Too linked to fail or too contagious to ignore?

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Abstract

This thesis empirically investigates the role of investor sentiment as a determinant of financial contagion during crises periods. The focus is on developed - as well as emerging equity markets during 1990-2015. By using a multivariate GARCH methodology, cross-equity market correlations are documented to be increasing substantially during financial crises. Investor sentiment is a strong driver of these correlations, indicating the existence of financial contagion. Yet, interdependence (through the Fed fund rate, U.S. terms of trade, and exchange rate volatility) also exhibit significant explanatory power. The findings are robust to changes in crises definitions, and the use of copula estimation. Moreover, contagion due to investor sentiment seems to be stronger for emerging markets during the great financial crisis. On the other hand, the results indicate that financial contagion within the sovereign bond market is limited.

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1. Introduction

The true value of financial stability is best exposed in its absence, namely in periods of system-wide failures of financial markets. For example, the recent global financial crisis (GFC) has led to sharp declines in international equity markets. During this crisis period (from July 2007 to May 2009), the U.S. equity market alone lost about 40 percent of its market capitalisation. One remarkable observation was how rapidly this country-specific shock sequentially transmitted from one market to another, around the globe. Not only did asset prices plunge around the globe, but the crisis also jeopardised real economic growth.

The financial turmoil of 2007-2009 has increased the need for financial stability among investors, and policy makers alike, more than ever before. Simultaneously, cross-financial market linkages strengthened over time due to global financial integration. This development makes the global financial system more prone to spillover and contagion effects, thereby increasing the likelihood of a financial crisis. In addition, the correlation between financial markets tends to increase during episodes of high market volatility (Longin & Solnik, 2001). It appears that fundamental relationships, that link financial markets together, are dependent on the state of the market. This suggests the existence of time-varying correlations between financial markets. Especially, these markets exhibit a great extent of co-movements during crises periods.

This suggestion poses a serious challenge for the asset - and risk management industry, regulators, and academics since the underlying nature of the correlation provides practical value for them. For asset managers

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and risk managers, diversification benefits that can be achieved for asset portfolios are impacted by the correlation between assets. The lower the correlation between assets, the higher the diversification benefit and the lower the portfolio risk. In the presence of time-varying correlation, these diversification benefits may unsolicited fluctuate with the state of the market, leaving large asset portfolios exposed to cross-border and cross-asset shocks. From the perspective of a regulator, it might be possible that a destabilising country-specific shock spills over through another country, thereby negatively affecting the financial stability. In addition, policy responses to crisis heavily depend on the nature of the transmission channel across financial markets.

A challenge for academia lies in the estimation and conceptualisation of such (dynamic) asset market linkages and correlations between asset markets. Previous, both theoretically and empirically, researchers have taken the challenge to model as well as to identify contagion effects between asset markets. The theory on contagion effects, firstly, shows no universally acceptable definition of contagion. In general, contagion is defined as a significant increase in cross-market linkages after a shock (Longin & Solnik, 1995). It conveys the idea that transmission mechanism is discontinuous due to financial panics. In addition, the theoretical work on financial crises considers an extensive amount of reasons for crises to contagiously appear in clusters and identifies several transmission channels (Masson, 1999; Kaminsky & Reinhart, 2000). Some models are based on behavioural aspects of individuals and assume that the investor behaviour changes after a large negative shock. On the other hand, it can be argued that such shocks are propagated via economic fundamentals (such as trade) of countries (Kaminsky & Reinhart, 2000).

Although there exists a certain degree of ambiguity on what contagion exactly contains, empirical work has been focused on measuring contagion effects using various econometric procedures and is even more extensive than the theoretical work. Especially this area shows sharp disagreement on the existence of contagion effects during crises periods. In a seminal study, King & Wadhwani (1990) measured contagion as a significant increase in the correlation coefficient between stock returns. Their findings suggest that the degree of correlation had increased after October 1987, after analysing US, UK, and Japanese equities. An extensive literature on this type of test followed after King & Wadhwani (1990), in particular on improving the reliability of estimates in correlation analysis between asset returns. Lee & Kim (1993) extend this analysis to other major markets and provides similar results. Forbes & Rigobon (2002) argue that simple correlation analysis provide biased results (in presence of heteroscedasticity), in the context of financial contagion. Using an adjusted correlation coefficient, Forbes & Rigobon (2002) find that increases in correlation are due to increased interdependence, and not due to contagion. In a different fashion, Dungey & Martin (2001) estimate a factor model of correlation analysis, while Hartmann, Straetmans, & De Vries (2004) use an extreme dependence measure. Thus, the empirical evidence on contagion effects shows a great dispersion concerning to both the results as well as the methodology.

This study also accepts the challenge to investigate contagion effects between asset markets over time. The focal point of this research project is financial crises in the past 25 years (1990-2015), including the GFC (GFC). A stylized fact of the GFC is that financial asset markets around the world suffered from tremendous losses, thereby also affecting real markets and whole economies. In order to provide a deeper understanding of the dynamics across countries and between asset classes, this recent crisis will be analysed in depth. More specifically, the purpose of this project is multiple. Earlier literature has been focused on examining the fundamental determinants of contagion (such as trade). For example, Syllignakis & Kouretas (2011) analyse the determinants of time-varying correlations, and shows that macroeconomic fundamentals and monetary variables have substantial explanatory power in explaining conditional correlations during the financial crisis of 2007-2009. Fluctuations in investor sentiment are often mentioned as an element that could explain the financial crises (White, 1990; De Long & Shleifer, 1991). Baker & Wurgler (2006) document that investor sentiment systematically affects the cross-section of asset returns. Especially assets that are hard to arbitrage and difficult to value are prone to investor sentiment. Baker, Wurgler, & Yuan (2012) document that investor sentiment in one market may affect investor sentiment through private capital flows. In addition, the authors find that high current sentiment predicts low future returns. Following this line of reasoning, one might argue that during financial crises, when current investor sentiment is low, asset prices are decreasing. Since investor sentiment is contagious, asset prices may decrease in other markets as well. This line of reasoning is consistent with financial contagion and hints the potential role of investor sentiment in explaining financial contagion. Yet, the role of investor sentiment with respect to contagion remains unexplored. Therefore, another goal of this thesis is to assess the explanatory power of investor sentiment in explaining financial contagion, while controlling for macroeconomic fundamentals. This is the first paper to connect investor sentiment to financial contagion explicitly. Third, this project touches upon the question whether contagion effects are stronger in emerging markets than developed markets. Only Celık (2012) specifically analysed this and finds that emerging equity markets are more sensitive to contagion effects than developed markets. To meet these research goals, this study utilises various econometric tools such as GARCH modelling and copula modelling.

The main results of this research project reveal that cross-equity market correlations increase substantially during financial crises. Such increases can potentially be motivated by changes in fundamentals (interdependence) and by changes in investor behaviour (contagion). This thesis documents that the latter motivation explains increases in cross-equity market correlations during periods of financial crises. This finding implies the existence of contagion effects in equity markets, consistent with the arguments made by Hwang & Salmon (2009). This finding persists after the inclusion of a broad set of control variables, allowing for endogenously determined crises periods, and the use of left tail dependence instead of correlations. These results are weaker for the sovereign bond market, where it is documented that the role of investor sentiment in explaining sovereign bond correlations is limited. However, changes in correlations between equity markets (and also for the sovereign bond market) is not solely driven by financial contagion. Common random shocks and interdependence do also exhibit explanatory power. It is documented that the Fed fund rate, the U.S. Terms of Trade, and exchange volatilities are negatively related to the dynamic conditional correlations. Lastly, there is not sufficient evidence in favour of stronger contagion effects in emerging markets. Only during the GFC, it is found that contagion effects between the U.S. and emerging equity markets are significantly stronger than contagion effects between the U.S. and developed equity markets. This finding is consistent with Celık (2012).

The outline of the paper is structured as follows. In section II the related literature is presented, in conjunction with the hypotheses of interest. Section III elaborates on the data analysed during this research project. Section IV elaborates on the research methodology that has been deployed. Section V presents the results and the corresponding economic interpretation. Section VI is centred on robustness checks. Section VII offers conclusive and reflective remarks.

2. Literature overview

This chapter first addresses the theoretical causes and transmission of contagion. The set of theoretical work can be, broadly speaking, divided into a set of fundamental or non-crisis-contingent theories and a set of behavioural or crisis-contingent theories. These two sets of theories are not necessarily mutually exclusive. The first set of theories assume that transmission mechanisms are the same during a crisis as during more stable periods. Thus, cross-market linkages do not change after a shock according to these theories. In that case, financial crises resulting from interdependency should be predictable using macroeconomic fundamentals. On the other hand, crisis-contingent theories aim to explain why transmission channels change during volatile periods and thus why cross-market linkages increase after a shock. Any test of contagion should be supportive of the latter set of theories. Afterwards, an empirical literature review will be provided with respect to the quantification of contagion effects in financial markets. This thesis draws clear-cut testable predictions from both the theoretical as well as the empirical literature.

2.1. Theoretical overview

2.1.1. non-crisis-contingent theories/causes

Non-crisis-contingent theories stress out that spill-over effects result from the interdependence (and not contagion) among economies. Thus, transmission channels after a shock do not differ significantly than before shock. Cross-market correlations are rather a persistency of linkages that existed even before the shocks. Shocks will be transmitted across economies due to real and financial linkages between these economies. Calvo & Reinhart (1996) classify such transmission as fundamental-based contagion, which is simply classified as interdependence in this thesis (Forbes & Rigobon, 2002). In what follows, the most important fundamental linkages will be discussed.

Trade linkages: Interdependence via trade linkages has been very prominent in the context of contagion. The most obvious form of cross-country linkages is through bilateral trade. Given high levels of trade between two trade partners, an adverse shock in one country is likely to affect its trading partners, via the loss of competitiveness and through the fall in demand in the country where the adverse shock was initiated (Gerlach & Smets, 1995). The trading partner may experience crashes in asset prices, significant capital outflows or become the target of a speculative attack because investors predict a deterioration in the trade accounts of an economy. Another trade link is through third-market competition, whereby a financial crisis in one country is contagious to other countries that export to the same third market. Lastly, interdependence may occur due to competitive devaluation. In this scenario, an economy loses competitiveness when the currency of a major trading partner is devalued. Such devaluations may especially put pressure on economies that have pegged currencies. Regulators and policy-makers may attempt to restore the competitiveness of an economy by also devaluing its currency, in response to the initial devaluation. If investors predict that such strategic interactions are probable, they are likely to withdraw capital from these countries. Thereby bringing a fall in asset prices and further declination in the currency value. Eventually, this may trigger a crisis. Corsetti, Pesenti, & Roubini (1999) model competitive devaluations in a game-theoretical setting, and argue that such devaluations can cause greater currency depreciation than required by fundamentals, leading to a negative spiral. These channels suggest that proxies of trade, that drive time-varying conditional correlations between asset prices, provide evidence of interdependence rather than contagion.

For example, Eichengreen, Rose, & Wyplosz (1996), using thirty years of panel data from twenty industrialised countries, find that contagion (in the sense of interdependence) appears to be spread quickly to economies which are closely tied by international trade linkages. Kaminsky & Reinhart (2000) find sharing a common trade bloc will make an economy interdependent from a member economy. Glick & Rose (1999) suggest that international trade patterns are crucial in understanding how crises spread in foreign exchange markets. Using data for different currency crises, the authors find that those crises affect clusters of economies that are tied by trade linkages. In addition, the authors find that trade linkages drive cross-country correlations in financial markets during volatile periods, after controlling for macroeconomic factors. Their results suggest that increases in cross-country correlations are due to interdependence rather than contagion.

Financial Linkages: Fundamental causes of contagion also include shocks that are transmitted through financial links. Financial links stem from the process of increasing globalisation as countries try to be more economically integrated with global financial markets, thereby causing a higher level of interdependencies. While trade linkages exhibit some explanatory power, some cases of financial crises are not explained by these theories (such as the Russian and Brazilian case in the 90s), but through financial linkages. There are several paths through which financial linkages exists and persists, which is partially determined by the extent of financial market integrations. The first linkage is the common lender effect, which was proposed by Kaminsky & Reinhart (2000). It asserts that a country that shares a common lender as a country struck by a crisis is more likely also to experience a crisis. The crisis in the latter country creates a need to reassess and rebalance the overall risk exposure of the creditors asset portfolio. The former country might face withdrawal and retrenchment from these common creditors induced by a crisis in the latter country. Caramazza, Ricci, & Salgado (2004) examine the role of the common creditor effect empirically. Using panel probit regressions for 41 emerging market countries, the authors find that the common creditor increases the probability of contagion. The second financial linkage is the cross-border capital flow between two countries. Similar to multilateral trade, more capital flows between economies lead directly to more interdependence.

Common random shocks: A common random shock is a change in the global economic environment, such as a deterioration in the aggregate world demand, a shift in international interest rates or changes in commodity prices, which adversely impacts the fundamentals of several countries simultaneously. For example, variation in the U.S. interest rate adversely affected the funding of emerging market economies, potentially resulting in a crisis in some of these economies (Moser, 2003). In addition, the strengthening of the U.S. dollar against the yen in 1995-1996 has been shown to play a significant role in the weakening of East-Asian economies and its crisis in 1997-1998 (Corsetti et al., 1999). Such commonalities lead to co-movement of asset prices or capital flows in those affected economies such that cross-country correlations could increase. Therefore, proxies for common random shocks (such as oil prices) ought to explain variation in the correlation between two equity indices. Such evidence would favour interdependence rather than contagion. More generally, any macroeconomic variable driving the time-variation in cross-equity market correlation favours interdependency.

2.1.2. Crisis-Contingent Theories

Crisis-contingent theories pertain the transmission of financial crises which is not attributable to observed disruptions in macroeconomic or other fundamental variables. These theories argue that such transmission is solely due to investor behaviour of other financial agents. This type of contagion is often said to be the result of irrational behaviour, such as financial panic, herding behaviour, and investor sentiment. Several theories explain investor-based contagion from different angles and can be classified into three groups: multiple equilibria (1), liquidity problems (2), and herding behaviour (3).

Multiple equilibria: Contagion can be partially explained by theories of multiple equilibria, arising as a result of changes in investors self-fulfilling expectations (Masson, 1999). Masson (1999) shows how a crisis in one country coordinate investors expectations, shifting from a good to a bad equilibrium for another economy, characterised by devaluations, fall in asset prices, and capital outflows. Another example of multiple equilibria is related to the bank-run model of Diamond & Dybvig (1983). In their model, individual depositors ought to form expectations about the behaviour of other depositors. If other depositors run, it will be optimal for the individual to run too. The bank-run decreases banks liquid asset, possibly resulting in bankruptcy. Sachs (1983) applied the bank-run model in the interbank market and argued that if each bank believes that all other banks will stop lending, all banks will stop lending. This may lead to contagion across economies. Although multiple equilibria play a significant role in contagion, quantifying changes in equilibria is nearly impossible.

Liquidity problems and portfolio rebalancing: The second category of contingent theories is endogenous liquidity shocks. Goldfajn & Valdés (1997) propose a theoretical model whereby a crisis in a country may reduce the liquidity of market participants. This results in investors recomposing their portfolio of financial assets and sell assets in other markets in order to satisfy margin calls, or to meet regulatory requirements. In addition, if the liquidity shock is large enough, a crisis in one country may increase the extent of credit rationing and force investors to sell their holdings in other countries that were not affected by the initial crisis. Brunnermeier & Pedersen (2008) show that funding liquidity and market liquidity are mutually reinforcing and might induce liquidity spirals during crises periods. Traders become reluctant to take on positions when funding liquidity is low, which in turn lowers market liquidity, leading to higher price sensitivity. When investors do not meet their margin calls, they will sell their assets. Since liquidity is low, the prices of these assets drop substantially, thereby decreasing the value of these assets in other portfolios. This results in other investors selling assets to meet their margin requirements, thus creating a negative spiral of fire-sales. Kodres & Pritsker (2002) explain financial market contagion using a rational expectation model of asset prices. In this model, the long-run value of assets is determined by macroeconomic risks (shared by several countries) and country-specific factors. According to Kodres & Pritsker (2002), contagion occurred when informed investors act, due to the arrival of private information on a country-specific factor, by rebalancing the exposure of portfolios to the shared macroeconomic risks in other countries. In the other countries, uninformed investors are not able to identify the source of the change in the asset demand. Thus, these investors rebalance as if the information is related to the own country-specific factor (while it is not). That being said, an idiosyncratic shock generates excess co-movement across countries asset markets, which can be classified as contagion. The model, empirically, implies that economies with larger liquid markets should be more vulnerable to contagion. Small and illiquid markets are likely to have a lower weight in international portfolios and are thereby shielded from contagion as generated in the model of Kodres & Pritsker (2002). There are several motivations behind the behaviour of liquidation and rebalancing across markets. First, liquidation is generated due to correlated liquidity shocks. Investors that anticipate greater redemption may need to obtain cash by selling part of their holdings in other economies. Second, a negative shock in one country decreases the value of a leveraged investors collateral, resulting in liquidating assets in unaffected economies to meet margin calls. Banks from a common creditor country may also experience liquidity problems when they experience a deterioration in the quality of their loans in one country. Therefore, banks try to reduce the risk of their loan portfolios by reducing their exposure in other high-risk countries. Third, under the correlation information channel, the arrival of new information in one market leads to price changes in that market, but also leads to implications for the values of assets in other economies. This causes the prices of assets to change in other markets as well. Lastly, portfolio rebalancing may also stem from cross-market hedging of macroeconomic risks. International investors decide how much they ought to invest in a risky foreign country by weighting the expected return to the associated risks. Wealth shocks make investors re-examine investors the riskiness of their portfolio.

Herding behaviour and investor sentiment: Lastly, explanations for financial contagion are based on changes in investor behaviour. Some examples that can cause contagion are increased risk aversion, lack of confidence and financial fears. Especially herding behaviour in the presence of inefficient markets and information asymmetries has been deployed to explain financial contagion. Investors do not have complete information regarding the fundamentals of a country and its state.

Uninformed investors frequently make investment decisions based on the actions of others, causing rational herding behaviour. This behaviour is explained by information cascade models using two premises. One, there is a significant difference in private information across agents. Two, there are significant transaction costs in order to generate sequential behaviour. In a seminal paper, Bikhchandani, Hirshleifer, & Welch (1992) model mass behaviour due to informational cascades. According to the authors, information cascade arises when it is optimal for an agent, after observing another agent ahead of him, to follow the behaviour of the agent ahead of him without any regard to the own information of the individual. These cascades occur under mild conditions and often will go in the wrong direction. In these cases, a few early individuals have a disproportionate impact on others. Banerjee (1992) argues that the decisions of others in itself may reflect private information and that individuals also consider the decisions of other people. Under sequential decision making, there exists a herding externality with a positive feedback loop. If agents join the crowd, there is more incentive for outsiders to join the crowd too. The decisions of the first few decision makers, which are not per se correct, determine where the crowd forms and grows, thereby amplifying the impact of the decision made by the initial individuals. Calvo & Mendoza (2000) argue that information costs induce herding behaviour, even when investors are rational. According to the authors, there exist equilibria in which the marginal cost exceeds the marginal gain of gather information. In such cases, it is rational for individuals to mimic market portfolios.

Devenow & Welch (1996) argue that herding is an irrational phenomenon, which can be explained from a socio-psychological point of view. They propose that investors disregard their own information set and follow others due to an intrinsic preference for conformity with the market consensus and certainty. Christie & Huang (1995) argue that herding behaviour is more pronounced during market stress and extreme market return movements. In times of uncertainty, following the market consensus reduces the concern of making incorrect decisions. Lao & Singh (2011), for example, identified that herding behaviour in the Chinese market is greater when the market is falling. In addition, extreme market return movements often occur in periods of financial crisis. This suggests that behavioural herding patterns play a role in explaining financial crisis.

Chiang & Zheng (2010) study herding behaviour in global stock markets. The evidence shows that a financial crisis induces herding behaviour, which in turn produces contagion effects. Thus, herding behaviour drives contagion effects. Another documentation is that herding behaviour is more likely in emerging markets, due to the characteristics of this market, in comparison with developed markets (Economou, Kostakis, & Philippas, 2011). For these reasons, contagion effects are likely to be stronger in emerging markets. The relative lack of transparency, weak reporting requirements, lower accounting standards, lax enforcements of regulations, and costly information acquisition inevitably lead to herding behaviour in emerging markets (Bikhchandani & Sharma, 2000). Celık (2012) empirically documents that contagion effects are stronger in emerging markets. This raises the following hypothesis:

Hypothesis 1. *Contagion effects are stronger in emerging markets*

Hwang & Salmon (2009) propose a model which incorporates the interaction between sentiment and herding to show that herding activity increases with (global) sentiment. According to the authors, individual asset returns, on average, decrease when market-wide sentiment is lower, regardless of systematic risk. Mondria & Quintana-Domeque (2013) find that sudden shifts in market sentiment and expectations are important factors causing contagion. There exist several channels through which financial contagion due to investor sentiment occurs. One, pessimistic international investors may sell-off securities from different markets simultaneously, thereby rapidly declining prices across markets. Second, sentiment in a foreign market affects sentiment in the domestic market directly due to herding behaviour of noise traders, through which market prices are affected. It is documented that ”word-of-mouth” social interactions can affect sentiment and investment decisions Brown, Ivković, Smith, & Weisbenner (2008). Therefore, it is likely that proxies for investor sentiment might drive contagion. Baker et al. (2012) investigate whether sentiment is contagious across countries. The absolute value of U.S. capital flows with other countries is used to obtain cross-sectional variation in the extent of integration between these markets. They do not only find that local and global sentiment predict the cross-section of those countries' returns, but also that capital flows appear to be one mechanism by which sentiment spreads across markets and forms global sentiment.

In this section, several causes of contagion have been discussed. Financial contagion caused by fundamental channels is classified as interdependence. This form can be, in principle, predicted and managed. Contagion causes by crisis-contingent causes, on the other hand, is harder to predict and quantify. These kind of causes explain why transmission mechanisms significantly change during a crisis. In this paper, the aim is to document support for the latter group of theories. This implies that any quantification of contagion should be (partially) driven by proxies of these theories and not by fundamentals of an economy. Therefore, the following hypothesis will be tested:

Hypothesis 2. *Contagion is driven by proxies for investor sentiment during crises periods.*

However, it is challenging to distinguish both conceptually and empirically whether contagion occurs due to innovations in the fundamentals of a country or to changes in investor behaviour. In addition, both types of contagion are interacting with each other to amplify the propagation of shocks across countries. In the next section, an overview is given about the development of testing for contagion.

2.2. Empirical overview

Contagion, the spread of a financial crisis from one market to another, is a causal concept. This implies a number of econometric challenges, especially with respect to the identification and empirical conceptualisation of contagion. The empirical literature on testing the existence of contagion is even more extensive than the theoretical work. There exists a plethora of empirical literature on the identification of financial contagion, deploying an extensive arsenal of statistical models. In general, there is no consensus on which methodology is appropriate to identify contagion in financial markets. First of all, the most straightforward test on contagion, correlation analysis, will be discussed. Afterwards, more advanced empirical work will be discussed.

2.2.1. Correlation analysis

Correlations are a very popular measure of dependence due to its simple nature. A significant increase in the correlation in returns between two markets after a shock can be interpreted as an increase in the transmission mechanism between the two markets and thus contagion occurred. In a seminal study, King & Wadhwani (1990) measured contagion as a significant increase in the contemporaneous correlation coefficient between stock returns. These authors find that the degree of correlation had increased after October 1987, after analysing US, UK, and Japanese equities. An extensive literature on this type of test followed after King & Wadhwani (1990), using the same operationalisation of contagion. Using correlation analysis, Lee & Kim (1993) find evidence of the existence of contagion in twelve major stocks markets after the 1987 U.S. stock market crash. On average, the correlation increased from 0.23, before the crash, to 0.39 after the crash. Calvo, Leiderman, & Reinhart (1996), using a similar approach, analyse contagion effects after the 1994 Peso crisis. Calvo et al. (1996) document a significant increase in the correlation between stock prices and Brady bonds in Asian and Latin-American countries. Lastly, Baig & Goldfajn (1999) test for contagion effects in stock market indices, currencies, interest rates, and sovereign spread for East Asian countries during the 1997-1998 crisis. The results suggest patterns of contagion during the Asian currency crisis. Correlations during calm periods were significantly lower than the correlations in crisis periods in debt markets, and currencies markets. In addition, Baig & Goldfajn (1999) show that these results are robust to own-country news. All these researchers provide evidence that shocks originating from one market can be transmitted to other markets, resulting in a source of substantial financial instability and turmoil. Therefore, the main prediction of this thesis is as follows:

Hypothesis 3. *Cross-market correlations increase substantially during crisis periods.*

To test this hypothesis, correlation analysis will be used as an intuitive starting point. However, simplicity often comes with great costs, which was already noticed by King & Wadhwani (1990), there exists a heteroscedasticity problem when measuring correlations, caused by increased volatility in financial markets during the crisis. The contemporaneous correlation coefficient is conditional on market movements over time, so that during crisis periods when the stock market volatility increases, the correlations will be biased upward. Suppose that the following relationship holds (Forbes & Rigobon, 2002):

$$y_t = \alpha + \beta x_t + \epsilon_t \tag{1}$$

Where ϵ_t is a white noise series, and assume that the exogeneity assumption holds. No further distributional assumptions are made. The observations are divided in a group of low variance (L), and a group of high variance (H). The high/low-ratio of the variances for the explanatory variable is defined as $1 + \delta = \frac{\sigma^h_{xx}}{\sigma^l_{xx}}$. The variance of the dependent variable can be expressed as:

$$\sigma^h_{yy} = \beta^2 \sigma^h_{xx} + \sigma_{\epsilon\epsilon} = \beta^2 (1 + \delta) \sigma^l_{xx} + \sigma_{\epsilon\epsilon} = \sigma^l_{yy}(1 + \delta [\rho^l]^2) \tag{2}$$

The correlation in the high variance period can be derived as follows:

$$\rho^h = \frac{\sigma_{xy}^h}{\sigma_{xx}^h \sigma_{yy}^h} = \frac{(1+\delta)\sigma_{xy}^l}{\sqrt{(1+\delta)\sigma_{xx}^l}\sqrt{\sigma_{yy}^l(1+\delta[\rho^l]^2}} \tag{3}$$

Equation (3) shows that the correlation coefficient is an increasing function of the volatility, which causes an upward bias during the estimation procedure. This being proved, the measure of cross-market correlations, central to this simple analysis, ought to be adjusted. Forbes & Rigobon (2002) provide a heteroscedasticity-adjusted correlation coefficient, and tests for stock market contagion during the Asian currency crisis (1997-1998), the Mexican Peso crisis (1994), and the 1987 U.S. stock market crash. In all cases, tests based on adjusted correlation coefficients find no contagion, but only the continuation of strong cross-market linkages.

Second, correlation tests may not be reliable when it comes to assessing the stability of a dependence structure (Rodriguez, 2007). The contemporaneous correlation (and also the corrected version of Forbes & Rigobon (2002)) does not take volatility continuously into account, while time-varying volatility can be perceived as a stylized fact of stock returns (Tse & Tsui, 2002). Third, the contemporaneous correlation does not provide information about the direction of causality (for example, it does not enable the researcher to pin down the source of contagion). Fourth, the use of correlations as dependence measures is only justified for multivariate normal distributions. It is generally accepted that financial time series do not meet the criteria of multivariate normality, causing correlations to fail to reveal the underlying dependence structure. Lastly, correlation analysis is not sufficient to trace the path of transmission (e.g. what drives the contagion effects, and via which routes).

2.2.2. Beyond simple correlations: GARCH models

To overcome the limitations encountered by early contributors, advanced econometric techniques were deployed by later researchers. By now, it is well accepted that correlation analysis needs further refinements in order to estimate contagion effects. In this section, a review of more advanced techniques and contributions will be provided.

The previous section suggests that the correlation analysis should be adapted in a dynamic sense, as the correlation is time-varying. One strand of literature focuses on stochastic modelling of time-varying volatility processes in financial time series using GARCH class specifications. Such specifications allow capturing the dynamic nature of the contemporaneous correlation coefficient. Several parsimonious multivariate GARCH specifications have been used in the literature. Longin & Solnik (1995) were among one of the first to apply a multivariate GARCH model in the context of modelling cross-market linkages. Using monthly excess returns for seven major economies over the period 1960-1990, the authors show that the international correlation matrices are time-varying and that the correlations have been increasing. More specifically, in periods of high conditional volatility of markets, the correlations rise, which is in line with King & Wadhwani (1990). Engle & Sheppard (2001) and Engle (2002) developed the DCC-GARCH (Dynamic conditional correlation GARCH) to examine time-varying correlations. Unlike the adjusted correlation of Forbes & Rigobon (2002), DCC-GARCH is able to adjust the correlation for time-varying volatility continuously. Chiang, Jeon, & Li (2007) utilise a DCC-GARCH model to test contagion between nine Asian stock returns from 1990 to 2003. Dummy variables are used to delimit the sample in three phases. The authors find contagion effects at the beginning of a crisis, followed by a phase of herding behaviour in which investors behaviour converged.

Cho & Parhizgari (2008) also document the presence of contagion in East-Asian equity markets during the East-Asian financial crisis in 1997. Celık (2012) tests the existence of contagion during the U.S. subprime crisis using a sample consisting of emerging and developed foreign exchange markets. By employing a DCC-GARCH, the results indicate the existence of contagion in foreign exchange markets. In addition, emerging markets had a greater sensitivity to the U.S. crisis than developed markets.

2.2.3. Extreme value theory and copulas

A substitute to the above mentioned statistical approaches to analyse contagion in financial markets is extreme value theory (EVT). EVT is involved with the study of the asymptotic distribution of extreme realisations (large infrequent observations that exceed a given threshold value). Multivariate EVT procedures aim to quantify the joint behaviour of such observations. These procedures have been increasingly deployed in finance, especially in risk measurement (Value-at-Risk estimation, for example). Yet, the application of EVT in the context of contagion is limited. Crashes in financial markets occur in the left tail of the return distribution. Rather than studying the full distribution (as done by the previous approaches), one should focus on the joint left-tail dependence to study co-crashes. This is exactly the purpose of EVT: it provides the tools to analyse these joint behaviour and offers a more robust approach in modelling contagion. Thus, in according to EVT, contagion can be interpreted as the probability of observing an extreme realisation conditional on simultaneous extreme realisations in different financial markets.

Longin & Solnik (2001), using EVT to model multivariate distribution tails for a wide class of return distributions, test the hypothesis that international equity market correlation increases during volatile times. Empirically, Longin & Solnik (2001) reject multivariate normality for the negative tail and find that correlation of negative extremes increases during bear markets. Bae, Karolyi, & Stulz (2003) capture contagion through the coincidence of extreme return shocks across countries within a region and across regions. They find that contagion is predictable and driven by regional interest rates, exchange rates changes, and conditional stock return volatility. Hartmann et al. (2004) provide an interesting insight by studying asset return linkages during periods of stress across equity markets, bond markets, and stock-bond contagion in G-5 countries. Rather than focusing on probability, the authors estimate the expected number of crashes in a market, conditional that one crash occurred elsewhere, using non-parametric approaches to multivariate EVT. Hartmann et al. (2004) found that once one market crashed, the probability of a crash in a different market was about one in five. In addition, extreme cross-border linkages within the same asset class turn out to be stronger for stock markets than for bond markets, while bivariate stock-bond co-crashes are weaker.

One way to study extreme dependency in asset markets, in an EVT context, while taking the notion of multivariate distributions into account, is to apply a copula methodology. These models isolate the interdependence structure from the structure of the marginal distributions. This approach is becoming increasingly popular and is independent of distributional premises of joint normality, which often do not hold in financial data (Goldstein, McCarthy, & Orlov, 2016). Fitting copulas make it achievable to test whether periods of heightened dependence can also be characterised by changes in the tails of the multivariate distribution. To capture such shifts in the structure of interdependency, copulas are required to be time-varying. Rodriguez (2007) explores whether financial crises can be described as periods of change in the dependence structure between markets, using a mixture of time-varying copulas. Rodriguez (2007) indicates the existence of changing dependence during periods of turmoil in Asian countries. In this thesis, several copula measures of extreme dependence will be deployed to assess the robustness of the main prediction, namely that contagion effects are present during crises periods. Aloui, Aïssa, & Nguyen (2011) examine the extent of the GFC and the contagion effects it induced by considering extreme financial interdependencies of some selected emerging markets with the US. Several copula functions, both linear as well as nonlinear, are used to model the degree of cross-market linkages. The empirical result shows strong evidence of time-varying dependence between BRIC markets and the U.S. market.

3. Data

To meet the research goals of this paper, a rich dataset consisting of financial returns and macroeconomic variables will be analysed during 1990 till 2015. The dataset is drawn from various sources and is composed of three blocks. The first block is made of monthly financial time-series on which measures of time-varying correlations are empirically fit. The second block consists of the main explanatory variables of interest, namely proxies for investor sentiment. The third block is composed of variables that control for financial and trade linkages.

3.1. Stock market returns

In order to provide a measure of correlation over time, $\rho_{ij,t}$, first the stock market returns needs to be defined. The sample consists of monthly dollar denominated stock market index returns retrieved from Thomson Reuters Datastream. Monthly returns are defined as $r_t = ln(p_t) - ln(p_{t-1})$. There are 12 countries in the sample, consisting of seven developed countries and five other emerging markets (as classified by Dow Jones): The United States of America (S&P 500), Germany (DAX), France (CAC 40), United Kingdom (FTSE 100), Japan (Nikkei 225), Netherlands (AEX) and Canada (TSX). The emerging markets consist of China (SSE composite), Russia (MICEX), India (NSE), Mexico (MEXBOL) and Indonesia (IHSG). The sample spans the period from January 1, 1990, till September 30, 2015. It covers known episodes of global crisis and contagion periods, such as the Asian Flu (1997), the Russian crisis (1998), the Dot-com bubble (2001), the GFC (2007), and the European debt crisis (2009). Due to limited data availability, the sample for China and Russia starts in 1/1/1991 and 22/9/1997 respectively.

Table 1 presents the descriptive statistics of the examined stock market index returns. There is some variation in the average monthly return, with Japan exhibiting the lowest return (-19.9%) and China the highest (101.5%). A notable observation is the dispersion in the standard deviation between emerging markets and developed countries. The former group has a larger standard deviation. This possible could imply that emerging markets are more prone to contagion. All countries face negative skewness, implying fat left tails. The null hypothesis of normality is rejected in all cases, using the Shapiro Wilk test. Most countries do not exhibit significant autocorrelations, as indicated by the Ljung-Box test statistic. The null hypothesis of no ARCH effects is rejected for all countries, except China. Table 1 also provides some preliminary support for the hypothesis that the correlation between two equity markets increases during crises periods. During periods of crises, the correlation (between the U.S. stock market and other markets) increases. It seems to be that the change in correlations is larger for emerging markets, compared to developed markets. Lastly, note that the level of the correlation for emerging markets is substantially lower than for developed countries. This finding indicates that these countries are possibly less integrated with the global market as expected.

Table 1: Descriptive statistics. The table presents the summary statistics for the stock market indices in the dataset, which are estimated using monthly return series. From" is the start date of the return series of a particular index. All returns are calculated as log returns. SD denotes the standard deviation. SW denotes the Shapiro-Wilk test statistic for non-normality. LB denotes the Ljung-Box statistic for autocorrelation with 10 lags. "ARCH" is Engle's test for Arch effects. ρ_{no} denotes the correlation during non-crises periods between the S&P500 and the equity market from the j^{th} row. Likewise, ρ_{crisis} shows the correlation during crises periods. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The data ends 30/9/2015.

Index (Country)	From	Min	Max	Mean	SD	SW	LB(10)	ARCH(5)	ρ_{no}	ρ_{crisis}
S&P 500 (U.S)	1/1/1990	-0.186	0.106	0.005	0.042	0.967***	7.255	33.214***	-	-
DAX 30 (Germany)	1/1/1990	-0.286	0.216	0.005	0.067	0.956***	7.541	17.164***	0.710	0.839
CAC 40 (France)	1/1/1990	-0.247	0.143	.003	.061	0.979***	12.021	27.254***	0.708	0.834
FTSE 100 (UK)	1/1/1990	-0.211	0.131	0.003	0.048	0.985***	6.250	32.816***	0.734	0.846
AEX 25 (Netherlands)	1/1/1990	-0.316	0.151	0.004	0.061	0.938***	5.619	36.431***	0.718	0.848
NIKKEI 225 (Japan)	1/1/1990	-0.199	0.245	-0.002	0.065	0.989***	13.293	36.665***	0.412	0.663
TSX (Canada)	1/1/1990	-0.320	0.187	0.003	0.057	0.944***	9.812	11.124**	0.741	0.843
SSE Comp. (China)	1/1/1991	-0.485	1.015	0.010	0.131	0.813***	16.135*	7.003	0.065	0.397
MICEX (Russia)	22/9/1997	-1.043	0.348	0.001	0.120	0.824***	34.416***	31.889***	0.402	0.672
NSE (India)	1/1/1991	-0.369	0.356	0.005	0.093	0.976***	8.947	17.479***	0.223	0.725
IHSG (Indonesia)	1/1/1990	-0.523	0.431	0.001	0.112	0.928***	34.396***	67.087***	0.350	0.559
MEXBOL (Mexico)	1/1/1990	-0.461	0.198	0.009	0.092	0.926***	18.802***	23.888***	0.536	0.818

3.2. Investor sentiment

To test whether contagion in stock indices returns is driven by investor sentiment, several proxies are utilized as investor sentiment is not directly observable. First of all, Baker & Wurgler's investor sentiment index (2006) is used to identify investor sentiment on a monthly frequency. Data is retrieved from the website of Jeffrey Wurgler. This composite index equals the first principal component extracted from six indirect measures of U.S. focused investor sentiment: trading volume (NYSE turnover), dividend premium, closed-end fund discount, the P/E ratio, the equity share in new issues, the number of IPOs, and their first-day returns. Specifically, the orthogonalized sentiment index is deployed which is free from business cycle related variations. Therefore, this sentiment index is expected to be uncorrelated with macroeconomic fundamentals. Positive values of this index are associated with a high level of investor sentiment (more optimism). Baker & Wurgler's index is expected to load negatively on cross-market correlations during crisis periods.

However, Baker & Wurgler's index is an indirect measure of investor sentiment. The investor sentiment indicator from the American Association of Individual Investors (AAII) offers a more direct measure to capture investor sentiment. This indicator is obtained from Datastream. This metric is directly obtained from the investors that participate in the weekly AAII's survey on their expectations pertaining the stock market performance in the next six months. The sentiment survey provides three variables, $BULL_t$, $BEAR_t$, and $NEUTRAL_t$, which measures the proportion (in %) of individual investors who are bullish, bearish, and neutral on the U.S. stock market, respectively. $NEUTRAL_t$ is excluded in the regression analysis to avoid perfect multicollinearity. A disadvantage of the use of AAII's indicator is that results may be inaccurate due to common behavioural biases that occur during surveys (Hudson & Green, 2015).

Lastly, the CBOE's Volatility Index of the S&P 500 (VIX) is used as a proxy of investor sentiment. The VIX index is a measure of implied volatility, which is the expectation of the volatility for the S&P500 over the next 30 days. The VIX index is perceived as a leading barometer of investor sentiment in global capital markets, and is often referred as the "fear index". This index is obtained from Datastream.

3.3. *Control variables: Common Shocks, Financial and trade integration*

Several control variables are used in order to distinguish contagion (due to investor sentiment) from interdependence. Shocks in oil and gold price returns are used as proxies for common random shocks since any change in these prices affects all countries simultaneously (Edison, 2003). In addition, the overnight discount rate of the FED is used as a proxy for the international interest rate. The international interest rate is a determinant of international capital flows. Countries that depend on these flows are sensitive to changes in the international interest rate (Calvo et al., 1996), which may give rise to triggering a financial crisis (Frankel & Rose, 1996).

Monthly bilateral changes in trade flows are used to take interdependence through trade linkages between countries into account. Monthly import and export flows (in USD) between the U.S. and all other countries are obtained from the Direction of Trade Statistics of the IMF. Rather than using the current account, separating export flows and import flows allows to reveal a more detailed description of the source of time-varying cross-equity market correlations. For each country, the monthly change in import from / export to the U.S. is calculated by using a log-transformation. To directly take the relative competitive advantage due to relative price changes into account, the Terms of Trade (ToT) of the U.S. relative to all other countries (weighted) will be used. A loss in competitiveness may deteriorate the current account and thereby hurt the real sector. Lastly, to take competitive devaluation into account, (conditional) exchange rate volatilities are obtained via a GARCH(1,1) model. Unstable exchange rates are partially due to strategic and competitive devaluations between countries (such as "beggar thy neighbour policies"). Lower exchange rate volatility is therefore expected to be associated with higher co-movement between markets. In addition, from a financial perspective, investors price currency risk, which is determined by (expected) exchange rate volatility. Exchange rate changes alter the return a foreign investor's yields in terms of domestic currency. However, if currency volatility is lower, the costs of rebalancing portfolios is lower. This implies a higher co-movement of equity markets. Monthly exchanges rates relative to the USD are obtained from Datastream for the countries in the sample. For European countries, the exchange rates are corrected for the introduction of the Euro. To control for macroeconomic similarities, monthly inflation rates (via the CPI) and industrial production growth data for each country is obtained. The inflation rate is likely to be correlated with high nominal interest and may proxy macroeconomic mismanagement, which negatively affects the real sector and the banking system (Semlali & Collyns, 2002). Negative growth in the industrial production may induce a crisis in the real sector which precedes financial crises (Edison, 2000)

Since there exist no detailed data for FDI flows or bank lending for this sample (which was preferred), this paper relies on imperfect proxies for financial linkages and - integration. For each country, the monthly aggregate sales flow of bonds and stocks, from that corresponding country, to U.S. citizens is identified. In addition, for each country, the monthly aggregate purchase flow of U.S. bonds and stocks from U.S. citizens is obtained. These monthly aggregates (expressed in million dollars) are obtained from the U.S. Department of the Treasury. The reason to utilise these variables is that they are indicators of cross-border capital flows and foreign participation in the U.S. financial market. These variables thereby contribute to financial linkages (through cross-border capital flows) and financial integration (through domestic participation) simultaneously. High values of these flows are associated with a higher level of interdependence between financial markets, due to increased financial integration.

The M2 supply growth is used as a simple proxy for funding liquidity, which is the ease at which funding is obtained. High levels of growth in M2 may lead to excess funding liquidity, thereby amplifying the growth of asset bubbles. Monthly M2 data is obtained from all corresponding domestic central bank from the countries in the sample. For European countries, the time series are adjusted for their contribution to the ECB's M2 supply after the EMU. Lastly, the liquidity factor of Pástor & Stambaugh (2006) is used as a proxy of U.S. market liquidity, which is the ease at which assets are traded. This factor is based on order flows and expected return reversals. According to Brunnermeier & Pedersen (2008) funding - and market liquidity are important drivers of bubble bursts.

Presenting correlation matrices for panel data, without pooling, is too cumbersome. However, there are a few notable observations. All sentiment indicators are weakly correlated with most independent variables, especially with macroeconomic variables. Pastor's liquidity factor is also weakly correlated with all sentiment indicators. Lastly, the correlation between Baker & Wurgler's index and AAII bullish sentiment indicator is 0.053, and -0.171 for the AAII bearish indicator. This suggests potential added value in terms of explanatory power when using both a direct and indirect proxy of investor sentiment.

4. Methodology

4.1. Estimating the time-varying correlation

There is a conjecture that contagion occurs during crises periods. This is equivalent to a higher correlation between equity markets in these periods. In this section, a dynamic method is proposed to capture heteroscedasticity in asset return volatility, while estimating the time-varying nature of the correlation.

A dynamic conditional correlation is estimated through multivariate generalised autoregressive conditionally heteroscedastic (MGARCH) models. In such models, the conditional variances and covariances of the residuals follow an ARMA-structure. A nonlinear combination of univariate GARCH models with time-varying cross-equation weights is used to compute the conditional covariance matrix of the residuals. Thus, by employing the MGARCH DCC model, one is able to capture the information of time-varying characteristics of the correlation matrix. In addition, the MGARCH model offers several benefits. Firstly, the DCC-GARCH estimates correlation coefficients of the standardised residuals, thereby accounting for heteroscedasticity directly. Moreover, the model offers flexibility in the mean equation to specify the model correctly. Lastly, and most importantly, it allows to examining multiple asset returns simultaneously in a parsimonious manner. In a single representation, multiple pair-wise correlations coefficient series can be obtained through this methodology. These time series allows to examine the correlation behaviour of the WML portfolios to the market portfolio over time. Let the multivariate return equation be specified in each separate equation, as:

$$\boldsymbol{R_t} = \boldsymbol{X_t}\boldsymbol{\beta} + \epsilon_t, \epsilon_t|\boldsymbol{\Omega_{t-1}} \sim N(0, \boldsymbol{H_t}), \tag{4}$$

Where $\boldsymbol{R_t}$ represents a $n \times 1$ vector with the i^{th} element denoting the ith dependent variable of the ith equation. $\boldsymbol{\beta}$ represents a $k \times 1$ vector of parameters, and $\boldsymbol{X_t}$ is a $n \times k$ data-matrix. The multivariate conditional variance is modelled as $\boldsymbol{H_t} = \boldsymbol{D_t}\boldsymbol{R_t}\boldsymbol{D_t}$. Estimating $\boldsymbol{H_t}$ involves a two-step estimation procedure. $\boldsymbol{D_t}$ is a $n \times n$ diagonal matrix containing time-varying standard deviations ($\sqrt{h_{ii,t}}$) on its diagonals. Each time-varying standard deviation comes from an univariate GARCH model in the first step of the estimation procedure. In the second step, each equity index return residual $\epsilon_{i,t}$ is rescaled by its time-varying standard deviation from step one, which provides $\gamma_{i,t}$.$\gamma_{i,t}$ in turn is used to estimate the conditional time-varying covariance matrix of γ_t. The evolution of this time-varying covariance matrix is given by:

$$\boldsymbol{\Sigma_t} = (1-\lambda_1-\lambda_2)\boldsymbol{\Sigma^*} + \lambda_1 u_{t-1}u_{t-1}^T + \lambda_2\boldsymbol{\Sigma_{t-1}}, \qquad \lambda_1+\lambda_2<1 \tag{5}$$

$\boldsymbol{\Sigma_t}$ is a $n \times n$ time-varying covariance matrix of γ_t, and $\boldsymbol{\Sigma^*}$ is the expected value of the outer product of γ_t. $\boldsymbol{\Sigma_t}$ can be rescaled into a time-varying correlation matrix $\boldsymbol{P_t}$ by simply observing that $\boldsymbol{P_t} = (diag(\boldsymbol{\Sigma_t}))^{-(1/2)}\boldsymbol{\Sigma_t}(diag(\boldsymbol{\Sigma_t}))^{-(1/2)}$. Thus, the eventual aim is to estimate $\boldsymbol{P_t}$.
In this article, for each country, the dynamic conditional correlation between the corresponding equity market and the U.S. equity market is estimated. In the mean equation, a constant-only model will be specified for simplicity. In the variance equation, a GARCH(1,1) structure is specified. Student's T-distribution will be used in the log-likelihood function, thereby taking the fat tails into account (in comparison with the Gaussian distribution).

4.2. Determinants of contagion

To analyse the determinants and the dynamics of the estimated dynamic conditional correlations, the following system of equations is estimated through the use of seemingly unrelated regression (SUR) since dynamic conditional correlations are likely to be contemporaneously correlated (Beine, Cosma, & Vermeulen, 2010):

$$\boldsymbol{\rho_{ij,t} = \alpha_{ij} + \psi_{1,ij}SENT_t + \psi_{2,ij}BEAR_t + \psi_3 BULL_t + X'_{ij,t}\gamma_{ij} + \sum \delta_{ij,t}d_t + \epsilon_{ij,t}} \tag{6}$$

Where $\rho_{ij,t}$ is the dynamic conditional correlation between country i and the U.S. (j) at time t. autoregressive terms are added to describe the dynamics of the correlation. $SENT_t$ denotes Baker & Wurgler's sentiment indicator. $BEAR_t$ and $BULL_t$ are AAII's bearish and bullish sentiment indicator. Both indicators measure the proportion of investors that are bearish and bullish respectively. The neutral indicator is excluded to overcome perfect multicollinearity. $X'_{ij,t}$ is a matrix consisting of the control variables and interaction terms between the controls and sentiment indicators. $\sum \delta_t d_t$ is a set of time dummies, also including the NBER recession time dummy. Feasible Generalised Least Squares (FGLS) is used to estimate equation (6) because the covariance matrix is unknown. The larger the contemporaneous correlation between $\epsilon'_{ij,t}s$, the larger is the information gain of FGLS compared to OLS (Moon & Perron, 2006). This will result in SUR being more efficient than OLS. Contemporaneous correlation is assessed by the Breusch-Pagan LM test (1980).

To test hypothesis 3, equation (6) is estimated only with time dummies, for each country [1]. First, the NBER time dummy is simply used. Afterwards, separate time dummies are employed for each different crisis in the sample, including the Mexican peso crisis (1994), the Asian currency crisis (1997), the Russian rubble crisis (1998), the Dot-com Bubble (2000), the GFC (2007) and the European debt crisis (2010). This will not only allow to assess whether cross market correlations increase substantially during crisis periods, but also provide insight whether this change differs by crisis. Furthermore, these separate time dummies are merged to one new time dummy ($D_{CRISIS,t}$) which denotes whether a crisis occurred in month t. This dummy will be used in the further analysis unless specified otherwise. To test hypothesis 2, equation (6) is estimated

[1] This boils down to simple OLS.

with all variables of interests and control variables. To test hypothesis 1, the coefficients of the sentiment indicators will be tested for joint equality during crisis periods. If these effects do differ across developed and emerging markets, there is evidence in favour of hypothesis 1.

4.3. Copula modelling

Financial returns are not normally distributed as suggested by a vast body in empirical finance. Financial returns are likely to display asymmetric dependence that can not be captured by correlation-focused methodologies. One way of accounting for such types of dependence is by deployed copulas. Copulas allow modelling the patterns of dependence between variables separate from the marginal distributions of financial returns. For continuous variables, a joint distribution (with n dimensions) can be decomposed into n marginal distributions and a copula function, that characterises dependence between the n variables. An important implication is that multivariate distributions can be obtained from marginals that are not necessarily in the same class. Formally, let the $G(y_1, ..., y_n)$ be a n-dimensional cumulative distribution function with univariate marginals $F_i(y_i)$ for $i = 1, ..., n$. Then, following Sklar (1959), there exists a copula (C) that maps $[0, 1]^n$ to $[0, 1]$ such that:

$$G(y_1, ..., y_n) = C(F_1(y_1), ..., F_n(y_n)) \tag{7}$$

The joint probability distribution is given by the product of the marginal probability distribution function and the copula density :

$$\frac{\partial G(y_1, ..., y_n)}{\partial y_1 ... \partial y_n} = \prod_{i=1}^{n} f_i(y_i) \frac{\partial C(F_1(y_1), ..., F_n(y_n))}{\partial y_1 ... \partial y_n} \tag{8}$$

Using probability integral transformation, the copula function now can be defined as a multivariate distribution with standard Uniform margins:

$$C(F_1(y_1), ..., F_n(y_n)) = G(F_1^{-1}(F_1(y_1)), ..., F_n^{-1}(F_n(y_n))) \tag{9}$$

Reversely, with the use of copulas, it is also possible to transform Uniform margins to a n-dimensional CDF. This applies independently of the type and degree of dependence among the variables. An important property of copulas is that they are able to capture the lower and upper tail dependence coefficients. The tail dependence measure can be seen as the probability limit that an extreme event occurs conditionally that this event also occurred in another return series. The lower tail dependence coefficient is defined as:

$$\lim_{\alpha \to 0^+} \mathbb{P}[Y < F_Y^{-1}(\alpha) | X < F_X^{-1}(\alpha)] = \lambda_L \tag{10}$$

Provided that a limit $\lambda_L \in [0, 1]$ exists. A copula C is said to be exhibiting lower dependency if λ_L is non-zero. A similar definition can also be provided for the upper tail. The aim of copula modelling in this paper is to estimate these tail dependence coefficients. Many functional forms of copulas exist, the most common copulas are the Gaussian Copula, Clayton Copula, and the Symmetrised Joe-Clayton (SJC) copula. These copulas will also be considered here. However, the copulas will be extended to allow for time-varying dependencies, following Pelletier (2006). This methodology will provide a time-series of tail dependencies which can be further analysed according to section 4.2. Appendix I provides a technical description of Markov-Switching Copulas.

5. Results

5.1. *Dynamic conditional correlation*

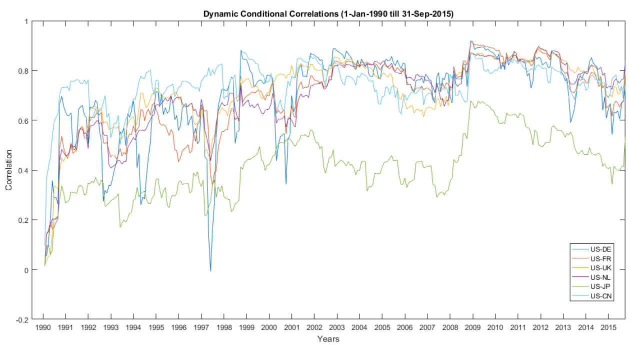
Table 2 reports the estimates of the conditional variance equations for each pair with the U.S., obtained with the DCC-GARCH methodology. Specifically, the parameter estimates of a DCC-GARCH(2,2) model is shown below. The estimates for the lagged squared error terms and lagged variance are highly significant at 1% in all US-variance equations, with some exceptions (upper panel, table 2). These estimates suggest that this model is able to capture time-varying volatility for the U.S. stock index. The variance equations for the other countries show less consistency with respect to significance (middle panel, table 2). The variance equation of Canada is the only equation that has no significant estimates of the lagged terms. Thus, this model is not able to sufficiently model the heteroscedasticity in the Canadian stock index. The variance equations of the remaining have at least one significant lagged term at 5%. However, to model time-varying correlations, at least one of the variance equations within a country-pair should exhibit significant estimates. Thus, table 2 suggests that the presented estimated model is likely to model the dynamic conditional correlation sufficiently. In addition, in the lower panel of table 2, the estimates of the adjustment terms λ_1 and λ_2 and their significance are shown. These terms govern the dynamic correlation process. The DCC model reduces to the CCC model when the adjustment terms are jointly zero. The null hypothesis of joint significance is rejected in all cases [2]. Thus all estimated models are able to predict sufficiently non-constant conditional correlations. Furthermore, note that the sum of the estimated coefficients in all variance equations is close to unity for all country-US pairs. This indicates that the return volatility is highly persistent and clustered, which is consistent with the occurrence of crises periods in financial markets.

Param.	DE	FR	UK	NL	JP	CA	CN	RU	IN	ID	MX
$\epsilon^2_{US,t-1}$	0.152^{***}	0.146^{***}	0.148^{***}	0.118^{**}	0.194^{***}	0.186^{***}	0.252^{***}	0.236^{***}	0.136^{**}	0.220^{***}	0.193^{***}
	(0.055)	(0.044)	(0.039)	(0.056)	(0.062)	(0.056)	(0.082)	(0.060)	(0.064)	(0.063)	(0.070)
$\epsilon^2_{US,t-2}$	0.117^{***}	0.110^{***}	0.126^{***}	0.096	0.132^{***}	0.142^{***}	0.178^{***}	0.202^{***}	0.145^{***}	0.184^{**}	0.145^{**}
	(0.054)	(0.046)	(0.040)	(0.116)	(0.061)	(0.056)	(0.079)	(0.081)	(0.058)	(0.095)	(0.061)
$\sigma^2_{US,t-1}$	-0.184^{***}	-0.183^{***}	-0.179^{***}	0.272	-0.216^{***}	-0.253^{***}	-0.242^{***}	-0.251^{***}	0.119	-0.224^{***}	-0.231^{***}
	(0.081)	(0.073)	(0.054)	(0.713)	(0.081)	(0.091)	(0.077)	(0.066)	(0.525)	(0.065)	(0.080)
$\sigma^2_{US,t-2}$	0.787^{***}	0.789^{***}	0.803^{***}	0.415	0.767^{***}	0.717^{***}	0.744^{***}	0.730	0.546^{***}	0.763^{***}	0.764^{***}
	(0.074)	(0.789)	(0.049)	(0.575)	(0.079)	(0.086)	(0.077)	(0.064)	(0.453)	(0.064)	(0.079)
α_{US}	0.000^{*}	0.000^{**}	0.000^{**}	0.000	0.000^{*}	0.000^{*}	0.000^{*}	0.000^{**}	0.000	0.002^{***}	$(0.000)^{*}$
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)
$\epsilon^2_{i,t-1}$	0.081^{*}	0.088^{***}	0.135^{**}	0.093^{***}	0.212^{***}	0.133^{*}	0.253	0.511^{***}	0.041^{***}	0.179^{***}	0.134
	(0.048)	(0.035)	(0.056)	(0.030)	(0.082)	(0.073)	(0.278)	(0.127)	(0.006)	(0.043)	(0.101)
$\epsilon^2_{i,t-2}$	0.121^{*}	0.125^{***}	-0.037	0.083^{***}	0.173^{**}	-0.054	0.076	0.120	0.148^{**}	0.106^{***}	0.131
	(0.065)	(0.043)	(0.087)	(0.032)	(0.090)	(0.085)	(0.986)	(0.194)	(0.074)	(0.049)	(0.100)
$\sigma^2_{i,t-1}$	0.143	-0.038	0.623	-0.159	-0.218	0.805	0.223	0.225	0.353	-0.156	-0.238
	(0.383)	$(0.034)^{***}$	(0.636)	$(0.050)^{***}$	$(0.085)^{**}$	$(0.489)^{*}$	(3.642)	(0.322)	(0.240)	$(0.050)^{***}$	(0.172)
$\sigma^2_{i,t-2}$	0.579^{**}	0.754^{***}	0.248	0.856^{***}	0.794^{***}	-0.011	0.384	0.298	0.317	0.792^{***}	0.773^{***}
	(0.225)	(0.091)	(0.568)	(0.050)	(0.093)	(0.372)	(2.683)	0.212	(0.200)	(0.045)	(0.175)
α_i	0.000^{*}	0.000^{*}	0.000	0.000^{**}	0.000	0.000	0.0001	0.000^{***}	0.001^{***}	0.001^{**}	0.002^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
λ_1	0.068^{**}	0.061^{***}	0.051^{***}	0.051^{***}	0.015	0.072^{*}	0.012	0.072^{***}	0.110^{***}	0.046	0.263^{***}
	(0.028)	(0.021)	(0.019)	(0.019)	(0.015)	(0.039)	(0.016)	(0.022)	(0.034)	(0.033)	(0.071)
λ_2	0.913^{***}	0.915^{***}	0.925^{***}	0.931^{***}	0.967^{***}	0.813^{***}	0.972^{***}	0.912^{***}	0.798^{***}	0.822^{***}	0.034
	(0.038)	(0.024)	(0.022)	(0.021)	(0.012)	(0.067)	(0.011)	(0.025)	(0.055)	(0.108)	(0.066)
$log(\mathcal{L})$	1113.69	1196.27	1283.28	1216.88	1110.94	1229.41	912.36	1045.59	953.30	954.99	1044.14

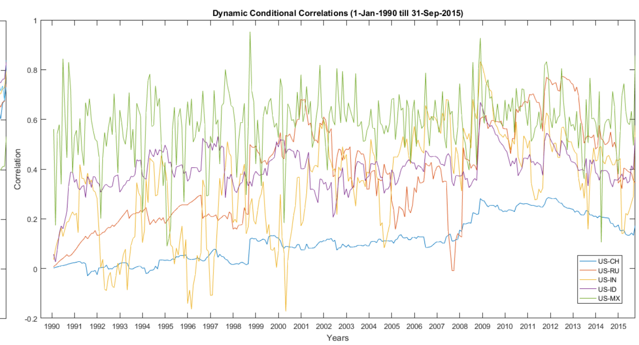
Table 2: DCC-GARCH parameters estimates. $\epsilon^2_{i,t-j}$ and $\sigma^2_{i,t-j}$ denotes the $j-th$ ARCH/GARCH term respectively for country i. The λ terms denote the adjustment terms in the DCC-GARCH model. Semi-robust standard errors are always applied. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

[2] using a Wald test (unreported).

Figure (a) and (b) show the predicted in-sample dynamic conditional correlation between the U.S. and all other developed markets (a), and between the U.S. and all emerging markets (b). There are three striking patterns, in both figures, that can be observed visually. First, the correlation between the U.S. and other countries (abruptly) increases during known episodes of high financial stress. An increase in the correlations can be observed for each pair in the period between 2000-2003 and 2008-2009. These episodes correspond to the Dot-Com bubble and the GFC . Between the U.S. and European countries, an increase can be observed around 2013, consistent with the European sovereign debt crisis. Second, there seems to be an upward trend in the time-varying correlations over time. This observation is consistent with the financial integration of markets over time. Lastly, there exists heterogeneity in these correlations across the pairs. European countries, Canada, and Mexico, have a higher level of correlation with U.S. in general. Again, this finding is consistent with the known interdependence between these countries and the U.S. For the emerging markets, the level of correlations seem to be lower. Table 2 and these figures suggest that the DCC-GARCH model is able to capture dynamic correlations that are consistent with historical events and patterns.



(a) In-sample predicted dynamic conditional correlations of developed economies.



(b) In-sample predicted dynamic conditional correlations of emerging economies.

To reiterate, the obtained dynamic conditional correlation of each US-country pair is regressed on a set of variables in order to provide a deeper insight into what is driving these correlations between equity markets. Table 3 provides the OLS estimates of three different dummy-variable regressions for each correlation pair with the US. In model 1, the dynamic correlations are regressed on a constant and the NBER time dummy ($D_{NBER,t}$). Model (2) uses six different time dummies corresponding to the dates of six financial crisis. Model (3) uses one single time dummy ($D_{Crisis,t}$) that equals one if one of the six crisis occurred in month t. The results from model (1) suggest weak evidence in favour of hypothesis 3 because $D_{NBER,t}$ is positive across all countries, however not always significant across the countries. The Germany equity market, for example, becomes significantly more correlated with the U.S. equity market. The correlation increases, approximately, by 6.4 percent point during NBER recessions. Yet, for the Netherlands, the correlation increases by an insignificant 2.1 percent point. It might be possible that the NBER recession dates imperfectly proxies the dates of financial crises or that the correlation between specific markets only increases for specific financial crises. To take the latter notion into account, Model (2) provides the estimates of the effect of six different crisis dummies on the dynamic conditional correlation. Indeed, the effects of crisis periods on correlations differ by crisis and by country. Cross-equity market correlations are mostly insignificant and negative for the Mexican 'Tequila' crisis and the Asian currency crisis. The correlation between U.S. equity markets and the Mexican equity market is significantly lower at the 1% level during the Mexican crisis. This finding, however, is not consistent with hypothesis 3, as a positive effect of the crisis period was expected. Possibly this has to do with the nature of the crisis, which occurred in the Mexican FX market and subsequently in the Mexican real sector. During this period the Mexican trade - and financial linkages were predominantly disrupted by the increasing volatility of the Mexican Peso rather than irrational causes. A similar explanation also holds for the Asian currency crisis in 1997. All other crises exhibit a reasonably consistent positive pattern with respect to the cross-equity market correlations. Especially the GFC and the European debt crisis seems to have the most consistent pattern: each dynamic conditional correlation increases significantly at the 1% level during these periods. Model (3) uses the aggregated time dummy. For this model, the effect of crisis periods on dynamic correlations is estimated to be positive and significant at the 5% for each pair. Table 3 provides reasonable evidence in favour of hypothesis 3: cross-equity market correlations seem to increase during periods of high volatility. However, the estimated effect differs by crisis and country. Note that the results of table 3 do not provide any evidence of contagion nor interdependence since no information is provided which factor exactly drives this increase in correlation.

Model	Var	DE	FR	UK	NL	JP	CA	CN	RU	IN	ID	MX
(1)	α	0.688^{***}	0.682^{***}	0.711^{***}	0.696^{***}	0.439^{***}	0.738^{***}	0.109^{***}	0.378^{***}	0.317^{***}	0.398^{***}	0.583^{***}
		(0.104)	(0.009)	(0.009)	(0.009)	(0.008)	(0.005)	(0.005)	(0.012)	(0.012)	(0.005)	(0.008)
	$D_{NBER,t}$	0.084^{***}	0.047^{*}	0.021	0.003	0.020	0.040^{***}	0.036^{***}	0.028	0.181^{***}	0.011	0.032
		(0.031)	(0.028)	(0.026)	(0.027)	(0.022)	(0.015)	(0.012)	(0.035)	(0.035)	(0.015)	(0.023)
	R^2	0.023	0.009	0.002	0.000	0.003	0.022	0.018	0.002	0.078	0.002	0.006
(2)	α	0.652^{***}	0.648^{***}	0.657^{***}	0.657^{***}	0.391^{***}	0.715^{***}	0.081^{***}	0.298^{***}	0.294^{***}	0.389^{***}	0.576^{***}
		(0.012)	(0.010)	(0.009)	(0.010)	(0.008)	(0.006)	(0.004)	(0.010)	(0.013)	(0.006)	(0.009)
	$D_{Mexican,t}$	-0.010	-0.095^{*}	0.046	0.020	-0.056	0.006^{*}	-0.039	-0.067^{*}	-0.101	0.022	-0.133^{***}
		(0.046)	(0.059)	(0.034)	(0.039)	(0.028)	(0.022)	(0.016)	(0.038)	(0.071)	(0.022)	(0.035)
	$D_{Asian,t}$	$-.013$	-0.088^{**}	-0.016	-0.087	-0.010	0.034	-0.053^{*}	-0.097^{***}	0.037	-0.036^{*}	0.051
		(0.043)	(0.036)	(0.032)	(0.036)	(0.026)	(0.021)	(0.015)	(0.035)	(0.046)	(0.021)	(0.033)
	$D_{Russia,t}$	0.143^{***}	0.075	0.097^{**}	0.009	0.045	0.112	0.042^{***}	0.175^{***}	-0.057	-0.011	0.003
		(0.056)	(0.047)	(0.042)	(0.047)	(0.034)	(0.027)	(0.019)	(0.046)	(0.061)	(0.027)	(0.043)
	$D_{DotCom,t}$	0.068^{**}	0.057^{**}	0.139^{***}	0.024	0.108	0.065^{***}	0.012^{***}	0.245^{***}	0.042	-0.010	0.033
		(0.031)	(0.026)	(0.023)	(0.026)	(0.019)	(0.015)	(0.011)	(0.026)	(0.034)	(0.015)	(0.024)
	$D_{GFC,t}$	0.159^{***}	0.170^{***}	0.132^{***}	0.124^{***}	0.142^{***}	0.052^{***}	0.118^{***}	0.089^{***}	0.300^{***}	0.060^{***}	0.067^{***}
		(0.035)	(0.029)	(0.026)	(0.029)	(0.022)	(0.017)	(0.011)	(0.029)	(0.038)	(0.017)	(0.022)
	$D_{Eurodebt,t}$	0.149^{***}	0.177^{***}	0.185^{***}	0.178^{***}	0.196^{***}	0.075^{***}	0.166^{***}	0.361^{***}	0.150^{***}	0.051^{***}	0.040^{**}
		(0.027)	(0.022)	(0.019)	(0.022)	(0.016)	(0.013)	(0.009)	(0.022)	(0.029)	(0.013)	(0.020)
	R^2	0.141	0.263	0.282	0.197	0.388	0.172	0.595	0.538	0.244	0.100	0.079
(3)	α	0.652^{***}	0.649^{***}	0.657^{***}	0.661^{***}	0.391^{***}	0.714^{***}	0.082^{***}	0.299^{***}	0.292^{***}	0.389^{***}	0.578^{***}
		(0.013)	(0.011)	(0.010)	(0.011)	(0.009)	(0.006)	(0.006)	(0.013)	(0.015)	(0.006)	(0.009)
	$D_{Crisis,t}$	0.103^{***}	0.086^{***}	0.127^{***}	0.088^{***}	0.113^{***}	0.063^{***}	0.071^{***}	0.187^{***}	0.099^{***}	0.022^{**}	0.038^{**}
		(0.019)	(0.017)	(0.015)	(0.016)	(0.013)	(0.009)	(0.009)	(0.0197)	(0.022)	(0.009)	(0.018)
	R^2	0.0857	0.0741	0.1973	0.0857	0.1977	0.1371	0.1707	0.2261	0.0590	0.0185	0.0051

Table 3: Seemingly unrelated regression on Dynamic Conditional Correlations for each US-country pair. Model (1) only considers NBER recession dates. Model (2) considers six crises using six time dummies. Model (3) uses an aggregated time dummy which equals 1 if one of the 6 crises occurs in month t. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are shown between parentheses.

In order to test whether the increase in correlations is attributable to investor sentiment, these correlations are regressed against four proxies of investor sentiment. In addition, interaction terms between the crisis dummy and each of these proxies are included. In this setting, contagion occurs when the effect of investor sentiment is significantly stronger during crisis periods. Table 4 contains the results for the three estimated equations. Equation (4) regresses the dynamic correlation on the NBER time dummy, investor sentiment proxies, and the interaction of sentiment with the time dummy [3]. The results show that Baker & Wurgler's sentiment index has a negative effect on the dynamic correlations (except for Indonesia and Mexico) at

[3]Interaction between the NBER dummy and VIX_t is excluded but does not alter the result quantitatively nor qualitatively.

the 1% significance level. This implies that high investor sentiment on the U.S. stock market is associated with lower dynamic correlations during non-crises periods, on average. In addition, this effect seems to be economically sizable. For instance, an increase of one point in the index is associated with a 12.8 percent point decrease in the dynamic correlation between Germany and the U.S.. This finding is consistent with the notion of a home bias: improvements in the sentiment about home market (U.S.) will shift assets towards this market, thereby decreasing the correlation. For the bullish sentiment indicator, a similar finding is obtained. An increase in the proportion of investors that indicate to be bullish on the U.S. stock market is associated with a decrease in the dynamic correlation during non-crisis periods, on average. However, the economic significance is smaller. For instance, a one percentage point increase in the bullish indicator is associated with a 0.6 percentage point decrease in the US-German dynamic correlation. Consistent with this line of reasoning, the bearish indicator has a significantly positive effect on the dynamic correlations in seven out of the eleven cases. The magnitude of the effect is comparable to that of the bullish indicator. All three investor sentiment indicators seem to have a systematic effect on the dynamic correlations over time. What is more striking, is that this relationship seems to become stronger during periods of crisis. During crisis periods, the effect of $SENT_t$ becomes significantly more negative as indicated by the coefficients of the interaction term $SENT_t * D_{NBER,t}$. In ten out of the eleven correlations, this effect is statistically significant at the 5% level. The hypothesis that these coefficients are jointly zero is rejected at the 5% level ($F = 5.42$). Therefore, during crisis periods, when investor sentiment is low on average ($SENT_t < 0$), the dynamic correlations will increase substantially. This finding suggests that the increase in cross-equity market correlations is driven by investor sentiment consistent with Hwang & Salmon (2009). This evidence suggests the existence of financial contagion, since it represents changes in financial conditions that are likely to be driven by changes in the behaviour of investors or preferences unrelated to fundamentals.

A potential explanation for this result is as follows: when crises unravel with the arrival of a series of negative news, investors with non-bayesian beliefs will negatively overreact to this news (Barberis, Shleifer, & Vishny, 1998). This decline forces loss-averse investors to endure painful losses and deteriorate their sentiment. Thaler & Johnson (1990) suggest that these losses may have made investors more loss averse, resulting them to rebalance the share of risky assets in their portfolio and thereby causing further price declines. Such portfolios may be internationally diversified, thereby also inducing price declines in foreign assets. Losses can generate contagion between assets when those assets are held by common investors. This will result in portfolio rebalancing of loss averse foreign investors, creating a negative spiral. This negative spiral will result in joint losses in several markets simultaneously, thereby generating a higher co-movement of these markets by definition. Thus, investor overreaction can cause small negative shocks to trigger market-wide panics that can spread internationally. A second explanation of the results lies in the "competence hypothesis" (Heath & Tversky, 1991): an individual's feeling of competency in a given situation is determined by what is known relative to what can be known. During crises periods, market volatility increases. This results in a lower competency of investor to assess the market environment and lowers investor sentiment. According to Heath & Tversky (1991) will increase ambiguity aversion of individuals. In turn, due to this increase in ambiguity aversion, investors are more likely to show herding behaviour (Dong, Gu, & Han, 2010). When investors exhibit pessimistic expectations on the market and don't feel sufficiently competent to assess the market environment, the best thing to possibly do is to follow the market consensus. Herding behaviour by ambiguity (and loss) averse investors will increase cross-equity market correlations in crisis periods. These two potential interpretations are not mutually exclusive, but rather reinforce each other simultaneously.

Var	DE	FR	UK	NL	JP	CA	CN	RU	IN	ID	MX
(4) α	0.278^{**}	0.267^{***}	0.480^{***}	0.372^{***}	0.160^{*}	0.696^{***}	-0.019	0.108	-0.220^{*}	0.288^{***}	0.531^{***}
	(0.088)	(0.080)	(0.077)	(0.077)	(0.070)	(0.044)	(0.045)	(0.112)	(0.106)	(0.045)	(0.076)
$D_{NBER,t}$	0.521	0.351	0.111	0.275	0.104	0.158	0.095	0.057	0.642	0.199	-0.241
	(0.345)	(0.314)	(0.301)	(0.301)	(0.274)	(0.172)	(0.178)	(0.443)	(0.417)	(0.178)	(0.297)
$BEAR_t$	0.006^{***}	0.007^{***}	0.003^{**}	0.005^{***}	0.005^{***}	0.001	0.003^{***}	0.004^{*}	0.010^{***}	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
$BULL_t$	-0.006^{***}	-0.006^{***}	-0.004^{***}	-0.005^{***}	-0.004^{***}	-0.001	-0.002^{*}	-0.004^{*}	-0.006^{***}	-0.002^{*}	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
$SENT_t$	-0.128^{***}	-0.103^{***}	-0.065^{***}	-0.107^{***}	-0.052^{***}	-0.029^{***}	-0.062^{***}	-0.057^{*}	-0.073^{***}	0.014	-0.009
	(0.017)	(0.016)	(0.015)	(0.015)	(0.014)	(0.009)	(0.009)	(0.022)	(0.021)	(0.009)	(0.015)
$BEAR_t * D_{NBER,t}$	-0.008	-0.007	-0.003	-0.006	-0.003	-0.002	-0.002	-0.003	-0.010	-0.002	0.002
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.006)	(0.006)	(0.003)	(0.004)
$BULL_t * D_{NBER,t}$	-0.005	-0.003	-0.001	-0.003	-0.001	-0.001	-0.000	0.001	-0.004	-0.002	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)	(0.006)	(0.005)	(0.002)	(0.004)
$SENT_t * D_{NBER,t}$	-0.116^{***}	-0.091^{**}	-0.089^{**}	-0.086^{**}	-0.066^{**}	-0.049^{**}	-0.039^{**}	-0.100^{**}	-0.013	-0.075^{***}	-0.031^{***}
	(0.036)	(0.033)	(0.032)	(0.032)	(0.029)	(0.018)	(0.019)	(0.046)	(0.044)	(0.019)	(0.007)
VIX_t	-0.070	-0.066	-0.018	-0.025	-0.018	-0.023	-0.016	-0.066	-0.082	-0.034	-0.048
	(0.047)	(0.043)	(0.041)	(0.041)	(0.038)	(0.024)	(0.025)	(0.061)	(0.057)	(0.025)	(0.041)
R^2	0.2606	0.2408	0.1165	0.2210	0.1208	0.0841	0.2196	0.0650	0.2296	0.0966	0.0295
(5) α	0.325^{**}	0.375^{***}	0.605^{***}	0.428^{***}	0.270^{***}	0.708^{***}	0.054	0.227	-0.273^{*}	0.259^{***}	0.550^{***}
	(0.102)	(0.096)	(0.083)	(0.092)	(0.078)	(0.051)	(0.050)	(0.123)	(0.133)	(0.057)	(0.095)
$D_{Crisis,t}$	0.290	0.113	0.089	0.246	0.075	0.085	-0.005	0.226	0.223	0.077	-0.063
	(0.157)	(0.147)	(0.128)	(0.141)	(0.119)	(0.078)	(0.076)	(0.188)	(0.204)	(0.087)	(0.146)
$BEAR_t$	0.004^{*}	0.003^{*}	-0.001	0.002	0.001	-0.000	0.000	-0.000	0.010^{***}	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
$BULL_t$	-0.006^{***}	-0.005^{***}	-0.003^{*}	-0.005^{***}	-0.003^{**}	-0.001	-0.001	-0.002	-0.007^{***}	-0.002^{*}	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
$SENT_t$	-0.209^{***}	-0.132^{***}	-0.118^{***}	-0.122^{***}	-0.078^{***}	-0.050^{***}	-0.075^{***}	-0.133^{***}	-0.092^{**}	0.043^{**}	-0.024
	(0.026)	(0.024)	(0.021)	(0.023)	(0.020)	(0.013)	(0.013)	(0.031)	(0.033)	(0.014)	(0.024)
$BEAR_t * D_{Crisis,t}$	-0.000	0.003	0.003	0.000	0.003	0.000	0.003^{*}	0.002	-0.001	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)
$BULL_t * D_{Crisis,t}$	$-0.005*$	-0.004	-0.002	-0.005^{*}	-0.002	-0.001	-0.000	-0.003	-0.003	-0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)
$SENT_t * D_{Crisis,t}$	-0.176^{***}	-0.093^{***}	-0.109^{***}	-0.065^{**}	-0.061	-0.046^{**}	-0.030^{*}	-0.137^{***}	-0.055	-0.070^{***}	-0.024
	(0.030)	(0.028)	(0.025)	(0.027)	(0.033)	(0.015)	(0.015)	(0.036)	(0.039)	(0.017)	(0.028)
VIX_t	-0.077	-0.071	-0.015	-0.023	-0.014	-0.026	-0.018	-0.057	-0.104	-0.042	-0.049
	(0.044)	(0.041)	(0.036)	(0.039)	(0.033)	(0.022)	(0.021)	(0.053)	(0.057)	(0.024)	(0.041)
R^2	0.3622	0.3103	0.3359	0.2957	0.3109	0.2133	0.4082	0.2969	0.2402	0.1080	0.0294

Table 4: Seemingly unrelated regression on Dynamic Conditional Correlations for each US-country pair. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are shown between parentheses.

Despite this striking finding, direct investor sentiment measures provide no statistical significance in any case. Model (5) replaces the NBER recession dummy with the broader crisis dummy. These results are quantitatively and qualitatively the same, implying that the findings of model (4) also holds when a different crisis specification is considered. Model (4) and (5) suggest that either the survey provides noisy results due to common biases that occur in surveys (Podsakoff, MacKenzie, & Lee, 2003) or Baker & Wurgler's index measures something else (whatever that might be). However, the latter argument is unlikely since the index is orthogonalized against a broad set of macroeconomic variables.

To verify that the effect of investor sentiment on cross-equity markets is not biased due to omitted variables and limit endogeneity issues, the collection of control variables are included in the OLS regressions. These results of three different models can be found in table 5. For brevity, the bullish and bearish indicator are excluded from the analysis [4]. Model (6) controls for a range of variables that proxy common random shocks that affect all countries in the sample simultaneously. Gold and oil returns are included as common shocks in the global market that are imposed by the commodity market. The Fed Fund rate (FFR_t) proxies for the international interest rate. This interest rate is not necessarily set by market forces, but externally by the FED and used as a monetary policy instrument. Gold tends to load positively on the dynamic correlations,

[4] Unreported results reveal that the inclusion of these variables provides similar results as was shown in table 4.

with few exceptions. However, these estimates are not statistically significant in any case. In addition, a similar finding is obtained for oil returns. A striking finding is the significantly (at the 1% level) negative effect of the FFR_t on dynamic correlations. The FED especially decreases its base rates (through Open Market Operations or unconventional policies, such as quantitative easing) during a recession as an attempt to promote aggregate demand growth and interbank lending, but also induces higher risk-taking behaviour, not only in the domestic market per se. Furthermore, such decreases may directly cause capital outflows, thereby increasing financial linkages. Model (6) shows that such expansionary policy substantially increases all cross-equity market correlations in the sample. The second observation is that the effect of $SENT_t$ becomes less significant during non-crises periods after controlling for common random shocks (especially FFR_t). The coefficients of $SENT_t$ in model 6 seem to be higher than those of model (4) and (5). This indicates that the latter estimates are downward biased and that FFR_t and $SENT_t$ are positively correlated during non-crises periods. This is consistent with the empirical finding that an interest rate hike can signal a healthy economy, thereby increasing investor sentiment (Kurov, 2010). More important, in 9 out of the 11 correlations, the hypothesis of no sentiment effect during crisis periods is rejected. Thus the evidence of financial contagion persists, even after controlling for common random shocks.

Equation (7) controls for various trade-related and macroeconomic characteristics. The results show that the import - and export growth of the U.S. has no statistical significance in explaining the dynamic correlations between the U.S. and the other countries. Furthermore, industrial production and inflation rates seem not to exhibit significant explanatory power either. Exchange rate volatility has a significant negative effect on most of the dynamic correlations and no effect on the other countries. This indicates that stable exchange rates result in higher cross-equity market correlations, which is consistent with financial and economic integration, ceteris paribus. In addition, the U.S. terms of trade (ToT) is negatively associated with dynamic correlations in 9 countries and insignificant in the remaining two. A decreasing U.S. ToT implies that price of U.S. exports falls relative to U.S. imports. Therefore, to maintain at least the same level of imports, the U.S. must export more. This will increase trade linkages and economic integration between U.S. and other countries, ceteris paribus. In addition, consistent with the documented patterns in model (6), the estimated equation (7) in table 5 shows that investor sentiment remains to exhibit a significant adverse effect on the dynamic correlations during crisis periods. In 9 out of the 11 correlations, a statistically significant negative effect is found at the 1% level. Thus, even after controlling for trade linkages and macroeconomic characteristics, the negative effect of investor sentiment on dynamic correlations during crises persists.

What remains is to test whether sentiment effect persists after controlling for financial linkages. Model (8), table 5, adds several financial control variables such as Pastor's liquidity factor (market liquidity), Growth of the M2 money supply (funding liquidity), and asset flows from and to the U.S. by foreign investors. In addition, an interaction term between $SENT_t$ and Pastor's liquidity factor, and an interaction term between this liquidity factor and the crisis dummy is expected. When market liquidity and sentiment is low, it could be expected that pessimistic loss averse investors are not able to sell their assets without fire-sales (Brunnermeier & Pedersen, 2008). The results show that U.S. market liquidity, proxied by the liquidity factor, has no significant effect on the dynamic correlations for any of the countries. Similarly, the coefficients of the growth of M2 money supply of the U.S. and the other countries j are not significantly different from zero. Neither a statistically significant effect of the interaction between market liquidity and investor sentiment is documented. The effect of bond and stock flows from and to the U.S. are sporadically significant. Foreign

	Var	DE	FR	UK	NL	JP	CA	CN	RU	IN	ID	MX
(6)	α	0.785***	0.810***	0.800***	0.806***	0.523***	0.754***	0.166***	0.488***	0.412***	0.410***	0.605***
		(0.015)	(0.012)	(0.009)	(0.011)	(0.008)	(0.008)	(0.006)	(0.014)	(0.021)	(0.009)	(0.015)
	$D_{Crisis,t}$	0.047**	0.038**	0.074***	0.048***	0.073***	0.045***	0.055***	0.117***	0.068**	0.030**	0.010
		(0.016)	(0.013)	(0.010)	(0.012)	(0.009)	(0.008)	(0.006)	(0.015)	(0.022)	(0.009)	(0.016)
	FFR_t	−2.797***	−4.120***	−3.736***	−3.790***	−3.614***	−0.876***	−2.213***	−5.146***	−2.924***	−0.758***	−0.721**
		(0.334)	(0.262)	(0.211)	(0.250)	(0.189)	(0.172)	(0.127)	(0.321)	(0.464)	(0.198)	(0.333)
	$R_{oil,t}$	0.022	0.066	0.117*	0.052	0.045	0.063	0.013	0.117	−0.137	0.018	−0.020
		(0.075)	(0.059)	(0.047)	(0.056)	(0.043)	(0.039)	(0.029)	(0.072)	(0.104)	(0.044)	(0.075)
	$R_{gold,t}$	0.378$\ast$	0.252	0.086	0.166	0.106	0.093	0.058	−0.055	0.224	0.005	0.093
		(0.165)	(0.130)	(0.104)	(0.124)	(0.094)	(0.085)	(0.063)	(0.159)	(0.230)	(0.098)	(0.165)
	$SENT_t$	−0.164***	−0.048*	−0.029	−0.044*	0.006	−0.029*	−0.020*	−0.010	−0.058	0.051***	−0.007
		(0.025)	(0.019)	(0.015)	(0.018)	(0.014)	(0.013)	(0.009)	(0.024)	(0.034)	(0.015)	(0.024)
	$SENT_t * D_{Crisis,t}$	−0.161***	−0.054**	−0.072***	−0.036**	−0.024**	−0.037**	−0.000	−0.087***	−0.037	−0.071***	−0.090***
		(0.027)	(0.021)	(0.017)	(0.018)	(0.010)	(0.014)	(0.010)	(0.026)	(0.038)	(0.016)	(0.027)
	R^2	0.4477	0.5770	0.6547	0.5729	0.6672	0.2721	0.6840	0.6091	0.2427	0.1164	0.0281
(7)	α	0.717***	1.270***	1.179***	1.247***	1.546***	0.320***	0.857***	1.496***	2.303***	0.717***	0.351
		(0.203)	(0.124)	(0.099)	(0.114)	(0.101)	(0.091)	(0.070)	(0.226)	(0.281)	(0.122)	(0.206)
	$D_{Crisis,t}$	0.026	0.007	0.040***	0.014	0.038***	0.021*	0.029***	0.083***	0.036	0.016	0.030
		(0.015)	(0.010)	(0.008)	(0.009)	(0.009)	(0.008)	(0.006)	(0.019)	(0.024)	(0.009)	(0.018)
	$TOT_{US,t}$	0.001	−0.005***	−0.005***	−0.005***	−0.012***	0.004***	−0.008***	−0.012***	−0.021***	−0.003***	0.003
		(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)
	$\pi_{US,t}$	0.004	−0.014	−0.000	−0.020	−0.018	0.001	−0.012	−0.035	−0.068	−0.009	−0.019
		(0.025)	(0.017)	(0.013)	(0.014)	(0.014)	(0.014)	(0.009)	(0.031)	(0.039)	(0.015)	(0.027)
	$\pi_{j,t}$	0.003	0.017	−0.005	0.000	−0.006	−0.009	−0.004	−0.002	−0.021	−0.002	−0.046***
		(0.014)	(0.019)	(0.006)	(0.006)	(0.006)	(0.008)	(0.002)	(0.004)	(0.016)	(0.003)	(0.008)
	$IPGrowth_{US,t}$	0.005	−0.003	−0.007	0.005	−0.006	0.000	0.000	−0.004	−0.036*	−0.005	−0.002
		(0.011)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)	(0.014)	(0.017)	(0.007)	(0.012)
	$IPGrowth_{j,t}$	−0.005	0.001	−0.000	−0.000	0.001	−0.001	−0.000	−0.000	0.001	−0.000	0.001
		(0.003)	(0.002)	(0.003)	(0.001)	(0.001)	(0.003)	(0.000)	(0.001)	(0.002)	(0.001)	(0.006)
	$\sigma^2_{EX,t}$	−0.237***	−0.007***	0.765	−0.105***	−0.000	−0.725***	−0.027***	−0.000**	−0.000	0.000*	−0.001
		(0.029)	(0.000)	(0.627)	(0.009)	(0.000)	(0.104)	(0.002)	(0.000)	(0.000)	(0.000)	(0.001)
	$Im-Growth_{j,US,t}$	0.001	0.000	−0.000	0.000	−0.000	0.000	−0.000	−0.000	0.000	0.000	0.002
		(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
	$Ex-Growth_{j,US,t}$	−0.000	−0.000	0.000	−0.000	0.000	−0.000	−0.000	0.000	−0.001	−0.000	−0.002
		(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.002)
	$SENT_t$	−0.165***	−0.100***	−0.186***	−0.118***	−0.128***	−0.053***	−0.073***	−0.173***	−0.120***	0.003	−0.001
		(0.025)	(0.015)	(0.011)	(0.014)	(0.012)	(0.011)	(0.007)	(0.026)	(0.033)	(0.015)	(0.024)
	$SENT_t * D_{Crisis,t}$	−0.132***	−0.050**	−0.177***	−0.065***	−0.119***	−0.037**	−0.050***	−0.193***	0.086**	−0.070***	−0.081**
		(0.028)	(0.017)	(0.013)	(0.016)	(0.014)	(0.013)	(0.009)	(0.031)	(0.039)	(0.018)	(0.029)
	R^2	0.5705	0.7177	0.6399	0.7210	0.5965	0.3503	0.7741	0.4246	0.3163	0.0624	0.1320
(8)	α	0.744***	0.717***	0.745***	0.755***	0.417***	0.781***	0.099***	0.409***	0.333***	0.407***	0.627***
		(0.021)	(0.012)	(0.011)	(0.011)	(0.012)	(0.008)	(0.006)	(0.022)	(0.024)	(0.011)	(0.020)
	$D_{Crisis,t}$	0.033***	0.017	0.062***	0.013	0.039***	0.044***	0.051***	0.140***	0.076**	0.005	0.019
		(0.013)	(0.011)	(0.009)	(0.010)	(0.007)	(0.008)	(0.006)	(0.021)	(0.025)	(0.010)	(0.018)
	VIX_t	−0.055	−0.040	−0.021	−0.019	−0.012	−0.033*	−0.021	−0.068	−0.061	−0.036	−0.067
		(0.036)	(0.025)	(0.020)	(0.023)	(0.016)	(0.017)	(0.015)	(0.048)	(0.056)	(0.022)	(0.038)
	LIQ_t	−0.306	−0.152	−0.194	−0.167	0.130	0.027	0.092	0.086	−0.049	0.264*	−0.079
		(0.205)	(0.145)	(0.113)	(0.134)	(0.092)	(0.097)	(0.084)	(0.271)	(0.321)	(0.125)	(0.218)
	$SENT_t$	−0.233***	−0.173***	−0.180***	−0.126***	−0.070***	−0.049***	−0.047***	−0.172***	−0.077**	0.040***	−0.010
		(0.024)	(0.016)	(0.012)	(0.015)	(0.011)	(0.011)	(0.009)	(0.030)	(0.035)	(0.014)	(0.025)
	$M2Growth_{US,t}$	0.023	0.015	0.012	0.021	0.004	0.025**	0.010	0.044	−0.004	0.011	0.007
		(0.020)	(0.014)	(0.011)	(0.013)	(0.009)	(0.009)	(0.008)	(0.026)	(0.031)	(0.012)	(0.021)
	$M2Growth_{j,t}$	0.008	−0.001	0.006	−0.001	0.027	−0.029***	−0.000	0.003	−0.003	0.002	−0.010
		(0.008)	(0.002)	(0.005)	(0.002)	(0.014)	(0.009)	(0.002)	(0.002)	(0.003)	(0.002)	(0.006)
	$BondSale_t$	−8.022**	−2.601**	−0.092	3.973**	1.599	0.133	−0.153	0.024***	0.003	−0.019	−1.219
		(2.504)	(0.885)	(0.097)	(1.730)	(1.019)	(0.416)	(0.813)	(0.003)	(0.038)	(0.019)	(4.106)
	$StockSale_t$	7.870	5.719**	−0.195	1.418	−0.002	0.100	10.453**	−0.133*	0.037**	−0.026	−0.013
		(4.218)	(1.911)	(0.151)	(2.602)	(0.286)	(0.660)	(3.739)	(0.052)	(0.012)	(0.021)	(0.012)
	$BondPurchase_t$	3.874	2.619	−0.069	4.092	2.382***	−4.896**	0.272	2.075	0.124	−0.012	(6.641)
		(4.451)	(2.019)	(0.136)	(2.344)	(0.427)	(1.696)	(0.316)	(6.502)	(0.318)	(0.007)	(6.424)
	$StockPurchase_t$	−0.136	0.059	0.146	−3.398$\ast$	5.040***	−0.360	0.025***	−0.370*	−0.119	0.390**	4.592
		(0.829)	(0.128)	(0.091)	(1.712)	(1.314)	(0.429)	(0.003)	(0.147)	(0.073)	(0.128)	(0.013)
	$SENT_t * D_{Crisis,t}$	−0.185***	−0.125***	−0.160***	−0.061***	−0.041***	−0.035**	−0.040***	−0.140***	−0.040	−0.080***	0.003
		(0.027)	(0.018)	(0.014)	(0.017)	(0.012)	(0.013)	(0.011)	(0.035)	(0.040)	(0.016)	(0.028)
	$LIQ_t * SENT_t$	0.359*	0.180	0.074	0.087	0.005	0.172*	−0.078	−0.188	0.419	−0.102	0.143
		(0.149)	(0.104)	(0.081)	(0.096)	(0.066)	(0.069)	(0.060)	(0.195)	(0.227)	(0.090)	(0.155)
	$LIQ_t * D_{Crisis,t}$	0.411	0.276	0.298*	0.324*	0.012	0.044	0.059	0.437	−0.109	−0.196	−0.055
		(0.239)	(0.169)	(0.131)	(0.157)	(0.107)	(0.113)	(0.097)	(0.316)	(0.371)	(0.145)	(0.253)
	R^2	0.3156	0.4954	0.5424	0.4286	0.5137	0.2105	0.6287	0.3043	0.2185	0.1788	0.0448

Table 5: Seemingly unrelated regression on Dynamic Conditional Correlations for each US-country pair. Model (7) adds control variables for common random shocks. Model (8) adds control variables for trade linkages. Model (9) controls for financial linkages only. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are shown between parentheses.

bond sales to U.S. citizens negatively impacts the correlation for Germany and France, indicating that these equity markets exhibit less co-movement if more of German and French bonds are being bought by U.S.

citizens. One interpretation is that U.S. citizens replace their equity share in these countries by bonds. However, a similar effect is not present for the other countries. In addition, the sign of the effect is not consistent across the countries. The coefficients of the sentiment index remain statistically significant in 10 out of the 11 cases. In addition, this negative effect is significantly stronger during crises periods for all countries except India and Mexico. Thus, the results suggest that controlling for financial linkages does not alter the documented relationship between investor sentiment and cross-equity market correlations.

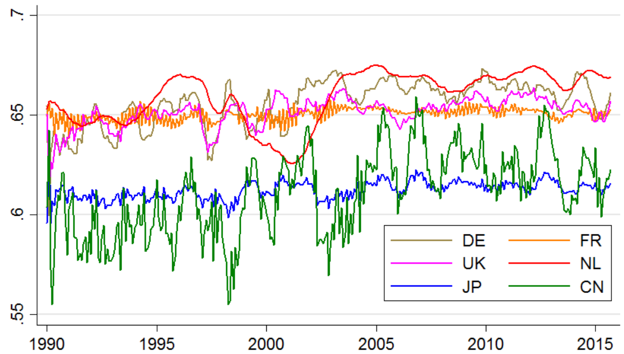
In sum, it is documented that cross-equity market correlations increase substantially during periods of crises. Thus hypothesis 3 is not rejected. Furthermore, the regressions indicate that the economically sizable and statistically significant negative relation between investor sentiment and dynamic conditional cross-equity market correlation persists after controlling for a large set of control variables. This result shows that financial contagion is driven by investor sentiment. Therefore, hypothesis 2 is not rejected. Despite these results, contagion is not the sole determinant of cross-equity market correlations. Interdependence and common shocks do play a role. The results presented here suggest that the Fed fund rate, exchange rate volatility and the U.S. Terms of Trade also explain the cross-equity market correlation. Finally, the hypothesis that the coefficients of the interaction between sentiment and the crises dummy are greater in emerging market than developed markets is rejected for all models [5]. Based on these coefficients tests, there is not sufficient evidence to accept hypothesis 1. This finding is inconsistent with Celık (2012), who documents the opposite pattern. The main difference between Celık (2012) and this thesis is that Celık (2012) only analyses the U.S. subprime crisis, while a broader coarser crises definition is implemented in this thesis.

5.2. Asymmetric dependence

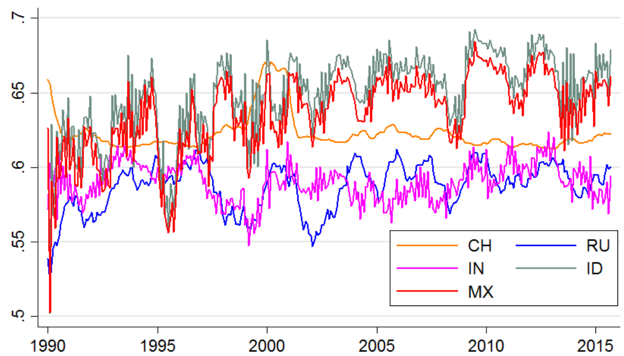
Copulas exhibit all the information pertaining the dependence structure of two financial time series. While correlation is a linear measure of dependence, copula estimations allow capturing nonlinear dependence among two financial time series. This methodology is especially relevant to model the joint behaviour of random variables in the tails of the distribution, which is of interest in the study of financial contagion. In this section, the results of the Symmetrized Joe-Clayton Copula estimation are discussed, with the focus on lower tail dependency. The results obtained from the Gaussian and Gumbel copulas are provided in Appendix III.

Figure (c) and (d) provide the estimated lower tail dependency for developed markets, and emerging markets respectively. A higher value of the lower tail dependency (τ^L) suggests that extreme negative returns are more likely to occur jointly. Figure (c) and (d) shows that the lower tail dependency is time-varying, similar to the dynamic conditional correlation. In addition, the estimated τ^L's seem to increase during periods of financial crises. All τ^L's are relatively higher during 2001-2002 (burst of the Dotcom-Bubble), and 2007-2009 (GFC). Furthermore, unlike the dynamic correlations, no clear upward trend can be observed in the lower tail dependencies, suggesting limited financial integration over time. Lastly, consistent with the dynamic correlations, cross-sectional heterogeneity in the lower tail dependencies can be observed. The lower tail dependency between European countries and the U.S. are high on average compared to all other countries. On average, these tail dependencies also seem to be more stable than the tail dependencies of the emerging markets. The latter may imply that emerging markets are more prone to contagion (risk).

[5] Obtained from F-tests (unreported).



(c) Lower tail dependency of the developed economies.



(d) Lower tail dependency of emerging economies.

The obtained time series of left tail dependencies is regressed against the set of independent variables. Table 6 and 7 provide the SUR estimates of 5 equations to test the hypotheses of this thesis in terms of tail dependency. Equation (9) tests whether left tail dependency between the U.S. equity market and the other equity markets increases during periods of financial crises. The SUR estimate of $D_{Crisis,t}$ is positive and statistically significant at the 1% level. This indicates that extreme negative returns exhibit substantially stronger co-movement during periods of financial stress, in favour of hypothesis 3. Equation (10) tests whether investor sentiment explains left tail dependency during crises periods. It is documented that investor sentiment is negatively associated with left tail dependency, irrespective of the time period. During periods of financial crises, this association becomes significantly stronger in magnitude for 9 out of the 11 left tail dependencies. This finding is similar to the earlier results in the correlation analysis. Equation (10) thus implies that investor sentiment may drive left tail dependencies during crises periods in particular. Equation (11) adds variables that control for common random shocks. The SUR estimates of this model are similar to those of equation (6) (table 5) in terms of significance and sign of the effects. The Fed Fund Rate has a strong negative effect for all lower tail dependencies. Expansionary monetary policy by FED is associated with increased co-movement of extreme negative returns between equity markets. The effect of investor sentiment on the left tail dependency during financial crises remains significantly negative, even after controlling for common random shocks. Table 7 contains the SUR estimates of equation (12) and (13). Equation (12) controls for trade related characteristics. Decreasing U.S. Terms of Trade, implying that U.S. becomes more competitive, is associated with an increase in the left tail dependence. Similarly, lower exchange rate volatility increases left tail dependence. Both findings suggest support for trade linkages being relevant for co-movement between markets. After controlling for these variables, the effect of investor sentiment is not eliminated. Investor sentiment has a strong negative impact on left tail dependencies. This effect becomes substantially stronger during financial crises, suggesting the presence of financial contagion. Equation (13) controls for financial characteristics. The estimates of equation (13) are similar to the estimates of equation (8) with respect to significance and sign of the estimates. No significant effect of U.S. market liquidity (LIQ_t) and funding liquidity (M2 growth) on the left tail dependency is documented. The sale of foreign bond/stocks to U.S. citizens and the purchase of U.S. bond/stocks by foreigners tend to have a positive effect on left tail dependencies. This result suggests that financial integration, in terms of higher investment flows, can increase the likelihood of a joint crash. However, these estimates are not consistent in terms of significance across the countries. For few flow variables, a significant estimate is documented, while most remain insignificant. Similar to all other results, investor sentiment has a strong negative effect on tail

	Var	DE	FR	UK	NL	JP	CA	CN	RU	IN	ID	MX
(9)	α	0.654***	0.651***	0.649***	0.661***	0.612***	0.609***	0.622***	0.588***	0.590***	0.647***	0.634***
		(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
	$D_{Crisis,t}$	0.004***	0.002***	0.005***	0.003***	0.002**	0.005**	0.002**	0.004***	0.002**	0.004***	0.004***
		(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	R^2	0.024	0.002	0.113	0.015	0.015	0.015	0.002	0.005	0.002	0.005	0.007
(10)	α	0.656***	0.651***	0.650***	0.662***	0.612***	0.610***	0.623***	0.587***	0.588***	0.650***	0.637***
		(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
	$D_{Crisis,t}$	0.003*	−0.000	0.004***	0.000	0.001	0.004	−0.002	−0.001	0.003	0.001	0.002
		(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
	VIX_t	0.001	0.000	−0.000	0.003	0.000	0.001	−0.000	−0.001	−0.004	0.001	−0.002
		(0.003)	(0.001)	(0.002)	(0.003)	(0.001)	(0.006)	(0.004)	(0.005)	(0.004)	(0.009)	(0.008)
	$SENT_t$	−0.008***	−0.002***	−0.005***	−0.005**	−0.001	−0.006**	−0.004**	−0.006**	−0.007***	−0.017***	−0.017***
		(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.005)	(0.005)
	$SENT_t * D_{Crisis,t}$	−0.005**	0.001	−0.004***	−0.009***	−0.002**	−0.007**	−0.012***	−0.008**	−0.008**	−0.016**	0.005
		(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)	(0.002)	(0.003)	(0.003)	(0.006)	(0.006)
	R^2	0.100	0.056	0.169	0.368	0.025	0.024	0.130	0.027	0.037	0.042	0.047
(11)	α	0.664***	0.653***	0.655***	0.667***	0.614***	0.621***	0.616***	0.594***	0.594***	0.669***	0.657***
		(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.003)	(0.003)
	$D_{Crisis,t}$	0.001	−0.001*	0.003***	−0.001	0.000	0.001	0.000	−0.002	0.001	−0.004	−0.003
		(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
	FFR_t	−0.252***	−0.055***	−0.161***	−0.171***	−0.050***	−0.347***	−0.224***	−0.213***	−0.173***	−0.613***	−0.620***
		(0.025)	(0.009)	(0.015)	(0.026)	(0.011)	(0.051)	(0.027)	(0.039)	(0.033)	(0.063)	(0.060)
	$R_{Oil,t}$	0.002	0.002	0.005	−0.001	0.000	0.003	0.007	0.009	−0.001	0.006	0.005
		(0.006)	(0.002)	(0.003)	(0.006)	(0.003)	(0.011)	(0.006)	(0.009)	(0.007)	(0.014)	(0.013)
	$R_{Gold,t}$	0.028*	0.001	0.007	0.005	0.001	0.012	−0.009	0.007	−0.016	0.002	0.025
		(0.012)	(0.004)	(0.007)	(0.013)	(0.006)	(0.025)	(0.014)	(0.019)	(0.016)	(0.031)	(0.030)
	$SENT_t$	−0.003**	−0.003***	−0.001	−0.001	−0.000	0.003	−0.009***	−0.011***	0.011***	−0.001	−0.000
		(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)	(0.002)	(0.003)	(0.002)	(0.005)	(0.004)
	$SENT_t * D_{Crisis,t}$	−0.004**	−0.001	−0.002**	−0.011***	−0.003***	−0.003	−0.014***	−0.010***	−0.010***	−0.009**	−0.009**
		(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
	R^2	0.348	0.174	0.403	0.448	0.085	0.157	0.297	0.116	0.119	0.271	0.303

Table 6: Seemingly unrelated regression on Symmetrized Joe-Clayton's lower tail dependencies for each pair with US. Model 9 adds the aggregated crisis definition. Model 10 adds the investor sentiment index. Model 11 controls for common random shocks. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are shown between parentheses.

dependencies. This effect becomes significantly stronger during financial crises as indicated by the estimates of the interaction term $SENT_t * D_{Crisis,t}$. Lastly, for equations 10-13, the hypothesis that $SENT_t * D_{Crisis,t}$ is jointly equal for each pair with the U.S. is not rejected. This indicates that the contagion effect is not per se stronger for emerging markets.

Tail dependencies are free of the limitations of correlation-based measures and allow to study the behaviour of random variables in the tails of the distribution. Even when these more specific dependence measures are used, the main result is strongly consistent with the results of subsection 5.1: investor sentiment matters, and it matters even more during periods of financial crises. During crises periods, when investors exhibit low sentiment, the likelihood of a joint crash in two different equity markets increase substantially.

6. Robustness checks

The results in the previous section strongly suggest that contagion between equity markets is driven by investor sentiment, as measured by Baker & Wurgler's sentiment index. This result persists after controlling for a range of financial and macroeconomic variables. The results are continued being examined on the sensitivity to a series of robustness checks. To assess the robustness of the obtained results, two assumptions made in this thesis will be altered.

First, the choice of the sample period may give rise to a sample selection bias due to the fact that crisis

	Var	DE	FR	UK	NL	JP	CA	CN	RU	IN	ID	MX
(12)	α	0.686***	0.657***	0.686***	0.770***	0.654***	0.838***	0.663***	0.697***	0.603***	0.788***	0.839***
		(0.014)	(0.006)	(0.009)	(0.017)	(0.006)	(0.029)	(0.023)	(0.022)	(0.020)	(0.037)	(0.035)
	$D_{Crisis,t}$	−0.001	0.001**	0.001	0.003***	−0.000	−0.004	−0.001	−0.005**	0.004**	−0.011***	−0.009***
		(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
	$TOT_{US,t}$	−0.000	−0.000	−0.000***	−0.001***	−0.000***	−0.002***	−0.001**	−0.001***	−0.000	−0.001***	−0.002***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	$\pi_{US,t}$	−0.000	−0.000	0.001	−0.002	−0.000	−0.004	0.004	0.003	−0.001	0.002	0.003
		(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
	$\pi_{j,t}$	−0.001	0.001	−0.000	0.001	0.000	−0.000	−0.001	0.000	0.001	0.001	−0.006***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
	$IPGrowth_{US,t}$	0.001	0.000	−0.000	0.002	−0.001	−0.004**	−0.001	0.002	0.001	0.001	0.001
		(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
	$IPGrowth_{j,t}$	0.000	0.000	−0.000	−0.000	−0.000	−0.000	0.000	0.000	−0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
	$\sigma^2_{FX,t}$	−0.017***	−0.000***	−0.109	−0.004***	−0.000	−0.053***	0.004***	0.000	0.000***	−0.000***	−0.000
		(0.002)	(0.000)	(0.069)	(0.001)	(0.000)	(0.018)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
	$ExGrowth_{j,US,t}$	−0.000	0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	0.000	−0.000	−0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	$ImGrowth_{j,US,t}$	−0.000	0.000	0.000	−0.000	0.000	0.000	−0.000	0.000	0.000	−0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	$SENT_t$	−0.003***	−0.002**	−0.008***	−0.004***	−0.002**	−0.004	−0.006***	0.009***	0.007***	−0.010**	−0.018***
		(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.005)	(0.004)
	$SENT_t * D_{Crisis,t}$	−0.004***	−0.000	−0.007***	−0.009***	−0.002**	−0.008**	−0.012***	−0.005***	−0.007**	−0.007**	−0.020***
		(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)	(0.003)	(0.001)	(0.003)	(0.003)	(0.005)
	R^2	0.450	0.213	0.160	0.515	0.226	0.291	0.112	0.168	0.150	0.340	0.315
(13)	α	0.658***	0.652***	0.653***	0.664***	0.612***	0.610***	0.626***	0.596***	0.587***	0.659***	0.647***
		(0.002)	(0.000)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
	$D_{Crisis,t}$	0.002**	0.003***	0.002**	−0.005***	−0.000	0.006**	0.002	0.007***	0.005**	0.002	0.003***
		(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)
	VIX_t	−0.001	0.000	−0.001	0.002	−0.000	−0.002	−0.002	−0.001	−0.001	−0.007	−0.011
		(0.003)	(0.001)	(0.002)	(0.003)	(0.001)	(0.006)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
	LIQ_t	−0.008	−0.001	−0.018	−0.005	0.006	0.061	0.003	0.040	−0.024	−0.059	−0.025
		(0.016)	(0.006)	(0.010)	(0.018)	(0.008)	(0.032)	(0.023)	(0.027)	(0.026)	(0.037)	(0.034)
	$SENT_t$	−0.004**	−0.002***	−0.007***	−0.009***	0.001	−0.011***	−0.011***	−0.006**	0.002	−0.016***	−0.016***
		(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
	$M2Growth_{US,t}$	0.002	0.000	0.000	0.001	0.000	−0.002	−0.002	−0.003	−0.001	−0.004	−0.003
		(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)
	$M2Growth_{j,t}$	−0.001*	0.000	0.000	−0.000	−0.000	0.004**	−0.001	0.000	−0.000	0.000	−0.001
		(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
	$BondSale_t$	0.491**	0.122**	0.023**	0.486**	−0.065	0.226**	−0.191	0.005	0.006**	0.001	−0.072
		(0.212)	(0.048)	(0.012)	(0.233)	(0.064)	(0.090)	(0.217)	(0.004)	(0.003)	(0.003)	(0.404)
	$StockSale_t$	0.337	0.165	0.004	0.189	0.044**	−0.192	0.844	0.003	0.438	(0.009)**	0.002**
		(0.352)	(0.110)	(0.018)	(0.405)	(0.019)	(0.146)	(1.003)	(0.006)	(0.911)	(0.004)	(0.001)
	$StockPurchase_t$	0.174**	0.002	0.001	0.348	0.078	0.442***	1.812*	0.015	0.000	−0.007	0.216
		(0.070)	(0.007)	(0.011)	(0.269)	(0.084)	(0.099)	(0.913)	(0.016)	−(0.006)	(0.022)	(1.178)
	$BondPurchase_t$	0.972***	0.068	0.007	0.173	0.036	0.970**	−0.007	0.406	0.027	0.390	0.283
		(0.373)	(0.112)	(0.016)	(0.372)	(0.029)	(0.338)	(0.086)	(0.709)	(0.024)	(1.347)	(0.556)
	$SENT_t * D_{Crisis,t}$	−0.004***	−0.002**	−0.006***	−0.015***	−0.000	−0.008**	−0.007**	−0.010***	−0.003	−0.015***	−0.014***
		(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)
	$LIQ_t * D_{Crisis,t}$	0.010	0.009**	−0.001	−0.012	−0.001	−0.007	−0.041**	−0.031	0.013	0.000	−0.016
		(0.011)	(0.004)	(0.007)	(0.013)	(0.005)	(0.023)	(0.017)	(0.019)	(0.018)	(0.027)	(0.024)
	$LIQ_t * SENT_t$	0.018	−0.000	0.020	0.032	−0.002	−0.033	−0.025	−0.026	0.051	0.072	0.046
		(0.018)	(0.006)	(0.012)	(0.022)	(0.009)	(0.037)	(0.027)	(0.031)	(0.030)	(0.043)	(0.039)
	R^2	0.240	0.189	0.207	0.552	0.091	0.247	0.214	0.151	0.087	0.139	0.171

Table 7: Seemingly unrelated regression on Symmetrized Joe-Clayton's lower tail dependencies for each US-country pair. Model 12 controls for trade related characteristics. Model 13 controls for financial characteristics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are shown between parentheses.

months are specified ex post, rather than a priori (Pesaran & Pick, 2007). In this paper, the crisis months are specified ex-post using the NBER crisis classification. It must be mentioned that correctly defining the crises periods is to some degree arbitrary, even when official data sources are used. One way is to use a different crisis period or definition. To assess the sensitivity of the results, model 5-8 will be re-estimated by replacing the crisis time dummy by a time dummy for the GFC . Celık (2012) does document that contagion effects are stronger for emerging markets than in developed markets, inconsistent with the results of this thesis. However, the author only analyses the GFC . This provides an additional motivation to conduct this robustness check.

In addition, Fong (2003) and Boyer, Kumagai, & Yuan (2006) alleviate this sample selection problem by allowing crisis states to be determined endogenously by using Markov regime switching models. Following these authors, the dynamic conditional correlations are allowed to be regime switching with two states: a high variance state, and a low variance state. Model 6-8 will be re-estimated in this Markov regime switching setting. Time dummies and interaction terms are excluded since the Markov switching model endogenously determines crises states. A detailed description of this methodology is provided in appendix II. Thus, two checks are implemented to assess the robustness.

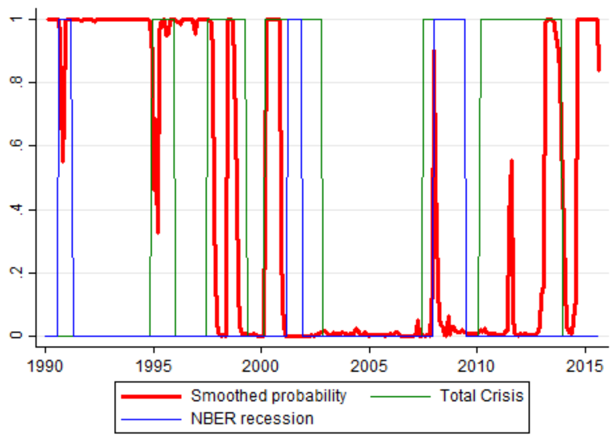
Second, this thesis has been focusing on equity markets and ignores other asset classes. As a check of robustness, contagion effects in the government bond market are analyzed. Hartmann et al. (2004) document significant co-crashes within the bond market, but does not examine what drives such co-crashes. This makes this robustness test interesting in particular. In addition, recent research suggests that contagion played a substantial role during the European sovereign-debt crisis (Mink & De Haan, 2013). Through Datastream, the monthly ex-post total returns on 10-year maturity ("on-the-run") sovereign bonds are obtained. All bonds are denominated in U.S. dollars, such that yields are net of changes in exchange rates between currencies. The same countries are used as in the initial sample. For these bonds, the dynamic conditional correlation is computed between the 10-year U.S. Treasury yield and the remaining bonds. The obtained time series of dynamic conditional correlations are regressed against Baker & Wurgler's investor sentiment index and the set of control variables. Model 6-8 will be replicated for these dynamic conditional correlations.

6.1. Markov Regime Switching

Two regimes of contagion risk are identified via a Markov switching model, which takes endogenous structural breaks into account. This allows the data to statistically determine the beginning and the end of each regime/crisis. To illustrate the added value of the Markov switching model, the smoothed transition probability of being in the volatile regime is shown below for US-Germany [6]. Figure (e) reveals that the volatile regime is mostly located within the crises periods based on the exogenously determined time dummies. However, there some small differences. For instance, the length of the crises according to the smoothed probability is relatively smaller compared to the time dummies. In addition, the transition probabilities capture crises regimes that are not included in the time dummies. For instance, during 2015, a volatile regime can be observed for the probabilities but not for the dummies.

Table 8 provides the Markov regime switching regression estimates for the equation that includes control variables for common random shocks and Baker & Wurgler's sentiment index, which is the variable of interest. The upper panel provides the estimates during high volatility periods (crisis state), while the lower panel provides the estimates for low volatility periods (normal state). Similar to model (6) from table 5, oil and gold returns do not drive dynamic conditional correlations in both states. Consistently, a statistically significant (at the 1% level) negative effect of the Fed Fund Rate on 10 out of the 11 dynamic conditional correlations, in both states. In addition, investor sentiment seems to be negatively associated in both states. However, this association is stronger and consistent during the high volatility regime, since all coefficients are negative and statistically significant. The last row of table 9 reports the χ^2 Wald test statistic for investor sentiment equality across both states. All Wald test statistics indicate that the investor sentiment coefficient differs statistically significant (at the 5%) across the regimes for each country in the sample. This support the

[6] Other transition probabilities show a similar pattern, and are available upon request.



(e) Time plot of smoothed transition probability, Total crisis and NBER recession. The smoothed transition probability shows the probability of being in the high volatility regime.

second hypothesis that investor sentiment drives contagion during crisis periods. Lastly, the hypothesis that this effect differs for developed markets, compared to emerging markets, is rejected for the high volatility regime ($F = 1.56$). Therefore, there is not sufficient evidence to claim that contagion is stronger in emerging markets. Controlling for common random shocks, in a Markov regime switching model, does not alter the results presented in the previous section.

(14)	Var	DE	FR	UK	NL	JP	CA	CN	RU	IN	ID	MX
High σ^2	α	0.689***	0.860***	0.754***	0.766***	0.512***	0.760***	0.243***	0.447***	0.343***	0.400***	0.555***
		(0.030)	(0.004)	(0.023)	(0.016)	(0.007)	(0.006)	(0.004)	(0.010)	(0.014)	(0.006)	(0.048)
	FFR_t	−3.868***	−2.708***	−4.930***	−5.110***	−4.929***	−2.771***	−2.956***	−4.546***	−2.997***	−1.364***	−0.720
		(0.325)	(0.136)	(0.409)	(0.334)	(0.170)	(0.219)	(0.090)	(0.261)	(0.379)	(0.171)	(1.211)
	$R_{Oil,t}$	0.062	−0.017	0.143	0.003	0.021	0.209***	0.004	0.041	−0.152	−0.012	0.105
		(0.135)	(0.024)	(0.095)	(0.090)	(0.040)	(0.047)	(0.021)	(0.060)	(0.089)	(0.041)	(0.242)
	$R_{Gold,t}$	0.486	0.034	−0.178	−0.110	−0.044	0.080	0.075	−0.193	−0.021	−0.060	1.162*
		(0.363)	(0.049)	(0.277)	(0.233)	(0.105)	(0.092)	(0.045)	(0.141)	(0.201)	(0.092)	(0.589)
	$SENT_t$	−0.112***	−0.020***	−0.055**	−0.060**	−0.045***	−0.063***	−0.014***	−0.042**	−0.226***	−0.028***	−0.178**
		(0.034)	(0.004)	(0.027)	(0.027)	(0.011)	(0.014)	(0.003)	(0.017)	(0.026)	(0.007)	(0.088)
Low σ^2	α	0.845***	0.725***	0.850***	0.850***	0.597***	0.827***	0.152***	0.664***	0.583***	0.522***	0.622***
		(0.006)	(0.016)	(0.005)	(0.005)	(0.006)	(0.008)	(0.005)	(0.011)	(0.021)	(0.010)	(0.011)
	FFR_t	−1.476***	−3.869***	−2.887***	−2.936***	−3.406***	−1.452***	−3.752***	−4.248***	−2.321***	−1.296***	−0.318
		(0.194)	(0.325)	(0.150)	(0.143)	(0.144)	(0.167)	(0.199)	(0.348)	(0.671)	(0.260)	(0.355)
	$R_{Oil,t}$	−0.020	0.011	0.019	−0.024	0.015	−0.014	0.016	0.094	−0.142	−0.026	−0.033
		(0.032)	(0.089)	(0.030)	(0.029)	(0.031)	(0.033)	(0.028)	(0.074)	(0.118)	(0.048)	(0.076)
	$R_{Gold,t}$	−0.001	−0.104	−0.016	0.080	0.064	0.026	−0.046	−0.219	0.153	0.021	−0.344**
		(0.068)	(0.230)	(0.061)	(0.059)	(0.061)	(0.078)	(0.065)	(0.156)	(0.207)	(0.100)	(0.145)
	$SENT_t$	−0.014***	0.004	−0.022***	−0.020***	0.020***	0.009	0.015	0.057***	−0.057***	−0.003	0.008
		(0.005)	(0.025)	(0.005)	(0.005)	(0.005)	(0.005)	(0.009)	(0.010)	(0.015)	(0.009)	(0.011)
	χ^2_1	8.02	9.30	7.53	20.74	32.20	24.14	8.14	26.59	30.45	18.30	4.28

Table 8: Markov regime switching model: dynamic conditional correlations are regressed on investor sentiment and proxies for common random shocks. The upper panel provides the estimates in the high volatility regime. The lower panel shows the estimates in the low volatility regime. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Tables 9 provides the Markov regression estimates for investor sentiment, controlled for trade related variables [7]. Consistent with equation 7 (table 5), inflation rates, growth in industrial production, import and export growth exhibit no significant explanatory power with respect to dynamic conditional correlations. This finding holds across both regimes. The U.S. Terms of Trade and exchange rate volatility have a negative and

[7] Due to severe optimisation problems, no parameter convergence was achieved for Russia.

significant effect on dynamic correlation for most countries in both regimes. This is consistent with equation 7 (table 5). More importantly, in line with the previous results, is that the effect of investor sentiment in the volatile regime becomes significantly stronger than in the normal regime (as indicated by the Wald test in the last row). Furthermore, there is no evidence that contagion effects are stronger in emerging markets after controlling for trade related characteristics. Thus, table 7 presents results in favour of hypothesis 1 and 2.

(15)	Var	DE	FR	UK	NL	JP	CA	CN	RU	IN	ID	MX
High σ^2	α	0.413***	1.532***	1.533***	0.875***	1.655***	0.258***	0.511***	–	2.808***	0.837***	0.575***
		(0.123)	(0.226)	(0.075)	(0.118)	(0.081)	(0.062)	(0.051)	–	(0.354)	(0.106)	(0.159)
	$TOT_{US,t}$	−0.004**	−0.010***	−0.008***	−0.001	−0.013***	−0.005***	−0.004***	–	−0.028***	−0.005***	0.001
		(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	–	(0.004)	(0.001)	(0.002)
	$\pi_{US,t}$	−0.020	−0.001	0.013	−0.041**	−0.005	0.007	−0.019	–	−0.150**	0.007	−0.021
		(0.017)	(0.012)	(0.011)	(0.016)	(0.013)	(0.011)	(0.010)	–	(0.069)	(0.017)	(0.024)
	$\pi_{j,t}$	−0.000	−0.091***	0.008	0.010	−0.012	−0.003	−0.020***	–	0.014	0.004	−0.004
		(0.014)	(0.013)	(0.008)	(0.009)	(0.010)	(0.008)	(0.004)	–	(0.019)	(0.002)	(0.009)
	$IPGrowth_{US,t}$	−0.003	−0.053***	0.000	0.007	−0.027***	0.003	−0.001	–	−0.034	−0.009	−0.013
		(0.007)	(0.006)	(0.004)	(0.007)	(0.005)	(0.004)	(0.004)	–	(0.023)	(0.008)	(0.011)
	$IPGrowth_{j,t}$	−0.004	−0.014***	−0.009**	0.000	−0.001	−0.000	−0.000	–	0.002	0.001	−0.003
		(0.003)	(0.002)	(0.003)	(0.002)	(0.001)	(0.003)	(0.001)	–	(0.002)	(0.001)	(0.005)
	$\sigma^2_{j,t}$	−0.217***	−0.017***	−3.723***	−0.149***	0.000***	0.855***	−0.048***	–	−0.000***	−0.000***	−0.001
		(0.016)	(0.000)	(0.776)	(0.009)	(0.000)	(0.095)	(0.004)	–	(0.000)	(0.000)	(0.000)
	$Im-Growth_{US,t}$	0.000	0.001***	0.000	0.000	−0.000	−0.001	−0.000	–	0.001	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	–	(0.001)	(0.000)	(0.001)
	$Ex-Growth_{US,t}$	−0.000	0.000*	−0.000	−0.000	0.000	0.001	0.000	–	0.000	−0.000	0.000
		(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	–	(0.001)	(0.000)	(0.001)
	$SENT_t$	−0.033***	−0.135***	−0.132***	−0.058***	−0.015***	−0.046***	−0.023**	–	−0.166***	−0.053***	−0.009
		(0.008)	(0.025)	(0.009)	(0.007)	(0.004)	(0.007)	(0.010)	–	(0.043)	(0.007)	(0.010)
Low σ^2	α	1.557	0.817***	1.245**	1.274***	1.968***	−0.060	0.594***	–	1.712***	−0.553***	0.741***
		(1.163)	(0.117)	(0.512)	(0.232)	(0.135)	(0.505)	(0.052)	–	(0.180)	(0.179)	(0.176)
	$TOT_{US,t}$	−0.010	−0.000	−0.008	−0.007**	−0.018***	−0.007	−0.004***	–	−0.013***	−0.012***	−0.006***
		(0.013)	(0.001)	(0.005)	(0.003)	(0.002)	(0.005)	(0.001)	–	(0.002)	(0.002)	(0.002)
	$\pi_{US,t}$	−0.087	−0.023	−0.047	−0.119***	−0.006	0.018	0.001	–	−0.030	−0.028	0.261***
		(0.079)	(0.018)	(0.064)	(0.016)	(0.023)	(0.044)	(0.008)	–	(0.026)	(0.017)	(0.030)
	$\pi_{j,t}$	−0.006	−0.024	−0.064**	0.200***	−0.008	−0.023	−0.004	–	0.004	−0.019***	0.003
		(0.034)	(0.029)	(0.027)	(0.021)	(0.013)	(0.028)	(0.003)	–	(0.011)	(0.006)	(0.004)
	$IPGrowth_{US,t}$	−0.042	0.001	0.030	−0.148***	0.005	0.001	−0.004	–	−0.037**	−0.001	−0.080***
		(0.044)	(0.007)	(0.034)	(0.011)	(0.008)	(0.019)	(0.003)	–	(0.012)	(0.007)	(0.010)
	$IPGrowth_{j,t}$	0.001	−0.000	−0.001	−0.013***	0.003	−0.005	−0.000	–	−0.001	−0.000	0.020***
		(0.011)	(0.003)	(0.018)	(0.002)	(0.003)	(0.010)	(0.000)	–	(0.001)	(0.001)	(0.004)
	$\sigma^2_{j,t}$	−0.296***	−0.009***	−13.722***	−0.290***	−0.000***	1.793***	−0.053***	–	−0.000***	−0.000***	−0.001***
		(0.091)	(0.000)	(0.533)	(0.023)	(0.000)	(0.473)	(0.002)	–	(0.000)	(0.000)	(0.000)
	$Im-Growth_{US,t}$	0.001	0.000	0.002	−0.000	−0.001	0.000	−0.000	–	−0.001	−0.000	−0.008***
		(0.002)	(0.000)	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	–	(0.001)	(0.000)	(0.002)
	$Ex-Growth_{US,t}$	0.002	0.000	−0.001	−0.003***	0.000	−0.001	−0.000	–	0.000	0.000	0.005***
		(0.002)	(0.000)	(0.001)	(0.000)	(0.001)	(0.002)	(0.000)	–	(0.000)	(0.000)	(0.001)
	$SENT_t$	−0.029	−0.058***	0.144***	0.007	0.065***	0.060**	−0.012***	–	−0.041***	−0.016***	0.006
		(0.043)	(0.007)	(0.019)	(0.010)	(0.022)	(0.022)	(0.002)	–	(0.010)	(0.004)	(0.023)
	χ^2_1	10.31	8.93	175.46	12.67	13.23	23.14	6.83		9.09	6.12	3.51

Table 9: Markov regime switching model: dynamic conditional correlations are regressed on investor sentiment and proxies for trade linkages. The upper panel provides the estimates in the high volatility regime. The lower panel shows the estimates in the low volatility regime. Russia is excluded due to optimization problems. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 10 presents the Markov switching regression estimates for investor sentiment, controlled for a set of financial characteristics. Similar to the other Markov switching regression estimates, there exists a large similarity between table 10 and its SUR variant in table 5 (model 8). The VIX is documented to be insignificant in explaining the dynamic conditional correlation across each country for both regimes. A similar inference can be made for Pastor's liquidity factor, the interaction between liquidity and investor sentiment, and the M2 money supply growth. Furthermore, sales and purchases of bonds and stocks to and by U.S. citizens have no significant impact on the left tail dependence. Lastly, and most relevant, the Wald test statistics indicate that the effect of investor sentiment on the dynamic correlation differs significantly by regime. More specifically, this effect is documented to be large in magnitude during crises periods. This effect, however, is not larger for emerging markets within the volatility regime ($F = 0.63$). Therefore, based on this robustness check, the results of this thesis are not qualitatively different when crisis periods are endogenously determined. A sample selection bias seems not to be substantial enough to becloud the initial results. Yet, another check will be conducted to assess whether the selection bias is relevant for the results.

(16)	Var	DE	FR	UK	NL	JP	CA	CN	RU	IN	ID	MX
High σ^2	α	0.344^{***}	0.732^{***}	0.655^{***}	0.703^{***}	0.308^{***}	0.577^{***}	0.122^{***}	0.274^{***}	0.149^{***}	0.370^{***}	0.438^{***}
		(0.012)	(0.008)	(0.006)	(0.010)	(0.005)	(0.013)	(0.015)	(0.009)	(0.006)	(0.013)	(0.015)
	VIX_t	0.049	-0.047^{***}	-0.032^{**}	-0.034^{*}	-0.007	0.021	-0.017	0.041^{*}	-0.054	0.001	0.007
		(0.062)	(0.018)	(0.016)	(0.018)	(0.016)	(0.037)	(0.017)	(0.024)	(0.047)	(0.015)	(0.160)
	LIQ_t	-0.353	-0.058	-0.037	-0.070	0.005	0.059	0.004	0.142	-0.225	0.119^{***}	0.327
		(0.469)	(0.045)	(0.004)	(0.067)	(0.053)	(0.026)	(0.043)	(0.186)	(0.166)	(0.046)	(0.406)
	$SENT_t$	-0.115^{**}	-0.024^{***}	-0.063^{***}	-0.054^{***}	-0.049^{***}	-0.061^{**}	-0.028^{***}	-0.067^{***}	-0.219^{***}	-0.038^{***}	-0.302^{***}
		(0.048)	(0.005)	(0.004)	(0.007)	(0.008)	(0.026)	(0.005)	(0.019)	(0.035)	(0.006)	(0.081)
	$M2GrowthUS,t$	-0.187^{***}	-0.012	0.010	0.012	0.001	0.007	0.018	-0.015	0.018	0.004	0.117
		(0.064)	(0.007)	(0.004)	(0.009)	(0.009)	(0.024)	(0.008)	(0.023)	(0.026)	(0.008)	(0.073)
	$M2Growthj,t$	-0.002^{***}	-0.001	0.018^{**}	-0.003	0.052^{***}	-0.023	0.000	-0.001	-0.007	0.002	0.002
		(0.012)	(0.002)	(0.008)	(0.002)	(0.018)	(0.022)	(0.003)	(0.001)	(0.026)	(0.001)	(0.016)
	$BondSale_t$	0.011	-0.003^{***}	0.000	0.002	-0.001	0.001	-0.002^{*}	0.098^{**}	0.029	0.026^{*}	-0.003
		(0.099)	(0.001)	(0.000)	(0.002)	(0.001)	(0.002)	(0.001)	(0.035)	(0.005)	(0.002)	(0.015)
	$StockSale_t$	0.028	0.011	0.002^{***}	0.007	0.021^{*}	0.005	0.009	-0.373^{***}	0.077	0.072	0.019
		(0.025)	(0.006)	(0.001)	(0.004)	(0.006)	(0.003)	(0.006)	(0.067)	(0.111)	(0.046)	(0.038)
	$StockPurchase_t$	0.023	0.183	-0.665	0.023	0.015	-1.875	0.051	0.337^{***}	0.378^{*}	-0.180	-0.042
		(0.090)	(0.161)	(0.372)	(0.016)	(0.020)	(1.781)	(0.048)	(0.117)	(0.193)	(0.128)	(0.047)
	$BondPurchase_t$	0.007	0.009	0.014^{**}	-0.005^{*}	0.006^{***}	0.007^{*}	-0.087	0.005	-0.004	-0.013^{*}	0.034
		(0.012)	(0.020)	(0.007)	(0.003)	(0.001)	(0.004)	(0.445)	(0.009)	(0.005)	(0.006)	(0.023)
	$SENT_t * LIQ_t$	0.232	0.014	0.023	-0.027	0.116	-0.082	0.034	-0.012	0.759	0.128	-1.300
		(0.544)	(0.070)	(0.050)	(0.097)	(0.114)	(0.261)	(0.052)	(0.016)	(0.468)	(0.087)	(0.945)
Low σ^2	α	0.618^{***}	0.477^{***}	0.440^{***}	0.482^{***}	0.222^{***}	0.763^{***}	0.055^{***}	0.536^{***}	0.402^{***}	0.498^{***}	0.606^{***}
		(0.012)	(0.016)	(0.025)	(0.019)	(0.017)	(0.007)	(0.007)	(0.021)	(0.023)	(0.014)	(0.017)
	VIX_t	-0.094^{***}	-0.040	0.014	-0.027	-0.002	-0.043^{***}	0.000	-0.079^{*}	-0.037	-0.038	-0.528
		(0.028)	(0.039)	(0.046)	(0.051)	(0.029)	(0.015)	(0.011)	(0.043)	(0.051)	(0.024)	(0.034)
	LIQ_t	0.032	-0.152	-0.313	-0.131	-0.054	-0.087^{*}	0.004	0.067	-0.102	-0.119	-0.032
		(0.073)	(0.206)	0.217	(0.154)	(0.101)	(0.048)	(0.036)	(0.110)	(0.143)	(0.078)	(0.109)
	$SENT_t$	-0.050^{***}	0.050^{***}	0.014	0.002	0.067^{***}	0.007	-0.015^{***}	0.033^{**}	-0.041^{**}	-0.028^{***}	0.013
		(0.008)	(0.019)	(0.031)	(0.019)	(0.008)	(0.006)	(0.006)	(0.013)	$(0.019)^{**}$	(0.009)	(0.011)
	$M2GrowthUS,t$	0.030^{***}	-0.038	-0.022	0.050	-0.007	0.018^{**}	-0.008	0.021	0.061^{**}	0.018	0.014
		(0.013)	(0.029)	(0.039)	(0.031)	(0.015)	(0.008)	(0.009)	(0.019)	(0.028)	(0.013)	(0.019)
	$M2Growthj,t$	-0.000	0.001	-0.014	-0.001	-0.106^{***}	0.005	-0.000	-0.004^{*}	-0.006^{*}	-0.003	-0.002
		(0.000)	(0.004)	(0.012)	(0.007)	(0.016)	(0.009)	(0.002)	(0.002)	(0.003)	(0.002)	(0.005)
	$BondSale_t$	-0.013^{***}	0.003	0.002^{***}	-0.030	-0.007^{*}	-0.002	-0.001	0.079	0.036	-0.020	-0.055
		(0.003)	(0.003)	(0.001)	(0.017)	(0.004)	(0.002)	(0.001)	(0.053)	(0.043)	(0.023)	(0.040)
	$StockSale_t$	0.021	0.023^{*}	0.001	0.010	0.043^{**}	-0.001	0.082	-0.284^{***}	0.074	-0.001	-0.004
		(0.040)	(0.013)	(0.001)	(0.012)	(0.002)	(0.001)	(0.047)	(0.057)	(0.051)	(0.034)	(0.012)
	$StockPurchase_t$	-0.002	-0.092	-0.026	0.098	0.009^{*}	0.002^{*}	0.019^{***}	0.569^{**}	-0.150	0.092	0.024
		(0.002)	(0.059)	(0.370)	(0.067)	(0.005)	(0.001)	(0.004)	(0.285)	(0.082)	(0.119)	(0.016)
	$BondPurchase_t$	0.034^{***}	0.009	0.322	0.053	0.005^{***}	0.002	3.036^{***}	-0.030^{**}	0.101	-0.018	-0.013
		(0.006)	(0.007)	(0.653)	(0.029)	(0.001)	(0.002)	(0.369)	(0.017)	(0.362)	(0.013)	(0.095)
	$SENT_t * LIQ_t$	0.059	0.235	0.689	0.217	0.045	0.076	0.133^{*}	0.006	0.274^{*}	0.053	0.026
		(0.107)	(0.237)	(0.583)	(0.207)	(0.096)	(0.068)	(0.072)	(0.137)	(0.160)	(0.072)	(0.128)
	χ^2_1	17.61	14.19	25.12	7.22	96.63	4.69	3.36	18.29	30.43	0.99	14.78

Table 10: Markov regime switching model: dynamic conditional correlations are regressed on investor sentiment and controls for financial linkages. The upper panel provides the estimates in the high volatility regime. The lower panel shows the estimates in the low volatility regime. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

6.2. GFC

In this section, model 5-8 will be re-estimated by using a time dummy for the GFC (GFC) rather than the previously used time dummy. This allows checking whether the results change due to a different selected crisis definition. The GFC started in December 2007 till June 2009, according to the NBER. Equation (17), table 11, provides the SUR estimates of the GFC time dummy on the dynamic conditional correlations. The GFC time dummy is statistically significant and positive for each SUR equation. This finding indicates that cross-equity market correlations increased substantially during the GFC, in line with hypothesis 3 and the previous results. Model (18) , table 11, provides the SUR estimates of the effect of the investor sentiment proxies, GFC time dummy, and their interactions. The AAII investor sentiment indicators and the VIX_t provide no statistically significant estimates, similar to the results in section 4. Nor do the interaction terms between AAII's sentiment indicator and the GFC time dummy provide significant estimates. However, the indirect proxy of investor sentiment $SENT_t$ has a significantly negative effect on 10 out of the 11 cross-equity market correlations during the GFC. This indicates that investor sentiment became stronger during the GFC, thereby increasing the cross-equity market correlation. In contrast to the results in section 4, one remarkable observation is documented: the negative effect of investor sentiment on the dynamic conditional correlation during the GFC is significantly stronger for emerging markets than developed markets ($F = 5.72$). This finding is consistent with Celık (2012). According to Celık (2012) this should have been expected since emerging markets are less efficient financial markets, which increases the impact of investor sentiment and makes herding behaviour more likely. However, this argument leaves one question open: Why is this effect stronger for emerging markets during the GFC and not for earlier financial crises, especially when emerging financial markets have become more efficient in the past decades? In that case, herding behaviour should be less problematic for financial markets. One possible argument is that contagion is a function of integration. In the past decades, emerging markets have been financially integrating quickly into the global market, thereby increasing the impact of investor sentiment. However, if this would be the case then after controlling for financial integration, the effect should not be stronger for emerging markets. Appendix IV provides SUR estimates including controls for common random shocks, trade linkages, and financial characteristics. Even after controlling for these characteristics, $SENT_t$ has a significant negative effect on dynamic conditional correlations during the GFC. The argument of Celık (2012) that emerging markets are less efficient, and therefore are more vulnerable, is highly questionable. The other possibility is that this effect is crisis-specific or country-specific. However, it is out of the scope of this thesis to test this statement. The persistent negative effect of investor sentiment is stronger during the GFC, especially for emerging markets. What causes the latter finding, however, remains puzzling.

	Var	DE	FR	UK	NL	JP	CA	CN	RU	IN	ID	MX
(17)	α	0.688***	0.676***	0.706***	0.689***	0.433**	0.740***	0.106***	0.381***	0.315***	0.395***	0.582***
		(0.010)	(0.009)	(0.008)	(0.009)	(0.007)	(0.005)	(0.005)	(0.012)	(0.011)	(0.005)	(0.008)
	$D_{GFC,t}$	0.124***	0.142***	0.082***	0.092***	0.101***	0.026***	0.093***	0.090***	0.279***	0.055***	0.060***
		(0.036)	(0.033)	(0.029)	(0.031)	(0.026)	(0.010)	(0.018)	(0.042)	(0.040)	(0.017)	(0.027)
	R^2	0.0362	0.0585	0.0242	0.0271	0.0453	0.0070	0.0841	0.0001	0.1355	0.0320	0.0070
(18)	α	0.289**	0.320***	0.506***	0.420***	0.205**	0.677***	−0.003	0.012	−0.192	0.310***	0.508***
		(0.090)	(0.080)	(0.076)	(0.077)	(0.069)	(0.044)	(0.044)	(0.108)	(0.103)	(0.043)	(0.074)
	VIX_t	−0.068	−0.053	−0.004	−0.010	−0.001	−0.021	−0.010	−0.040	−0.076	−0.019	−0.042
		(0.050)	(0.044)	(0.042)	(0.043)	(0.038)	(0.024)	(0.024)	(0.059)	(0.057)	(0.023)	(0.041)
	$D_{GFC,t}$	0.492	0.577	0.534	0.542	0.396	0.041	0.429	1.404	1.268	0.285	−0.422
		(0.643)	(0.574)	(0.543)	(0.552)	(0.491)	(0.311)	(0.316)	(0.771)	(0.736)	(0.305)	(0.528)
	$BEAR_t$	0.006	0.005	0.002	0.003	0.003	0.001	0.002	0.005	0.009*	0.001	0.002
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)
	$BULL_t$	−0.004	−0.003	−0.001	−0.000	−0.004	−0.001	−0.002	−0.003	−0.003	−0.001	−0.001
		(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
	$SENT_t$	−0.073***	−0.058***	−0.032**	−0.068***	−0.019	−0.006	−0.043***	−0.001	−0.035**	0.003	−0.000
		(0.015)	(0.014)	(0.013)	(0.013)	(0.012)	(0.007)	(0.007)	(0.018)	(0.017)	(0.007)	(0.013)
	$BEAR_t * D_{GFC,t}$	−0.005	−0.006	−0.005	−0.006	−0.004	0.000	−0.005	−0.019	−0.016	−0.003	0.005
		(0.008)	(0.007)	(0.007)	(0.007)	(0.006)	(0.004)	(0.004)	(0.010)	(0.010)	(0.004)	(0.007)
	$BULL_t * D_{GFC,t}$	−0.007	−0.007	−0.007	−0.008	−0.005	−0.002	−0.005	−0.019	−0.012	−0.004	0.005
		(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.004)	(0.004)	(0.010)	(0.010)	(0.004)	(0.007)
	$SENT_t * D_{GFC,t}$	−0.049**	−0.073**	−0.115**	−0.066**	−0.117**	−0.100**	−0.068**	−0.360***	−0.187*	−0.212***	−0.128**
		(0.023)	(0.030)	(0.054)	(0.025)	(0.047)	(0.036)	(0.037)	(0.090)	(0.086)	(0.036)	(0.062)
	R^2	0.192	0.202	0.097	0.177	0.117	0.062	0.233	0.110	0.248	0.171	0.038

Table 11: Seemingly Unrelated Regressions on Dynamic Conditional Correlations: GFC *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are shown between parentheses.

6.3. *Contagion in government bonds?*

To investigate the robustness of the results from cross-equity market correlations, also cross-bond market correlations are analysed. Through Datastream, the monthly ex-post total returns on 10-year maturity ("on-the-run") sovereign bonds are obtained. All bonds are denominated in U.S. dollars, such that yields are net of changes in exchange rates between currencies. The same countries are used as in the initial sample. The descriptive statistics of the bonds are provided in appendix V (table 15). There is some variation in the average monthly return, with Japan exhibiting the lowest mean return (2.30%) and Russia the highest (15.60%). Such differences can partially be attributable to differences in default risk between countries. The null hypothesis of normality is rejected in all cases, as indicated by the Shapiro Wilk test statistics. All sovereign bonds exhibit autocorrelated returns, as indicated by the Ljung-Box test statistic. The null hypothesis of no ARCH effects is rejected for all countries. Table 15 also shows that the level of correlation is extremely high between the U.S. 10-year bond and the other developed market 10-year bonds, irrespective of the state. This might imply that financial contagion is weaker or absent among these bonds. In addition, these correlations tend to increase during crises periods slightly. The change in correlations is larger for emerging markets, compared to developed markets. Lastly, note that the level of the correlation for emerging markets is substantially lower than for developed countries. This finding indicates that these countries are possibly less integrated with the global market compared to developed markets.

The dynamic conditional correlation between the U.S. 10-year Treasury bond and the 10-year government bond of the other countries will be estimated and regressed against the set of independent variables. The DCC-GARCH parameter estimates are shown in table 16 (appendix V). A multivariate GARCH(2,2) specification is used, except for Russia, India, Indonesia and Mexico due to data gaps [8]. Table 12 provides the SUR estimates of two equations. Equation (19) indicates that government bonds exhibit a substantially higher correlation during periods of financial crises. This is in line with Hartmann et al. (2004), who document that bonds also exhibit higher co-movement during financial crises. However, the striking difference, compared to cross-equity market correlations, is that the inclusion of the investor sentiment proxies does not drive this increase in correlations. VIX_t nor $SENT_t$ is statistically significant at the 5% for all correlations. During periods of financial crises, the effect of $SENT_t$ does not change significantly compared to normal periods. This striking finding suggests that financial contagion is less likely to be present in the government bond market. Table 17 (appendix V) provides the inclusion of SUR estimates for equations that control for common random shocks, trade related characteristics, and financial characteristics. After controlling for these characteristics, there is some weak evidence in favour of financial contagion. For some countries, low investor sentiment during crises periods is associated with higher correlations in the sovereign bond market. In addition, the magnitude of this effect is smaller compared to this effect on cross-equity market correlations. This finding suggests that financial contagion does occur in the sovereign bond market. However it is a less prominent driver of the correlations between sovereign bonds. Financial contagion in the bond market may occur due to similar reasons as laid out in subsection 5.1. However, note that Baker & Wurgler's sentiment index is a proxy for the U.S. equity investor sentiment. There is an additional channel that could explain financial contagion in the bond market via equity market investor sentiment: during financial crises, when investor sentiment is low, financial contagion in equity markets around the globe may occur. This induces investors to shift their wealth into safer assets, such as government bonds. This shift will drive bond prices up (and yields down), thereby generating more co-movement between these government bonds

[8] For these countries a multivariate GARCH(1,1) is estimated

during financial crises. This explanation is consistent with the "flight-to-quality"-phenomenon, which is also documented by Hartmann et al. (2004). Lastly, table 16 shows that the Fed Fund rate, the U.S. terms of trade, and exchange rate volatilities have a significant negative effect on the sovereign bonds correlations.

	Var	DE	FR	UK	NL	JP	CA	CN	RU	IN	ID	MX
(19)	α	0.453^{***}	0.389^{***}	0.492^{***}	0.397^{***}	0.780^{***}	0.977^{***}	-0.227^{***}	-0.165	-0.266^{***}	0.804^{***}	0.644^{***}
		(0.061)	(0.068)	(0.062)	(0.068)	(0.033)	(0.003)	(0.088)	(0.096)	(0.086)	(0.052)	(0.069)
	$D_{Crisis,t}$	0.410^{***}	0.425^{***}	0.399^{***}	0.417^{***}	0.083	0.014^{***}	0.624^{***}	0.085	0.497^{***}	0.212^{***}	0.063
		(0.088)	(0.099)	(0.090)	(0.099)	(0.048)	(0.004)	(0.128)	(0.139)	(0.126)	(0.076)	(0.101)
	R^2	0.132	0.116	0.122	0.111	0.020	0.094	0.143	0.003	0.099	0.052	0.003
(20)	α	0.483^{***}	0.421^{***}	0.507^{***}	0.429^{***}	0.782^{***}	0.976^{***}	-0.230^{***}	-0.145	-0.240^{***}	0.797^{***}	0.645^{***}
		(0.048)	(0.055)	(0.059)	(0.055)	(0.033)	(0.002)	(0.086)	(0.091)	(0.074)	(0.050)	(0.069)
	$D_{Crisis,t}$	0.371^{***}	0.389^{***}	0.376^{***}	0.385^{***}	0.079	0.015^{***}	0.688^{***}	-0.147	0.365^{***}	-0.158^{**}	-0.058
		(0.071)	(0.081)	(0.087)	(0.081)	(0.049)	(0.004)	(0.128)	(0.135)	(0.109)	(0.073)	(0.102)
	VIX_t	0.032	-0.031	0.048	-0.038	-0.017	0.003	-0.005	-0.225	0.096	-0.212	-0.099
		(0.171)	(0.194)	(0.208)	(0.195)	(0.118)	(0.009)	(0.306)	(0.324)	(0.261)	(0.176)	(0.246)
	$SENT_t$	-0.006	-0.009	-0.018	-0.007	-0.004	0.012	0.017	-0.048	-0.038	$-0.072*$	-0.037
		(0.028)	(0.045)	(0.055)	(0.005)	(0.007)	(0.007)	(0.028)	(0.041)	(0.094)	(0.039)	(0.183)
	$SENT_t * D_{Crisis,t}$	-0.007^{**}	-0.010	-0.005^{*}	-0.003	-0.030	-0.026^{**}	-0.051	0.014	-0.095	-0.028	-0.099
		(0.003)	(0.009)	(0.002)	(0.013)	(0.132)	(0.010)	(0.044)	(0.065)	(0.294)	(0.098)	(0.076)
	R^2	0.155	0.125	0.132	0.126	0.024	0.123	0.182	0.0545	0.149	0.147	0.005

Table 12: Seemingly unrelated regression on dynamic correlations for each pair with U.S. in the sovereign bond market. The upper equation adds the aggregated crisis definition. The lower equation adds the investor sentiment index. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are shown between parentheses.

7. Conclusion

The occurrence of financial crises is an unavoidable and unfortunate byproduct of our modern economic system. A stylized fact is that financial crashes are often clustered; e.g. crashes in different markets tend to occur simultaneously. Several explanations have been put forward to explain this stylized fact, such as interdependence (through fundamentals) and contagion (through irrational behaviour). The aim of this thesis was to investigate the presence of contagion effects in equity markets during 1990-2015. This paper contributes to the existing literature by analysing time-varying correlations and copula-based measures of asymmetric dependence. Specifically, this thesis is among the first ones to explore the role of investor sentiment as a determinant for financial contagion. The findings in this thesis indicate that equity markets become more dependent during crises periods, suggesting a high(er) probability of a joint crash. This increase is strongly related to low levels of investor sentiment. More specifically, investor sentiment has a negative effect on cross-equity market correlations, which becomes even stronger during crises periods. This finding implies the existence of contagion effects in equity markets, consistent with the arguments made by Hwang & Salmon (2009). This finding persists after the inclusion of a broad set of control variables, allowing for endogenously determined crises periods, and the use of left tail dependence instead of correlations. Thus, during financial crises, when investor sentiment is low, domestic loss-averse investors will rebalance the share of risky assets in their portfolio and become more loss-averse. Such rebalancing may induce a declining price spiral in both the domestic as well as foreign market, creating a joint crash. In addition, during financial crises, investors tend to become more ambiguity averse. This causes them to feel less competent to assess the financial environment Heath & Tversky (1991), resulting in herding behaviour (Dong et al., 2010). Herding behaviour, in turn, causes financial contagion. These results are weaker for the sovereign bond market, where it is documented that the role of investor sentiment in explaining sovereign bond correlations is limited. However, changes in correlations between equity markets (and also for the sovereign bond market) is not only driven by financial contagion. Common random shocks and interdependence do also exhibit explanatory power. It is documented that the Fed fund rate, the U.S. Terms of Trade, and exchange volatilities are negatively related to the dynamic conditional correlations.

Some limitations, however, of this paper needs to be addressed. First, and perhaps also obviously, caution is warranted in the external validity of this study. Although the sample consisted of major developed equity markets, major emerging asset markets, and a time-span of 25 years, the results might not hold in other settings that were not explored in this thesis. Second, and more important, is the internal validity of this thesis. One possible threat to the internal validity is an endogeneity issue embodied as an omitted variable bias. This thesis deploys a large set of control variables to limit omitted variable bias. In addition, the orthogonalized Baker & Wurgler's sentiment index is used, which is uncorrelated with a large set of macro-fundamentals. Yet, the existence of unobserved heterogeneity correlated with the variables of interest can not be fully ruled out. In addition, there might exist an endogeneity problem in the form of a measurement error, although less problematic. No perfect proxies, without measurement error, for investor sentiment exist. Endogeneity in the form of simultaneous causality may also exist: does low investor sentiment cause contagion or the other way around? To what extent endogeneity is problematic is unknown, but should be kept in mind. Lastly, in this thesis, one crucial assumption was made: contagion runs from the U.S. to the other countries. However, this may not per se be true and remains untested. These limitations provide scope for further research suggestions. The role of investor sentiment on contagion remains unexplored in other asset markets, such as the corporate bond market and the interbank market and remains open for future research. Another suggestion is to investigate the role of investor sentiment on contagion between asset classes instead of within asset classes.

Irrespective of the above-mentioned limitations, the presented results provide practical implications for financial regulators, and practitioners in the risk - and asset management industry. To reiterate, both irrational behaviour, as well as fundamentals, drive the dependency between equity markets. First, financial practitioners should become aware that international diversification of asset portfolios comes at an additional cost, namely contagion risk. During periods of low sentiment, contagion is likely to occur, which decreases diversification benefits due to co-crashes in different markets. The results of this thesis justify the local equity preference (home bias) of investors. Asset managers may exploit such preferences through the use of domestic mutual funds since such funds are expected to exhibit lower contagion risk. This raises another future research question in the field of asset pricing: is contagion risk an unique factor that should be incorporated in asset prices? From the perspective of policy makers', this thesis suggests going beyond "classical" measures to mitigate contagion. Adding funding liquidity by increasing the money supply is not an effective tool to alter cross-equity market correlations on the short-run, while it only increases long-run inflation rates. In addition, expansionary monetary policy, via lower base interest rates, increases the dependency between markets substantially. Central bankers ought to be careful with the timing of such policies. What is quintessential for monetary authorities is "sentiment management". While investor sentiment can not be regulated, it can be managed through "forward guidance": coordinating sentiment through the use of communication about future central bank actions. Our complex economic system is both too linked to fail and too contagious to ignore for human beings. It is up to policymakers to reassure financial stability by guiding investors, despite future imminent quakes in this complex system.

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Appendix I: Copula Modelling

In this Appendix, technical details will be provided regarding the copulas that are considered in this paper. Specifically, the Gaussian, Clayton, and the Symmetrized Joe-Clayton copula are considered. The copulas are extended to allow for time-varying tail dependence. The Gaussian copula (Gumbel, 1960), which is the corresponding copula of a multivariate distribution, is defined as:

$$C^N(u_1, u_2|\rho) = \int_{-\infty}^{\Phi^{-1}(u_1)} \int_{-\infty}^{\Phi^{-1}(u_2)} \frac{1}{2\pi\sqrt{1-\rho^2}} exp\left(\frac{2\rho rs - r^2 - s^2}{2(1-\rho^2)}\right) drds \tag{11}$$

Where $\Phi^{-1}(.)$ is the inverse of the normal CDF and ρ is the simple correlation coefficient. This copula is not allowed to exhibit any form of tail dependence. To introduce time-varying dependence in the parameter ρ. ρ is modeled as a restricted ARMA(1,10) process:

$$\rho_t = \Lambda(\omega_t^N + \beta^N \rho_{t-1} + \gamma^N \frac{1}{10} \sum_{n=1}^{10} \Phi^{-1}(u_{1,t-i}) \Phi^{-1}(u_{2,t-i})) \tag{12}$$

Where Λ denotes the modified logistic transformation in order to keep $\rho_t \in (-1, 1)$. β^N captures the extent of persistency in ρ_t. The moving average term captures the variation in the dependence.
The Clayton copula (Clayton, 1978) is defined as:

$$C^c(u_1, u_2|\theta) = (u_1^{-\theta} + u_2^{-\theta} - 1)^{-\frac{1}{\theta}} \tag{13}$$

$\theta \in [0, \infty)$ represents the degree of dependence. A higher value of θ represents a higher dependence between u_1 and u_2. The Clayton Copula only exhibits lower tail dependence, which is modeled as the following ARMA(1,10) process:

$$\tau_t^C = \Lambda(\omega_t^C + \beta^C \tau_{t-1}^C + \gamma^C |u_{1,t-i} - u_{2,t-i}|) \tag{14}$$

Where Λ is the standard logistic transformation in order to restrict $\tau_t^C \in (0, 1)$.

The Symmetrized Joe-Clayton (SJC) copula (Patton, 2006) is defined as:

$$C^{SJC}(u_1, u_2|\tau^U, \tau^L) = \frac{1}{2}\left(C^{JC}(u_1, u_2|\tau^U, \tau^L) + C^{JC}(1-u_1, 1-u_2|\tau^U, \tau^L) + u_1 + u_2 - 1\right) \tag{15}$$

With C^{JC} being the Joe-Clayton copula:

$$C^{JC}(u_1, u_2|\tau^U, \tau^L) = 1 - \left(1 - \left((1-(1-u_1)^\kappa)^{-v} + (1-(1-u_2)^\kappa)^{-v} - 1\right)^{\frac{-1}{v}}\right)^{\frac{-1}{\kappa}} \tag{16}$$

Whereby $\kappa = \frac{1}{log_2(2-\tau^u)}, v = \frac{-1}{log_2(\tau^L)}$ and $\tau^U, \tau^L \in (0, 1)$ denote the upper and lower tail dependency, respectively. The SJC copula thus allows for dependencies for both tails. The upper and lower tail dependence also follow a restricted ARMA(1,10) process similar as in the Clayton copula. For brevity, these formulas are not discussed. The parameters of these copulas are estimated in Matlab. In this thesis, the interest is to test whether the lower tail dependence increases during crises periods, and whether this is driven by investor sentiment (contagion).

Appendix II: Markov regime switching model

As argued earlier, sample selection biases may occur when crises periods are exogenously determined through time dummies. To overcome this problem, crisis periods are allowed to be determined endogenously. One way to allow for this, is to implement the Markov regime switching model. Regime switching models are able to parsimoniously capture abrupt changes in the behaviour of financial markets that often persist after such changes. It is able to capture nonlinear dynamics of asset returns in a linearly specified model within regimes. Such models are becoming increasingly popular in financial modelling, also due to its underlying intuition (Boyer et al., 2006). Markov regime switching models have been shown to be superior in modelling important characteristics of correlation dynamics in financial time series (Ang & Bekaert, 2002).

In this thesis, for simplicity, the existence of two market states is assumed: a high volatility regime (crises periods), and a low volatility regime (non-crises periods).This latent state approach does not require conditioning on predefined state indicators, and allows the regressors to be a function of the unobserved state of the market. This unobserved state follows a first-order Markov Chain. The Markov Switching model is specified as following in this thesis:

$$\rho_{ij,t} = \alpha_o + \boldsymbol{x_t}\boldsymbol{\alpha} + \boldsymbol{\psi_t}\boldsymbol{\beta_s} + \epsilon_s, \epsilon \sim N(0, \sigma_s^2), s \in \{1, 2\} \tag{17}$$

Where R_t is the dependent variable, α_o is the state-dependent intercept, x_t is a vector of regressors with state-invariant coefficients α, ψ_t is a vector of regressors with state-dependent coefficients β_s, and ϵ_s is an i.i.d. normal error with mean 0 and state-dependent variance σ_s^2. The unobserved state, s_t, follows an irreducible, aperiodic, first-order time-homogeneous Markov Chain with two states: A high volatility regime (1), and a low volatility regime (2). The probability that s_t equals $j \in [1, 2]$ depends only on the most recent realization (Markov property), s_{t1}, and is given by $Pr(s_t = j|s_{t1} = i) = p_{ij}$. All possible transitions probability can be summarized in a 2x2 transition matrix P:

$$\boldsymbol{P} = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix} \tag{18}$$

Where all p_{ij}'s are assumed to be time-invariant transition probabilities. Clearly, the elements in each row sum up to 1. The transition matrix governs the random behavior of the state variable, and it contains only two parameters (p_{11} and p_{22}). The parameter vector $\boldsymbol{\theta} = (\alpha_o, \beta_s, \sigma_s^2, p, q)$ is estimated using maximum likelihood estimation using the Expected Maximization (EM) algorithm.

Appendix III: Copula results

Var	DE	FR	UK	NL	JP	CA	CN	RU	IN	ID	MX
α	0.455***	0.437***	0.452***	0.447***	0.479***	0.437***	0.503***	0.496***	0.496***	0.476***	0.452***
	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.011)	(0.005)	(0.008)	(0.008)	(0.009)	(0.011)
$D_{crisis,t}$	0.060***	0.032**	0.057***	0.040**	0.017***	0.043**	0.008	0.030**	0.026**	0.011	0.015
	(0.015)	(0.016)	(0.014)	(0.016)	(0.004)	(0.016)	(0.008)	(0.012)	(0.012)	(0.014)	(0.016)
R^2	0.048	0.009	0.049	0.021	0.004	0.023	0.004	0.019	0.009	0.002	0.003
α	0.441***	0.427***	0.444***	0.441***	0.478***	0.435***	0.500***	0.494***	0.494***	0.472***	0.442***
	(0.010)	(0.012)	(0.010)	(0.011)	(0.010)	(0.012)	(0.006)	(0.009)	(0.009)	(0.010)	(0.011)
$D_{Crisist}$	0.045***	−0.020	−0.051	−0.039**	−0.020	−0.033	−0.008	0.029	0.020	0.009	0.011
	(0.015)	(0.017)	(0.035)	(0.017)	(0.016)	(0.017)	(0.009)	(0.023)	(0.013)	(0.014)	(0.017)
VIX_t	−0.060**	−0.048	−0.021	−0.024	0.005	−0.046	−0.006	−0.005	−0.006	0.010	−0.023
	(0.026)	(0.030)	(0.026)	(0.028)	(0.027)	(0.029)	(0.015)	(0.023)	(0.022)	(0.025)	(0.029)
$SENT_t * D_{Crisis,t}$	−0.188***	−0.191***	−0.136***	−0.175***	−0.060	−0.147***	−0.060**	−0.099***	−0.069**	−0.162***	−0.164***
	(0.039)	(0.044)	(0.038)	(0.041)	(0.039)	(0.043)	(0.021)	(0.033)	(0.033)	(0.036)	(0.043)
$SENT_t$	−0.060**	−0.056**	−0.028	−0.042	−0.010	−0.021	−0.012	−0.008	−0.011	−0.012	−0.041
	(0.022)	(0.025)	(0.022)	(0.024)	(0.023)	(0.025)	(0.012)	(0.019)	(0.019)	(0.021)	(0.025)
R^2	0.1294	0.0795	0.0887	0.0855	0.0160	0.0707	0.0319	0.0469	0.0246	0.0705	0.0571
α	0.421***	0.401***	0.431***	0.421***	0.469***	0.428***	0.496***	0.480***	0.474***	0.463***	0.414***
	(0.015)	(0.017)	(0.014)	(0.016)	(0.015)	(0.017)	(0.008)	(0.013)	(0.012)	(0.014)	(0.016)
$D_{Crisis,t}$	0.040**	0.014	0.038**	−0.034**	−0.018	−0.031	−0.006	−0.025	−0.014	0.011	−0.004
	(0.016)	(0.018)	(0.016)	(0.017)	(0.016)	(0.018)	(0.009)	(0.014)	(0.013)	(0.015)	(0.018)
FFR_t	−0.661**	−0.826**	−0.409	−0.635*	−0.308	−0.226	−0.145	−0.490**	−0.620**	−0.308	−0.928**
	(0.330)	(0.375)	(0.324)	(0.358)	(0.331)	(0.371)	(0.182)	(0.243)	(0.273)	(0.316)	(0.366)
$R_{Oil,t}$	0.159*	0.169**	0.147**	0.141	−0.029	0.151	0.062	0.053	0.172**	0.086	−0.065
	(0.075)	(0.084)	(0.073)	(0.080)	(0.075)	(0.083)	(0.041)	(0.064)	(0.061)	(0.071)	(0.082)
$R_{Gold,t}$	−0.140	−0.062	0.000	−0.016	0.087	−0.049	0.050	−0.108	−0.097	−0.028	0.126
	(0.166)	(0.186)	(0.161)	(0.177)	(0.164)	(0.184)	(0.090)	(0.140)	(0.135)	(0.157)	(0.181)
$SENT_t$	−0.035***	−0.027	−0.012	−0.052**	−0.010	−0.019	−0.007***	−0.130***	−0.082***	−0.039***	−0.010
	(0.005)	(0.028)	(0.024)	(0.026)	(0.024)	(0.027)	(0.001)	(0.021)	(0.020)	(0.013)	(0.027)
$SENT_t * D_{Crisis,t}$	−0.047***	−0.063**	−0.041***	−0.045**	−0.090***	−0.039***	−0.030**	−0.038**	−0.025	−0.032**	−0.009
	(0.017)	(0.030)	(0.016)	(0.019)	(0.027)	(0.011)	(0.015)	(0.013)	(0.022)	(0.012)	(0.030)
R^2	0.191	0.153	0.169	0.254	0.112	0.148	0.219	0.333	0.056	0.018	0.033
α	0.460**	0.071	0.376	0.246	−0.054	0.538**	0.283**	0.504***	−0.020	0.370	0.385
	(0.220)	(0.240)	(0.199)	(0.222)	(0.190)	(0.229)	(0.101)	(0.167)	(0.167)	(0.212)	(0.223)
$D_{Crisis,t}$	0.034**	0.001	0.047**	0.040**	−0.005	0.054**	0.002	0.023	0.002	0.016	0.021
	(0.017)	(0.019)	(0.017)	(0.018)	(0.018)	(0.022)	(0.007)	(0.014)	(0.015)	(0.016)	(0.019)
$TOT_{US,t}$	−0.004**	−0.008**	−0.007***	−0.002	−0.006***	−0.001	−0.002**	−0.006***	−0.005**	−0.001**	−0.000
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
$\pi_{US,t}$	0.009	0.007	0.009	0.009	0.007	0.013	0.027**	0.033	0.089	0.010	0.055**
	(0.027)	(0.032)	(0.027)	(0.028)	(0.027)	(0.036)	(0.011)	(0.022)	(0.053)	(0.026)	(0.029)
$\pi_{j,t}$	0.006	0.031	0.009	0.010	0.027	−0.000	0.011**	−0.002	0.004	0.002	0.032***
	(0.015)	(0.036)	(0.014)	(0.012)	(0.019)	(0.026)	(0.005)	(0.003)	(0.010)	(0.005)	(0.009)
$IPGrowth_{US,t}$	−0.005	0.007	0.001	−0.007	−0.006	0.006	−0.005	0.016	0.010	0.016	0.011
	(0.012)	(0.014)	(0.012)	(0.013)	(0.012)	(0.015)	(0.005)	(0.010)	(0.010)	(0.012)	(0.013)
$IPGrowth_{j,t}$	−0.006	0.005	0.000	−0.003	−0.002	−0.003	−0.001	0.000	−0.000	0.001	−0.007
	(0.004)	(0.004)	(0.006)	(0.002)	(0.003)	(0.009)	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)
σ_t^2	−0.024**	−0.010***	−0.398**	−0.091***	−0.000	−0.392***	−0.030***	−0.004***	−0.003***	−0.002**	−0.001
	(0.009)	(0.001)	(0.153)	(0.017)	(0.000)	(0.035)	(0.005)	(0.000)	(0.000)	(0.000)	(0.001)
$ExGrowth_{j,US,t}$	0.002**	0.001	−0.001	0.001*	−0.001	−0.001	−0.000	0.000	−0.000	−0.000	0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
$ImGrowth_{j,US,t}$	−0.000	−0.000	0.000	0.000	0.002*	0.001	−0.000	−0.000	−0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
$SENT_t$	−0.055**	−0.068**	0.025	−0.055**	−0.083***	−0.066***	−0.028***	−0.020	−0.029	−0.023	−0.018
	(0.027)	(0.029)	(0.023)	(0.027)	(0.022)	(0.027)	(0.009)	(0.019)	(0.020)	(0.026)	(0.026)
$SENT_t * D_{Crisis,t}$	−0.064**	−0.074***	−0.036**	−0.073**	−0.026**	−0.121***	−0.006	−0.050**	−0.023**	−0.080**	−0.031**
	(0.030)	(0.034)	(0.016)	(0.031)	(0.011)	(0.032)	(0.011)	(0.023)	(0.010)	(0.031)	(0.014)
R^2	0.339	0.369	0.313	0.305	0.398	0.313	0.312	0.276	0.319	0.338	0.315
α	0.439***	0.444***	0.440***	0.453***	0.501***	0.427***	0.497***	0.486***	0.518***	0.504***	0.440***
	(0.024)	(0.022)	(0.026)	(0.022)	(0.038)	(0.024)	(0.011)	(0.021)	(0.016)	(0.021)	(0.024)
$SENT_t * D_{Crisis,t}$	−0.189***	−0.163***	−0.117**	−0.168***	−0.022	−0.137**	−0.059**	−0.109**	−0.059	−0.145***	−0.156***
	(0.042)	(0.048)	(0.042)	(0.048)	(0.042)	(0.049)	(0.023)	(0.041)	(0.037)	(0.043)	(0.045)
LIQ_t	0.104	0.212	−0.007	0.030	0.360	−0.427	−0.145	−0.133	−0.020	0.028	0.080
	(0.236)	(0.272)	(0.239)	(0.274)	(0.244)	(0.283)	(0.131)	(0.231)	(0.209)	(0.246)	(0.260)
$SENT_t$	−0.064**	−0.073**	0.041	0.049	−0.083***	−0.092***	−0.001	−0.017	−0.050**	0.027***	0.083**
	(0.028)	(0.030)	(0.026)	(0.030)	(0.028)	(0.027)	(0.015)	(0.026)	(0.023)	(0.009)	(0.030)
$M2Growth_{US,t}$	−0.016	−0.055**	−0.018	−0.039	−0.049**	−0.034	0.015	−0.032	−0.024	−0.035	−0.018
	(0.023)	(0.026)	(0.023)	(0.027)	(0.024)	(0.027)	(0.013)	(0.023)	(0.020)	(0.024)	(0.025)
$M2Growth_{j,t}$	−0.007	0.000	0.017	0.001	−0.003	−0.005	0.002	0.004**	−0.002	0.002	0.003
	(0.009)	(0.004)	(0.014)	(0.004)	(0.045)	(0.025)	(0.003)	(0.002)	(0.002)	(0.004)	(0.008)
$BondSale_t$	0.000	0.002	0.001	0.003	0.006*	−0.002*	0.003	0.044	−0.028	0.029	−0.001
	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(−0.001)	(0.002)	(0.033)	(0.026)	(0.037)	(0.005)
$StockSale_t$	0.004	−0.002	0.000	−0.005	−0.002**	−0.001	−0.000	0.012	−0.088	0.056	−0.010
	(0.005)	(0.004)	(0.000)	(0.006)	(0.001)	(0.002)	(0.008)	(0.052)	(0.080)	(0.042)	(0.014)
$StockPurchase_t$	0.002**	−0.000	−0.000	0.004	0.002	0.001	−0.011	0.012	0.096*	−0.662**	0.014
	(0.001)	(0.000)	(0.000)	(0.003)	(0.004)	(0.001)	(0.007)	(0.152)	(0.053)	(0.244)	(0.015)
$BondPurchase_t$	−0.010	0.003	−0.000	−0.004	0.000	0.010**	−0.001	−0.003	0.080	−0.008	−0.000
	(0.006)	(0.004)	(0.00)	(0.005)	(0.001)	(0.005)	(0.001)	(0.007)	(0.223)	(0.013)	(0.008)
$D_{Crisis,t}$	0.040**	−0.008	0.045**	−0.026	−0.009	−0.026	0.008	−0.019	0.007	0.016	−0.015
	(0.018)	(0.021)	(0.019)	(0.021)	(0.020)	(0.024)	(0.010)	(0.018)	(0.016)	(0.020)	(0.021)
VIX_t	−0.057	−0.055	−0.032	−0.037	0.016	−0.044	−0.007	−0.003	−0.001	0.029	−0.017
	(0.031)	(0.034)	(0.030)	(0.035)	(0.032)	(0.037)	(0.016)	(0.030)	(0.026)	(0.032)	(0.034)
$SENT_t * LIQ_t$	0.157	0.162	0.069	−0.195	0.056	0.187	−0.142	0.140	−0.129	0.213	0.109
	(0.171)	(0.195)	(0.172)	(0.196)	(0.175)	(0.203)	(0.092)	(0.167)	(0.148)	(0.176)	(0.186)
$LIQ_t * D_{Crisis,t}$	0.078	−0.215	0.142	0.156	−0.360	0.499	0.318**	0.118	0.159	−0.292	0.053
	(0.275)	(0.319)	(0.278)	(0.322)	(0.283)	(0.331)	(0.150)	(0.270)	(0.241)	(0.285)	(0.302)
R^2	0.1997	0.1155	0.1165	0.1072	0.0417	0.1096	0.0992	0.0847	0.0731	0.1190	0.0738

Table 13: Seemingly Unrelated Regressions on Clayton's left tail dependency. The third model controls for common random shocks. The fourth equation controls for trade related characteristics. The fifth model controls for financial characteristics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are shown between parentheses.

Appendix IV: GFC DCC results

Var	DE	FR	UK	NL	JP	CA	CN	RU	IN	ID	MX
α	0.811***	0.823***	0.838***	0.830***	0.556**	0.777***	0.190***	0.554***	0.421***	0.413***	0.605***
	(0.011)	(0.009)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.012)	(0.013)	(0.007)	(0.011)
$D_{GFC,t}$	0.067***	0.087***	0.041***	0.037***	0.062***	0.004	0.058***	−0.065***	0.221*	0.024*	0.0189
	(0.014)	(0.010)	(0.007)	(0.008)	(0.007)	(0.011)	(0.006)	(0.023)	(0.023)	(0.015)	(0.026)
FFR_t	−3.4297***	−4.407***	−4.252***	−4.111***	−3.991***	−1.149***	−2.454***	−5.850***	−3.168***	−0.586**	0.0189
	(0.408)	(0.329)	(0.355)	(0.324)	(0.213)	(0.224)	(0.117)	(0.314)	(0.352)	(0.256)	(0.026)
$R_{oil,t}$	−0.035	0.083	0.129**	0.058	0.060	0.073*	0.024	0.134	−0.0811	0.044	−0.004
	(0.084)	(0.064)	(0.063)	(0.057)	(0.047)	(0.043)	(0.028)	(0.086)	(0.079)	(0.043)	(0.084)
$R_{gold,t}$	0.362***	0.214*	0.063	0.147	0.068	0.084	0.024	−0.048	−0.126	−0.032	0.078
	(0.152)	(0.121)	(0.109)	(0.118)	(0.093)	(0.089)	(0.072)	(0.172)	(0.079)	(0.094)	(0.084)
$SENT_t$	−0.024	0.007	0.046***	−0.004	0.044***	0.013	−0.005	0.088***	0.004	0.011	0.008
	(0.014)	(0.010)	(0.011)	(0.009)	(0.007)	(0.008)	(0.005)	(0.014)	(0.013)	(0.009)	(0.012)
$SENT_t * D_{GFC,t}$	−0.021***	0.000	−0.048***	−0.040***	−0.044***	−0.089***	−0.029***	−0.283***	−0.126***	−0.212***	−0.107***
	(0.004)	(0.016)	(0.014)	(0.012)	(0.011)	(0.017)	(0.010)	(0.038)	(0.044)	(0.032)	(0.043)
R^2	0.344	0.102	0.093	0.099	0.079	0.070	0.053	0.136	0.170	0.073	0.127
α	0.573**	1.273***	1.507***	1.431***	1.871***	0.439***	1.021***	2.553***	2.467***	0.963***	0.501**
	(0.217)	(0.126)	(0.149)	(0.117)	(0.128)	(0.094)	(0.081)	(0.242)	(0.297)	(0.115)	(0.217)
$D_{GFC,t}$	0.033	0.005	−0.052	−0.059***	−0.053**	0.001	−0.044***	−0.256***	0.078	−0.007	0.021
	(0.031)	(0.019)	(0.035)	(0.017)	(0.020)	(0.015)	(0.012)	(0.037)	(0.047)	(0.017)	(0.033)
$TOT_{US,t}$	0.002	−0.006***	−0.008***	−0.007***	−0.015***	0.003**	−0.009***	−0.023***	−0.023***	−0.006***	0.001
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.002)
$\pi_{US,t}$	0.002	−0.009	−0.003	−0.019	−0.017	0.003	−0.008	−0.028	−0.058	0.005	−0.014
	(0.026)	(0.017)	(0.020)	(0.014)	(0.017)	(0.013)	(0.010)	(0.031)	(0.039)	(0.014)	(0.027)
$\pi_{j,t}$	−0.003	0.015	−0.006	0.000	−0.007	−0.007	−0.007***	−0.002	−0.024	−0.001	−0.043***
	(0.013)	(0.020)	(0.008)	(0.006)	(0.007)	(0.008)	(0.002)	(0.004)	(0.016)	(0.003)	(0.008)
$IPGrowth_{US,t}$	0.006	0.005	−0.026**	−0.002	−0.017*	0.004	−0.006	−0.036*	−0.014	0.012	0.006
	(0.013)	(0.008)	(0.010)	(0.007)	(0.008)	(0.006)	(0.005)	(0.015)	(0.019)	(0.007)	(0.014)
$IPGrowth_{j,t}$	−0.004	0.002	0.000	0.000	0.001	−0.000	0.000	0.000	0.001	0.000	0.002
	(0.003)	(0.002)	(0.003)	(0.001)	(0.001)	(0.003)	(0.000)	(0.001)	(0.002)	(0.001)	(0.006)
$\sigma^2_{FX,t}$	−0.294***	−0.008***	0.244	−0.118***	0.000	−0.867***	−0.033***	−0.000***	−0.000	0.000***	−0.001
	(0.025)	(0.000)	(0.964)	(0.008)	(0.000)	(0.082)	(0.002)	(0.000)	(0.000)	(0.000)	(0.001)
$Im-Growth_{j,US,t}$	−0.000	0.000	0.000	−0.000	0.000	−0.000	−0.000	0.000	−0.001	−0.000	−0.002
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.002)
$Ex-Growth_{j,US,t}$	0.001	0.000	−0.000	0.000	0.000	0.000	−0.000	−0.000	0.000	0.000	0.002
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
$SENT_t$	−0.048***	−0.049***	−0.040***	−0.061***	−0.024***	−0.016**	−0.025***	0.001	−0.029	−0.001	0.000
	(0.012)	(0.007)	(0.009)	(0.007)	(0.007)	(0.006)	(0.004)	(0.014)	(0.017)	(0.006)	(0.012)
$SENT_t * D_{GFC,t}$	−0.070	−0.130***	−0.126**	−0.115***	−0.171***	−0.125***	−0.110***	−0.478***	−0.301***	−0.251***	−0.120**
	(0.059)	(0.036)	(0.045)	(0.033)	(0.038)	(0.028)	(0.022)	(0.071)	(0.089)	(0.032)	(0.060)
R^2	0.5163	0.7304	0.2499	0.7156	0.4342	0.3545	0.7325	0.4020	0.3299	0.2236	0.1374
α	0.732***	0.724***	0.766***	0.759***	0.402***	0.781***	0.112***	0.430***	0.339***	0.400***	0.625***
	(0.022)	(0.013)	(0.015)	(0.012)	(0.012)	(0.009)	(0.007)	(0.024)	(0.023)	(0.011)	(0.021)
$D_{GFC,t}$	0.019	0.006	0.039	0.009	−0.002	0.017	0.033**	−0.098**	0.164***	−0.014	−0.004
	(0.036)	(0.028)	(0.025)	(0.025)	(0.014)	(0.016)	(0.014)	(0.050)	(0.048)	(0.019)	(0.035)
VIX_t	−0.075**	−0.053**	−0.044	−0.027	−0.008*	−0.034*	−0.023	−0.073	−0.061	−0.019	−0.064
	(0.040)	(0.029)	(0.027)	(0.025)	(0.016)	(0.018)	(0.016)	(0.054)	(0.055)	(0.021)	(0.039)
LIQ_t	−0.036	0.031	−0.105	0.079	0.139**	−0.021	0.119**	0.210	−0.002	0.157**	−0.145
	(0.131)	(0.096)	(0.090)	(0.082)	(0.053)	(0.059)	(0.052)	(0.181)	(0.185)	(0.073)	(0.131)
$SENT_t$	−0.083***	−0.072***	−0.039***	−0.075***	−0.026***	−0.005	−0.032***	−0.033*	−0.014	−0.006	0.002
	(0.014)	(0.010)	(0.009)	(0.008)	(0.005)	(0.006)	(0.005)	(0.018)	(0.019)	(0.007)	(0.014)
$M2Growth_{US,t}$	0.036	0.018	0.029	0.022	0.005	0.028**	0.015	0.073**	−0.005	−0.004	0.006
	(0.022)	(0.016)	(0.015)	(0.014)	(0.009)	(0.010)	(0.009)	(0.030)	(0.030)	(0.012)	(0.022)
$M2Growth_{j,t}$	0.004	−0.001	0.010	−0.001	0.040**	−0.023**	−0.001	0.001	−0.000	0.003	−0.009
	(0.009)	(0.002)	(0.007)	(0.002)	(0.015)	(0.009)	(0.002)	(0.002)	(0.003)	(0.002)	(0.006)
$BondSale_t$	−5.156	−1.654	0.096	3.445	2.229**	0.416	−0.513	43.419	20.232	−5.067	−2.685
	(2.661)	(0.997)	(0.147)	(2.067)	(1.099)	(0.427)	(0.900)	(36.344)	(39.237)	(19.560)	(4.390)
$StockSale_t$	7.334	4.138*	0.116	3.016	−0.196	−0.484	10.440**	−28.160	42.778***	35.225	−12.000
	(4.787)	(2.169)	(0.211)	(3.337)	(0.344)	(0.670)	(4.071)	(64.122)	(12.274)	(20.468)	(12.864)
$StockPurchase_t$	−0.565	0.170	0.129	−5.231**	7.158***	0.661	31.564***	−155.937	−137.491	264.916*	11.789
	(1.018)	(0.181)	(0.122)	(2.357)	(1.342)	(0.389)	(3.624)	(164.428)	(76.388)	(136.823)	(13.923)
$BondPurchase_t$	8.704	1.324	−0.958***	5.742**	3.647***	−6.135***	0.099	5.968	66.062	−15.995***	−6.724
	(5.189)	−2.263	(0.197)	(2.715)	(0.431)	(1.765)	(0.362)	(7.053)	(328.096)	(6.952)	−6.522
$SENT_t * D_{GFC,t}$	−0.030	−0.075**	−0.103***	−0.028	−0.124***	−0.102***	−0.076***	−0.364***	−0.239***	−0.216***	−0.097**
	(0.057)	(0.035)	(0.038)	(0.037)	(0.023)	(0.024)	(0.022)	(0.078)	(0.076)	(0.030)	(0.044)
$SENT_t * LIQ_t$	0.169	0.040	−0.051	0.031	−0.092	0.125	−0.112	−0.384	0.171	−0.116	0.108
	(0.161)	(0.117)	(0.110)	(0.102)	(0.064)	(0.072)	(0.063)	(0.220)	(0.223)	(0.087)	(0.158)
$LIQ_t * D_{GFC,t}$	0.119	0.046	0.146	−0.033	−0.129	0.145	−0.031	0.013	−0.056	−0.221	0.006
	(0.280)	(0.205)	(0.191)	(0.177)	(0.111)	(0.125)	(0.110)	(0.382)	(0.391)	(0.152)	(0.278)
R^2	0.1876	0.3805	0.1649	0.3730	0.5477	0.1931	0.6083	0.1574	0.2989	0.3065	0.0616

Table 14: Seemingly Unrelated Regressions on Dynamic Conditional Correlations: GFC . *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are shown between parentheses.

Appendix V: Sovereign bonds DCC results

Table 15: Descriptive statistics. The table presents the summary statistics for 10-year sovereign bonds in the dataset. From" is the start date of the return series of a particular sovereign bond. SD denotes the standard deviation. SW denotes the Shapiro-Wilk test statistic for non-normality. LB denotes the Ljung-Box statistic for autocorrelation with 10 lags. "ARCH" is Engle's test for Arch effects. ρ_{no} denotes the correlation during non-crises periods between the 10-y U.S. bond and the 10-y sovereign bond from the j^{th} row. Likewise, ρ_{crisis} shows the correlation during crises periods. ***, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively. The data ends 30/9/2015.

Country	From	Min	Max	Mean	SD	SW	LB(10)	ARCH(5)	ρ_{no}	ρ_{crisis}
United States	1/1/1990	0.015	0.091	0.049	0.018	0.980***	2351***	281.386***	-	-
Germany	1/1/1990	0.002	0.090	0.046	0.021	0.979***	2507***	298.861***	0.962	0.988
France	1/1/1990	0.004	0.105	0.049	0.022	0.959***	2619***	297.898***	0.933	0.977
United Kingdom	1/1/1990	0.012	0.127	0.055	0.026	0.949***	2533***	298.309***	0.956	0.975
Netherlands	1/1/1990	0.003	0.092	0.047	0.021	0.974***	2558	299.436***	0.9535	0.9809
Japan	1/1/1990	0.003	0.083	0.023	0.018	0.804***	2583***	290.634***	0.843	0.923
Canada	1/1/1990	0.018	0.115	0.056	0.023	0.957***	2535***	292.848***	0.948	0.985
China	1/6/2002	0.025	0.049	0.036	0.005	0.967***	2632***	103.915***	-0.014	0.706
Russia	1/1/1999	0.066	1.106	0.156	0.199	0.469***	491***	183.993***	0.515	0.714
India	1/5/1996	0.051	0.139	0.087	0.022	0.912***	1811***	208.755***	0.582	0.888
Indonesia	1/5/2003	0.052	0.173	0.097	0.025	0.977***	961***	86.773***	0.114	0.839
Mexico	1/10/1999	0.011	0.077	0.040	0.016	0.972***	1495***	162.792***	0.766	0.870

Param.	DE	FR	UK	NL	JP	CA	CN	RU	IN	ID	MX
$\epsilon^2_{US,t-1}$	0.880***	0.884***	0.710***	0.910***	0.973***	0.995***	0.791***	1.312***	1.008***	0.855***	0.873***
	(0.097)	(0.106)	(0.105)	(0.101)	(0.114)	(0.137)	(0.188)	(0.258)	(0.134)	(0.188)	(0.115)
$\epsilon^2_{US,t-2}$	−0.146	−0.003	−0.678***	−0.241	−0.596	−0.840**	0.116	–	–	–	–
	(0.258)	(0.319)	(0.099)	(0.252)	(0.424)	(0.309)	(0.314)	–	–	–	–
$\sigma^2_{US,t-1}$	−0.023	−0.165	1.055***	0.047	0.428	0.879**	−0.251	−0.181	−0.040	0.121	0.044
	(0.267)	(0.305)	(0.148)	(0.251)	(0.459)	(0.335)	(0.287)	(0.167)	(0.097)	(0.170)	(0.051)
$\sigma^2_{US,t-2}$	0.204***	0.157**	−0.092	0.218***	0.181	−0.030	0.225	–	–	–	–
	(0.060)	(0.075)	(0.130)	(0.058)	(0.103)	(0.090)	(0.122)	–	–	–	–
α_{US}	0.127**	0.154**	0.003	0.101***	0.035	0.014	0.159**	0.300**	0.146***	0.127***	0.105***
	(0.055)	(0.067)	(0.003)	(0.046)	(0.041)	(0.027)	(0.078)	(0.110)	(0.042)	(0.049)	(0.027)
$\epsilon^2_{i,t-1}$	0.562***	0.705***	0.571***	0.663***	0.614***	0.129	0.899***	1.301***	0.786***	1.043***	0.938***
	(0.096)	(0.094)	(0.087)	(0.104)	(0.095)	(0.094)	(0.155)	(0.183)	(0.153)	(0.153)	(0.125)
$\epsilon^2_{i,t-2}$	0.692***	−0.592***	−0.477***	0.710***	−0.520***	0.691***	0.633***	–	–	–	–
	(0.105)	(0.105)	(0.080)	(0.099)	(0.097)	(0.154)	(0.196)	–	–	–	–
$\sigma^2_{i,t-1}$	−0.597***	1.099***	1.093***	−0.686***	1.10***	0.432**	−0.659***	−0.093**	0.186	−0.093	0.032
	(0.096)	(0.094)	(0.161)	(0.101)	(0.146)	(0.174)	(0.164)	(0.035)	(0.126)	(0.065)	(0.048)
$\sigma^2_{i,t-2}$	0.235**	−0.225***	−0.201	0.219**	−0.205	−0.214**	0.138	–	–	–	–
	(0.095)	(0.073)	(0.123)	(0.088)	(0.107)	(0.078)	(0.071)	–	–	–	–
α_i	0.081***	0.008	0.008**	0.074**	0.002	0.050***	0.048**	0.090***	0.053**	0.610**	0.074***
	(0.022)	(0.004)	(0.004)	(0.023)	(0.001)	(0.014)	(0.019)	(0.024)	(0.018)	(0.260)	(0.023)
λ_1	0.619***	0.638***	0.598***	0.611***	0.503***	0.421***	0.851***	0.812***	0.728***	0.721***	0.461***
	(0.048)	(0.061)	(0.044)	(0.049)	(0.045)	(0.041)	(0.038)	(0.082)	(0.056)	(0.072)	(0.051)
λ_2	0.319***	0.309***	0.391***	0.345***	0.468***	0.557***	0.071*	0.159	0.221***	0.143**	0.524***
	(0.051)	(0.069)	(0.046)	(0.052)	(0.045)	(0.041)	(0.037)	(0.088)	(0.060)	(0.071)	(0.055)
$log(\mathcal{L})$	786.45	757.12	812.31	741.21	801.24	896.51	815.72	781.93	755.96	817.51	864.35

Table 16: DCC-GARCH parameters estimates. $\epsilon^2_{i,t-j}$ and $\sigma^2_{i,t-j}$ denotes the $j-th$ ARCH/GARCH term respectively for country i. The λ terms denote the adjustment terms in the DCC-GARCH model. Semi-robust standard errors are always applied. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Var	DE	FR	UK	NL	JP	CA	CN	RU	IN	ID	MX
α	0.901^{***}	0.883^{***}	0.878^{***}	0.901^{***}	0.945^{***}	0.991^{***}	0.010	−0.083	−0.084	1.089^{***}	1.175^{***}
	(0.055)	(0.063)	(0.077)	(0.061)	(0.046)	(0.003)	(0.125)	(0.136)	(0.109)	(0.066)	(0.084)
$D_{Crisis,t}$	0.163^{***}	0.157^{**}	0.192^{**}	0.148^{**}	−0.003	0.008^{**}	0.565^{***}	−0.185	0.288^{**}	0.104	0.020
	(0.058)	(0.066)	(0.081)	(0.065)	(0.049)	(0.003)	(0.132)	(0.143)	(0.115)	(0.070)	(0.088)
FFR_t	-21.080^{***}	-23.260^{***}	-18.935^{***}	-23.768^{***}	-8.263^{***}	-0.739^{***}	-12.004^{**}	−2.669	−7.800	-14.670^{***}	-26.474^{***}
	(2.081)	(2.384)	(2.937)	(2.336)	(1.750)	(0.125)	(4.768)	(5.158)	(4.136)	(2.525)	(3.189)
$R_{Oil,t}$	$0.408*$	0.075	0.506	0.239	0.299	−0.022	1.198	1.181	0.528	−0.362	−0.015
	(0.296)	(0.339)	(0.418)	(0.332)	(0.249)	(0.018)	(0.678)	(0.733)	(0.588)	(0.359)	(0.453)
$R_{Gold,t}$	−0.046	−0.081	0.712	−0.152	0.003	0.033	−0.509	−1.461	−0.286	0.118	−0.473
	(0.518)	(0.594)	(0.731)	(0.582)	(0.436)	(0.031)	−1.187	−1.284	−1.030	(0.629)	(0.794)
$SENT_t$	-0.029^{**}	-0.005^{**}	0.002	-0.032^{**}	-0.003^{***}	-0.014^{***}	0.042^{***}	-0.043^{**}	−0.074	0.062	0.048
	(0.013)	(0.002)	(0.002)	(0.015)	(0.001)	(0.003)	(0.014)	(0.021)	(0.258)	(0.157)	(0.099)
$SENT_t * D_{Crisis,t}$	−0.012	-0.003^{***}	−0.086	-0.007^{***}	-0.004^{***}	-0.031^{***}	−0.015	0.017	−0.029	−0.010	-0.005^{***}
	(0.054)	(0.001)	(0.218)	(0.002)	(0.001)	(0.009)	(0.053)	(0.038)	(0.031)	(0.019)	(0.001)
R^2	0.6887	0.6646	0.3911	0.6792	0.1606	0.3492	0.2299	0.1129	0.3672	0.3206	0.3492
α	−2.503	-3.610^{**}	−1.538	−3.160	-2.207^{**}	1.365^{***}	-6.027^{**}	-10.078^{***}	−0.840	2.269	9.642^{***}
	(1.464)	(1.612)	(1.819)	(1.632)	(0.974)	(0.081)	(2.803)	(2.566)	(2.279)	(1.502)	(1.878)
$D_{Crisis,t}$	0.515^{***}	0.573^{***}	0.507^{***}	0.557^{***}	0.123	0.011	1.007^{***}	0.111	0.306^{**}	-0.212^{**}	-0.338^{**}
	(0.096)	(0.106)	(0.119)	(0.107)	(0.069)	(0.007)	(0.180)	(0.167)	(0.147)	(0.099)	(0.123)
$TOT_{US,t}$	-0.033^{**}	-0.044^{**}	−0.024	-0.039^{**}	-0.033^{***}	-0.004^{***}	−0.061	-0.112^{***}	0.005	−0.016	-0.102^{***}
	(0.016)	(0.018)	(0.020)	(0.018)	(0.011)	(0.001)	(0.032)	(0.029)	(0.025)	(0.017)	(0.021)
$\pi_{US,t}$	0.032	0.147	0.101	0.176	−0.058	−0.006	0.106	0.116	0.187	−0.198	−0.091
	(0.110)	(0.124)	(0.140)	(0.123)	(0.075)	(0.007)	(0.198)	(0.193)	(0.169)	(0.113)	(0.142)
$\pi_{j,t}$	0.043	−0.057	0.043	−0.002	0.085	0.009	−0.076	−0.088	0.202^{*}	−0.038	−0.023
	(0.033)	(0.096)	(0.092)	(0.024)	(0.064)	(0.006)	(0.108)	(0.104)	(0.101)	(0.033)	(0.093)
$IPGrowth_{US,t}$	0.106^{**}	0.111	0.041	0.128^{**}	0.028	0.003	-0.210^{**}	0.008	−0.109	0.025	0.098
	(0.054)	(0.059)	(0.067)	(0.060)	(0.036)	(0.003)	(0.096)	(0.095)	(0.081)	(0.056)	(0.069)
$IPGrowth_{j,t}$	−0.012	0.001	0.015	0.001	0.011	−0.002	−0.003	−0.004	−0.001	−0.004	0.031
	(0.007)	(0.008)	(0.037)	(0.004)	(0.008)	(0.002)	(0.025)	(0.006)	(0.010)	(0.006)	(0.040)
σ_t^2	-8.697^{**}	−1.268	-36.605^{***}	-9.993^{***}	-0.009^{***}	−0.199	-0.253^{**}	-0.010^{***}	0.000	-0.000^{**}	-0.016^{***}
	(4.117)	(5.216)	(7.316)	(5.171)	(0.000)	(0.127)	(0.106)	(0.001)	(0.000)	(0.000)	(0.005)
$ExGrowth_{j,US,t}$	0.000	−0.000	0.002	−0.000	0.003	−0.000	−0.003	−0.001	0.001	−0.000	0.007
	(0.001)	(0.001)	(0.003)	(0.001)	(0.003)	(0.000)	(0.005)	(0.003)	(0.003)	(0.001)	(0.009)
$ImGrowth_{j,US,t}$	0.000	−0.001	−0.000	0.000	−0.001	−0.000	0.004	−0.000	0.003	−0.001	−0.007
	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.000)	(0.007)	(0.002)	(0.004)	(0.003)	(0.009)
$SENT_t$	-0.012^{***}	-0.012^{***}	−0.240	-0.010^{***}	−0.008	-0.014^{**}	−0.013	-0.064^{**}	-0.043^{***}	−0.008	−0.006
	(0.002)	(0.002)	(0.190)	(0.002)	(0.005)	(0.007)	(0.261)	(0.025)	(0.010)	(0.022)	(0.089)
$SENT_t * D_{Crisis,t}$	-0.015^{**}	-0.007^{**}	−0.026	-0.005^{***}	-0.012^{**}	-0.025^{**}	−0.008	-0.005^{**}	-0.008^{**}	−0.016	−0.006
	(0.007)	(0.004)	(0.020)	(0.001)	(0.004)	(0.012)	(0.005)	(0.002)	(0.003)	(0.015)	(0.032)
R^2	0.5112	0.4961	0.2697	0.4969	0.2002	0.3164	0.2340	0.2955	0.3890	0.1490	0.2384
α	0.446^{***}	0.577^{***}	0.612^{***}	0.499^{***}	1.020^{***}	0.954^{***}	-0.398^{**}	0.083	-0.578^{***}	0.432^{***}	−0.097
	(0.110)	(0.093)	(0.204)	(0.081)	(0.148)	(0.006)	(0.184)	(0.205)	(0.140)	(0.084)	(0.149)
$D_{Crisis,t}$	0.389^{***}	0.565^{***}	0.379^{***}	0.546^{***}	0.079	0.006	0.663^{***}	−0.025	0.315^{**}	-0.250^{**}	-0.240^{**}
	(0.075)	(0.078)	(0.103)	(0.082)	(0.058)	(0.005)	(0.153)	(0.151)	(0.123)	(0.086)	(0.115)
VIX_t	0.049	0.100	0.023	0.038	−0.019	−0.002	0.144	−0.149	−0.031	−0.209	−0.099
	(0.165)	(0.167)	(0.207)	(0.172)	(0.110)	(0.008)	(0.321)	(0.331)	(0.263)	(0.163)	(0.215)
LIQ_t	0.662	1.508	2.162	1.371	1.298	0.056	−1.543	−2.535	2.092	−1.297	−2.696
	(1.065)	(1.075)	(1.343)	(1.108)	(0.718)	(0.052)	(2.121)	(2.124)	(1.708)	(1.052)	(1.419)
$SENT_t$	-0.090^{**}	-0.009^{**}	-0.036^{**}	−0.221	-0.069^{**}	-0.025^{***}	−0.199	−0.091	−0.039	−0.079	-0.007^{**}
	(0.033)	(0.003)	(0.016)	(0.129)	(0.033)	(0.007)	(0.259)	(0.086)	(0.192)	(0.122)	(0.003)
$M2Growth_{US,t}$	0.054	0.031	−0.043	−0.015	−0.015	−0.004	−0.007	−0.066	−0.003	0.167	0.021
	(0.096)	(0.097)	(0.122)	(0.101)	(0.065)	(0.005)	(0.191)	(0.194)	(0.149)	(0.095)	(0.128)
$M2Growth_{j,t}$	−0.018	0.005	0.019	0.002	−0.134	0.005	0.059	0.006	−0.026	−0.013	0.056
	(0.041)	(0.011)	(0.095)	(0.010)	(0.136)	(0.005)	(0.053)	(0.018)	(0.032)	(0.013)	(0.037)
$BondSale_t$	0.021	0.013^{***}	−0.056	0.010	−0.007	0.242	−0.034	−0.000	0.075	0.149	0.038
	(0.012)	(0.004)	(1.360)	(0.009)	(0.010)	(0.207)	(0.018)	(0.000)	(0.168)	(0.131)	(0.025)
$StockSale_t$	0.003	−0.013	0.150	-0.038^{**}	-0.012^{***}	0.001	−0.037	0.000	0.207^{**}	0.001^{***}	−0.006
	(0.028)	(0.010)	(2.131)	(0.017)	(0.003)	(0.000)	(0.084)	(0.000)	(0.069)	(0.000)	(0.062)
$StockPurchase_t$	−0.000	-0.003^{***}	0.001	−0.017	0.029	0.121	−0.078	−0.002	0.377	0.001	0.028^{***}
	(0.003)	(0.001)	(0.001)	(0.010)	(0.016)	(0.232)	(0.089)	(0.001)	(0.326)	(0.001)	(0.006)
$BondPurchase_t$	−0.025	0.003	−0.003	0.051^{***}	−0.003	0.254	0.025^{**}	0.040	0.003	0.187^{***}	0.064^{**}
	(0.018)	(0.010)	(0.002)	(0.016)	(0.004)	(0.930)	(0.088)	(0.080)	(0.002)	(0.041)	(0.032)
$SENT_t * D_{Crisis,t}$	-0.005^{***}	-0.032^{**}	−0.065	-0.018^{***}	−0.009	-0.036^{***}	-0.003^{***}	−0.000	-0.006^{**}	−0.057	-0.028^{**}
	(0.001)	(0.013)	(0.062)	(0.002)	(0.132)	(0.010)	(0.000)	(0.000)	(0.003)	(0.198)	(0.011)
$SENT_t * LIQ_t$	0.781	0.790	0.278	0.980	0.424	−0.106	−0.781	−0.454	0.374	−0.043	−1.505
	(1.492)	(1.524)	(1.896)	(1.571)	(0.994)	(0.074)	(2.910)	(3.045)	(2.352)	(1.476)	(1.972)
$LIQ_t * D_{Crisis,t}$	0.691	−1.101	−1.542	−0.357	−1.369	−0.053	1.570	5.227	−1.002	2.493	2.417
	(1.272)	(1.295)	(1.635)	(1.337)	(0.843)	(0.062)	(2.449)	(2.926)	(1.979)	(1.229)	(1.672)
R^2	0.5069	0.5735	0.2832	0.5415	0.2442	0.3711	0.2089	0.1479	0.4497	0.3293	0.3115

Table 17: Seemingly Unrelated Regressions on Dynamic Conditional Correlations: GFC . *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are shown between parentheses.