight and in the parameters of the constituent copulas, respectively. The Markov-Switching framework is suitable for modelling both recurrent changes between a limited set of dependence configurations and non-recurrent, permanent changes in dependence. Importantly, we assume that the regime switches in the mixture weight and in the copula parameters are governed by independent latent Markov processes. This approach enables us to formally test whether both types of time-variation are present. More generally, it allows us to assess the relative importance of changes in the dependence strength and dependence structure.

An empirical application to daily returns on a number of international stock markets shows that the dependence indeed displays distinct periods with weak and strong strength of dependence and periods of symmetric and asymmetric dependence structure. The models with either only time-varying strength or time-varying structure of dependence are statistically rejected, indicating the need of both types of dependence. It is important to allow for both types of time variation in asset return dependence, instead of considering these characteristics in isolation. In the application we show that not including time-varying strength of dependence leads to serious wrong estimations of Value-at-Risk, while this is less true for not including time-varying structure of dependence.

Chapter 5

Forecasting Value-at-Risk under Temporal and Portfolio Aggregation*

5.1 Introduction

In many different disciplines of the financial industry, forecasts of risk measures for different horizons are needed. For instance, each day risk managers of banks need to report their ten-day Value-at-Risk levels according to the Basel accord. Also, in active portfolio management multi-period forecasts for volatility are used. In practice, a risk manager usually models portfolio returns on a daily frequency, from which he obtains a one-day forecast for a risk measure such as VaR. Assuming that the risk of the portfolio is constant over the following days, he scales his one-day forecast into a longer period forecast. This approach, which is even advocated in the Basel accord, might be not the best approach to construct longer period forecasts. Other approaches, that take into account more of the asset return dynamics, could lead to better forecasting performance.

A risk manager often observes individual components of the aggregate he wants to forecast. For instance, when the risk measure is based on a portfolio of returns, two different forecasting approaches can be used. Either the risk manager models the returns of the individual assets multivariately and then forecasts the risk measure for the portfolio, or he first computes portfolio returns and forecasts the risk measure

*This chapter is based on the article by Markwat, Kole, and Van Dijk (2010).

from a univariate model. Additionally, asset prices are often observed more frequently than the horizon for which a risk manager wants to forecast a risk measure. This gives a risk manager the choice between different data frequencies to construct a forecast. Either he uses the data frequency of the forecast horizon so that the one-period forecast is already at the correct forecast horizon, or he uses a higher data frequency and then extrapolates his one-period forecast to the required forecast horizon.

When the risk manager models the portfolio returns directly, fewer dynamics are modelled than when he models the components of the portfolio. If the returns of portfolio components are multivariately modelled, the probability of misspecification is higher than when the portfolio returns are modelled univariately. Consequently, the univariate approach might have a better performance from this perspective. However, if the dynamics of the portfolio components have an important contribution in forecasting the risk measure, then due to aggregation to portfolio returns these dynamics are lost, and worse forecasts may result.

The choice between a higher or lower modelling frequency presents an important trade-off between efficiency and model specification.[1] Using a higher modelling frequency results in more efficient estimates, but misspecification amplifies biases in the forecasts, if one-period forecasts are extrapolated to multi-period forecasts. However, if a higher frequency model is correctly specified, forecasts from this model will be more accurate. Forecasting by a lower frequency model, for instance the forecast horizon, is less sensitive to these biases resulting from extrapolation. On the other hand, aggregation to lower frequencies results in less observed data, and thus less efficient estimation of the forecast model. Forecasts with the frequency equal to the forecast horizon, are called direct forecasts and are effectively one-period forecasts.

When the data are modelled at a higher frequency, different methods to extrapolate one-period forecasts to multi-period forecasts are available. Scaled multi-period forecasts are constructed using the assumption that the moments of the model stay constant over the forecast horizon. For scaled volatility forecasts this correspond to the-square-root-of-time-rule (see Diebold et al., 1997), where the one-period forecast is multiplied by the square root of the length of the forecast horizon.[2][3] Iterated fore-

[1]See Findley (1983); Lin and Granger (1994); Clements and Hendry (1996); Bhanzali (1999); Chevillon and Hendry (2005).

[2]The the-square-root-of-time-rule holds under normality, but not when fat-tailed distributions are concerned. However, in case of fat-tailed distributions, the α-root lule of Dacorogna et al. (2001) can be used.

[3]For these scaled forecasts, Diebold et al. (1997) show that this method may lead to spurious volatility magnifications, particularly for larger forecast horizons. Daníelsson and Zigrand (2006) show that when the possibility of large losses are present scaling underestimates the likelihood of these large losses.

casts also take into account shocks that can occur during the multi-period forecast period.[4]

In this chapter we examine the effects of data aggregation on forecasting Value-at-Risk of a portfolio of assets. We consider Value-at-Risk as it is widely used in practice, for instance by risk managers of large financial institution. A risk manager can aggregate the data generating process in the time dimension, and he can aggregate the individual asset returns into portfolio returns, or he can aggregate in both dimensions. Regarding aggregation in the time dimension, we investigate the forecasting performance using higher versus lower modelling frequencies. For data with a higher frequency, we also consider the difference in forecasting performance between scaled and iterated forecasts. We distinguish between forecasting the risk measure by modelling and forecasting the portfolio returns univariately, as well as multivariately. The possibility of using portfolio aggregation and different data frequencies results in a set of different forecasting strategies. For this set of strategies, we perform a comprehensive study on how data aggregation affects the forecasts performance for a risk measure on financial returns.

Another choice concerning forecasting risk measures we consider is between using empirical distributions or Gaussian distributions to forecast risk measures. The tails of the Gaussian distribution are too thin to model financial data well (see Mandelbrot, 1963; Fama, 1965). Therefore, it is worthwhile to investigate the use of the empirical distribution as well, as the empirical distribution is better able to model fat tails, and to see how this choice interacts with the other choices.

In our analysis we examine the forecast performance for ten-day Value-at-Risk for a portfolio consisting of stocks and bonds. We consider stocks and bonds as these are two major asset classes, which often have large weights in portfolios of institutional investors and pension funds. Additionally, stocks and bonds are two asset classes, that react differently to shocks in the economy. If the risk manager model the portfolio returns univariately, these different reaction to shocks cannot be identified. This might decrease the forecasting performance.

We model the bivariate stock-bond distribution and forecast the Value-at-Risk for the portfolio, and we univariately forecast Value-at-Risk from the portfolio returns directly. As the stock and bond returns are available on a daily frequency, and we need a ten-day forecast, we examine the performance for scaled, iterated and direct forecasts. As forecast models we use the widely-used RiskMetrics model. For the bivariate modelling approach, we extend this model with Markov switching dynamics in the dependence (see Pelletier, 2006). For ten-day VaR we examine an extra pos-

[4]See Marcellino et al. (2006) for iterated forecasts in an autoregressive framework and Ghysels et al. (2009) for iterated forecasts in a GARCH framework.

sibility of using a five-day model and then iterate or scale. This can be interpreted as an intermediate case of direct and indirect modelling. We add this intermediate case, as using a five-day frequency could lead to a better trade-off between estimation efficiency and model misspecification.

Our main results can be summarized as follows. First, regarding portfolio aggregation, for the 1% Value-at-Risk forecasts the bivariate modelling approach outperforms the univariate modelling approach, while for the 5% Value-at-Risk forecasts it is reversed. The difference in performance between both methods is substantially smaller for the 5% VaR. Second, due to temporal aggregation important information of the return dynamics is lost, as the daily frequency models overall have the best performance. Third, iterated forecasts perform on average better than scaled or direct forecasts, and direct forecast perform on average better than scaled forecasts. Fourth, if the weight on stocks in the portfolio increases, resulting in a higher unconditional volatility (i.e., a higher weight on stocks), the performance of iterated forecasts increases relative to the performance direct and scaled forecasts. Finally, using the empirical distribution instead of the Gaussian distribution leads to more accurate forecasts. This is particularly true for the iterated forecasts.

We contribute to the existing literature in the following three ways. First, we examine the difference in forecasting performance between forecasting with a univariate model and forecasting with a multivariate model. Although this approach has extensively been discussed theoretically (see Grunfeld and Griliches, 1960; Kohn, 1982; Granger, 1987; Pesaran et al., 1989) and applied to macroeconomics (see Fair and Shiller, 1990; Zellner and Tobias, 2000; Marcellino et al., 2003), its practical applications in finance are relatively unexplored. We extend the work of Ghysels et al. (2009), who only consider univariate modelling. The difference between aggregating forecasts or forecasting aggregates has been discussed in macroeconomics (see Hendry and Hubrich, 2010, for a recent overview), with most empirical applications about forecasting inflation. No comprehensive study on forecasting risk measures using univariate or multivariate dynamics in finance exist.

Second, we look at the VaR violations in the iterated, scaling or direct method, instead of the root mean squared error of the volatility forecasts as Ghysels et al. (2009) do. Differences in performance between scaled, iterated and direct forecasts can be different for VaR forecasts, than for the volatility forecasts. Our VaR application shows the economic relevance of temporal aggregation, instead of a purely statistical analysis as in Ghysels et al. (2009). To the best of our knowledge there has not been an investigation of the effects of scaling, direct, iterated forecasting on VaR forecasting. Not only is it relevant to examine multi-period VaR forecasts, multi-period forecasting in general is relatively unexplored.[5] A notable exception is Christoffersen and Diebold (2000), who find that for different asset classes forecasting volatility for horizons longer than 10 days is difficult.

Third, we investigate how temporal aggregation interacts with portfolio aggregation. Both types have in common that aggregation leads to modelling less dynamics, resulting in a lower probability of misspecification, which may increase forecasting performance. However, they also have in common that due to aggregation important information of the return dynamics may be lost, which may result in worse forecasting performance. This chapter provides a comprehensive study of the forecasting performance using both temporal and portfolio aggregation. Additionally, the interaction of both types of aggregation with using empirical or Gaussian distributions is considered.

The remainder of this chapter is organized as follows. Section 5.2 describes the general framework, and introduces the applications of the general model. Further, this section describes the estimation and Value-at-Risk evaluation. Results are reported in section 5.3. Section 5.4 concludes.

5.2 Methodology

5.2.1 General framework

Suppose a risk manager is concerned with portfolio returns $r_{t,t+h}$ of a portfolio build of assets x and y. Here h denotes the horizon over which the risk of this portfolio is measured. Typically, this horizon is larger than the frequency at which the risk manager can observe the value of the portfolio. Throughout this chapter we assume that the highest frequency of observation is a (trading) day. Therefore, we express all different points in time in days.

Let $x_{t,t+k}$ and $y_{t,t+k}$ be the log returns of the two assets of interest over days t to $t+k$. Here $k \leq h$ denotes the data frequency that the risk manager uses to construct a model for the portfolio return. For simplicity we assume that h is a multiple of k. The goal of the risk manager is to make a h-day forecast for a risk measure R of the $r_{t,t+h}$. To forecast the risk measure R the risk manager needs a distribution for the h-day portfolio returns

$$r_{t,t+h} \sim f_{r,t,t+h}. \tag{5.1}$$

The risk manager could use a direct model for the distribution (5.1) of the h-day portfolio returns to forecast the risk measure R. However, the returns are available

[5] Particularly compared to the large amount of literature on one-period forecasting (see Bollerslev, 1986; Andersen and Bollerslev, 1998; Hansen and Lunde, 2005; Andersen et al., 2006, for instance).

at a higher frequency. It may be that information in data with frequency higher than the forecast horizon h, is important for forecasting R. The risk manager also observes the individual price fluctuations of x and y, which might contain valuable information for forecasting the risk measure R as well.

When data frequency k is used, the h-day portfolio returns can be written as

$$r_{t,t+h} = \sum_{\tau=1}^{h/k} r_{t+k(\tau-1),t+k\tau}. \tag{5.2}$$

Information in the data with frequency $k = h$ is partially lost due to temporal aggregation. Therefore, the risk manager might better use a higher frequency of returns. This effect will be particularly important when the return distribution shows time-varying properties.

If the risk manager concentrates directly on the portfolio returns, he actually aggregates the h-period returns of assets x and y into

$$r_{t,t+h} = wx_{t,t+h} + (1-w)y_{t,t+h}, \tag{5.3}$$

where ω is the weight on asset x.[6] Note that the portfolio aggregation in (5.3) only holds for discrete returns. As we look at log returns (5.3) is an approximation. However, for the short horizons we consider, the approximation is accurate. Portfolio aggregation can also hide valuable information, as there might be certain dynamics in the portfolio components x and y, which are important for forecasting a risk measure R of the portfolio returns r. If these dynamics are lost due to aggregation to portfolio returns, the bivariate approach will show better performance. This could happen, for instance, if the effects of shocks in x have different impact on the return dynamics than shocks in y. If we model the portfolio returns directly, these different effects of x and y are not identified anymore. As both approaches are used to forecast the same h-day risk measure R, these approaches can be compared directly.

If the risk manager expects the information from using a higher frequency and the information from individual components to be important, he can also consider the temporal and portfolio aggregation simultaneously, which gives the following

[6] We assume the portfolio weights ω to be constant over time, although in practice portfolio weights often vary. However, for analyzing the effects of data aggregation constant weights are a reasonable assumption. In fact, constant weights make it easy to compare the effect of data aggregation for different levels of ω.

decomposition of the h-day portfolio returns

$$r_{t,t+h} = w \sum_{\tau=1}^{h/k} x_{t+k(\tau-1),t+k\tau} + (1-w) \sum_{\tau=1}^{h/k} x_{t+k(\tau-1),t+k\tau}. \tag{5.4}$$

Thus, the individual components $x_{t+k(\tau-1),t+k\tau}$ and $y_{t+k(\tau-1),t+k\tau}$ could be modelled at frequency k, from which the risk measure R can be computed.

We use $R_t(f_{r,t,t+h}, h, k)$ to denote the forecast, made at time t, with forecast horizon h and data frequency k, for the risk measure. The aggregation level that the manager chooses determines in how much detail the distribution $f_{r,t,t+h}$ is constructed. In the most detailed version it is a convolution of the distributions of x and y at all time-periods between t and $t+k$.

Consider the density of the k-day portfolio returns $f_{r,t,t+k}$. We assume that the location parameters, the means of the returns, are equal to zero (see Jorion, 1995). We focus on the scale parameters as the parameters that determine the distribution, as most risk measures used in practice are based on second moments. We write the distribution of the k-day portfolio returns as

$$f_{r,t,t+k} = f(r_{t,t+k}; \sigma^2_{r,t,t+k}), \tag{5.5}$$

where $\sigma^2_{r,t,t+k}$ is the variance of the portfolio returns and where the subscript $t, t+k$ indicates the variance of the portfolio returns over time t to $t+k$. Some possibilities for f are GARCH type models or Markov switching models as long as the second moment is sufficient to define the distribution f.

If the risk manager observes the dynamics of the individual components $x_{t,t+k}$ and $y_{t,t+k}$ of the portfolio returns $r_{t,t+k}$, as in (5.3) and (5.4), he can also model the bivariate dynamics of these components. He needs to specify a joint distribution function for the returns. We denote this bivariate distribution by

$$f_{xy,t,t+k} = f(x_{t,t+k}, y_{t,t+k}; \Sigma_{xy,t,t+k}), \tag{5.6}$$

where $\Sigma_{xy,t,t+k}$ is the covariance matrix of $x_{t,t+k}$ and $y_{t,t+k}$. In this bivariate case we need a model f that can describe the dependence between x and y. Copula models or multivariate GARCH models are possible candidates for the distribution f.

In the univariate approach we only need to model the dynamics of $\sigma^2_{t,t+k}$, whereas in the bivariate approach $\Sigma_{t,t+k}$ need to be modelled. Note that we have dropped the subscripts r and xy, as σ^2 and Σ always represent the variance for univariate and bivariate modelling. In the bivariate case more, and possibly more complicated, dynamics are modelled, thus the probability of misspecification will increase.

Consequently, the univariate approach might have a better performance from this perspective.

Direct forecasts have a modelling frequency k equal to the forecasts horizon h of the risk measure forecasted. Thus, direct forecasts are one-period forecasts with horizon h. To forecasts the risk measure, we estimate models (5.5) and (5.6) on data with frequency h. The direct forecasts for the time-varying scale parameters are denoted $\hat{\sigma}^2_{t,t+k}(d)$ and $\hat{\Sigma}_{t,t+k}(d)$, where d denotes "direct".

If a frequency k higher than the forecast horizon is used, the one-period forecasts $\hat{\sigma}^2_{t,t+k}$ and $\hat{\Sigma}_{t,t+k}$ for the scale parameters, have to be converted to multi-period forecasts. An advantage of using a higher frequency is more efficient estimation, as no information is lost due to temporal aggregation. A disadvantage of using higher frequencies is that, if the model is misspecified, biases in one-period forecasts can become amplified if the forecast is converted to a multi-period forecast. The direct forecast does not suffer from this amplification, although the estimation of the direct forecasting model is less efficient.

There are two methods to construct j-period forecast out of one-period forecasts, namely, scaling and iterating.[7] We use $j = \frac{h}{k}$ for the number of forecast periods. Scaling risk measures is easy and is often applied in finance, it is even advocated in the Basel accord. However, Diebold et al. (1997) show that as the forecast horizon increases the scaling method becomes poor. The square root of time rule states that if the volatility on a given day is σ, then the h-day volatility is $\sqrt{j}\sigma$. Thus, for variances we multiply by j in stead of $\sqrt{j}$. We scale the one-period forecasts $\hat{\sigma}^2_{t,t+k}$ and $\hat{\Sigma}_{t,t+k}$ into a j-period forecasts $\hat{\sigma}^2_{t,t+jk}(s)$ and $\hat{\Sigma}_{t,t+jk}(s)$ by multiplying with j, where s denotes scaling.

Opposed to the scaling method, iterated forecasts do take into account return shocks that occur between $t + k$ and $t + kj$. However, for a given model in (5.5) or (5.6), there is generally no explicit formula to compute the associated j-period risk measure.[8] With simulations the iterated forecast for the second moments can be computed relatively easyly. Suppose we have a one-period forecasts for the scale parameters $\hat{\sigma}^2_{t,t+k}$ and $\hat{\Sigma}_{t,t+k}$, and our objective is again a j-period forecasts $\hat{\sigma}^2_{t,t+jk}(i)$ and $\hat{\Sigma}_{t,t+jk}(i)$, where i denotes iterating. Then, we simulate returns shocks according to the distribution from (5.5) or (5.6), with variances $\hat{\sigma}^2_{t,t+k}$ and $\hat{\Sigma}_{t,t+k}$. These simulated shocks affect the volatility over the period $t + k$ to $t + 2k$, and with these shocks and model (5.5) or (5.6) we compute $\hat{\sigma}^2_{t+k,t+2k}(i)$ and $\hat{\Sigma}_{t+k,t+2k}(i)$. This

[7] Ghysels et al. (2009) also consider MIDAS forecasts (see Ghysels et al., 2004, 2005, 2006) and show its superiority over the other methods for forecasts windows longer than one month. As our forecasting horizon is shorter, we do not consider this forecasting method.

[8] There are models for which the iterated forecast can be computed analytically (see Drost and Nijman, 1993, for instance), but for most models this is not the case.

is continued until we reach $t + jk$. As the iterated approach does not result in a closed form expression for f, we use the simulated returns shocks to determine the distribution of f.

5.2.2 Specification forecast models

In this section we specify which forecasting models we use for (5.5) and (5.6). We introduce the models for the k-day frequency returns $x_{t,t+k}$, $y_{t,t+k}$ and $r_{t,t+k}$. As the RiskMetrics model is often used in practice, we set (5.5) and (5.6) equal to the univariate and bivariate RiskMetrics models respectively. Thus we let the time-variation in (co)variances, $\sigma^2_{t,t+k}$ and $\Sigma_{t,t+k}$, evolve according to the RiskMetrics model. The univariate RiskMetrics model (see also JPMorgan and Reuters, 1994), which we use for $r_{t,t+k}$ in (5.5), is described by

$$\sigma^2_{t,t+k} = (1-\lambda) r^2_{t-k,t} + \lambda \sigma^2_{t-k,t}, \tag{5.7}$$

where r_t and σ_t are the portfolio return and volatility. The bivariate version of the RiskMetrics model is denoted by

$$\Sigma_{t,t+k} = (1-\lambda)[x_{t-k,t} \;\; y_{t-k,t}]'[x_{t-k,t} \;\; y_{t-k,t}] + \lambda \Sigma_{t-k,t}, \tag{5.8}$$

where

$$\Sigma_{t,t+k} = \begin{bmatrix} \sigma^2_{x,t,t+k} & \sigma_{xy,t,t+k} \\ \sigma_{xy,t,t+k} & \sigma^2_{y,t,t+k} \end{bmatrix},$$

is the covariance matrix of the returns $x_{t,t+k}$ and $y_{t,t+k}$, and λ is the decay parameter. We make one-period forecasts from the univariate RiskMetrics model (5.7) as

$$\hat{\sigma}^2_{t,t+k} = (1-\hat{\lambda}) r^2_{t-k,t} + \hat{\lambda} \hat{\sigma}^2_{t-k,t}, \tag{5.9}$$

and for the bivariate RiskMetrics model (5.8) as

$$\hat{\Sigma}_{t,t+k} = (1-\hat{\lambda})[x_{t-k,k} \;\; y_{t-k,k}]'[x_{t-k,k} \;\; y_{t-k,k}] + \hat{\lambda} \hat{\Sigma}_{t-k,k}. \tag{5.10}$$

From equations (5.9) and (5.10) we get the one-period forecasts $\hat{\sigma}^2_{t,t+k}$ and $\hat{\Sigma}_{t,t+k}$, which are converted to j-period forecasts with either iterating or scaling. If the frequency k is equal to the forecast window h, then $\hat{\sigma}^2_{t,t+k}$ and $\hat{\Sigma}_{t,t+k}$ are the direct forecast for the scale parameters..

To explore whether the effect of model uncertainty and the different modelling frequencies increases when models get less parsimonious, we let the correlation $\rho_{xy,t,t+k}$

between the assets vary according to a Markov switching model. This is a version of the model from Pelletier (2006), and is more complicated than the RiskMetrics model. Markov switching model can resemble substantially different dependence structures than GARCH-type models, like RiskMetrics, do. Correlation dynamics are highly persistent and show structural breaks. Markov switching models are able to deal with these characteristics of the correlation dynamics, while multivariate GARCH models have difficulties modelling these features. The use of Markov switching models can lead to different results than for the RiskMetrics model, as the effect of model uncertainty and the need for efficient estimates might now have more influence.

The marginal distributions of $x_{t,t+k}$ and $y_{t,t+k}$ in (5.6) again evolve according to the RiskMetrics model, while the dependence now behaves as a Markov switching model. Both $x_{t,t+k}$ and $y_{t,t+k}$ follow their own univariate RiskMetrics model (5.7). With the variances $\sigma^2_{x,t,t+k}$ and $\sigma^2_{y,t,t+k}$ from these univariate RiskMetrics models, we construct the standardized residuals. Define $u^x_{t,t+k}$ and $u^y_{t,t+k}$ as the standardized residuals from (5.7). Then the two state state Gaussian Markov switching model is

$$f_t(u^x_{t,t+k}, u^y_{t,t+k}) = \begin{cases} \phi(\rho_1), & \text{if } S_{t,t+k} = 1; \\ \phi(\rho_2), & \text{if } S_{t,t+k} = 2, \end{cases} \tag{5.11}$$

where $\phi(\rho)$ denotes the Gaussian distribution with zero means, unit variances one and correlation parameter ρ. The process during the period $t, t+k$ is in state $S_{t,t+k} = 1$ or in state $S_{t,t+k} = 2$, with correlation parameters ρ_1 and ρ_2. The transition between the states S_1 or S_2 is governed by a Markov switching model with transition matrix

$$P = \begin{bmatrix} p_{11} & 1 - p_{22} \\ 1 - p_{11} & p_{22} \end{bmatrix},$$

where $p_{11} = P(S_{t,t+k} = 1 | S_{t-k,t} = 1)$ and $p_{22} = P(S_{t,t+k} = 2 | S_{t-k,k} = 2)$.[9] At time t, for the Markov model on data with frequency k, we have inference probabilities

$$\xi_{t|t} = \begin{bmatrix} P_t(S_{t-k,t} = 1) \\ P_t(S_{t-k,t} = 2) \end{bmatrix},$$

where $P_t(S_{t-k,t} = j)$ denotes the probability of being in regime j between $t-k$ and t, given information up to time t. The forecasted probabilities of being in regime i during $t, t+k$ are

$$\xi_{t|t+k} = P^k \xi_{t|t}. \tag{5.12}$$

[9] See Chapter 4 for a more detailed description of Markov switching models.

Constructing h-period correlation forecasts out of one-period correlation forecasts for this Markov switching approach is an iterating approach. Therefore, we only examine the iterated and direct forecasts for the variance forecasts of the marginals $\hat{\sigma}^2_{x,t,t+k}$ and $\hat{\sigma}^2_{y,t,t+k}$. Thus, for each period m, with $m = 1, \ldots, j$, we now have forecasts for the variances from the iterated univariate RiskMetrics forecasts, and we have correlation forecasts from the Markov switching model. Together they give a forecast for $\hat{\Sigma}_{t+(m-1)k,t+mk}$, for $m = 1, \ldots, j$.

5.2.3 Estimation

This section describes how we estimate the RiskMetrics and the Markov switching models. If the modelling frequency is k, we estimate model (5.5) and (5.6) on data $r_{1,k}, r_{k,2k}, \ldots, r_{T/k-k,T/k}$, where the same holds for x and y. From these estimated models we obtain one-period forecasts $\hat{\sigma}^2_{t,t+k}$ and $\hat{\Sigma}_{t,t+k}$. To start with the RiskMetrics model, the decay parameter λ is estimated by minimizing the in-sample root mean squared error (RMSE) of the one-period variance forecasts from the model (see JPMorgan and Reuters, 1994). The root mean squared error for the variances is

$$\mathrm{RMSE}_x = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(x^2_{t,t+k} - \hat{\sigma}^2_{x,t,t+k}\right)^2}, \tag{5.13}$$

and similar for y. The root mean squared error for the covariances is

$$\mathrm{RMSE}_{xy} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(x_{t,t+k}y_{t,t+k} - \hat{\sigma}_{xy,t,t+k}\right)^2}. \tag{5.14}$$

First for the variances we estimate λ_x and λ_y by minimizing RMSE_x and RMSE_y. Further, we estimate λ_{xy} by minimizing RMSE_{xy}. Then the decay parameter λ in (5.8) is computed by

$$\lambda = \frac{\mathrm{RMSE}_x^{-1} \cdot \lambda_x + \mathrm{RMSE}_y^{-1} \cdot \lambda_y + \mathrm{RMSE}_{xy}^{-1} \cdot \lambda_{xy}}{\mathrm{RMSE}_x^{-1} + \mathrm{RMSE}_y^{-1} + \mathrm{RMSE}_{xy}^{-1}}. \tag{5.15}$$

Thus, the decay parameter for the bivariate RiskMetrics model is a weighted average of univariate RiskMetrics models for the variances and the covariance. The weights are proportional to the inverse of the corresponding RMSE, so that λ's with more accurate (co)variance forecasts get a larger weight in (5.15). In the univariate approach, where we model portfolio returns, we also use the RiskMetrics approach. With this approach we only need one λ, which is estimated by minimizing (5.13).

González-Rivera et al. (2007) estimate λ by directly incorporating VaR in their loss function. Although their estimates of λ do sometimes differ from using quadratic loss-functions like RMSE, the differences for out-of-sample forecasting are negligible.

Note that the model could also be written having three different decay parameters λ_i. Then, there are two different decay parameters for the variances and one decay parameter for the covariance. However, different decay parameters do not necessarily result in positive definite covariance matrices, therefore we use equation (5.15).

The Markov switching model is estimated in a two-step approach. First, we estimate for both margins the univariate RiskMetrics model, again by minimizing (5.13), resulting in two estimated $\hat{\lambda}_i,\ i = 1, 2$. Then, we estimate the two state Markov switching model (5.11) on the standardized residuals $\hat{u}^x_{t,t+k}$ and $\hat{u}^y_{t,t+k}$. In the second step we estimate the parameters that describe the time-variation in dependence. We use the expectation maximization algorithm as in Hamilton (1989) to obtain the estimates for $\hat{\rho}_1, \hat{\rho}_2, \hat{p}_{11}, \hat{p}_{22}$.

5.2.4 Value-at-Risk and evaluation

Value-at-Risk

We examine the forecasting performance for h-day Value-at-Risk, using the different forecasting approaches. VaR_q of a portfolio is the amount of money such that the probability that the loss will be larger than this amount is q. Thus, $\text{VaR}_{0.01}$ is the upper boundary of the 1% largest losses. If $r_{t,t+h}$ again denotes the h-day return of a portfolio, we denote the h-day q Value-at-Risk by,

$$\text{VaR}_{q,t,t+h} = -\text{argmax}\{l : P(r_{t,t+k} < l) \leq q\}, \tag{5.16}$$

where the subscript $t, t+h$ means that the VaR forecast is made at time t for the period $t, \ldots, t+h$. We evaluate these h-day Value-at-Risk forecasts for portfolios build of returns of asset x and y with weight $0 \leq \omega \leq 1$ on asset x.

For the models in equation (5.5) and (5.6) we have different choices to construct $\text{VaR}_{q,t,t+h}$. The formula from which we compute VaR is expressed in the following way,

$$\text{VaR}_{t,t+h,q} = z_q \cdot \hat{\sigma}_{t,t+h}, \tag{5.17}$$

where z_q is the q-quantile of a standardized distribution and $\hat{\sigma}_{t,t+h}$ is the h-day volatility forecast for the portfolio returns.[10] Using the univariate approach, $\hat{\sigma}_{t,t+h}$

[10]Note that equation (5.17) holds under normality. If for instance the Student's t distribution is used, we cannot simply scale up the quantile proportional to volatility. However, we can still compute VaR from the inverse Student's t cumulative density function.

is already in portfolio format, while in the bivariate approach we still need to compute the portfolio volatility from the forecasted covariance matrix $\hat{\Sigma}_{t,t+h}$. If we use the bivariate approach, the portfolio volatility is computed as,

$$\hat{\sigma}_{t,t+h} = \sqrt{w'\hat{\Sigma}_{t,t+h}w}, \tag{5.18}$$

where,

$$w = \begin{bmatrix} \omega \\ 1-\omega \end{bmatrix}.$$

For $\hat{\Sigma}_{t,t+h}$ and $\hat{\sigma}^2_{t,t+h}$ we can use the iterated, scaled or direct forecast.

Next, we need to choose how we compute z_q in (5.17). There is a large literature on the fat tails of the returns on financial assets staring with Mandelbrot (1963) and Fama (1965). Up to the lower and upper 5% quantiles the Gaussian distribution seems to describe these returns quite accurate, but for returns in the smaller quantiles the the tails of the Gaussian distribution are too thin. Using the empirical distribution for the stock returns is a suitable solution to model the smaller quantiles more accurate. Therefore, we choose to compute this quantile z_q with two different methods, namely, using the Gaussian distribution $z_q(g)$ and using the empirical distribution $z_q(e)$.

If we use the Gaussian approach, then $z_q(g) = N^{-1}(q)$, where N^{-1} is the inverse of the standard Gaussian distribution. Using the empirical distribution approach $z_q(e)$ is computed differently. In the univariate approach $z_q(e)$ is computed as the q quantile of the standardized residuals $\hat{u}_r$, obtained from (5.5). For the bivariate approach in (5.6), we have the $T \times 2$ matrix $U = [\hat{u}_x \ \hat{u}_y]$ of standardized residuals. We compute standardized portfolio returns as $\hat{u}_r = Uw$, obtained from (5.6), then $z_q(e)$ is computed as the q quantile of these standardized residuals $\hat{v}_r$. For the scaled and direct forecasts $\hat{\sigma}^2_{t,t+h}(s)$ and $\hat{\sigma}^2_{t,t+h}(\mathrm{d})$, we now have the parts needed to compute (5.17).

For the iterated forecasting approach, $\mathrm{VaR}_{t,t+h,q}$ is computed by simulation, as there is no explicit way to compute the parts in (5.17) due to the iteration. We have one-period forecasts $\hat{\sigma}^2_{t,t+k}$ and $\hat{\Sigma}_{t,t+k}$ from (5.9) and (5.10). In section 5.2.1 we described that for each period m, with $m = 1, \ldots, j$, we simulate N returns (either with Gaussian or empirical draws), with second moments $\hat{\sigma}^2_{t+(m-1)k,t+mk}(i)$ and $\hat{\Sigma}_{t+(m-1)k,t+mk}(i)$. We sum these returns over the m periods, resulting in N h-day returns. For the bivariate approach we compute the portfolio returns from the simulated returns for the individual assets. Then, we compute $\mathrm{VaR}_{t,t+h,q}$ by taking the q quantile of these simulated h-day portfolio returns.

For the Markov switching approach we start with describing forecasting $\text{VaR}_{t,t+h,q}$ assuming Gaussian distributions. For every $t+m$ for $m = 1, \ldots, h/k$ we draw N random draws from a bivariate Gaussian distribution with mean zero and variance one. The correlation for each draw is ρ_1 with probability $P(S_{t+k} = 1)$ and ρ_2 with probability $P(S_{t+k} = 2)$. These draws are multiplied by the current volatility forecasts from the univariate RiskMetrics model $\hat{\sigma}_{x,t,t+k}$ and $\hat{\sigma}_{y,t,t+k}$. Then, for each of the N simulations the volatilities for x_t and y_t are updated to $\hat{\sigma}_{x,t+k,t+2k}$ and $\hat{\sigma}_{y,t+k,t+2k}$ with (5.7). This is continued until we have N random drawings for $t+(m-1)k$ to $t+mk$, for $m = 1, \ldots, h/k$. Then, $\text{VaR}_{t,t+h,q}$ is the q quantile of the simulated h-day returns.

When forecasts are constructed using the empirical approach there is a substantial difference regarding the random drawings from the empirical distribution. While drawing from the empirical distribution, the correlation structure implied by the Markov switching model should be preserved. Therefore we proceed in the following way. We draw N random numbers from the bivariate Gaussian distributions with different correlations. This gives us two vectors v_x and v_y. We use the empirical cumulative density function transformation on the simulated series v_x and v_y. We multiply these transformed series by T and round up to the nearest integer to obtain a_x and a_y. The $N \times 1$ series a_x and a_y now contain numbers between 1 and T, and each entry corresponds to a standardized return from the corresponding empirical distribution. We define random draw $\hat{u}_x(a_{x,n})$ as the $a_{x,n}$th standardized residual from the vector of residuals $\hat{u}_x$, from the univariate RiskMetrics model, where $a_{x,n}$ denotes the nth number of the vector a_x. Thus, our random draws are $u_x(a_{x,n})\hat{\sigma}_{x,t+m}$ and $u_y(a_{y,n})\hat{\sigma}_{y,t+m}$, for $n = 1, \ldots, N$ and $m = 1, \ldots, h/k$. From here, the empirical approach is equal to the Gaussian approach.

Evaluation

To asses the predictive ability of the Value-at-Risk forecasts $\text{VaR}_{t,t+h}$ for the different modelling approaches we calculate the actual violations. Following Christoffersen (1998), at each point in time t and for all different models, we have a VaR forecast $\text{VaR}_{t,t+h}$. Define the binary violation variable $X_t = 1$ if $r_{t,t+h} < \text{VaR}_{t,t+h}$ and zero otherwise. Thus, the variable $X_t = 1$ is one if the h-day portfolio return $r_{t,t+h}$ is lower than the forecasted Value-at-Risk.

Christoffersen (1998) develops tests to test the unconditional coverage as well as the conditional coverage. However, these tests are only valid if the returns used to construct $X_t = 1$ are non-overlapping returns. By construction, $X_t = 1$ is serially correlated as we use overlapping returns. Therefore we adjust these tests. For the unconditional coverage we use a t-test to test whether the fraction of violations $\hat{p} = \frac{1}{T}\sum I[X_t = 1]$ is equal to q, where we use Newey-West standard errors for this test. This test is one-sided as regulatory supervisors only care about too much violations and not too few.[11]

Regarding the conditional coverage test we cannot use the test from Christoffersen (1998) either. We propose the following test to test for conditional coverage. As we use 10 day overlapping returns $X_{t,t+h}$ is autocorrelated with its past nine lags. The null hypothesis H_0 of the test is no serial dependence after lag 9. The alternative hypothesis H_1 is serial dependence after lag 9. Therefore, under H_0 we regress $X_t = 1$ on a constant and $X_{t-1}, \ldots, X_{t-9}$. Under H_1 we regress X_t on a constant and $X_{t-1}, \ldots, X_{t-10}$. We test with a likelihood ratio test for the significance of X_{t-10}, which we expect to be significant only if H_1 is true.

5.3 Results

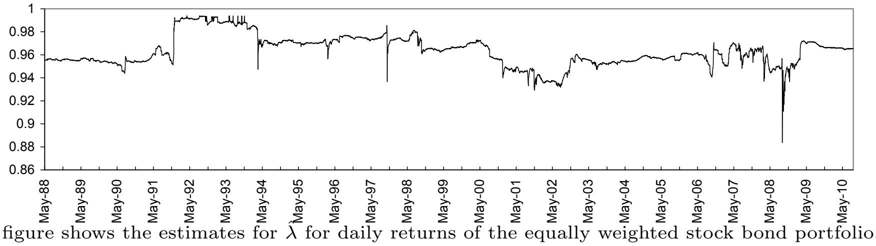
This section contains the results on forecasting the Value-at-Risk for a stock-bond portfolio. We set $h = 10$, thus we consider ten-day forecasts, which banks need to report according to the Basel accord. For the stock returns we use the S&P500 index and for the bond returns we use ten year treasury bonds. The data is obtained from DataStream and covers the period January 1980 - September 2010, containing 7420 returns. We consider the weights on stocks x in the portfolio r to be $\omega = 0.00,\ 0.25,\ 0.75,\ 0.50,\ 1.00$, so we consider five different stock-bond portfolios. For the data frequency we use $k = 1$, $k = 5$ and $k = 10$. For one-day and five-day we use both iteration and scaling to construct forecasts. If $k = 1$ or $k = 5$ we convert the one-period forecast into ten-day forecasts, by iterating over ten periods or two periods respectively. The ten-day frequency is corresponds with the direct approach.

First, we describe the results for the RiskMetrics approach. We estimate (5.8) in a rolling windows setup with window length $L = 1000$, which is approximately the period that banks use to compute their VaR (see JPMorgan and Reuters, 1994), starting in May 1988. Every day we re-estimate the model and construct new ten-day VaR forecasts. Finally, this results in 5420 VaR forecasts.

Figure 5.1 shows the rolling window estimates of λ in (5.15), for an equally weighted daily return portfolio using the bivariate modelling approach. The figure shows that the parameter λ attains values between 0.92 and 1, except for October 2008 during the large fall of the stock market as a result of the credit crisis. The large increase of $\hat{\lambda}$ in the end of 1991, is caused by the fact that the October 1987 crash fell

[11] Clearly, if the fractions of violations are much lower than q, there can also be adverse effects for the institution making the forecasts.

Figure 5.1: Estimated λ for daily equally weighted stock bond portfolio



This figure shows the estimates for λ for daily returns of the equally weighted stock bond portfolio.

out the estimation sample. The highest estimates are obtained during the prolonged bull market during the nineties. The lower frequency models show on average higher values for λ. These values for λ are in line with values documented in JPMorgan and Reuters (1994), who find $\lambda = 0.94$ and $\lambda = 0.97$ for daily and monthly returns.

Table 5.1 shows the unconditional coverage results for the 1% VaR for the RiskMetrics application. The numbers report the percentage deviation of the fraction of VaR violations from 1%. The results in columns two to five from the bivariate approach and columns six to nine are from the univariate approach. In general we see that portfolio aggregation as well as temporal aggregation leads to worse forecasting performance. This indicates that risk-managers should construct forecasts using data at the highest possible level of detail. Regarding portfolio aggregation this holds true, as the bivariate approach results in fewer rejections than the univariate approach. This even holds for the portfolios consisting of stocks or bonds only. Thus, it seems that certain dynamics in the bivariate distribution are important for forecasting 1% VaR. If these dynamics are lost due to aggregation to portfolio returns the performance decreases. Regarding temporal aggregation, we see that the higher frequency models perform better, as the iterated method has the best overall performance. Thus, using the information in data with higher frequency is valuable for forecasting purposes.

The iterated approach, combined with the empirical distribution, results in forecasts for which the unconditional coverage is never rejected. The scaling method overall performs worst, which is consistent with Diebold et al. (1997) and Ghysels et al. (2009). The reason for this are the fat tails of the return distribution, indicated by the large positive percentage deviations of the scaling method.

The direct forecasting performance is in between the performance of the iterating and scaling method. The fact that direct forecasts perform better than the scaling forecasts indicates that the second moments are not constant over the ten-day forecasting period, which is assumed when the scaling method is used. The outperformance of the iterated over the direct method shows that the direct method misses

Table 5.1: Performance of 1% VaR from RiskMetrics model

	Bivariate				Univariate			
	Empirical		Gaussian		Empirical		Gaussian	
	Scaled	Iterated	Scaled	Iterated	Scaled	Iterated	Scaled	Iterated
	$\omega = 0.00$							
1-day	20.1	20.1	57.1**	40.5*	22.0	18.3	68.2**	51.6**
	(26.2)	(27.0)	(31.6)	(29.6)	(27.1)	(27.2)	(32.2)	(30.8)
5-day	−2.0	−22.4	1.7	−0.2	5.4	−20.5	27.5	18.3
	(23.6)	(20.4)	(23.6)	(23.3)	(23.4)	(20.7)	(27.0)	(26.2)
Direct	−0.2		34.9		5.4		44.2*	
	(22.7)		(27.5)		(21.9)		(28.7)	
	$\omega = 0.25$							
1-day	40.5*	16.5	73.8**	51.6*	77.4**	−13.1	99.6***	62.7**
	(29.8)	(26.5)	(35.8)	(32.7)	(33.9)	(20.8)	(37.3)	(32.8)
5-day	27.5	−2.0	33.1	27.5	42.3*	5.4	55.3*	47.9*
	(30.2)	(25.2)	(32.1)	(31.6)	(31.4)	(26.9)	(34.8)	(33.3)
Direct	23.8		47.9*		42.3*		68.2**	
	(29.5)		(32.5)		(31.9)		(35.1)	
	$\omega = 0.50$							
1-day	46.0*	−16.8	38.6	29.4	25.7	−24.2	55.3**	33.1
	(29.9)	(23.4)	(31.6)	(29.8)	(28.1)	(20.7)	(32.1)	(30.5)
5-day	29.4	9.1	44.2*	40.5*	29.4	23.8	84.8***	73.8**
	(32.0)	(28.3)	(31.4)	(31.2)	(30.5)	(29.2)	(34.0)	(32.9)
Direct	27.5		75.6**		40.5		86.7***	
	(30.1)		(34.6)		(31.8)		(35.3)	
	$\omega = 0.75$							
1-day	33.1	12.8	9.7*	38.6*	27.5	−5.7	60.8**	46.0*
	(31.1)	(27.7)	(30.6)	(29.6)	(29.8)	(23.8)	(32.2)	(30.2)
5-day	44.2*	29.4	84.8***	79.3**	47.9*	27.5	110.7***	99.6***
	(33.0)	(29.6)	(36.5)	(36.0)	(33.3)	(29.0)	(37.6)	(36.4)
Direct	38.6		97.8***		49.7*		136.6***	
	(31.0)		(37.9)		(32.3)		(41.3)	
	$\omega = 1.00$							
1-day	34.9	27.5	59.0**	47.9*	36.8	9.1	70.1**	60.8**
	(32.2)	(30.2)	(33.4)	(32.2)	(32.0)	(28.0)	(34.4)	(33.6)
5-day	53.4*	34.9	97.8***	90.4***	55.3*	33.1	112.6***	105.2***
	(33.3)	(30.5)	(38.2)	(37.8)	(34.7)	(31.2)	(38.9)	(38.6)
Direct	42.3*		127.4***		53.4*		160.6***	
	(31.8)		(41.6)		(33.3)		(43.9)	

The table contains the percentage deviation of the fraction of VaR violations from 0.01 for the bivariate as well as the univariate approach. The table reports results for different distributions (empirical and Gaussian), different portfolio weights ω, different modelling frequencies ($k = 1$, $k = 5$, or $k = 10$), and different forecasting methods (scaled and iterated). Standard errors are reported in parenthesis. We denote significantly positive percentage deviations with *,** and *** for the 10%,5% and 1% significance levels.

some information of the return dynamics due to the temporal aggregation. Overall, we find that forecasts from the empirical distribution lead to better performance than using the Gaussian distribution. Further, the larger the weight on the stocks in the portfolio, the more difficult it is to construct accurate VaR forecasts.

For the portfolio consisting of bonds only ($\omega = 0.00$), all the forecast methods based on the empirical distribution pass the test for unconditional coverage, irrespective of the modelling frequency. The daily model does not perform well for the Gaussian approaches, as these are all rejected. For the five-day frequency models the test for the conditional coverage is never rejected. If the fraction of stocks in the portfolio is increased to ($\omega = 0.25$), the models overall perform worse. Now, 12 of the 20 models reject the hypothesis of correct unconditional coverage (of which half are the empirical iterated models). Again, for the bivariate model the five-day models all pass the test. However, in the univariate case, only the for the empirical iterated models the hypothesis is not rejected. For the portfolios with weights larger than $\omega = 0.50$ the daily model outperforms the other models, with the empirical approach better than the Gaussian approach. It is remarkable how poor the performance of the Gaussian models is. This holds for scaling and iterating as well as for the distinction between bivariate and univariate. For the portfolios $\omega = 0.75$ and $\omega = 1.00$ all the Gaussian models are rejected, where 12 out of the 20 are rejected at the 1% significance level. The more volatile the portfolio, the more important is the use of empirical distributions.

Table 5.2 shows the results for the 5% Value-at-Risk levels. The relative performance of univariate against bivariate modelling, is now the other way around, indicating a different effect of portfolio aggregation. For the 1% VaR the bivariate modelling approach performed better, for the 5% VaR the univariate approach outperforms. This suggests that more complicated dynamics, which are modelled if the bivariate approach is used, are particularly useful to model the small VaR levels. For higher VaR levels, such as the 5% level, these asset specific dynamics are less important. The iterated approach again performs the best, thus the effect of temporal aggregation holds for the 5% as well as the 1% VaR. Therefore, information in the data sampled a higher frequencies, contains valuable information for forecasts risk measures.

Looking at the table in general, it is substantially easier to predict the 5% ten-day VaR than the 1% VaR. Scaled forecasts again perform worst. This holds particularly for the scaled forecast using the empirical distribution, as this method predicts the 5% Value-at-Risk the worst of all different methods. Compared to the 1% VaR results, the direct forecasting method performs almost as good as the iterated forecast method. Except for the stocks only portfolio, the direct method almost never reject the conditional coverage test. Although the one-day and five-day empirical iterated methods still perform the best for this VaR quantile, both the Gaussian scaling and iterating approach perform almost as good as the empirical iterated methods. This shows that less extreme quantiles are forecasted accurately using the Gaussian distribution. For the portfolios ($\omega = 0.00, \omega = 0.25$ and $\omega = 0.50$) the five-day method never rejects the unconditional coverage, irrespective of whether either scaling or it-

Table 5.2: Performance of 5% VaR from RiskMetrics model

	Bivariate				Univariate			
	Empirical		Gaussian		Empirical		Gaussian	
	Scaled	Iterated	Scaled	Iterated	Scaled	Iterated	Scaled	Iterated
$\omega = 0.00$								
1-day	14.6	23.5**	22.4**	24.6**	1.3	19.0*	25.3**	27.2**
	(13.2)	(13.7)	(13.5)	(13.7)	(12.3)	(13.3)	(13.8)	(13.9)
5-day	0.9	−1.7	2.0	3.9	−3.1	−2.0	2.8	2.0
	(11.7)	(11.5)	(11.8)	(11.9)	(11.8)	(11.8)	(12.2)	(12.2)
Direct	3.1		8.7		2.4		11.6	
	(11.7)		(12.2)		(11.8)		(12.6)	
$\omega = 0.25$								
1-day	17.2*	10.2	6.8	7.6	3.9	−10.2	17.6*	22.0**
	(13.0)	(12.8)	(12.6)	(12.6)	(12.1)	(11.1)	(13.0)	(13.3)
5-day	3.5	−5.0	−4.3	−2.4	1.7	−8.3	−2.8	−2.4
	(12.0)	(11.5)	(11.5)	(11.6)	(12.0)	(11.6)	(11.7)	(11.8)
Direct	1.7		4.6		−0.6		7.2	
	(11.8)		(12.2)		(12.0)		(12.3)	
$\omega = 0.50$								
1-day	28.7**	−2.4	−7.2	−6.1	0.2	−17.2	−1.3	−0.9
	(14.2)	(12.1)	(11.5)	(11.6)	(12.3)	(10.9)	(12.2)	(12.1)
5-day	8.3	−6.8	−9.4	−9.4	6.8	−7.6	2.8	3.9
	(12.5)	(11.2)	(11.1)	(11.1)	(12.1)	(11.4)	(11.5)	(11.6)
Direct	3.1		2.8		8.3		12.8	
	(12.0)		(12.2)		(12.4)		(12.6)	
$\omega = 0.75$								
1-day	37.5***	3.1	−6.1	−5.4	4.6	−16.8	−1.7	−0.6
	(14.8)	(12.7)	(11.8)	(11.8)	(12.5)	(11.2)	(12.0)	(12.1)
5-day	20.5*	1.3	−4.6	−3.9	18.3*	−0.6	7.9	9.1
	(13.4)	(12.2)	(11.7)	(11.8)	(13.2)	(11.8)	(12.2)	(12.3)
Direct	17.9*		7.2		13.5		13.5	
	(13.4)		(13.0)		(12.6)		(13.1)	
$\omega = 1.00$								
1-day	38.3***	7.9	−2.8	−1.7	2.4	−13.1	3.9	5.4
	(14.8)	(12.9)	(11.9)	(12.0)	(12.5)	(11.3)	(12.4)	(12.5)
5-day	25.3**	2.4	−2.4	−2.4	20.5*	−1.3	17.6*	18.3*
	(13.8)	(12.4)	(12.1)	(12.1)	(13.3)	(12.0)	(13.0)	(13.0)
Direct	24.6**		11.6		21.3*		19.0*	
	(14.0)		(13.5)		(13.2)		(13.4)	

The table contains the percentage deviation of the fraction of VaR violations from 0.05 for the bivariate as well as the univariate approach. The table reports results for different distributions (empirical and Gaussian), different portfolio weights ω, different modelling frequencies ($k = 1$, $k = 5$, or $k = 10$), and different forecasting methods (scaled and iterated). Standard errors are reported in parenthesis. We denote significantly positive percentage deviations with *,** and *** for the 10%,5% and 1% significance levels.

erating, or either empirical or Gaussian is used. The percentage deviations seem to be evenly distributed positive and negative, whereas for the 1% almost all deviations are positive.

In Table 5.6 and 5.7 in appendix 5.B we show the results for the unconditional coverage tests, when an estimation window of $L = 2000$ is used to estimate the RiskMetrics model. The results with estimation window $L = 2000$ are remarkably similar to those with estimation window $L = 1000$, particularly for the 1% VaR results in Table 5.6. The main difference is that some of the rejections are less significant for the results with $L = 2000$. This can be explained from the fact that if a longer estimation window is used, λ is estimated more efficiently. The difference for the 5% VaR forecasts are somewhat larger. The outperformance of the univariate modelling approach is stronger for the 5% VaR with $L = 1000$. For instance, using the univariate approach, there are eleven rejections in total for $L = 1000$, while there are only four rejections using $L = 2000$. Again, this difference can be attributed to the more efficient estimation if $L = 2000$ is used.

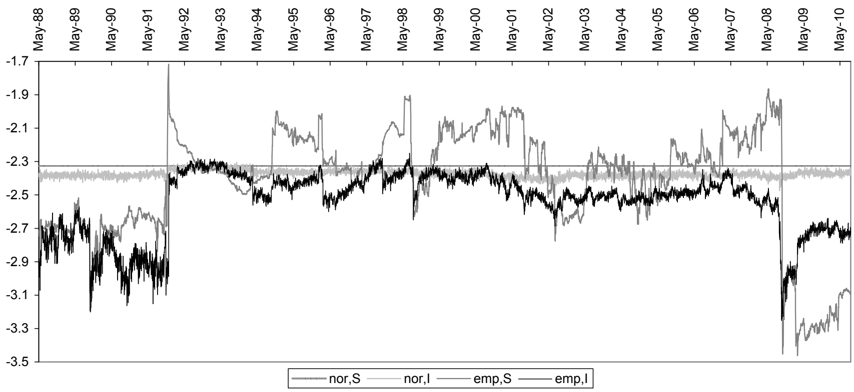
Table 5.1 showed that for the 1% VaR the iterated forecasts performed better than scaling, and using the empirical distribution performed better than using the Gaussian distribution. For the 5% VaR in Table 5.2 the results were different. Although iterating was again better than scaling, using the Gaussian distribution outperformed using the empirical distribution. Therefore, we examine how scaling and iterating interact with the choice between the use of either empirical or Gaussian distributions. To illustrate this we focus on ten-day VaR forecasts for a portfolio with weight $\omega = 0.5$, where we use a daily frequency and bivariate modelling approach. For each time t we compute the standardized VaR forecasts as

$$Q_t = \frac{\mathrm{VaR}_{t,t+10,q}}{\sqrt{h}\hat{\sigma}_{t,t+1}}.$$

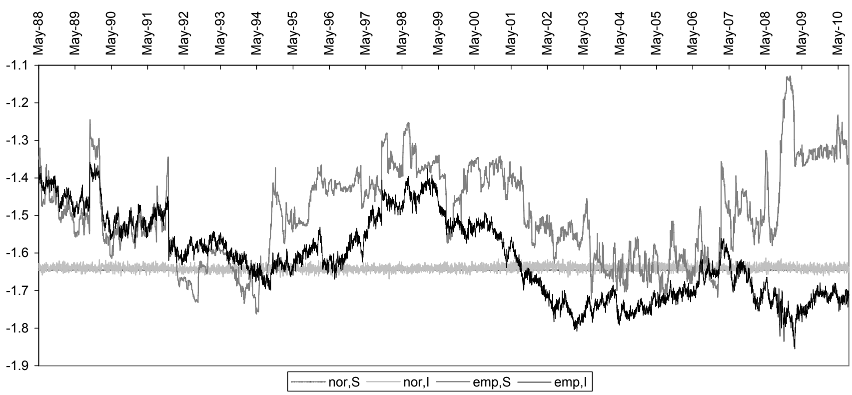
The numerator in the expression for Q_t varies for the different models, while the denominator is the same for the different models, and equal to the daily frequency scaled volatility forecast.

Figure 5.2 shows Q_t for the 1% VaR in panel (a) and for the 5% VaR in panel (b). In both graphs S and I denote scaling and iterating, "nor" and "emp" indicate using the Gaussian and empirical distribution in the computation of Q_t. At each day t we divide the ten-day value-at-risk forecast by the ten-day scaled volatility forecasts. The Gaussian scaling approach trivially shows a straight line. The Gaussian iterated approach standardized quantiles are a bit lower than the scaled counterparts, but on average they are interestingly equal. The time-variation introduced by iterating for Gaussian forecasts is quite small. The empirical approaches show a different picture. The scaling as well as the iterating approach result in large time-variation in the standardized quantiles. The iterating approach seems to result in somewhat more stable forecasts for the quantiles, than the scaling approach does. This hold for the 1% as well as the 5% quantiles. Thus, the difference between iterating and scaling is larger for the empirical approach, than for the Gaussian approach. Further, irrespective for the choice between scaling and iterating, the empirical approach results in much more

Figure 5.2: standardized quantiles 50% bond 50% stock



(a) $q = 0.01$



(b) $q = 0.05$

This figure shows the effects of the different forecasting methods. The lines in the graphs are the forecasted standardized quantiles of the ten-day returns. The quantiles are standardized by dividing by the forecasted volatility on day $t+1$.

time-variation in Q_t, than the Gaussian approach does. Note that the variation in Q_t, for the empirical approaches, is larger for the 5% quantiles than for the 1% quantiles. The 1% empirical quantile is calculated as the tenth smallest standardized residual, while the 5% quantile is calculated as the fiftieth smallest residual. Thus, the 1% quantile is more sensitive to large residuals moving in or out the rolling window.

Figure 5.1 showed $\hat{\lambda}$ over the sample. First, for the Gaussian approaches, the closer $\hat{\lambda}$ is to 1, the more equal are the scaled and the iterated standardized quantiles Q_t. This comes from the fact that if $\lambda = 1$ in the RiskMetrics model, return shocks do not have an effect on the variance. In that case the variance stays constant over the sample, which is also the case for the scaling approach. Second, for the empirical distribution in (a), the figure shows that a lower $\hat{\lambda}$ corresponds with a much lower quantile than the Gaussian quantile. For a higher $\hat{\lambda}$, the empirical quantiles are more in line with the Gaussian quantiles, as shocks have a lower impact when $\hat{\lambda}$ is high.

Table 5.3 reports the results on conditional coverage. The upper part reports the p-values for the bivariate approach, and the lower part reports the results for the univariate approach. Contrary to the results of the unconditional coverage test, there is no substantial difference between the univariate or bivariate modelling method for the conditional coverage test. The direct method seems to perform best in terms of conditional coverage. For the unconditional coverage this ten-day frequency modelling approach performed worse. The daily frequency approach fared well for the unconditional test, but performs much less for the conditional test. In line with the results for the unconditional coverage, the test for conditional coverage passes more often for the less volatile portfolios (with weights $\omega = 0.50, w = 0.75, w = 1.00$). For as well the univariate and bivariate approach, there is no rejection for the portfolios with $\omega = 0.00$ and $\omega = 0.25$, except for the 5% VaR from the univariate five-day empirical scaling approach.[12] We refer the reader to appendix 5.A for the results of an alternative conditional coverage test, where do not include lags $t-2$ to $t-9$ in the null and alternative hypothesis.

We turn to the results for the Markov switching model from Pelletier (2006). Because the dependence is now modelled with four parameters, and the stock and bond volatilities are estimated with asset specific decay parameter λ, this model is much less parsimonious than the RiskMetrics model. As efficient estimation becomes more important for this model, we expect the daily models to perform relatively better. As described in section 5.2.2 we only consider iterated and direct forecasts. We do not consider the portfolios consisting of either only stocks or only bonds, as these are exactly equal to the corresponding univariate RiskMetrics results.

Table 5.4 reports the unconditional and conditional coverage results for the Markov switching application. First, the empirical approach leads to much too conservative estimates for the VaR levels. Although in our one-sided setup this does not lead to a rejection, the systematic negative deviations still indicates that this empirical approach does not perform well. The reason for this structural underestimation comes from the fact that the draws from the empirical stock and bond distributions are not from the same point in time. This is due to the well-known flight-to-quality and flight-from-quality phenomena, where large positive returns in one market are often offset by large negative returns in the other market. In the RiskMetrics application

[12]Test is at the 5% significance level.

Table 5.3: Dependence Test

	1%				5%			
	Empirical		Gaussian		Empirical		Gaussian	
	Scaled	Iterated	Scaled	Iterated	Scaled	Iterated	Scaled	Iterated
Bivariate	$\omega = 0.00$							
1-day	0.326	0.232	0.396	0.476	0.357	0.304	0.218	0.250
5-day	0.606	0.490	0.591	0.596	0.930	0.377	0.914	0.862
Direct	0.610		0.165		0.035		0.451	
	$\omega = 0.25$							
1-day	0.708	0.950	0.289	0.143	0.199	0.761	0.393	0.389
5-day	0.268	0.301	0.410	0.749	0.096	0.195	0.158	0.101
Direct	0.753		0.255		0.013		0.169	
	$\omega = 0.50$							
1-day	0.003	0.749	0.535	0.013	0.028	0.001	0.000	0.000
5-day	0.778	0.613	0.637	0.685	0.015	0.023	0.199	0.359
Direct	0.562		0.940		0.012		0.015	
	$\omega = 0.75$							
1-day	0.022	0.314	0.023	0.026	0.004	0.019	0.093	0.037
5-day	0.266	0.325	0.315	0.389	0.061	0.014	0.005	0.006
Direct	0.748		0.566		0.132		0.476	
	$\omega = 1.00$							
1-day	0.439	0.100	0.031	0.276	0.001	0.003	0.004	0.004
5-day	0.010	0.149	0.464	0.903	0.063	0.416	0.141	0.141
Direct	0.350		0.104		0.086		0.583	
Univariate	$\omega = 0.00$							
1-day	0.389	0.572	0.333	0.401	0.143	0.346	0.445	0.257
5-day	0.253	0.694	0.012	0.012	0.253	0.694	0.778	0.800
Direct	0.101		0.287		0.345		0.309	
	$\omega = 0.25$							
1-day	0.912	0.957	0.866	0.820	0.249	0.170	0.935	0.853
5-day	0.341	0.220	0.588	0.447	0.049	0.070	0.098	0.423
Direct	0.446		0.253		0.090		0.314	
	$\omega = 0.50$							
1-day	0.261	0.744	0.317	0.383	0.000	0.000	0.000	0.000
5-day	0.937	0.456	0.290	0.268	0.068	0.020	0.949	0.567
Direct	0.710		0.874		0.144		0.068	
	$\omega = 0.75$							
1-day	0.263	0.109	0.036	0.027	0.000	0.001	0.000	0.000
5-day	0.228	0.303	0.687	0.641	0.323	0.057	0.094	0.092
Direct	0.093		0.032		0.201		0.159	
	$\omega = 1.00$							
1-day	0.056	0.074	0.024	0.232	0.011	0.015	0.000	0.000
5-day	0.019	0.240	0.277	0.286	0.068	0.244	0.010	0.010
Direct	0.175		0.251		0.095		0.203	

The table contains the p-values a likelihood ratio tests for independence for the VaR violations in the RiskMetrics models. The null hypothesis H_0 of the test is: no dependence after lag 10, the binary violation variable X_t is regressed with a logit regression on a constant and X_{t-1} to X_{t-9}. Under H_1: serial dependence after lag 10, X_t is regressed on a constant and X_{t-1} to X_{t-10}.

these extremes are always drawn simultaneously. Here the drawings are effectively based on inverse copula transformations, where the specific draw for stock of bonds is determined by mixed standard normal random drawings with correlation ρ_1 or ρ_2, based on the forecasted probabilities.

Table 5.4: VaR from MSW model

	1%			5%		
	1-day	5-day	Direct	1-day	5-day	Direct
Panel A			Empirical			
$\omega = 0.25$	−48.2	−16.8	−0.2	−9.8	−16.8	−9.1
	(15.5)	(23.1)	(23.9)	(11.3)	(10.7)	(11.4)
$\omega = 0.50$	−39.0	−9.4	−3.9	−22.0	−17.9	−0.6
	(19.3)	(23.7)	(24.2)	(10.5)	(10.7)	(11.6)
$\omega = 0.75$	−11.3	20.1	42.3^{*}	−17.9	−2.8	18.3^{*}
	(23.8)	(29.4)	(31.7)	(10.9)	(11.7)	(12.8)
			Gaussian			
$\omega = 0.25$	33.1	20.1	27.5	−3.9	−7.9	2.8
	(27.7)	(29.4)	(27.8)	(11.6)	(11.3)	(11.8)
$\omega = 0.50$	23.8	38.6^{*}	66.4^{**}	−4.3	−2.4	5.0
	(26.7)	(29.9)	(32.1)	(11.8)	(11.5)	(12.1)
$\omega = 0.75$	33.1	79.3^{**}	121.8^{***}	0.2	11.6	19.4^{*}
	(29.3)	(35.4)	(38.9)	(12.0)	(12.4)	(13.1)
Panel B			Empirical			
$\omega = 0.25$	0.102	0.057	0.948	0.960	0.026	0.088
$\omega = 0.50$	0.377	0.410	0.093	0.000	0.163	0.002
$\omega = 0.75$	0.562	0.700	0.209	0.003	0.509	0.050
			Gaussian			
$\omega = 0.25$	0.783	0.792	0.828	0.685	0.807	0.089
$\omega = 0.50$	0.802	0.031	0.194	0.055	0.021	0.117
$\omega = 0.75$	0.711	0.655	0.099	0.094	0.672	0.370

The table contains the percentage deviation of the fraction of VaR violations from q. The table reports results for different portfolio weights ω, different quantiles ($q = 0.01$ and $q = 0.05$) and different modelling frequencies ($k = 1$, $k = 5$, or $k = 10$). We denote significantly positive percentage deviations with *,** and *** for the 10%,5% and 1% significance levels.

Second, for the Gaussian approach the one-day models cannot reject the unconditional coverage tests. For the 1% VaR, the five-day and ten-day models do reject the unconditional coverage, except for the least volatile portfolio. Note the large deviations for the five- and ten-day methods for the more volatile portfolios. The 5% VaR levels are forecasted relatively accurate for all models, with the only exception the ten-day $\omega = 0.75$ portfolio. Thus, we see indeed, that if the model becomes more complicated, the performance of the higher frequency models improves relative to models based on a lower frequency. Thus, the effect of temporal aggregation is particularly strong when more complicated models are estimated.

The conditional coverage test for the 1% VaR is passed by the daily frequency models. This test rejects more for the 5% VaR violations than for the 1% violations. Additionally, it seems that the equally weighted portfolio results in the worst performance with respect to conditional coverage. Interestingly, the p-values for the conditional coverage in this Markov switching application are generally higher than for the RiskMetrics application. This is probably the result from the incapability of the RiskMetrics model (and other GARCH-type models as well) to adjust quickly to new levels for the second moments. Thus this could result in clustered violations, if (co)variances do not adjust quick enough to a new financial environment. However, the Markov switching model can adjust immediately to new correlation levels, which might lead to less dependent violations.

5.4 Conclusion

We have investigated the performance of different models for the prediction of ten-day Value-at-Risk. The forecasting methods differed in the modelling frequency: one-day, five-day, or ten-day. For the forecasting strategy we used scaling as well as iterating. The distribution we used to compute the VaR quantiles was either the Gaussian or the empirical distribution.

We have several conclusions. First, for the 1% VaR levels richer dynamics are needed, thus the bivariate approach performs better and higher frequencies performs better. On the other hand, for the 5% VaR levels lower frequencies and the univariate forecasting approach performs better. Second, the importance of using higher frequency models becomes larger as the portfolio returns become more volatile. Third, using the empirical distribution in stead of the Gaussian distribution, improves the performances of the VaR forecast. This holds particularly when the iterated forecasting method is used. Fourth, if models get less parsimonious, the difference in performance between the models with different modelling frequencies gets larger, in favor of the higher frequency models. Finally, irrespective of forecasting method it is substantially easier to predict the 5% ten-day VaR than the 1% ten-day VaR.

The finding that iterated forecasts outperform direct and scaled forecasts are in line with Ghysels et al. (2009). However, we find that scaled forecasts do not perform substantially better than direct forecasts, contrary to Ghysels et al. (2009). This worse performance of scaled forecast is in line with Diebold et al. (1997). The literature on forecasting aggregates or aggregating forecasts was mixed on what the best forecast method is Hendry and Hubrich (2010). We find that for the 1% VaR univariate forecasting outperforms, while for the 5% VaR multivariate forecasting outperforms.

These results have some important implication for practice. Risk-managers should examine whether they can improve their understanding and forecasting capability of the risks they are bearing, by modelling their risks using data at the highest possible level of detail. In practice, a risk-manager's portfolio often contains a large amount of assets, so it might be a challenge to build a multivariate model for returns of all those assets. However, the results in this paper show that the risk-manager can better predict VaR using a multivariate approach. The results also suggest that risk-managers should investigate using higher data frequencies, even when their forecast horizon is much larger than this data frequency.

5.A Alternative dependence test

In this section we describe an alternative test for conditional coverage. One of the problems associated with the test described in section 5.2.4, is the large amount of parameters that has to be estimated. Although the regressions contain 5420 violations X_t, these many estimated parameters could decrease the power of the test. The autocorrelation structure for the first 9 lags of X_t shows the pattern of an AR(1) process. Therefore, in our alternative test we include only 1 lag of X_t. Therefore, under H_0 we regress X_t on a constant and X_{t-1}. Under H_1 we regress X_t on a constant, X_{t-1} and X_{t-10}. We test with a likelihood ratio test for the significance of X_{t-10}, which we expect to be significant only if H_1 is true.

Table 5.5 reports the results for this alternative dependence test. In general, this test shows that the models have a sufficient unconditional coverage overall. The results from this test are mainly the same as for the original test, and on average both tests point in the same direction. Again, this test for conditional coverage also passes more often for the less volatile portfolios. For this test, this result is stronger for the univariate approach than for the bivariate approach. Additionally, the direct approach passes the test quite often and performs well regarding conditional coverage. Compared to the original test, the five-day approach now performs good as well.

5.B Sensitivity test

In this appendix the unconditional coverage test results using a estimation window of $L = 2000$ are reported.

Table 5.5: Additional Dependence Test

	1%				5%			
	Empirical		Normal		Empirical		Normal	
	Scaled	Iterated	Scaled	Iterated	Scaled	Iterated	Scaled	Iterated
Bivariate	$\omega = 0.00$							
1-day	0.376	0.408	0.296	0.331	0.532	0.862	0.546	0.543
5-day	0.456	0.567	0.456	0.460	0.900	0.610	0.810	0.794
Direct	0.469		0.319		0.083		0.545	
	$\omega = 0.25$							
1-day	0.474	0.985	0.982	0.894	0.843	0.795	0.860	0.847
5-day	0.044	0.065	0.355	0.176	0.856	0.702	0.897	0.935
Direct	0.074		0.767		0.431		0.745	
	$\omega = 0.50$							
1-day	0.019	0.583	0.197	0.034	0.523	0.023	0.003	0.003
5-day	0.307	0.429	0.487	0.515	0.861	0.641	0.825	0.591
Direct	0.495		0.308		0.685		0.948	
	$\omega = 0.75$							
1-day	0.032	0.119	0.036	0.041	0.138	0.274	0.123	0.085
5-day	0.457	0.538	0.335	0.319	0.696	0.282	0.510	0.524
Direct	0.533		0.433		0.682		0.619	
	$\omega = 1.00$							
1-day	0.091	0.104	0.027	0.092	0.018	0.133	0.067	0.059
5-day	0.012	0.103	0.563	0.612	0.411	0.752	0.945	0.945
Direct	0.096		0.039		0.232		0.966	
Univariate	$\omega = 0.00$							
1-day	0.388	0.429	0.248	0.305	0.350	0.893	0.719	0.554
5-day	0.170	0.582	0.126	0.138	0.318	0.568	0.571	0.558
Direct	0.179		0.106		0.555		0.670	
	$\omega = 0.25$							
1-day	0.650	0.317	0.801	0.587	0.572	0.389	0.841	0.958
5-day	0.401	0.239	0.359	0.265	0.570	0.727	0.703	0.363
Direct	0.575		0.591		0.996		0.702	
	$\omega = 0.50$							
1-day	0.117	0.601	0.087	0.103	0.002	0.002	0.005	0.005
5-day	0.202	0.263	0.477	0.384	0.668	0.815	0.279	0.384
Direct	0.787		0.826		0.970		0.887	
	$\omega = 0.75$							
1-day	0.100	0.152	0.031	0.039	0.014	0.033	0.003	0.002
5-day	0.475	0.583	0.890	0.914	0.815	0.377	0.854	0.848
Direct	0.549		0.401		0.392		0.919	
	$\omega = 1.00$							
1-day	0.086	0.115	0.023	0.081	0.040	0.062	0.019	0.011
5-day	0.008	0.094	0.140	0.142	0.333	0.663	0.319	0.309
Direct	0.087		0.353		0.271		0.446	

The table contains the p-values of a second likelihood ratio tests for independence for the VaR violations in the RiskMetrics models. The null hypothesis H_0 of the test is: no dependence after lag 10, the binary violation variable X_t is regressed with a logit regression on a constant and X_{t-1}. Under H_1: serial dependence after lag 10, X_t is regressed on a constant, X_{t-1} and X_{t-10}.

Table 5.6: Performance 1% VaR from RiskMetrics model, estimation window $L = 2000$

	Bivariate				Univariate			
	Empirical		Gaussian		Empirical		Gaussian	
	Scaled	Iterated	Scaled	Iterated	Scaled	Iterated	Scaled	Iterated
	$\omega = 0.00$							
1-day	7.2	7.2	42.3*	20.1	−2.0	−11.3	46.0*	27.5
	(25.0)	(24.4)	(30.3)	(27.2)	(24.9)	(22.0)	(30.0)	(27.8)
5-day	−20.5	−16.8	3.5	−7.6	14.6	−9.4	31.2	25.7
	(21.8)	(22.2)	(25.0)	(23.2)	(24.6)	(22.1)	(28.1)	(27.4)
Direct	−24.2		25.7		29.4		36.8	
	(19.8)		(27.0)		(27.7)		(29.6)	
	$\omega = 0.25$							
1-day	29.4	18.3	64.5**	40.5	40.5	−9.4	116.3***	77.4**
	(29.8)	(27.8)	(34.6)	(32.3)	(31.7)	(23.7)	(40.2)	(35.8)
5-day	29.4	7.2	47.9*	40.5	46.0*	1.7	53.4*	46.0*
	(30.5)	(28.2)	(33.5)	(32.8)	(32.1)	(27.2)	(34.2)	(33.1)
Direct	18.3		62.7**		25.7		46.0*	
	(28.6)		(34.6)		(29.5)		(32.5)	
	$\omega = 0.50$							
1-day	46.0*	5.4	34.9	25.7	10.9	−26.1	57.1**	40.5*
	(32.7)	(26.6)	(31.3)	(29.2)	(26.3)	(20.4)	(31.6)	(30.3)
5-day	25.7	9.1	42.3*	36.8	9.1	−2.0	62.7**	55.3**
	(29.4)	(27.7)	(30.8)	(30.3)	(26.9)	(25.8)	(32.6)	(32.0)
Direct	9.1		59.0**		16.5		68.2**	
	(26.2)		(33.4)		(29.0)		(34.2)	
	$\omega = 0.75$							
1-day	60.8**	9.1	46.0*	33.1	14.6	−9.4	59.0**	44.2*
	(33.7)	(26.4)	(30.5)	(28.7)	(26.4)	(22.7)	(31.7)	(30.2)
5-day	31.2	14.6	68.2**	62.7**	27.5	3.5	95.9***	83.0***
	(29.8)	(27.1)	(34.3)	(33.2)	(27.9)	(24.2)	(36.1)	(34.6)
Direct	46.0*		103.3***		23.8		101.5***	
	(31.2)		(39.1)		(30.0)		(38.0)	
	$\omega = 1.00$							
1-day	62.7**	16.5	59.0**	55.3**	18.3	−5.7	73.8**	57.1**
	(33.6)	(27.4)	(32.9)	(32.5)	(28.0)	(23.8)	(33.9)	(32.4)
5-day	40.5*	12.8	84.8**	81.1**	29.4	3.5	90.4***	81.1**
	(30.0)	(26.9)	(37.2)	(36.9)	(28.6)	(24.3)	(36.7)	(35.9)
Direct	46.0*		123.7***		20.1		101.5***	
	(31.4)		(41.2)		(28.7)		(38.3)	

The table contains the percentual deviation of the fraction of VaR violations from 0.01 for the bivariate as well as the univariate approach. The table reports results for different distributions (empirical and Gaussian), different portfolio weights ω, different modelling frequencies ($k = 1$, $k = 5$, or $k = 10$), and different forecasting methods (scaled and iterated). Standard errors are reported in parenthesis. We denote significantly positive percentual deviations with *,** and *** for the 10%,5% and 1% significance levels.

Table 5.7: Performance 5% VaR from RiskMetrics model, estimation window $L = 2000$

	Bivariate				Univariate			
	Empirical		Gaussian		Empirical		Gaussian	
	Scaled	Iterated	Scaled	Iterated	Scaled	Iterated	Scaled	Iterated
				$\omega = 0.00$				
1-day	9.4	19.8*	19.8*	21.3*	−8.3	14.2	20.9*	22.7**
	(12.5)	(13.3)	(13.2)	(13.3)	(11.5)	(12.9)	(13.3)	(13.5)
5-day	3.5	4.6	4.3	5.0	7.2	7.6	7.6	7.6
	(11.9)	(11.9)	(11.8)	(11.8)	(12.3)	(12.3)	(12.4)	(12.4)
Direct	−2.8		1.3		6.1		9.8	
	(11.5)		(12.0)		(12.2)		(12.6)	
				$\omega = 0.25$				
1-day	9.4	9.1	3.1	3.5	−0.6	−10.9	18.7*	23.5**
	(12.7)	(12.6)	(12.2)	(12.2)	(11.9)	(11.3)	(13.0)	(13.3)
5-day	2.0	−3.9	−3.1	−2.4	3.9	−3.5	−4.3	−3.9
	(12.2)	(11.9)	(11.9)	(12.0)	(12.4)	(12.0)	(11.8)	(11.8)
Direct	0.2		1.3		−7.2		−6.8	
	(11.9)		(12.1)		(11.5)		(11.6)	
				$\omega = 0.50$				
1-day	25.3**	0.6	−9.1	−7.2	−1.3	−13.9	−1.7	−0.6
	(13.9)	(12.1)	(11.5)	(11.6)	(12.0)	(11.2)	(12.0)	(12.1)
5-day	12.8	−3.1	−9.4	−9.1	−3.5	−16.1	−9.4	−8.7
	(12.7)	(11.7)	(11.3)	(11.3)	(11.6)	(10.8)	(11.2)	(11.3)
Direct	11.6		3.1		9.4		4.6	
	(12.8)		(12.5)		(12.5)		(12.2)	
				$\omega = 0.75$				
1-day	34.9***	5.4	−7.2	−6.5	−0.9	−14.6	−0.6	0.9
	(14.4)	(12.6)	(11.7)	(11.8)	(12.2)	(11.3)	(12.0)	(12.2)
5-day	19.4*	−0.9	−6.5	−6.8	6.1	−9.4	2.0	3.1
	(13.3)	(12.2)	(11.6)	(11.7)	(12.4)	(11.5)	(12.0)	(12.1)
Direct	24.6**		9.8		6.8		6.8	
	(13.9)		(13.3)		(12.3)		(12.7)	
				$\omega = 1.00$				
1-day	40.5***	13.1	−1.3	−0.6	−0.6	−9.8	3.9	5.7
	(14.6)	(13.0)	(12.1)	(12.1)	(12.2)	(11.7)	(12.5)	(12.5)
5-day	23.8**	4.6	−3.9	−3.5	5.7	−5.4	7.2	6.8
	(13.9)	(12.7)	(11.8)	(11.8)	(12.6)	(11.9)	(12.5)	(12.4)
Direct	26.4**		15.0		9.1		9.4	
	(14.2)		(13.5)		(12.6)		(12.8)	

The table contains the percentual deviation of the fraction of VaR violations from 0.01 for the bivariate as well as the univariate approach. The table reports results for different distributions (empirical and Gaussian), different portfolio weights ω, different modelling frequencies ($k = 1$, $k = 5$, or $k = 10$), and different forecasting methods (scaled and iterated). Standard errors are reported in parenthesis. We denote significantly positive percentual deviations with *,** and *** for the 10%,5% and 1% significance levels.

Nederlandse samenvatting (Summary in Dutch)

Inleiding

De mate van afhankelijkheid tussen aandelenrendementen ten tijden van financiële crises is hoger dan gedurende perioden van relatieve rust op aandelenmarkten. Deze hogere afhankelijkheid tussen aandelenrendementen gedurende perioden van onrust heeft tot gevolg dat aandelenmarkten de neiging hebben gezamenlijk te crashen. Voor investeerders betekent dit dat hun mogelijkheid tot diversificatie lager is, aangezien grote negatieve rendementen tegelijkertijd kunnen optreden in meerdere markten waarin zij geinvesteerd hebben.

In dit proefschrift doen we onderzoek naar de afhankelijkheid tussen grote negatieve rendementen op verschillende aandelenmarkten. De afhankelijkheid tussen minder grote rendementen, zowel positieve als negatieve, is doorgaans lager dan dat van grote rendementen. De afhankelijkheid tussen extreem grote rendementen heet extreme afhankelijkheid en staat centraal in dit proefschrift. We kijken specifiek naar aandelenmarkten aangezien aandelen nog altijd een van de meest belangrijke financiële instrumenten zijn om te investeren. Dit blijkt ook uit het grote percentage aandelen in de portefeuilles van pensioenfondsen of institutionele investeringsmaatschappijen. Bovendien komen gelijktijdige crashes in aandelenmarkten relatief vaak voor, waardoor er duidelijk sprake is van extreme afhankelijkheid. In de laatste twee decennia, gezamenlijke crashes in aandelenmarkten gebeurde bijvoorbeeld tijdens Azië crisis, de uiteenspatting van de internet zeepbel, en de recente kredietcrisis.

De standaard multivariate verdeling om aandelenrendementen te modelleren is de normale verdeling. Deze verdeling is echter niet geschikt voor het modelleren van de afhankelijkheid van rendementen. De reden hiervoor is dat de afhankelijkheid tussen rendementen staartafhankelijk en asymmetrisch is, waarbij geldt dat de afhankelijkheid tussen negatieve rendementen groter is. De normale verdeling legt symmetrie en staartonafhankelijkheid op, waardoor de kans op gelijktijdige grote negatieve rendementen door de normale verdeling onderschat wordt. In dit proefschrift gebruiken we verschillende technieken om deze kenmerken van extreme rendementen op een betere manier te modelleren. Copulas zijn multivariate verdelingen met specifieke afhankelijkheidsstructuren. Met deze copulas kunnen kenmerken zoals staartafhankelijkheid en asymmetrie beter gemodelleerd worden. Het gebruik van copulas voor financiële data is vrij recent, daarom is een substantieel gedeelte van dit proefschrift gewijd aan nieuwe toepassingen van copulas. Overige econometrische technieken in dit proefschrift zijn onder andere GARCH, Markov regime-switching, en geordende logit modellen.

De motivatie voor het onderzoeken van extreme afhankelijkheid in wereldweide aandelenmarkten is marktintegratie. Wanneer markten meer geïntegreerd raken, neemt mogelijk de extreme afhankelijkheid tussen deze markten toe. In dat geval zal diversificatie minder goed werken, aangezien alle aandelenmarkten gelijktijdig crashen. We maken onderscheid tussen twee vormen van marktintegratie. De eerste is de integratie van opkomende markten, de tweede is de algehele globalisatie van de financiële sector. Voor beide vormen verwachten we hetzelfde effect, namelijk dat de extreme afhankelijkheid tussen de corresponderende aandelenmarkten toeneemt, zodat een goed gediversificeerde risicomanager of investeerder meer blootgesteld is aan schokken vanuit deze markten. Samenvattend, door de globalisatie van financiële markten zijn aandelenmarkten kwetsbaarder voor schokken vanuit andere markten, wat de extreme afhankelijkheid tussen aandelen vergroot.

Empirische Toepassingen

In de verschillende hoofdstukken van dit proefschrift doen we empirisch onderzoek naar de tijdsvariatie van extreme afhankelijkheid in wereldweide aandelenmarkten. In ieder hoofdstuk kijken we op een andere manier naar extreme afhankelijkheid. In hoofdstuk twee onderzoeken we of crashes besmettelijk zijn, en hoe we dat kunnen verklaren en modelleren. In hoofdstuk drie kijken we of, en in welke mate, de integratie van opkomende markten de kans op wereldweide globale crashes heeft vergroot. Hoofdstuk vier gaat dieper in op tijdsvariatie in extreme afhankelijkheid, waar we onderscheid maken tussen twee specifieke vormen van veranderingen in afhankelijkheid. Hoofdstuk vijf heeft een meer praktische inslag. We kijken hier wat het effect is van data-aggregatie op voorspellingen van extreme rendementen. In de vervolg van deze samenvatting gaan we iets dieper in op de vier empirische toepassingen.

In hoofdstuk twee kijken we naar tijdsvariatie in extreme afhankelijkheid in een raamwerk waarin markten elkaar 'besmetten'. Met besmetten bedoelen we het overspringen van paniek in een markt, naar andere markten. Dit heeft tot gevolg dat als een markt ineenstort, dit andere markten besmet, die daaropvolgend ook ineenstorten. Dit gebeurde bijvoorbeeld tijdens de Azië crisis, waar de Thaise markt als eerste crashte, vervolgens stortte verscheidene andere Aziatische markten ineen, gevolgd door de markten in Noord Amerika en Europa. Meer specifiek modelleren we crashes in dit hoofdstuk als een domino effect, waar kleine crashes in opkomende markten, uitgroeien tot regionale crashes, die op hun beurt een globale crash worden. We modelleren het domino effect met een logit model, aangezien de lokale, regionale en globale crashes een natuurlijke ordening hebben. We gebruiken dagelijkse aandelenrendementen van de markten in Latijns Amerika, Azië, Verenigde Staten en Europa. De hoofdconclusie van dit onderzoek is dat we inderdaad een domino effect vinden, waarbij kleine locale crashes op significante wijze de kans op grotere crashes vergroten. Verder maken onderscheid tussen veranderingen in afhankelijkheid die verklaard kunnen worden door veranderingen in economische of financiële variabelen, en veranderingen die niet door deze variabelen verklaard kunnen worden. Deze laatste vorm van verandering in afhankelijkheid is het zojuist besproken domino effect. Voor de eerste vorm, die ook wel interafhankelijkheid wordt genoemd, vinden we ook significant bewijs dat deze aanwezig is. Renteniveau, rendementen op de obligatiemarkten, en volatiliteit op aandelenmarkten hebben significante invloed op de kans dat aandelenmarkten gelijktijdig crashen. Tot slot vinden we dat, wanneer we globale crashes willen voorspellen, dat ons domino model meer voorspel kracht heeft dan hetzelfde model zonder domino component.

Het derde hoofdstuk vervolgd het onderzoek naar globale crashes. In dit hoofdstuk kijken we echter meer naar het lange termijn gedrag van globale crashes dan in hoofdstuk 2. Door de financiële globalisering is de afhankelijkheid tussen aandelenmarkten over de hele wereld toe genomen. Dit geldt niet alleen voor ontwikkelde markten, maar ook in grote mate voor de opkomende markten. Veel van deze opkomende markten hebben eind jaren negentig hun aandelenmarkten geliberaliseerd, waardoor deze aandelenmarkten meer geïntegreerd werden met ontwikkelde aandelenmarkten. We kijken in dit hoofdstuk specifiek naar het effect van deze globalisering op de kans dat de geaggregeerde aandelenmarkten van Latijns Amerika, Azie, Verenigde Staten en Europa allen tegelijk crashen. Gebruikmakend van wekelijkse rendementen, vinden we dat de kans op een globale crash is toegenomen van eens elke 21 jaar in 1992 naar eens elk anderhalf jaar in 2010. De Azië crisis en de recente kredietcrisis hebben grote invloed gehad op de kans op globale crashes. Deze crises hebben deze kansen niet alleen tijdelijk, maar ook blijvend, verhoogd. Voor de analyse gebruiken we verschillende copulas met verschillende afhankelijkheidsstructuren, om het niet-lineaire en asymmetrische karakter van de afhankelijkheid van aandelenmarkten goed te modelleren. In deze studie gebruiken we dus Gaussische, Student's t, Gumbel en Clayton copulas om te onderzoeken welke afhankelijkheidsstructuur het meest geschikt is voor wekelijkse rendementen op aandelenmarkten. Hoewel er een aantal perioden zijn waar vooral de negatieve rendementen een sterke afhankelijkheid vertonen, kan het grootste gedeelte van de tijd het beste voor symmetrische afhankelijkheid gekozen worden.

In hoofdstuk vier onderscheiden we twee verschillende soorten afhankelijkheid tussen aandelenrendementen, namelijk de graad en de structuur van de afhankelijkheid. De graad refereert naar de mate van afhankelijkheid, bijvoorbeeld hoger of lager. De structuur refereert naar de vorm van de afhankelijkheid, bijvoorbeeld symmetrisch of asymmetrisch, staartafhankelijkheid of staartonafhankelijkheid. Hoewel beide vormen in de huidige literatuur al zijn onderzocht, zijn deze alleen afzonderlijk bekeken. Zowel de graad als de structuur van afhankelijkheid toont tekenen van tijdsvariatie, wat gelinked kan worden aan financiële globalisatie of de staat van de economie. Bijvoorbeeld, de graad van de afhankelijkheid neemt toe door de financiële globalisatie, en ten tijden van financiële crises is de structuur meer asymmetrisch en de staartafhankelijkheid voor negatieve rendementen is hoger. Dus om beide vormen van afhankelijkheid correct te modelleren, gebruiken we een model wat tijdsvariatie in zowel de sterkte als de structuur mee neemt. In meer detail, we gebruiken een mix van copulas, waar zowel de gewichten in de mix door de tijd kunnen variëren, als dat de parameters van de copulas zelf door de tijd kunnen varieren. Tijdsvariatie in de gewichten op de copulas refereert naar veranderingen in de structuur, terwijl tijdsvariatie in de parameters refereert naar veranderingen in de graad. Voor beide vormen modelleren we de tijdsvariatie met latente Markov regime-swithching processen. In de analyse gebruiken we dagelijkse rendementen op internationale aandelen markten. Voor de tijdsvarierende copula-mix gebruiken we een Gaussische copula en een geroteerde Gumbel copula. De hoofdconclusie is dat beide vormen van afhankelijkheid duidelijk aanwezig zijn, en modellen met slecht één vorm van afhankelijkheid zijn significant minder geschikt. We zien ook duidelijk verschil tussen perioden met sterke en zwakke afhankelijkheid (graad), en perioden met symmetrische en asymmetrische afhankelijkheid (structuur). Tenslotte, het niet opnemen van een vorm, leid tot onzuivere schattingen van risicomaatstaven. Het is voor risicomanagement en portefeuille allocatie dus van belang beide vormen mee te nemen.

Hoofdstuk vijf heeft een meer praktische insteek dan de overige hoofdstukken. In het algemeen kijken we hier wat het effect is van data aggregatie op tiendaagse Value-at-Risk voorspellingen voor een portefeuille bestaande uit aandelen en obligaties. We beschouwen twee vormen van data aggregatie, namelijk, aggregatie in de tijd dimensie en aggregatie in de portfolio dimensie. Ten eerste, aggregatie in de tijdsdimensie is gebruikt wanneer de data gemodelleerd wordt op een frequentie lager dan de hoogst beschikbare frequentie. Voorspellingen gemaakt uit modellen waar de data is geaggregeerd tot de frequentie van voorspelhorizon, noemen we directe voorspellingen. Indien we een hogere frequentie gebruiken, moeten we de voorspellingen over één periode extrapoleren tot voorspellingen over meerdere perioden. Dit doen we zowel door deze voorspellingen te schalen als te itereren. Geschaalde voorspellingen zijn geconstrueerd door voorspellingen over één periode te vermenigvuldigen met een constante die proportioneel is aan de tijd. Geïtereerde voorspellingen nemen ook informatie mee over schokken tussen het eind van de één periode voorspelling en het eind van de voorspelhorizon. Ten tweede, voor aggregatie in de portefeuille dimensie hebben we twee keuzen. We kunnen de portefeuille rendementen uitrekenen en modelleren, waaruit we de voorspellingen kunnen doen. Echter, we kunnen de aandelen en obligatie rendementen ook bivariaat modelleren, waarna we voorspellingen maken voor de portefeuille rendementen met behulp van het bivariate model en de portefeuille gewichten. De hoofdconclusie met betrekking tot aggregatie in de portefeuille dimensie is dat voor de 1% Value-at-Risk de bivariate aanpak beter presteert, terwijl voor de 5% de univariate aanpak beter presteert. Met betrekking tot aggregatie in de tijdsdimensie vinden we dat geïtereerde voorspellingen beter zijn dan geschaalde en directe voorspellingen. Dit geldt voornamelijk voor de 1% Value-at-Risk voorspellingen

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Biography

Thijs Markwat was born in Rotterdam on 26 July, 1982. He obtained his Gymnasium diploma from the Christelijke Scholengemeenschap Johannes Calvijn in 2000. From 2001 to 2006 Thijs studied financial econometrics at the Erasmus University Rotterdam. He obtained his Master's degree with the judicium cum laude. His Master's thesis was based on an internship at Robeco. This thesis was titled *Chartists, Fundamentalists, and Trading in Emerging Market Currencies*, of which an improved version was published as De Zwart et al. (2009). In November 2006 he started as a PhD-student at the Econometric institute (EI) and Erasmus Research Institute of Management (ERIM) at the Erasmus University Rotterdam. During his PhD-track he presented his work at international conferences in Dublin, Washington, Paris, Florence, Singapore and Perth. He also went to Sydney, Australia for a four months research visit at the University of New South Wales (UNSW). The article version of Chapter 2 is published in the *Journal of Banking & Finance*. After his PhD-track, he started as a Medior Quantitative Researcher at Robeco investment company, with asset allocation as his specific field of interest.

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Design & layout: B&T Ontwerp en advies (www.b-en-t.nl) Print: Haveka (www.haveka.nl)