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List of Abbreviations

ADL	Autoregressive Distributed Lag approach
BIC	Bayesian Information Criterion
CET	Central European Time
EDT	Eastern Daylight Time
EMH	Efficient Market Hypothesis
ESTX	Euro Stoxx 50 Index
HAR-DL	Heterogeneous Autoregressive Distributed Lag model
HAR-GARCH	Heterogeneous Autoregressive Generalized Autoregressive Conditional Heteroskedasticity model
HAR-RV	Heterogeneous Autoregressive model of Realized Volatility
HKT	Hong Kong Time
HSI	Hang Seng Index
H-VAR	Heterogeneous Vector Autoregressive model
ICSS	Iterated Cumulative Sums of Squares
IV	Integrated Variance
Log-RV	Logarithmized Realized Volatility
LWZ	Schwarz Criterion
NYSE	New York Stock Exchange
OLS	Ordinary Least Squares
RV	Realized Volatility
RVAR	Realized Variance
RTQT	Realized Tri-Power Quarticity
SIRCA	Securities Industry Research Centre of Asia-Pacific
S&P	S&P 500 Index
SSR	Sum of Squared Residuals
SVAR	Structural Vector Autoregressive model
US	United States of America
UTC	Universal Time Coordinated
VAR	Vector Autoregressive model
V-HAR-MGARCH	Vector Heterogeneous Autoregressive Multivariate Generalized Autoregressive Conditional Heteroskedasticity model

Chapter 1

Introduction

'Efficient markets hypothesis' inefficient [...] For more than four decades, financial markets and the regulations that govern them were underpinned by what is known as the efficient markets hypothesis. All that changed after the financial crisis.

Financial Times (January 24, 2012)

1.1 Motivation

Early contributions on the linkages between international financial markets focused on the benefits of globally integrated financial markets. Studies, such as Grubel (1968), Levy and Sarnat (1970) or Grubel and Fadner (1971) were inspired by the groundbreaking ideas on portfolio selection of Markowitz (1952) and Tobin (1958). They dealt with potential welfare gains from risk-reduction by means of international diversification.

More recent studies, however, tend to focus on the potential downside of globally integrated financial markets. As Kindleberger and Aliber (2011) state, periods of high asset price volatility and financial crises have frequently been observed across various countries worldwide since the early 1970s. A key challenge in this context is to understand the exact mechanisms that drive the transmission of financial market crises across countries. Current motivation for research comes from the financial crisis of 2007 which led the international financial system to the brink of collapse.

Press quotations, such as the one given in the introductory statement, reflect a deep public discomfort with the hitherto existing financial market theory and a belief in the necessity to reconsider fundamental economic principles in response to the crisis. Conventional economic theory, however, suggests that informational efficiency ensures that cross-market information transmission and the resulting price movements instantaneously reflect the underlying deeper roots of crises-transmission such as trade-links, common lenders or foreign investment.[1] Market participants' information processing itself is hence not a fundamental source of crises transmission across international financial markets.

However, despite a large number of general studies on financial crises and the linkages between international markets, the precise knowledge of the process of information transmission is surprisingly limited. In particular, it is unclear whether the mechanism of cross-market information transmission changes over time or over different states of the economy. Further, the question is how far the dynamics and interdependence of returns and volatilities are affected and whether such changes can be attributed to market inefficiencies, to fundamental or only temporary differences.

Non-linearities, such as the potential time- and state-dependence of cross-market linkages, have received little attention so far. Closely related, the notion of contagion is controversial. It suggests that sudden shifts in behavior and changes in investor information processing might occur in times of crises. As a result, crises might spread suddenly, quickly and in an unpredictable manner. However, empirically proving the existence of contagion is technically demanding and confined to measurement issues.

Moreover, the number of studies, considering latest high-frequency stock market data to measure cross-market linkages in returns and volatilities, is limited as well. A key issue is that trading hours across international financial markets differ and that stock markets' intra daily price observations are only available over active trading periods.

[1] See, for example, Kaminsky and Reinhart (2000).

The information flow in international financial markets, however, can be considered as continuous. How to optimally deal with this situation is not clear a priori.

This thesis addresses the above-mentioned points in four different studies. The common focus of all analyses is a long-term investigation of cross-market information transmission. Special consideration is given to the impact of the financial crisis of 2007 as well as the aspect of potential state-dependence in cross-market linkages. The following points provide a summary of the studies' key questions:

1. Is there evidence for time- and state-dependence of return spillovers between stock markets in Hong Kong, Europe and the US? What are the implications for informational efficiency?
2. Are there structural breaks in volatility spillovers between the markets considered? If so – are these effects consistent with the notion of contagion as a strong and sudden synchronization of chronologically succeeding volatilities?
3. Do quantile regressions provide new insights into return spillovers from the US to stock markets in Asia? Which conclusions can be drawn about Asian traders' information processing at market opening?
4. Which new insights can be obtained from measuring transatlantic volatility interdependence based on synchronous 24-hour realized volatilities? How to estimate 24 hour realized volatilities despite intermittent high-frequency data and non-synchronous trading hours across stock markets in Europe and the US?

Answers to these questions are of direct relevance for international policy makers and investors. As Goodhart (2011) or Buiter (2012) report, maintaining financial stability has recently gained in importance in various important institutions all over the world. A solid understanding of financial market linkages is not only important in the context of international asset allocation and risk management. It is also crucial with a view to improving the current financial architecture and to make the international financial system more resilient towards crises in the future.

1.2 Structure of the Thesis

This thesis is divided into six chapters. Chapter 1 presents the motivation and the structure of the thesis. Chapters 2 to 5 consist of four different stand-alone studies. The first, the third and the fourth study are single-authored. The second study is co-authored with Robert Jung. The common theme of all studies is the modeling of the dynamics and interdependence of global financial markets by means of innovative econometric techniques.

Specifically, Chapter 2 performs an investigation of information transmission between stock markets in Hong Kong, Europe and the US from 2000 to 2011. It is based on the paper *Information Transmission between Stock Markets in Hong Kong, Europe and the US: New Evidence on Time- and State-dependence*, published in the Pacific-Basin Finance Journal (see Maderitsch (2014)). The particular focus of the paper is on the time- and state-dependence of return spillovers and autocorrelations as well as the related potential deviations from informational efficiency. After discussing the related literature and introducing the empirical framework with non-overlapping intra-day returns, the article provides new evidence on cross-market return spillovers. In particular, it presents results from structural break tests, moving window regressions and threshold regressions. Further, it elaborates on the economic implications of the results – inter alia with regard to market efficiency. Moreover, it takes various robustness considerations into account.

Chapter 3 analyzes the same markets over the same time period. It is based on the paper *Structural Breaks in Volatility Spillovers between International Financial Markets: Contagion or mere Interdependence?*, co-authored with Robert Jung and published in the Journal of Banking and Finance (see Jung and Maderitsch (2014)).[2] The focus of

[2] The fundamental question of this paper has been developed jointly by the two authors. Robert Maderitsch essentially prepared the data, further developed the research question, conducted the econometric estimations, presented at various conferences and prepared a first version of the paper. Robert Jung basically accompanied the whole process and contributed substantially to joint revisions and the preparation of a ready-to-publish version of the paper.

the article is on the cross-market transmission of realized volatilities and the potential presence of contagion. Firstly, it discusses the related literature and clarifies important terminology. Secondly, it presents the empirical framework, inter alia a newly developed Heterogeneous Autoregressive Distributed Lag Model of Realized Volatility. Then it presents estimation results for the total sample as well as for moving windows. Subsequently, it investigates the role of structural breaks in realized volatilities and the role of conditional heteroskedasticity. Finally, it summarizes the economic implications of the results with respect to cross-market volatility contagion.

In Chapter 4, cross-market return spillovers are under investigation. The basis of the chapter is the paper *Spillovers from the USA to Stock Markets in Asia: A Quantile Regression Approach*, published in Applied Economics (see Maderitsch (2015)). This time, the focus is on spillovers from the US to several different stock markets in Asia. Further, quantile regression techniques are used and the sample period is longer, lasting from about 1990 up to 2014. After presenting the data and the institutional framework, the paper introduces a new Quantile Spillover Model and elaborates on the so called structure and degree of spillovers. Then it presents estimation results for a baseline model as well as for selected extensions of this model, assessing inter alia the impact on spillovers of weekends and the financial crisis of 2007. Moreover, it presents various robustness checks and provides a detailed discussion of the economic implications of the findings.

Chapter 5 investigates volatility interdependence between stock markets in Europe and the US. It is based on the working paper *24-Hour Realized Volatilities and Transatlantic Volatility Interdependence*, currently under review.[3] This paper conducts a first time investigation of the interdependence in 24-hour realized volatilities across stock markets in Europe and the US. In particular, it proposes an innovative economet-

[3] Earlier versions have been presented at the Joint Doctoral Seminar in Econometrics, University of Hohenheim and Tübingen 2013 in Blaubeuren, Germany, the IWH-CIREQ Macroeconometric Workshop: Forecasting and Big Data 2013 in Halle, Germany and the CIdE Workshop in Econometrics and Empirical Econometrics 2014 at the Bank of Italy-SADiBa, Perugia, Italy.

ric approach to deal with non-synchronous trading hours and intermittent high-frequency data during overnight non-trading periods. After introducing the data and the institutional framework, the article considers the concept of Hansen and Lunde (2005) for the computation of 24-hour realized variances. Subsequently, it extends this approach to obtain synchronous 24-hour realized volatilities across stock markets in Europe and the US. Then it demonstrates the new possibilities that the approach opens up, estimating a vector heterogeneous autoregressive multivariate generalized autoregressive conditional heteroskedasticity (V-HAR-MGARCH) model of transatlantic volatility interdependence. Eventually, it discusses the results' economic implications.

Chapter 6 recaps, providing answers to the articles' key questions as well as a final synthesis.

Chapter 2

Information Transmission Between Stock Markets in Hong Kong, Europe and the US: New Evidence on Time- and State-Dependence

This article performs a long-term investigation of information transmission between stock markets in Hong Kong, Europe and the US. The particular focus is on the time- and state-dependence of return spillovers and autocorrelations as well as the related deviations from informational efficiency. We use intra-daily data for the Hang Seng, the Euro Stoxx 50 and the S&P 500 index from 2000 to 2011 and conduct Granger causality inference based upon non-overlapping intra-day returns. Results from structural break tests suggest that the process of information transmission is structurally stable over time. Moving window regressions, however, reveal short-lived temporary deviations from informational efficiency in the form of weak, but significant spillovers and return autocorrelations. Most pronounced are temporary negative spillovers from the US to Hong Kong as well as temporary positive spillovers from Europe to the US. Threshold model estimations finally indicate that the former are only significant if the chronologically directly preceding US market is in a low volatility state. The latter, however, are only significant if the chronologically directly preceding European market is in a high volatility state. [1]

[1]This article is printed with kind permission of Elsevier. It has been originally published as *Maderitsch R. (2014). Information transmission between stock markets in Hong Kong, Europe and the US: New evidence on time- and state-dependence. Pacific-Basin Finance Journal. Doi:10.1016/j.pacfin.2014.07.006.*

2.1 Introduction

This paper analyzes information transmission between stock markets in Hong Kong, Europe and the US over more than a decade. In particular, we provide new evidence on the structural stability as well as the time- and state-dependence of information transmission across the markets.

Exploiting the chronological order of trading across Asia, Europe and the US, we measure return spillovers and autocorrelations within a joint econometric framework. Spillovers, according to our understanding, are effects of the conditional means of foreign intra-day returns onto the conditional means of intra-day returns in chronologically succeeding domestic markets. To ensure appropriate Granger causality inference, we use a unique sample of non-overlapping intra-day returns. To construct this sample, we resort to high frequency data for the Hang Seng, the Euro Stoxx 50 and the S&P 500 Index between January 2000 and September 2011. Using particular proxies instead of the original index opening quotes, we take potential stale prices, contained in index opening quotes into account.

(Strong-form) market efficiency suggests that cross-market return spillovers, according to the definition from above, are not statistically distinguishable from zero. Further, it suggests that statistically significant return autocorrelations do not exist. The reason is that in informationally efficient markets, information generated in chronologically preceding foreign markets should be fully incorporated into market opening prices. Yet, numerous studies provide evidence that statistically significant spillovers and autocorrelations do appear (see Section 2.2). Typically, however, the effects are found to be short-lived and only of a weak magnitude.

The long sample period that we analyze contains various important events such as the bursting dotcom bubble in 2000, the terrorist attacks on September 11, 2001, the financial crisis of 2007 and the subsequent European sovereign debt crisis of 2009. The popular press suggests that informational efficiency has been affected severely, particularly in the wake of the financial crisis of 2007. The public skepticism towards the concept of market efficiency even goes so far as that the chief economics commentator of the Financial Times, Martin Wolf, stated that 'a belief in efficient markets proved wrong' and that this belief 'must be abandoned'.[2]

Motivated by this statement, we start from an analysis of the total sample, moving on to investigate the time-dependence of spillovers and autocorrelations by structural break tests and moving window regressions. The former allow us to evaluate the structural stability of the process of information transmission over time. The latter enable us to identify potentially crisis-related temporary deviations from informational efficiency.

To further take the potential state-dependence of spillovers and autocorrelations into account, we estimate non-linear threshold models, according to Chan (1993), Hansen (1996) and Hansen (2000). These models allow us to test for a possible linkage between the degree and the significance of spillovers and the current level of realized volatility. Theoretically, we accommodate the fact that the level of volatility, prevailing in the markets, might affect traders' behavior. In a state of low volatility, for example, traders might face little uncertainty and process information, generated in previously trading markets, quickly. Spillovers should hence be weak, if significant at all. In a state of high volatility, however, traders might be confronted with a lot of valuation insecurity. They might over- and underreact or incorporate information in a time-delayed manner. This, in turn, might induce both statistically and economically significant spillovers.

The findings of our study are important, not only with respect to evaluating statements, such as the one given above. More importantly, we contribute to an ongoing academic discussion on time-varying market efficiency.[3] In this context Lo (2004)'s Adaptive Markets Hypothesis, for example, states that market efficiency should not

[2]Financial Times (October 27, 2009).

[3]For an excellent summary article see Lim and Brooks (2011).

be seen as an all-or-none condition. Leaving the general concept of market efficiency beyond doubt, it suggests that the particular degree of market efficiency might well vary across markets and over time.

In addition, we add to improve the understanding of information transmission across international stock markets. This is of great importance for international policy makers and investors. Both rely on a solid functioning of market mechanisms. For policy makers, return spillovers and autocorrelations are foremost important with regard to the evaluation of stock markets' integration and maturity. Further, they are relevant in terms of understanding, as well as preventing, the propagation of financial crises. Moreover, they play a role for financial regulation, for example, with regard to circuit breakers and short-sale constraints. For international investors, spillovers and return autocorrelations are important in the context of optimal investment strategies and international portfolio diversification.

The remainder of this paper is organized as follows. In Section 2.2 we discuss the related literature. In Section 2.3 we present our empirical framework. We introduce our data with the institutional particularities and the econometric model. In addition, we present descriptive statistics for the particular return data that we use. Thereupon, in Section 2.4, we present the results of our total sample estimations, the structural break tests, the moving window estimations and the threshold regressions. Then we provide robustness considerations, before we conclude in Section 2.5.

2.2 Related Literature

Using our definition of spillovers from above, we follow particularly Hamao et al. (1990) who initiated a body of literature, continued, for example, by Lin et al. (1994), Susmel and Engle (1994), Wei et al. (1995), Baur and Jung (2006) and Dimpfl and Jung (2012). Characteristic for this literature is the fact that information transmission between stock markets is analyzed on the basis of Granger causality inference and non-overlapping intra-day returns. Return autocorrelations are typically not of central interest in these studies.

Generally though, return autocorrelations receive a lot of attention in the literature, too. Lim and Brooks (2011), for example, provide an overview on recent developments, particularly with regard to an ongoing academic discussion on time-varying market efficiency. A popular statistical technique in this context is moving window regression. Timmermann (2008), Ito and Sugiyama (2009) or Kim et al. (2011), for example, use it to detect short-lived periods of significant autocorrelations in index returns. To rationalize their findings, they resort to the Adaptive Markets Hypothesis, in line with Lo (2004). In contrast to the Efficient Markets Hypothesis, according to Fama (1970) and Fama (1991), this concept provides a consistent framework that explicitly allows for a time-varying degree of return autocorrelations. Concerning cross-market spillovers, moving window regressions have, to the best of our knowledge, not been conducted up to now. However, with regard to the ongoing discussion on time-varying market efficiency, it appears obvious that the degree of spillovers might be time-varying, too.

By contrast, structural breaks and regime-dependence of spillovers have been taken into account recently. Example studies are Gebka and Serwa (2006), Gallo and Otranto (2008) and Gebka and Karoglou (2012). However, the econometric models that these authors use, differ strongly from ours. In the particular setting with non-overlapping intra-day returns, both aspects are still entirely new. Specifically, the realized volatility, which can be regarded as a proxy for uncertainty and information flow, has not yet been considered as a threshold variable.

From a theoretical point of view, the literature provides mainly two perspectives on spillovers and autocorrelations. According to the believers in rational expectations, they can be explained by partial price adjustment in the sense of, for example, Kyle (1985) or Admati and Pfleiderer (1988). A delayed incorporation of information into opening prices then results from strategic behavior of traders at the beginning of a new trading day. If traders are insecure about the information content of price movements in previous markets, they are supposed to exert their private informational advantage in a step-wise manner. Significant spillovers and autocorrelations hence do not necessarily imply market inefficiency. According to this line of reasoning, they are consistent with weak-form market efficiency.

Following the adherents of behavioral finance theory, however, significant spillovers and autocorrelations can be explained as irrational and psychologically grounded phenomena. Fung et al. (2000) and Fung et al. (2010), for example, diagnose that Asian market participants tend to overreact to chronologically preceding US market movements. Particularly, this might happen if uncertainty is high and if traders only have short time to process information. This explanation for spillovers as a mispricing phenomenon is not consistent with any form of informational efficiency.

2.3 Empirical Framework

2.3.1 Data

To be able to compute non-overlapping intra-day returns, as required to measure spillovers to our definition, we obtain minute-by-minute high frequency data. To represent the Hong Kong stock market, we use the Hang Seng Index (HSI), provided by Hang Seng Indexes Company in Hong Kong.[4] For the European stock market, we use the Euro Stoxx 50 (ESTX) from Stoxx Limited in Zurich and for the US market we use the S&P 500 (S&P) from Standard and Poor's in New York. The provider for the latter two series is Olsen Financial Technologies. Each series represents a free-float

[4]Note that our motivation to consider this particular market stems from the fact that this market is currently the third largest stock market in Asia in terms of market capitalization (after Tokio and Shanghai, see http://www.world-exchanges.org/statistics/time-series/market-capitalization). Despite this, it has only received little attention in the literature on stock market spillovers so far.

capitalization weighted price index. All indexes are leading stock market indicators, most closely followed in the corresponding regions. Further, they all represent mature and highly liquid stock markets. With each single series reaching from January 3, 2000 to September 30, 2011, we have data on approximately 2700 trading days at our disposal. In the regressions, we proceed as common in the literature. We exclude holidays and weekends. Further, we only consider days on which trading took place in all three different markets.

2.3.2 Econometric Model

If trading hours do not overlap, then, within one day, information can only transmit from east to west. We use this fact straightforwardly to build the econometric model, given in Equations (2.1) to (2.3).

$$r_{HSI_t} = \alpha_0 + \alpha_1 r_{S\&P_{t-1}} + \alpha_2 r_{ESTX_{t-1}} + \alpha_3 r_{HSI_{t-1}} + u_{HSI,t} \tag{2.1}$$

$$r_{ESTX_t} = \beta_0 + \beta_1 r_{HSI_t} + \beta_2 r_{S\&P_{t-1}} + \beta_3 r_{ESTX_{t-1}} + u_{ESTX,t} \tag{2.2}$$

$$r_{S\&P_t} = \gamma_0 + \gamma_1 r_{ESTX_t} + \gamma_2 r_{HSI_t} + \gamma_3 r_{S\&P_{t-1}} + u_{S\&P,t} \tag{2.3}$$

The basic idea behind this model is to investigate spillovers to intra-day returns in domestic markets, by measuring the Granger-causal impact of within 24 hours, non-overlapping chronologically preceding foreign market intra-day returns. To analyze autocorrelation in domestic markets' returns, additionally previous day intra-day returns from the domestic markets are taken into account. Details on the particular chronology of trading that we exploit to build this model can be found in Appendix A.1.

We refer to Equation (2.1) as the HSI-Equation because it represents the Hong Kong stock market. In this market, the domestic market's intra-day returns (r_{HSI_t}) are potentially affected by previous day foreign market intra-day returns in the US and Europe, as well as its own previous day domestic intra-day returns. The right hand side of Equation (2.1) hence includes lagged intra-day returns from all three different markets ($r_{S\&P_{t-1}}$, $r_{ESTX_{t-1}}$ and $r_{HSI_{t-1}}$). In the ESTX-Equation, representing the European market in Equation (2.2), domestic intra-day returns (r_{ESTX_t}) are potentially affected by the directly preceding same day foreign market intra-day returns from Hong Kong. Additionally, previous day intra-day returns, this time only from Europe and the US, can play a role. Therefore, the right hand side of Equation (2.2) includes same day Hong Kong intra-day returns (r_{HSI_t}), as well as lagged returns from Europe and the US ($r_{ESTX_{t-1}}$, $r_{S\&P_{t-1}}$). Regarding the US market, represented by the S&P-Equation in Equation (2.3), the potentially important preceding intra-day returns from foreign markets are all of the same day. Hence the equation includes same day intra-day returns from Europe and Hong Kong (r_{ESTX_t}, r_{HSI_t}) as well as previous day US domestic market intra-day returns ($r_{S\&P_{t-1}}$). The disturbance terms $u_{HSI,t}$, $u_{ESTX,t}$ and $u_{S\&P,t}$ are assumed to consist of independent white noise processes.

We do not include further lagged returns. From a theoretical perspective, there are no plausible economic reasons to consider them. From a practical, econometric point of view, there is no motivation to include them, as we do not find any statistically significant dependencies, when considering them in our equations. This is relevant, considering that each of our equations can essentially be interpreted as a parsimoniously specified autoregressive distributed lag model. Further, as Dimpfl and Jung (2012) have shown, the specific framework with non-overlapping trading times, can be exploited to build a structural VAR (SVAR) model, with restrictions following naturally from the chronology of trading. Our econometric model is close to theirs in spirit. However, we do not use an SVAR model, but a set of (seemingly) unrelated regressions. This enables us to achieve an even more parsimonious specification, considering intra-day returns only within 24-hour time windows. Despite the parsimony, however, our model exhibits the same advantages as Dimpfl and Jung (2012)'s model. Counter-clockwise feedback effects between the markets' returns are excluded, spillovers can only act into one direction and Granger-causality inference is feasible.

Equations (2.1) to (2.3) can be estimated simply by using Ordinary Least Squares (OLS), equation by equation. Spillovers to the definition employed here, then correspond to the resulting foreign market coefficients $\alpha_1, \alpha_2, \beta_1, \beta_2, \gamma_1and\gamma_2$. The lagged domestic markets' coefficients α_3, β_3 and γ_3 measure intra-day return autocorrelations.

2.3.3 Non-Overlapping Devolatized Returns

In addition to the chronology of trading, we take another important institutional feature for the computation of non-overlapping open-to-close returns into account. We consider stale prices, potentially contained in index opening quotes, by using opening proxies instead of the original index opening quotes. In particular, we use the proxies 'open plus three minutes'. Detailed explanations on this are provided in Appendix A.2. We hence define the intra-day return in a market on a given trading day ($r_{i,t}$) as the change of the logarithm of the market index quote between our particular opening proxy and the index closing quote. Column 2 in Table 2.1 provides descriptive statistics for the resulting (raw) returns. Unfortunately, excess kurtosis and pronounced negative skewness are immediately apparent for the returns in all three markets. Considering that the financial crisis of 2007 is contained in our data, this might not be surprising. However, these properties render the raw returns essentially useless to be used in linear regressions.[5] Therefore, we choose to use devolatized returns ($\widetilde{r}_{i,t}$) instead of the raw returns. The use of such returns has been proposed recently, for example, by Pesaran and Pesaran (2010), Andersen et al. (2010) or Dimpfl and Jung (2012). From an economic point of view, these returns can be interpreted as intra-day risk adjusted quantities. To obtain them, we divide our original daily raw return observations by a contemporaneous standardization factor $\sigma_{i,t}$, the estimated realized volatility for market i on day t:

$$\widetilde{r}_{i,t} = \frac{r_{i,t}}{\sigma_{i,t}}, \tag{2.4}$$

where the realized volatility for market i and day t is computed according to

$$\sigma_{i,t} = \sqrt{\sum_{j=1}^{M} r_{i,t,j}^2}. \tag{2.5}$$

It is hence computed as the square root of the estimated daily integrated variance which, in turn, results from the cumulated squared intra-day returns ($r_{i,t,j}$) over the corresponding M five-minute intra-day intervals. The use of the five-minute frequency is very common in the literature. As stated by Andersen et al. (2010) it has been shown to be empirically most adequate to solve the trade-off between market microstructure bias and variance.[6]

Columns 3 to 5 in Table 2.1 show the resulting descriptive statistics. The realized volatilities in column 4 are characterized by excess kurtosis and positive skewness,

[5] Note that we find the regression residuals from the models with these raw returns to be highly non-normal and distinct from white noise.

[6] In our particular case, market microstructure bias might arise at the very high frequencies, for example, due to non-synchronous trading. At the lower frequencies, however, the variance might increase as a consequence of discretization. Note, however, when computing volatility signature plots, we find these plots to flatten out at the five-minute frequency.

TABLE 2.1: *Descriptive statistics.*

	Raw returns	Devolatized returns	Realized volatilities	Log-realized volatilities
HSI				
Observations	2434	2434	2434	2434
Mean	-0.0372	-0.0088	0.8739	-0.2446
Median	-0.0176	-0.0259	0.7557	-0.2797
Minimum	-12.0327	-2.8068	0.2450	-1.4066
Maximum	8.6128	2.6429	6.5705	1.8826
St. Dev.	1.0232	0.9383	0.4930	0.4471
Skewness	-0.3074	0.0879	3.3638	0.5709
Kurtosis	16.7451	2.5761	24.4676	3.8573
ESTX				
Observations	2519	2519	2519	2519
Mean	-0.0380	0.0011	0.8650	-0.2891
Median	-0.0056	-0.0092	0.7331	-0.3101
Minimum	-7.3756	-3.3262	0.1621	-1.8194
Maximum	6.5378	3.1412	8.5718	2.1485
St. Dev.	1.0304	0.9996	0.5441	0.5205
Skewness	-0.0999	0.0617	3.2342	0.3512
Kurtosis	7.8265	2.5786	27.1745	3.1912
S&P				
Observations	2602	2602	2602	2602
Mean	-0.0074	0.0417	0.9023	-0.2465
Median	0.0505	0.0927	0.7565	-0.2787
Minimum	-8.8281	-2.8068	0.1948	-1.6357
Maximum	7.5619	2.6429	9.5443	2.2559
St. Dev.	1.1333	1.0534	0.5981	0.5084
Skewness	-0.1421	0.0141	3.7083	0.5810
Kurtosis	9.7277	2.6665	30.3161	3.6454

whereas their logarithmized counterparts in column 5 are more close to Gaussian. The devolatized returns are not perfectly normally distributed, however, their distributions are very close to Gaussian, as apparent in Figure 2.1. This is very remarkable, given the fact that the period of the financial crisis of 2007 is contained in our sample. Further, it is highly interesting with respect to the academic discussion on how to deal with particularly adverse distributional properties of financial returns in times of crises. The generally favorable properties of devolatized returns, as reported for tranquil periods in Pesaran and Pesaran (2010), Andersen et al. (2010) and Dimpfl and Jung (2012), are hence confirmable, given our particular sample, too. With the devolatized returns we obtain regression residuals not statistically distinguishable from white noise anymore. Further, we are able to avoid potential adverse effects of conditional heteroskedasticity on our spillover estimates in the sense of Forbes and Rigobon (2002). The devolatized returns allow us to preserve the direction of movement of the (raw) returns, at the same time avoiding volatility clustering, as observed typically in financial return series. The modeling of temporal dependencies in second order moments, as done in previous studies, is hence unnecessary. As Figure 2.2, 2.3 and 2.4 show, the approximately constant variance over time is given, even throughout the financial crisis of 2007.

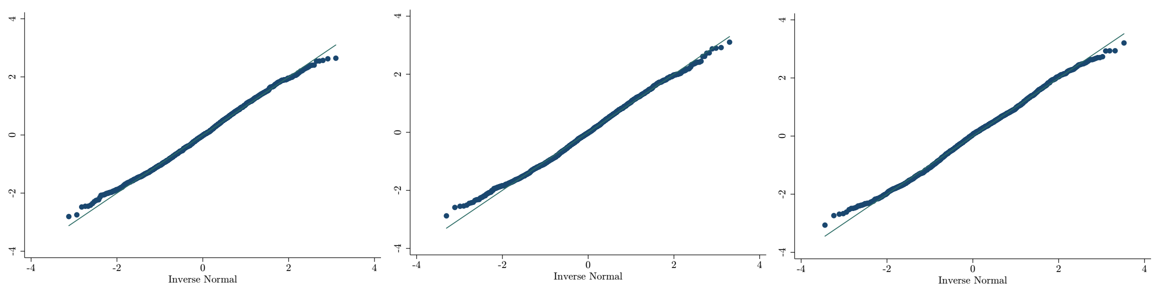

FIGURE 2.1: *Normal-quantile plots for the devolatized returns.*

Notes: HSI (left). ESTX (middle). S&P (right).

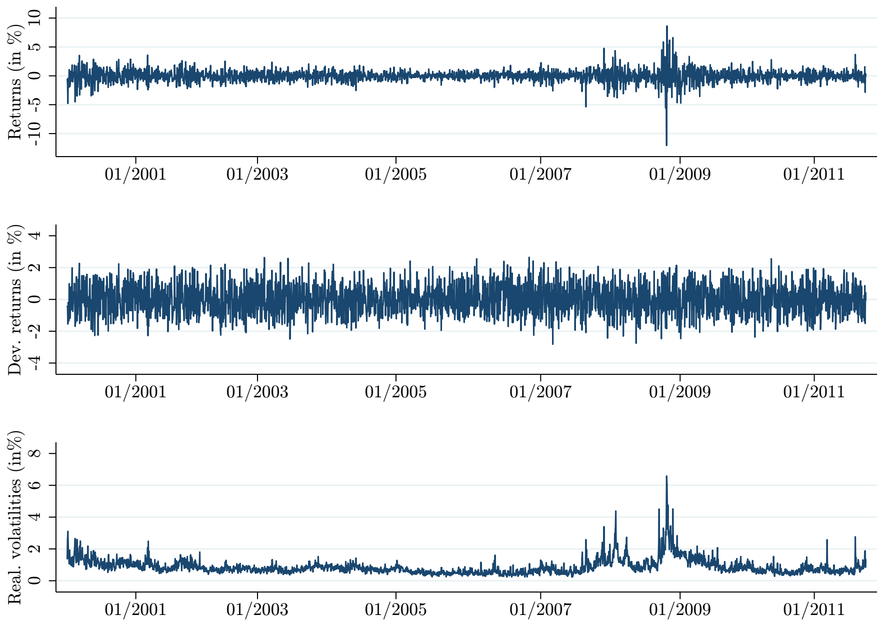

FIGURE 2.2: *Hang Seng Index.*

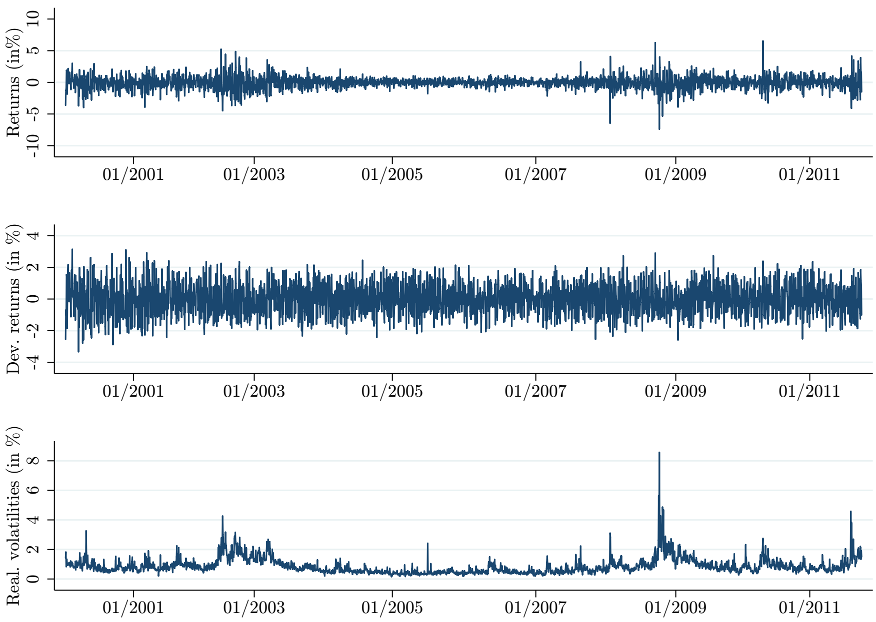

FIGURE 2.3: *Euro Stoxx 50.*

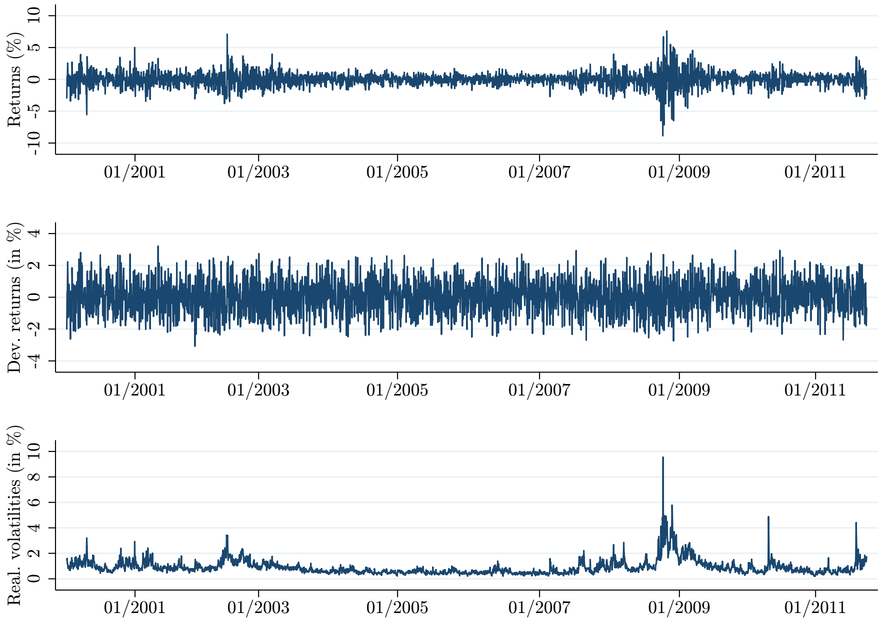

FIGURE 2.4: *S&P 500.*

2.4 Empirical Results

2.4.1 Total Sample Regressions

In this section, we first present the estimated spillover and autocorrelation coefficients from our total sample between January 2000 and September 2011. Motivated by hitherto unprecedented events on financial markets during the last decade, we secondly present the results from testing for breaks in the mechanism of information transmission between the markets over time. Based on the non-overlapping devolatized returns, we estimate Equations (2.1) to (2.3) separately from each other via OLS. We find the regression residuals not to be statistically distinguishable from white noise. The results are depicted in Table 2.2. Overall, it is most notable that the estimated return spillovers and autocorrelations tend to be weak. Apart from a few exceptions, most of the coefficients are statistically not distinguishable from zero at the 1 % level.

TABLE 2.2: *Total sample: Estimation results.*

(1) Spillovers from directly preceding markets		(2) Spillovers from secondarily preceding markets		(3) Autocorrelation		(4) Constant		(5) Sample size and SSR
				HSI-Equation				
$S\&P_{t-1}$		$ESTX_{t-1}$		HSI_{t-1}		$Const$		Obs=2434
-0.0847	***	-0.0091		-0.0539	***	-0.0055		2114.813
(<0.001)		(0.634)		(0.008)		(0.770)		
				ESTX-Equation				
HSI_t		$S\&P_{t-1}$		$ESTX_{t-1}$		$Const$		Obs=2519
0.0524	**	0.0101		-0.0637	***	0.0011		2499.569
(0.013)		(0.597)		(0.001)		(0.955)		
				S&P-Equation				
$ESTX_t$		HSI_t		$S\&P_{t-1}$		$Const$		Obs=2602
0.1078	***	0.0559	**	-0.0095		0.0419	**	2846.971
(<0.001)		(0.011)		(0.628)		(0.041)		

*Notes: The opening proxy is 'open plus three minutes'. SSR=sum of squared residuals. Significance at the 1% level: ***, at the 5% level: **, at the 10% level: *. P-values in parentheses.*

Specifically, the HSI-Equation reveals a pronounced negative, statistically significant spillover of a magnitude of almost -0.09 from the directly preceding US market to Hong Kong. This result is consistent with the overreaction phenomenon reported by Fung et al. (2010). For the years 1997 to 2003, they document significant intra-daily price reversals for the Hang Seng Index Future as well as for four other Asian index futures, following US market returns. Further, the spillover from the secondarily preceding market in Europe is not statistically different from zero. The coefficient for the HSI intra-day return autocorrelation, however, is statistically significant at the 1% level, but only weak, with a magnitude of approximately -0.05.

In the ESTX-Equation, we find only weak evidence for significant spillovers. The estimated spillover from Hong Kong is only statistically different from zero at the 5%

level. The spillover from the US is insignificant at all common levels of significance. Regarding the ESTX intra-day return autocorrelation, we find evidence for a weak negative significant effect of approximately -0.06.

Finally, the S&P-Equation indicates a pronounced positive and statistically significant spillover of approximately 0.11 from Europe to the US market. The spillover from the secondarily preceding market in Hong Kong is significant at the 5% level, but weak with a magnitude of approximately 0.05. The autocorrelation in S&P intra-day returns is not statistically significant at all common levels of significance.

Overall, concerning intra-day return autocorrelation, the evidence for significant weak negative autocorrelation is only apparent for the Hong Kong and the European market. Regarding cross-market spillovers, the most pronounced effects are those from the US to Hong Kong and from Europe to the US. Both are spillovers from chronologically directly preceding markets. Spillovers from secondarily preceding markets are generally not statistically significant at the 1% level.

As mentioned in the introduction, the process of information transmission might be adversely affected by various important events in our sample period. Potential time-variation might be hidden by the total sample estimates. To investigate the structural stability of the process of information transmission, we therefore test for breaks in linear regression relations over time. Specifically, we use the test according to Andrews (1993), Andrews and Ploberger (1994) and Zeileis et al. (2002). For each of our three linear regressions from Equations (2.1) to (2.3), we formulate 'H_0: No structural break' versus 'H_1: One single parameter shift'. As the potential break dates are unknown, we compute the following F-statistic due to Andrews (1993) for all potential break dates and each single market:

$$F_t = \frac{\widehat{u}^T \widehat{u} - \widehat{e}_t T \widehat{e}_t}{\widehat{e}_t^T \widehat{e}_t / (n - 2k)} \tag{2.6}$$

with $\widehat{e_t} = (\widehat{u}_{<t}, \widehat{u}_{>t})'$ denoting the residuals from the model with coefficients estimated separately from each other on subsamples before and after potential break dates t, $\widehat{u}$ denoting the residuals from the model estimated over the total sample, n denoting the sample size, k the degrees of freedom and $[(0.075 \cdot n); (n - 0.075 \cdot n)]$ denoting the interval of potential break dates t. We depict the resulting F-statistics in Figure 2.5. The boundaries are computed so that the probability for the supremum of the F-statistic to exceed them is $\alpha = 1\%$. Obviously, none of the F-statistics for the three different markets crosses its boundary. Therefore, we cannot reject 'H_0: No structural break'. For our long-term sample there is, hence, no evidence against the structural stability of the process of information transmission over time. Fundamental changes in regression relations over time, as might have been presumed to occur during the financial crisis of 2007, do not exist according to these tests. However, there might be temporary changes in parameters, not substantial enough to be detected by the tests. Further, as Carrasco (2002) demonstrates, structural break tests according to Andrews (1993), Andrews and Ploberger (1994) and Zeileis et al. (2002) have a lack of power if the data is actually generated by a nonlinear threshold model. At this point, we therefore only conclude that at least no dramatic change in the process of return transmission seems to have occurred according to the tests. An alternative threshold model specification will be dealt with in Section 2.4.3.

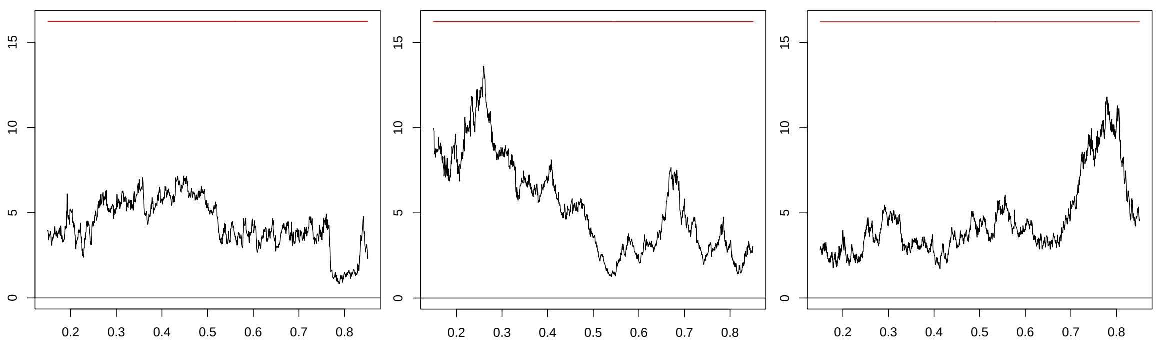

FIGURE 2.5: *Testing for breaks in linear regression relations: F-statistics.*

Notes: HSI-Equation (left), ESTX-Equation (middle), S&P-Equation (right).
F-Statistics (jagged, black), boundaries for $\alpha = 1\%$ (upper, red lines).

2.4.2 Moving Window Regressions

The structural break tests suggest that no fundamental change in the linkages between the markets occurred. We hence conclude that our original model according to Equations (2.1) to (2.3) is suitably specified to be estimated throughout subsamples. To detect smooth parameter changes over time, we estimate Equations (2.1) to (2.3) over 250 days moving windows, corresponding to the length of approximately one trading year. Rolling the windows from the beginning to the end of the total sample, we cannot provide estimates for the first 250 days. The reason is that our estimated spillovers and autocorrelations refer to the point estimates for the observations $t-250$. However, given our sample size of approximately 2500 daily observations for each market, this is only a minor drawback. We still conduct approximately 2250 regressions with four times about 2250 corresponding coefficients for each of our three markets. We depict the results graphically in the Figures 2.6, 2.7 and 2.8 as sequences of spillovers and autocorrelations over time. The jagged lines depict the 250 days moving window point estimates together with their corresponding 99% confidence bands. The continuous lines show the total sample estimates, already presented in Section 2.4.1, together with their 99% confidence bands.[7] Most striking in these figures is the fact that the confidence bands enclose zero in almost all graphs and over large parts of the sample period. Apart from a few short-lived exceptions, dependence on own lagged returns is virtually non-existent and spillovers from foreign stock markets are insignificant for almost all the time and in all markets. Overall, the results provide strong evidence that markets process information efficiently.

[7]Note that we are very rigorous, using wide confidence bands. With the 95% and the 90% confidence bands, the spillovers tend to be significant over slightly longer time periods. Further, note that we conduct robustness checks based on window sizes of 50 and 500 days. The corresponding graphical results are available upon request. On the one hand, temporary deviations from informational efficiency should tend to be detected using small window sizes. On the other hand, the confidence bands should get tighter and the power of the significance tests should increase if large window sizes are used. Overall, we find the 250 days windows to provide a good compromise between the two counteracting effects.

A close look at the moving window regression results, however, reveals weak temporary potential deviations from informational efficiency in the form of statistically significant spillovers and autocorrelations (highlighted by the blue windows). For the HSI-Equation, the first line in Figure 2.6 shows that the pronounced negative spillover from the US, detected by the previous total sample regressions, now appears strongly time-varying. Particularly before 2005, the confidence bands shift downwards over short-lived time spans, not enclosing zero any more. Hence, the significance of the negative total sample spillover is not only driven by a large sample size, but also by certain time spans with particularly pronounced spillovers. Regarding the spillovers from Europe in line two, there is no evidence for any significant effects. The confidence bands enclose zero throughout the whole sample period. The autocorrelation for the HSI intra-day returns in line three, by contrast, turns out to be driven by certain time periods, too. Particularly during the financial crisis since mid-2007 and at the end of 2008, we find evidence for weak and significant negative autocorrelations.

The moving window regression results for the ESTX-Equation in Figure 2.7 provide a different picture. The European market appears to be hardly affected by foreign market returns. Potential spillovers from Hong Kong in line one are virtually insignificant. Spillovers from the US, depicted in line two, are only significant throughout short-lived periods in 2006. Line three shows that statistically significant negative ESTX intra-day return autocorrelation occurs within short time windows in 2004/2005 and in 2008.

For the S&P, the results in line one of Figure 2.8 show that the overall positive spillover from Europe, measured in Section 2.4.1, is actually strongly time-varying, too. Particularly between 2002 and 2003, as well as in 2008/2009, the spillovers are pronounced, with the confidence bands both being located above zero. Spillovers from Hong Kong in line two, however, are generally insignificant, with an exception of a very weak and short-lived period of positive and significant spillovers in 2010.

For S&P intra-day return autocorrelation, depicted in line three, we find no evidence for significant negative autocorrelation.

Overall, regarding domestic markets' dependence on own past intra-day returns, we find short periods of significant negative autocorrelation in all three markets. From a strict point of view, this finding is not consistent with informational efficiency. The phases of significant autocorrelation are not synchronous across the markets and associations between significant autocorrelations and particular external events are hard to find. A uniform effect of the financial crisis is not apparent. However, it is obvious that each of the markets is characterized by at least one short-lived such phase between mid 2007 and the end of 2010. Altogether, the sporadic deviations from informational efficiency are best in line with the recent literature on time-varying market efficiency according to Timmermann (2008), Ito and Sugiyama (2009), Kim et al. (2011) or Lim et al. (2013). The latter, for example, conduct automatic Portmanteau Box-Pierce tests based on Escanciano and Lobato (2009) and Wild-Bootstrapped Automatic Variance Ratio Tests according to Kim (2009). Inter alia for the S&P 500 index throughout the period of the financial crisis of 2007, they find 'pockets in time when evidence of local predictability is detected'. Concerning the economic explanations, they adhere to the Adaptive Markets Hypothesis according to Lo (2004) and Kim et al. (2011). This concept essentially states that market efficiency has to be considered as a characteristic that varies continuously across markets and over time. The reasons can be found in changes in market conditions and investors' information processing over time, particularly in periods of major exogenous events.

The empirical evidence concerning our estimated spillovers fits well into this context. All of the originally in Section 2.4.1 measured significant total sample spillovers turn out to be driven by sporadic and short-lived times of pronounced significant spillovers. Clear associations with particular external events are hard to identify. Generally though, the considerations on time-varying market efficiency and return autocorrelations, appear to apply in the context of cross-market spillovers, too. How-

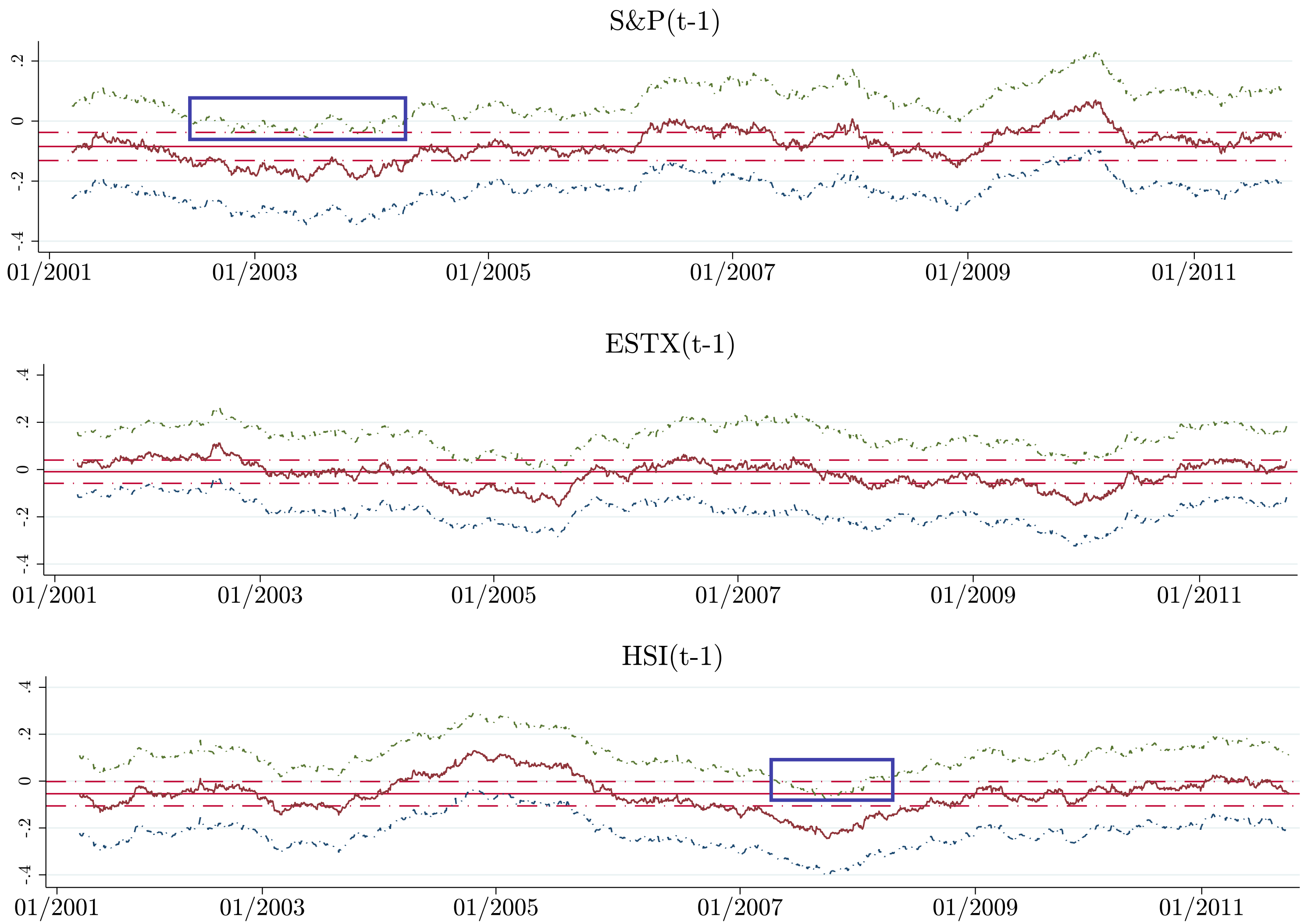

FIGURE 2.6: *HSI-Equation: 250 days moving window estimations.*

Notes: Horizontal lines: Total sample spillovers (continuous) with 99% confidence bands (dotted). Jagged lines: 250 days moving window spillovers with 99% confidence bands. Plotted spillover at time t: Estimate for the subperiod t-250 to t.

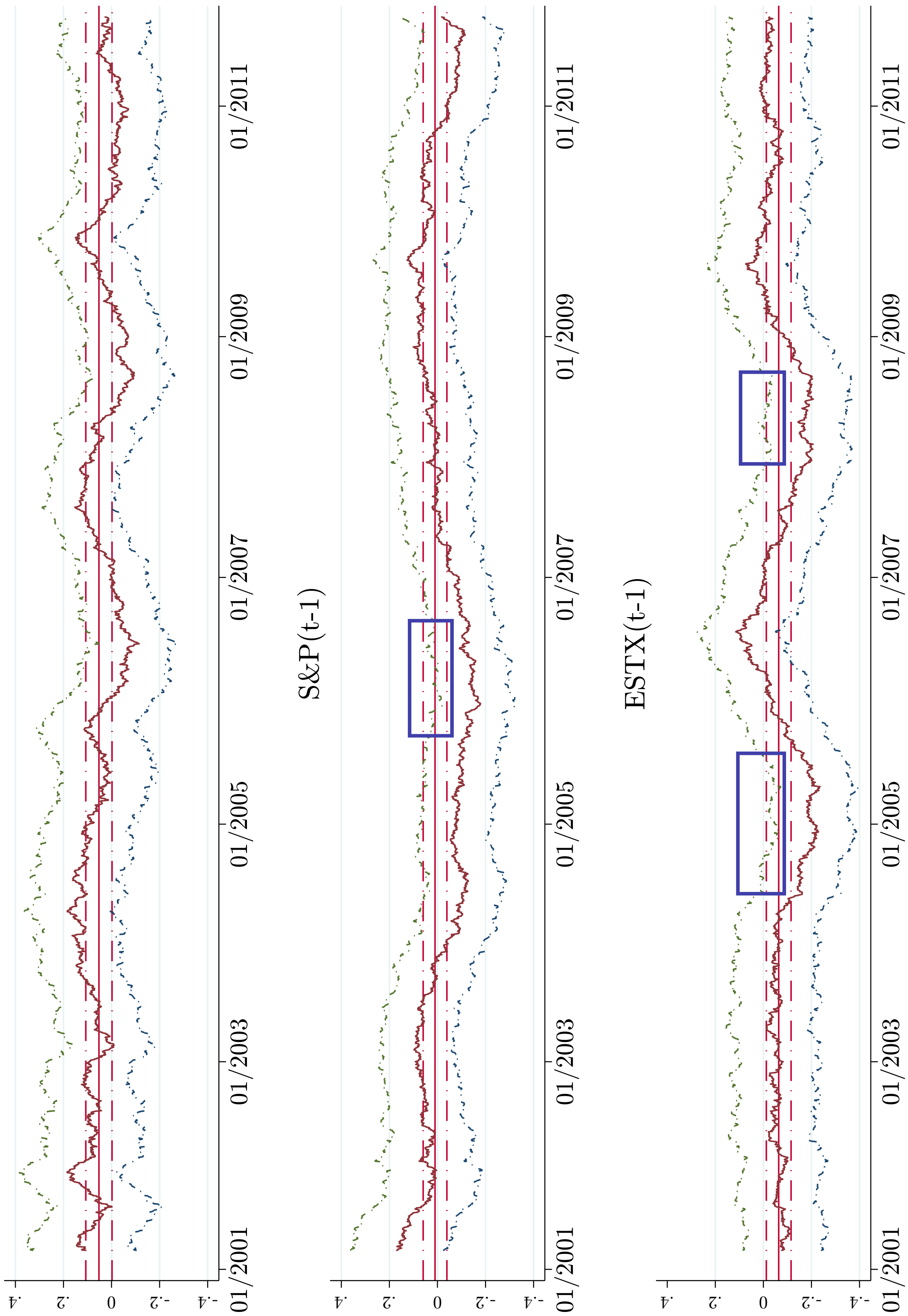

FIGURE 2.7: *ESTX-Equation: 250 days moving window estimations.*

Notes: Horizontal lines: Total sample spillovers (continuous) with 99% confidence bands (dotted). Jagged lines: 250 days moving window spillovers with 99% confidence bands. Plotted spillover at time t: Estimate for the sub-period t-250 to t.

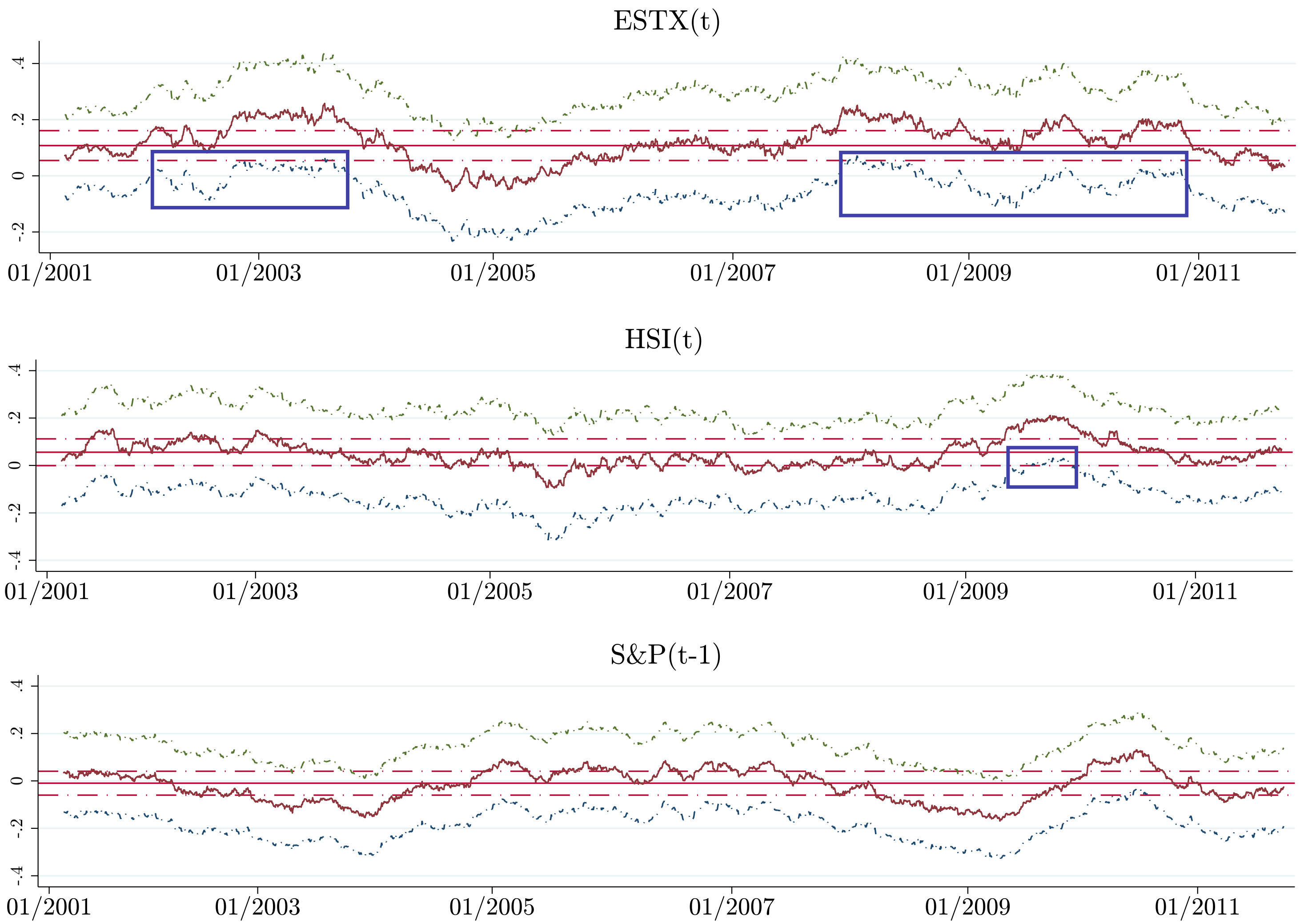

FIGURE 2.8: *S&P-Equation: 250 days moving window estimations.*

Notes: Horizontal lines: Total sample spillovers (continuous) with 99% confidence bands (dotted). Jagged lines: 250 days moving window spillovers with 99% confidence bands. Plotted spillover at time t: Estimate for the sub-period t-250 to t.

ever, at least two important differences have to be mentioned. Firstly, movements in chronologically preceding foreign markets are of differing importance for domestic markets. According to our estimation results, the Hong Kong market exerts only little influence on other markets. The US and the European market, however exert relatively strong influence. Secondly, the time span that market participants have to process foreign news is relatively short, compared to the time they have to process information revealed in domestic markets' previous day returns. In case of the US, for example, traders can process the information content of previous day own market movements throughout the whole overnight non-trading period. By contrast, they only have little time to assess information revealed in the directly preceding trading in Europe. The reason is that trading in the US begins when markets in Europe are still open. This aspect appears important to us from both perspectives on return spillovers, taken in Section 2.1. From the viewpoint of spillovers as a result of market participants' rational behavior, the incentive for strategic behavior of US traders to reveal their private share of information only stepwise might be higher if time to process information is short. From the perspective of spillovers as the consequence of traders' irrational behaviour, short time might make mispricing and overreaction more likely, too. A good argument for the latter hypothesis is that Fung et al. (2010) find overreaction to be less pronounced on Mondays than on other days of the week. As an explanation, they propose that markets calm down over the weekend. Based on our data, we are able to test for such an effect, too. We indeed find the corresponding regression coefficient to have a negative sign. Unfortunately, however, the corresponding calm-down effect is not statistically significant.[8]

2.4.3 Threshold Regressions

To investigate to what extent the statistically significant spillovers and deviations from informational efficiency, identified in Section 2.4.2, relate to volatility, we con-

[8]The results are available upon request.

duct threshold regressions. According to Weber and Strohsal (2012), we consider volatility as a proxy for both uncertainty and the rate of information flow. Being able to resort to daily realized volatilities in all three different markets, we can treat the markets' volatilities essentially as observed. Further, compared to other volatility proxies, the realized volatility is known to suffer from less noise. Using it as a threshold variable, we hypothesize that spillovers might differ, depending on the volatility-regime, prevailing in previously trading markets. On the one hand, in case of high volatility, traders might find it overly hard to evaluate the information content of price movements in the chronologically preceding market. Incentives for a strategically motivated delayed incorporation of information into prices might be particularly strong then. On the other hand, high volatility might either reinforce or decrease potential overreaction around market opening. More difficult information processing and potential mispricing might be the consequence. More attention, more cautiousness and accuracy in traders pricing decisions on high volatility days, however, are plausible, too.

The particular threshold models that we consider are the following:

(2.7)

$$r_{HSI_t} = \begin{cases} \alpha_{1,0} + \alpha_{1,1} r_{S\&P_{t-1}} + \alpha_{1,2} r_{ESTX_{t-1}} + \alpha_{1,3} r_{HSI_{t-1}} + u_{1,HSI_t} \text{ if } LogRV_{S\&P_{t-1}} > \tau_{HSI} \\ \alpha_{2,0} + \alpha_{2,1} r_{S\&P_{t-1}} + \alpha_{2,2} r_{ESTX_{t-1}} + \alpha_{2,3} r_{HSI_{t-1}} + u_{2,HSI_t} \text{ if } LogRV_{S\&P_{t-1}} \leq \tau_{HSI} \end{cases}$$

(2.8)

$$r_{ESTX_t} = \begin{cases} \beta_{1,0} + \beta_{1,1} r_{HSI_t} + \beta_{1,2} r_{S\&P_{t-1}} + \beta_{1,3} r_{ESTX_{t-1}} + u_{1,ESTX_t} \text{ if } LogRV_{S\&P_{t-1}} > \tau_{ESTX} \\ \beta_{2,0} + \beta_{2,1} r_{HSI_t} + \beta_{2,2} r_{S\&P_{t-1}} + \beta_{2,3} r_{ESTX_{t-1}} + u_{2,ESTX_t} \text{ if } LogRV_{S\&P_{t-1}} \leq \tau_{ESTX} \end{cases}$$

(2.9)

$$r_{S\&P_t} = \begin{cases} \gamma_{1,0} + \gamma_{1,1} r_{ESTX_t} + \gamma_{1,2} r_{HSI_t} + \gamma_{1,3} r_{S\&P_{t-1}} + u_{1,S\&P_t} \text{ if } LogRV_{S\&P_{t-1}} > \tau_{S\&P} \\ \gamma_{2,0} + \gamma_{2,1} r_{ESTX_t} + \gamma_{2,2} r_{HSI_t} + \gamma_{2,3} r_{S\&P_{t-1}} + u_{2,S\&P_t} \text{ if } LogRV_{S\&P_{t-1}} \leq \tau_{S\&P}, \end{cases}$$

where τ_{HSI}, τ_{ESTX} and $\tau_{S\&P}$ are the corresponding market-specific thresholds in $LogRV_{S\&P_{t-1}}$, the particular level of the corresponding previous day log-realized volatility of the US market. u_{1,HSI_t}, u_{2,HSI_t}, $u_{1,ESTX_t}$, $u_{2,ESTX_t}$, $u_{1,S\&P_t}$ and $u_{2,S\&P_t}$ are different independent white noise processes. To determine the optimal (unknown) thresholds, we proceed as common in the literature. We follow Chan (1993), Hansen (1996) and Hansen (2000) and conduct grid-searches over all potential threshold specifications to obtain super-consistent threshold estimates, based on a minimization of the sum of squared residuals. Conducting Lagrange multiplier tests to test for the significance of the thresholds, we use trimming parameters of 15% and 1000 bootstrap replications, respectively. Compared to a naive empirical sample splitting strategy, this approach is econometrically well-grounded. More importantly, we are able to avoid arbitrary decisions on where to split the samples and we get explicit information on the levels of the realized volatilities, on which significant changes in spillovers tend to occur.[9]

Regarding the potential threshold variables, we consider all three volatilities, realized in the different markets trading within 24 hours before the particular market analyzed. Overall, we do not find huge differences in the resulting minimum sums of squared residuals across the different threshold variables. This is not surprising. The realized volatilities are characterized by typical long memory properties and tend to co-move across the markets (see Figures 2.2, 2.3 and 2.4). However, in each single

[9]Note that we also considered alternative ad-hoc sample splitting procedures, e.g. based on mean and median realized volatilities and positive and negative returns. The results, however, were less conclusive than those from the threshold models.

market, the sum of squared residuals gets minimal, if the log-realized volatility of the preceding US market is used as the threshold variable. Therefore, we finally use this particular log-realized volatility ($LogRV_{S\&P_{t-1}}$) as the threshold variable in all three Equations (2.7), (2.8) and (2.9). Economically, this is in line with the major global importance of the US market. The resulting thresholds that we use for our conditional least squares estimations are $\tau_{HSI} = 0.0973$, $\tau_{ESTX} = -0.0485$ and $\tau_{S\&P} = -0.3895$. The finally resulting test results are provided together with the regression results in Table 2.3.

The test results essentially suggest that significant threshold effects occur in the European as well as the US stock market. In case of the Hong Kong market, however, the null hypothesis of no significant threshold effect cannot be rejected. The lowest threshold is identified for the US market. In this market, significant changes in the regression relations hence tend to occur at lower volatility levels than in the other markets.

Regarding the regression results, it is apparent for the HSI-Equation that, despite the insignificant threshold, spillovers from the US essentially differ across the volatility regimes.[10] The negative spillovers from the US are pronounced (about -0.1) and highly significant in the state of low volatility, when the previous day US log-realized volatility is below the threshold. By contrast, if the log-realized volatility for the US is above the threshold, the spillovers are not statistically different from zero at the 1% and the 5% level. The other coefficients are not statistically distinguishable from zero at the 1% level. However, most apparently, there is negative autocorrelation at the 5% level in the high volatility state.

A different picture emerges for the ESTX-Equation. Here, spillovers from previously trading markets (both Hong Kong and the US) are positive, pronounced (both approximately 0.13) and statistically significant in the high volatility regime. Further,

[10] Note that we do not regard the insignificance of the threshold in case of the Hong Kong market as a huge drawback. Under the alternative of an empirical sample splitting procedure such issues would not have received attention at all.

TABLE 2.3: *Threshold tests and regressions.*

Threshold tests

Market	LM test (H_0: no threshold)	Bootstrap p-value	Threshold estimate	95% confidence level
Hong Kong	8.837	(0.483)	0.0973	[-1.289, 1.576]
Europe	24.138	(0.002)	-0.0485	[-0.327, 0.112]
United States	22.356	(0.004)	-0.3895	[-0.440, -0.339]

Threshold regressions

Spillovers from dir. preceding markets	Spillovers from sec. preceding markets	Autocorrelation	Constant	Sample size, τ and SSR
HSI-Equation				
$S\&P_{t-1}$	$ESTX_{t-1}$	HSI_{t-1}	$Const$	Obs=1777
-0.0999 ***	0.0089	-0.0404 *	0.0194	$\tau \leq 0.0973$
(<0.001)	(0.692)	(0.087)	(0.374)	SSR=1493.332
$S\&P_{t-1}$	$ESTX_{t-1}$	HSI_{t-1}	$Const$	Obs=504
-0.0688 *	-0.0372	-0.1141 **	-0.0955 **	$\tau > 0.0973$
(0.099)	(0.369)	(0.011)	(0.031)	SSR=478.170
ESTX-Equation				
HSI_t	$S\&P_{t-1}$	$ESTX_{t-1}$	$Const$	Obs=1624
0.0162	-0.0509 **	-0.0780 ***	0.0099	$\tau \leq$ -0.0485
(0.532)	(0.028)	(0.002)	(0.680)	SSR=1500.071
HSI_t	$S\&P_{t-1}$	$ESTX_{t-1}$	$Const$	Obs=735
0.1331 ***	0.1265 ***	-0.0578	0.0193	$\tau >$ -0.0485
(0.001)	(0.001)	(0.116)	(0.625)	SSR=817.130
S&P-Equation				
$ESTX_t$	HSI_t	$S\&P_{t-1}$	$Const$	Obs=1006
0.0341	0.0240	0.0418	0.0738 **	$\tau \leq$ -0.3925
(0.309)	(0.493)	(0.191)	(0.024)	SSR=1025.193
$ESTX_t$	HSI_t	$S\&P_{t-1}$	$Const$	Obs=1428
0.1725 ***	0.0479 *	-0.0587 **	0.0095	$\tau > 0.3925$
(<0.001)	(0.095)	(0.025)	(0.736)	SSR=1587.366

*Notes: The opening proxy is 'open plus three minutes'. SSR=sum of squared residuals. Significance at the 1% level: ***, at the 5% level: **, at the 10% level: *. P-values in parentheses. Number of bootstrap replications: 1000. Trimming percentage: 15%.*

the autocorrelation tends to be negative in the low volatility regime, whereas evidence for weak negative spillovers from the US is only significant at the 5% level.

Finally, for the S&P-Equation, the threshold regressions reveal a strong and highly significant positive spillover from Europe in the high volatility regime (approximately 0.17). In the low volatility regime, there is no evidence for susceptibility to foreign market spillovers for the US market. No spillover is statistically distinguishable from zero at common levels of significance.

Overall, the spillovers, identified in the total sample regressions, turn out to be substantially related to the volatilities in the chronologically directly preceding markets. Most importantly, the negative spillovers from the US to Hong Kong tend to be significant in the state of low volatility. By contrast, spillovers from Hong Kong and the US to Europe as well as from Europe to the US are only significant in the state of high volatility. The different signs of the phenomena suggest that different mechanisms might be at work.

In case of the spillovers from Hong Kong and the US to Europe and from Europe to the US, the results tend to support rational explanations. Traders might have difficulties in assessing the information content of preceding price movements, when volatility is high. This might lead to a delayed incorporation of information as traders strategically reveal their private share of information in a stepwise manner. Likewise possible in principle, however, is a psychological explanation, according to which traders might underreact at market opening. If traders are overly pessimistic (optimistic) after high volatility days in the US, this might result in a too low (high) value of the opening price in case of positive (negative) returns in the preceding market. The correction of this falsely set price over the trading day, might then explain the positive sign of the spillover.

By contrast, in case of spillovers from the US to Hong Kong, the spillovers' negative sign strongly points towards psychological explanations. Strategic behavior of traders in the sense of Kyle (1985) or Admati and Pfleiderer (1988) is less plausible as, according to this line of reasoning, traders primarily have incentives for a delayed incorporation of information, but not for overreaction. In the literature, this explanation is only associated with positive spillovers and autocorrelations. Overall, opening prices in Hong Kong might hence be too high (low) in case of positive (negative) returns in the previously trading market. A subsequent price reversal, particularly in times of low volatility in the preceding US market, might be the consequence. At first sight, this pattern might be puzzling. Theoretically, however, it is well in line with other authors' findings. Overreaction, for example, is a well known phenomenon, at least since De Bondt and Thaler (1985) and Barberis et al. (1998). Further, Veronesi (1999) suggests that it might occur particularly after bad news in good times, e.g. low volatility. Most interestingly, the differences in the spillovers' signs are consistent with recent findings, showing that Asians suffer differently from cognitive biases than, for example, Europeans and Americans (see Kim and Nofsinger (2008) and the literature mentioned therein).

However, to preclude that our results are adversely affected by market microstructure noise, we present robustness checks and considerations in the following Section 2.4.4. Particularly, we discuss estimation results based on alternative opening proxies and address the issue of non-synchronous trading.

2.4.4 Robustness Considerations

To investigate to what extent our specifically chosen opening proxies affect our results, we present estimation results based on alternative opening proxies in Table 2.4. In particular, we present results for proxies between 'open plus one minute' and 'open plus fifteen minutes'. Regarding the HSI-Equation, we find the S&P-spillover to be negative and statistically significant at the 1% level until to the proxy 'open plus nine minutes'. However, from the fourth minute onwards, the measured spillovers decline. This finding is consistent with a quick price reversal, following an overreaction phenomenon in the sense of Fung et al. (2010). Further, it highlights the importance of a sensible opening proxy to measure spillovers in a meaningful way. Regarding the other coefficients, similar patterns are not apparent. The ESTX-spillover is insignificant throughout all opening proxies and the weak negative significant autocorrelation remains virtually the same over the alternative opening quotes. This persistence, however, might indicate that intra-day return autocorrelation, if present, tends to be related to rational behavior according to Admati and Pfleiderer (1988) and Kyle (1985) and not to psychologically grounded, quickly self-correcting, overreaction as proposed by Fung et al. (2010).

Similarly, for the ESTX-Equation, the weak negative statistically significant autocorrelation remains virtually constant throughout the alternative opening proxies. Significant spillovers at the 1% level from the US only occur based on the proxy 'open plus one minute'. Spillovers from Hong Kong are only statistically significant at the 1% level if based on the very first two proxies. Again, these results argue for the importance of the opening proxy.

Most interestingly, for the S&P-Equation, the spillover from Europe is pronounced and significant at the 1 % level throughout all alternative proxies. A reversal, as in the case of the spillover from the US to Hong Kong, is not apparent. This again suggests that different mechanisms are at work. In case of spillovers from Europe to the US, the persistence across the opening proxies tends towards an explanation in the sense of Admati and Pfleiderer (1988) and Kyle (1985). The other two coefficients, however, are only significant at the 1% level if the first two opening proxies are used. Again, regarding autocorrelation, the opening proxy does not play an important role.

To check in how far differences in stale quotes across the volatility regimes, identified in Section 2.4.3, affect our results, we compare the average times from the beginning of trading to the first transactions of corresponding constituent stocks between these regimes. However, considering the use of our particular opening proxy and the fact that we use minute-by-minute data, we are not able to find considerable differences, neither in the times to the first, nor in the times to the 'last first' transactions of the index constituents.

Overall, these results again support our particular proxy 'open plus three minutes'. In addition to stale quotes, however, the problem of non-synchronous trading might play a role.[11] This problem implies that index quotes, no matter if at market opening or closing, are potentially distorted because they represent weighted prices of transactions of index constituents, potentially occurring infrequently and at different points in time. The spillover literature according to Hamao et al. (1990), Lin et al. (1994), Susmel and Engle (1994) typically does not take this issue into account. Generally though, it is widely recognized that non-synchronous trading can induce significant correlation as an artefact of the data sampling process. To get an impression of the degree of this potential problem in our particular case, we analyze the time distances between transactions of constituent stocks in the three markets over time. Again, we use our intra-daily transactions data for the first fifteen minutes of trading in the markets. However, we cannot find any obvious associations between these time distances and our previously estimated spillover sequences. In addition, we compare the differences between these time distances across the volatility regimes. We find the average time distances between trades to be slightly longer in the high volatility than in the low volatility regimes. The differences between the averages though are smaller than one second and negligible, considering that we use minute-by-minute data. Our overall conclusion is hence that non-synchronous trading cannot explain the patterns in spillovers and autocorrelations that we observe empirically.

This conclusion is indeed in line with other authors' results, studying the consequences of non-synchronous trading in the context of portfolio and index return autocorrelation. Atchison et al. (1987), Lo and MacKinlay (1990), Kadlec and Patterson

[11] Note that an additional market microstructure-related source for return autocorrelation is the so called bid-ask-bounce. Using minute-by-minute index quotes, however, it is not a concern in our particular case.

(1999), Chordia and Swaminathan (2000) or Ahn et al. (2002), for example, find that the levels of empirically observed autocorrelations are substantially higher than those that might be expected to be induced by non-synchronous trading. Therefore, they state that additional sources to non-synchronous trading must exist to explain empirically observed significant autocorrelations. In our particular case, the existence of such other sources is additionally supported by the fact that if we observe (temporary) statistically significant autocorrelation in our intra-day returns, then these autocorrelations exclusively have a negative sign. Lo and MacKinlay (1990) and Ahn et al. (2002), however, report that non-synchronous trading generally tends to induce positive autocorrelation. Anderson et al. (2013) recently separate stock return autocorrelation into a so called spurious and a genuine component. The spurious component stands for autocorrelation arising from market microstructure bias due to non-synchronous trading or bid-ask-bounce. The genuine component denotes partial price adjustment in the sense of Admati and Pfleiderer (1988) and Kyle (1985). Using sixteen years of NYSE intra-day transaction data, Anderson et al. (2013) find the latter genuine component to be the main source, particularly for negative autocorrelation, in daily portfolio returns. Overall, we therefore conclude that our results are neither significantly affected by stale quotes nor by non-synchronous trading.

TABLE 2.4: *Total sample: Estimation results according to different opening proxies.*

HSI-Equation															
Minute	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
$S\&P_{t-1}$	**-0.0705**	**-0.0840**	**-0.0847**	**-0.0859**	**-0.0718**	**-0.0652**	**-0.0612**	**-0.0544**	**-0.0595**	-0.0227	-0.0236	-0.0176	-0.0123	-0.0174	-0.0198
P-value	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.001)	(0.003)	(0.001)	(0.167)	(0.159)	(0.289)	(0.465)	(0.296)	(0.218)
$ESTX_{t-1}$	-0.0083	-0.0081	-0.0091	0.0016	-0.0009	-0.0038	-0.0008	0.0033	0.0107	0.0193	0.0169	0.0114	0.0100	0.0098	0.0126
P-value	(0.683)	(0.673)	(0.634)	(0.932)	(0.964)	(0.844)	(0.966)	(0.865)	(0.583)	(0.281)	(0.348)	(0.525)	(0.584)	(0.589)	(0.489)
HK_{t-1}	**-0.0559**	**-0.0513**	**-0.0539**	**-0.0590**	**-0.0598**	**-0.0611**	**-0.0547**	**-0.0557**	**-0.0522**	**-0.0545**	**-0.0600**	**-0.0627**	**-0.0680**	**-0.0672**	**-0.0683**
P-value	(0.008)	(0.012)	(0.008)	(0.003)	(0.003)	(0.002)	(0.007)	(0.006)	(0.009)	(0.007)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Constant	-0.0294	-0.0205	-0.0055	-0.0001	0.0049	0.0085	0.0077	0.0090	0.0078	0.0106	0.0084	0.0119	0.0149	0.0144	0.0185
P-value	(0.137)	(0.279)	(0.770)	(0.996)	(0.794)	(0.653)	(0.684)	(0.634)	(0.679)	(0.534)	(0.628)	(0.490)	(0.394)	(0.402)	(0.281)
Observations	2296	2410	2434	2448	2454	2458	2462	2464	2466	2472	2472	2474	2434	2480	2474
Overall F	8.14	10.30	10.40	10.95	8.60	7.67	6.53	5.69	5.96	3.41	3.90	3.78	4.06	4.26	4.57
Prob ≥ F	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.001)	(0.017)	(0.009)	(0.010)	(0.007)	(0.005)	(0.003)
ESTX-Equation															
Minute	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
HSI_t	**0.0871**	**0.0685**	**0.0524**	0.0375	0.0283	0.0290	0.0313	0.0333	0.0279	**0.0488**	0.0434	0.0386	0.0406	0.0345	0.0324
P-value	(<0.001)	(0.001)	(0.013)	(0.077)	(0.176)	(0.157)	(0.125)	(0.103)	(0.170)	(0.028)	(0.051)	(0.082)	(0.067)	(0.116)	(0.140)
$S\&P_{t-1}$	**0.0670**	**0.0388**	0.0101	-0.0160	-0.0224	-0.0276	-0.0278	-0.0277	-0.0274	-0.0272	-0.0199	-0.0183	-0.0227	-0.0149	-0.0050
P-value	(0.001)	(0.043)	(0.597)	(0.401)	(0.234)	(0.141)	(0.133)	(0.136)	(0.142)	(0.136)	(0.283)	(0.319)	(0.221)	(0.415)	(0.776)
$ESTX_{t-1}$	**-0.0650**	**-0.0694**	**-0.0637**	**-0.0602**	**-0.0595**	**-0.0552**	**-0.0591**	**-0.0645**	**-0.0564**	**-0.0595**	**-0.0588**	**-0.0560**	**-0.0537**	**-0.0497**	**-0.0507**
P-value	(0.002)	(0.001)	(0.001)	(0.002)	(0.003)	(0.005)	(0.003)	(0.001)	(0.004)	(0.003)	(0.003)	(0.005)	(0.007)	(0.012)	(0.011)
Constant	0.0046	-0.0023	0.0011	0.0013	0.0018	-0.0006	-0.0074	-0.0095	-0.0088	-0.0082	-0.0123	-0.0148	-0.0197	-0.0159	-0.0169
P-value	(0.823)	(0.908)	(0.955)	(0.948)	(0.926)	(0.976)	(0.702)	(0.624)	(0.648)	(0.666)	(0.521)	(0.435)	(0.304)	(0.402)	(0.371)
Obs	2375	2493	2519	2534	2540	2544	2548	2551	2553	2558	2558	2560	2518	2566	2559
Overall F	10.89	7.97	5.48	4.66	4.42	4.35	4.89	5.55	4.37	5.63	4.79	4.18	4.24	3.27	2.99
Prob ≥ F	(<0.001)	(<0.001)	(0.001)	(0.003)	(0.004)	(0.005)	(0.002)	(0.001)	(0.005)	(0.001)	(0.003)	(0.006)	(0.005)	(0.020)	(0.030)
S&P-Equation															
Minute	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
$ESTX_t$	**0.1978**	**0.1404**	**0.1078**	**0.0920**	**0.0836**	**0.0793**	**0.0759**	**0.0749**	**0.0793**	**0.0813**	**0.0818**	**0.0830**	**0.0818**	**0.0802**	**0.1329**
P-value	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
HSI_t	**0.0937**	**0.0709**	**0.0559**	**0.0518**	**0.0505**	**0.0441**	**0.0491**	**0.0448**	**0.0457**	**0.0542**	**0.0534**	**0.0637**	**0.0661**	**0.0673**	**0.0732**
P-value	(<0.001)	(0.001)	(0.011)	(0.019)	(0.021)	(0.041)	(0.023)	(0.037)	(0.033)	(0.024)	(0.023)	(0.007)	(0.005)	(0.004)	(0.003)
$S\&P_{t-1}$	-0.0328	-0.0167	-0.0095	-0.0058	-0.0122	-0.0144	-0.0140	-0.0137	-0.0175	-0.0275	-0.0296	-0.0310	-0.0302	-0.0351	-0.0126
P-value	(0.096)	(0.393)	(0.628)	(0.765)	(0.532)	(0.461)	(0.475)	(0.483)	(0.369)	(0.157)	(0.128)	(0.110)	(0.122)	(0.071)	(0.516)
Constant	0.0515	0.0505	0.0419	0.0392	0.0362	0.0329	0.0314	0.0316	0.0351	0.0363	0.0354	0.0372	0.0432	0.0371	0.0395
P-value	(0.013)	(0.014)	(0.041)	(0.056)	(0.078)	(0.108)	(0.125)	(0.121)	(0.084)	(0.076)	(0.082)	(0.067)	(0.034)	(0.068)	(0.061)
Observations	2489	2580	2602	2610	2613	2615	2617	2619	2620	2623	2623	2625	2599	2630	2623
Overall F	39.09	20.09	12.01	8.87	7.65	6.71	6.57	6.20	6.94	7.71	7.99	8.90	8.85	9.05	15.72
Prob ≥ F	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)

*Notes: Significance at the 1% level: ***, at the 5% level: **, at the 10% level: *. P-values in parentheses. Coefficients for spillovers and autocorrelation given in bold if corresponding p-value < 0.05.*

2.5 Conclusion

This paper provides a comprehensive long-term view on information transmission between stock markets in Hong Kong, Europe and the US. Particularly, we present new evidence on the time- and state-dependence of return spillovers between 2000 and 2011. Using devolatized returns, we are able to conduct linear regressions with residuals not distinguishable from white noise, even though the financial crisis of 2007 is contained in our sample. Our overall evidence is in favor of informational efficiency. If present, deviations from it tend to be weak and temporary. Particular adverse effects of the financial crisis of 2007 on the process of information transmission are not apparent. To return to the public skepticism towards market efficiency, as mentioned in the beginning, our results do not provide reasons that 'a belief in efficient markets proved wrong'. Rather, our results support the opposite: We find informational efficiency to describe the relations between the markets very well, even though there is sporadic evidence, supporting a more comprehensive view on market efficiency, in line with, for example, the Adaptive Markets Hypothesis.

Specifically, the total sample estimations show that generally spillovers and return autocorrelations tend to be weak, if significant at all. We only find spillovers from the US to Hong Kong and from Europe to the US to be pronounced. The fact that statistically significant spillovers at the 1% level can only be confirmed to occur from chronologically directly preceding foreign to domestic markets argues for the importance of the time span that traders have to process information. Furthermore, the structural break tests argue against fundamental changes in cross-market information processing. Events such as the financial crisis of 2007 did not have any fundamentally adverse effects.

The moving window regressions, however, reveal that previously measured total sample spillovers tend to be driven by temporary phases of statistical significance. Overall, the return spillovers turn out to be well in line with recent elaborations on time-varying market efficiency and the Adaptive Markets Hypothesis according to Lo (2004). The latter points out that market efficiency should not be seen as an all-or-none condition. Weak and temporary deviations from informational efficiency are possible according to the Adaptive Markets Hypothesis despite an undoubted prevalence of market efficiency. The short-lived periods of statistically significant spillovers and autocorrelations that we detect with our moving window regressions, support this notion, too. Most notably, we detect weak and short-lived statistically significant autocorrelation in all three markets in the wake of the financial crisis of 2007.

The results from our threshold regressions are consistent with these ideas, too. In particular, they emphasize the important role of market conditions in terms of volatility. We find the negative spillovers from the US to Hong Kong to be only statistically significant in the low volatility state. This finding is consistent with the psychologically grounded overreaction phenomenon, reported by Fung et al. (2010). By contrast, regarding the positive spillovers from Hong Kong and the US to Europe and from Europe to the US, we find these spillovers to be only statistically significant if the chronologically directly preceding European market is in a state of high volatility. The robustness checks show that a quick reversal, as in the case of spillovers from the US to Hong Kong, is not apparent. Taken together with the spillovers' positive sign, this strongly points to rational explanations in the sense of partial price adjustment in line with, for example Kyle (1985) and Admati and Pfleiderer (1988) and not to psychologically grounded overreaction.

A Appendix

A.1 Chronology of Trading

The institutional framework that we use to build our econometric model is given in Figure A1. It depicts the trading times in the three markets that we exploit to compute non-overlapping intra-day open-to-close returns. The times are given in Universal Time Coordinated (UTC) and the respective local times (Hong Kong Time, Central European Time and Eastern Daylight Time). They correspond to two typical trading days during summer time both in Europe and the United States. Moreover, Figure A1 refers to two trading days after the change of trading times in Hong Kong on March 7, 2011, when continuous trading was changed to begin at 9:30 local time.

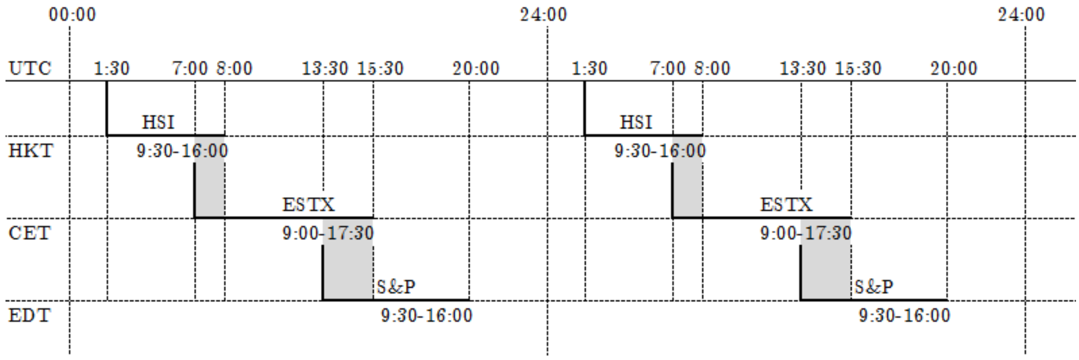

FIGURE A1: *Chronology of trading.*

Notes: The graphic refers to two trading days in 2011 with summer time both in Europe and the US. UTC is Universal Time Coordinated, HKT is Hong Kong Time, CET is Central European Time, EDT is Eastern Daylight Time.

Figure A1 demonstrates that trading on a new day begins with the market opening in Hong Kong at 1:30 UTC. As time shifts do not exist in Hong Kong, trading in this market lasts until 8:00 UTC throughout the whole sample period. This fact results in a one-hour overlap (depicted by a grey shaded area) with trading in Europe which begins at 7:00 UTC. The end of trading in Europe at 15:30 UTC, in turn, leads to a two-hour overlap (again depicted by a grey shaded area) with trading in the US. There, trading lasts from 13:30 UTC until 20:00 UTC. For the computation of non-overlapping intra-day returns we take these overlaps into account. For chronologically preceding markets, we use index quotes only up to the point when trading in the subsequent market begins. For the times of prolonged index dissemination between 2000 and 2003 in Europe and for winter time we proceed analogously.[12] In

[12]Note, however, that an overlap of trading times does not occur between Hong Kong and Europe during winter time.

summer, we use 7:00 UTC as the close value for the HSI. In winter, we use 8:00 UTC. For the ESTX, we use 13:30 UTC and 14:30 UTC respectively. The S&P data need no adjustment. Between the end of trading in New York at 20:00 UTC and the beginning of trading in Hong Kong, there is a time gap of 5.5 hours in summer and 4.5 hours in winter. In addition to (non-synchronous) clock changes in Europe and the US, we take all changes of trading times between 2000 and 2011 into account, too. Table A1 provides an overview of these changes.

TABLE A1: *Changes in trading times.*

Hang Seng Index	
January 2, 2000 to March 4, 2011	10:00–12:30/14:30–16:00
March 7, 2011 to March 2, 2012	9:30–12:00/13:30–16:00
March 5, 2012 to present	9:30–12:00/13:00–16:00
Euro Stoxx 50	
January 3, 2000 to June 1, 2000	9:00–17:30
June 2, 2000 to October 10, 2003	9:00–20:00
November 3, 2003 to present	9:00–17:30
S&P 500	
January 3, 2000 to present	9:30–16:00

Notes: Local times (HKT, CET, EDT).

A.2 Stale Quotes

An important institutional feature that has to be taken into account when computing open-to-close intra-day returns is the fact that index quotes directly after market opening are potentially distorted. The reason is that each of our indexes analyzed is disseminated directly with the beginning of trading on a new day (see S&P Dow Jones Indices LLC (2012), Hang Seng Indexes Company Limited (2012) and Stoxx Limited (2011)). Not all stocks, however, are traded immediately. For some stocks it takes up to several minutes until a first transaction occurs. During this time span, index providers resort to previous day close prices which leads to index quotes potentially reflecting stale information.

The literature provides various different ways on how to deal with this problem. Becker et al. (1990), for example, neglect the problem totally. Pan and Hsueh (1998) as well as Dimpfl and Jung (2012) use futures data to circumvent it. The idea behind this approach is that futures prices theoretically always reflect the current status of information because they are self-contained traded contracts. With the very close relation between futures and their underlying indexes being well documented in various studies (see for example Theissen (2011) and the literature mentioned therein), this strategy appears to be most elegant. However, it has one drawback. From a strict point of view it cannot provide an answer to the question to what extent spillovers and intra-day return autocorrelation are phenomena which are only confined to the futures markets or if they actually constitute market-wide phenomena. Due to stale quotes, potentially contained in index quotes directly at and after market opening, it is unclear if the close relation between future and underlying also holds during the very first minutes of trading. Therefore, studies such as Theissen (2011), which investigate cointegrating relations between futures and indexes, typically avoid potential distortions by leaving the very first minutes of trading out of their samples.

To be able to draw conclusions on the 'market-wideness' of spillovers, we hence decide to use a suitable opening proxy such as for example 'open plus five, ten or fifteen minutes'. This strategy is most common in the literature and followed, for example, by Lin et al. (1994), Wei et al. (1995) or Baur and Jung (2006). In contrast to these previous authors, we base our decision for a proxy on an extensive analysis of intra-day trades data for index constituent stocks, sampled at the millisecond level. We receive this data from the Thomson Reuters DataScope Tick History archive, accessed via the Securities Industry Research Centre of Asia Pacific (SIRCA).[13] With this dataset, we are able to directly measure the exact time points of the first transactions on respective new trading days for huge parts of our stock index constituents. For the HSI, for example, we are able to access transactions during the first 15 minutes of continuous

[13]We thank Börse Stuttgart and SIRCA for providing access to the Thomson Reuters DataScope Tick History archive, http://www.sirca.org.au/.

trading on every trading day and on every stock listed in the index since January 1, 2000. For the Hang Seng data, we are able to consider the exact times during which single stocks were listed in the index. Moreover, we account for the change in trading times on March 7, 2011. Due to a lack of availability, the samples for the other two indexes are smaller. For the ESTX, we resort to data for the current constituents (state: July 31, 2012). However, this might not be a huge drawback as for the HSI we find using current constituents instead of factual constituents keeps the results concerning the optimal opening proxy virtually unchanged. For the S&P, we only have transactions data for some particular stocks, but the situation is particular. 500 stocks are contained in the index. Compared to the other indexes even the largest stocks only have a very small weight in the index.

Overall, we find trading to begin very quickly after market opening in our sample period from January 2000 to September 2011. For the HSI, for example, it takes on average only 32.38 seconds from the beginning of trading until the first transaction occurs. Further, approximately 97% of the first transactions take place during the first three minutes. The point in time when the last constituent stock is updated on a given trading day (i.e. when definitely no more stale quotes are present) is on the average 278.64 seconds after the beginning of trading. About 85% of these 'last first' transactions take place during the first ten minutes. A closer look at the specific stocks frequently traded late reveals that these are foremost titles of companies with relatively small market capitalization and low liquidity. Many of them are often at the edge of being deleted from the index. As a consequence, they only have a small weight in the index.

Altogether, we conclude that the delayed beginning of trading after market opening is a stock-specific phenomenon, mainly concerning small-liquidity stocks. In general, stale quotes are still problematic at the very beginning of a trading day. However, the huge majority of stocks, contained in our sample, is traded so quickly that the effects of any remaining stale quotes can be expected to be minimal after very short time already. We finally decide to use the conservative proxy 'open plus three minutes'. Compared to previous studies, this is an earlier opening proxy. Results based on alternative opening proxies and various robustness considerations can be found in Section 2.4.4.

Chapter 3

Structural Breaks in Volatility Spillovers Between International Financial Markets: Contagion or mere Interdependence?

This paper conducts an investigation of volatility transmission between stock markets in Hong Kong, Europe and the United States, covering the time period from 2000 up to 2011. Using intra-daily data we compute realized volatility time series for the three markets and employ a Heterogeneous Autoregressive Distributed Lag Model as our baseline econometric specification. Motivated by the presence of various crisis events contained in our sample, we detect time-variation and structural breaks in volatility spillovers. Particularly during the financial crisis of 2007, we find effects consistent with the notion of contagion, suggesting strong and sudden increases in the cross-market synchronization of chronologically succeeding volatilities. Investigating the role of mean breaks and conditional heteroskedasticity in the realized volatilities, however, we find the latter to be the main driver of breaks in volatility spillovers. Taking the volatility of realized volatilities into account, we find no evidence of contagion anymore. [1]

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3.1 Introduction

This paper investigates the volatility transmission between three major financial markets around the globe. Our sample period runs from January 2000 to September 2011 and comprises intra-daily data for the Hang Seng Index, the Euro Stoxx 50 and the S&P 500 Index. Adopting a long term perspective allows us to analyze the impact of crisis events, such as the dotcom bubble, September 11, 2001, the financial crisis of 2007 and the European sovereign debt crisis since 2009, on volatility transmission across international stock markets.

Specifically, our study aims at answering three questions. Firstly, are the dynamics of volatility transmission structurally stable and constant over time? Secondly, can we find evidence for contagion during our sample period and in particular during the financial crisis of 2007? And thirdly, does measured contagion truly reflect breaks in stock market linkages as an increased synchronization of chronologically succeeding volatilities? In particular, what is the role for structural breaks and conditional heteroskedasticity in this context?

To address these questions empirically, we compute realized volatility time series based on non-overlapping trading hours, separately for each of the three financial markets analyzed. To cope with strong persistence in our volatility series, we adopt the framework of Corsi (2009)'s Heterogeneous Autoregressive Model of Realized Volatility (HAR-RV) for our empirical analysis. Taking the chronological order of trading in the different markets into account, this framework allows us straightforwardly to include measures of volatility transmission from foreign markets into domestic markets. Moreover, it enables us to measure cross-market volatility spillovers as effects of the realized volatilities in one market onto the realized volatilities in chronologically following markets. Proceeding in this way, we follow benchmark volatility spillover studies, such as Hamao et al. (1990), Lin et al. (1994) and Susmel and Engle (1994).

Given the relatively long sample period of our study, including crisis events, it seems logical to investigate the structural stability of volatility transmission, as well as its typically assumed time invariation. Both aspects have only been rarely addressed in the literature so far.

Further, our empirical framework allows us to identify strong and sudden breaks in measured spillovers as potential contagion effects. Indeed finding evidence for such effects, we investigate if they truly reflect strong and sudden upwards shifts in the synchronization of chronologically succeeding volatilities or if they constitute a measurement issue. In particular, we investigate to what extent structural breaks and conditional heteroskedasticity induce potentially misdiagnosed contagion.

The findings of our study are of importance for policy makers as well as institutional and private investors. From the perspective of international policy makers, volatility spillovers are foremost relevant in the context of financial crises propagation. A key concern is that in times of crises volatility transmission might suddenly deviate from its 'normal' pattern, possibly in a disproportionate and unpredictable way. This applies even more so as the goal of maintaining financial stability has gained a lot in importance in the aftermath of the financial crisis of 2007.

Moreover, they become apparent through ever recurring discussions on financial regulation and institutional rules such as circuit breakers, transaction taxes or short-sale rules. Sound policy measures, however, should be based on a solid understanding of the transmission mechanisms in financial markets. Stock price volatility thereby plays a special role, reflecting market participants' uncertainty.

From the perspective of international investors, volatility transmission and contagion are highly relevant, too. To guarantee sufficiently diversified portfolios, they permanently have to monitor and assess changes in market linkages. An important question in this context is whether or not changes in these linkages are of persistent or only of transitory nature. Even for retail investors these points are of direct importance as the volume of financial products reflecting total market developments, such as exchange traded funds, is growing steadily.

The remainder of this paper is organized as follows. Section 3.2 reviews the relevant literature and defines important terminology. In Section 3.3 we present our empirical framework including the data, our specific way to compute non-overlapping realized volatilities and the Heterogeneous Autoregressive Distributed Lag (HAR-DL) model. In Section 3.4, we present the results suggested from our long term investigation of volatility spillovers together with the results from structural break tests and rolling window estimations. Finally, in Section 3.5 we assess the impact of mean breaks and conditional heteroskedasticity in the realized volatilities on our regression results. Section 3.6 summarizes and concludes.

3.2 Related Literature and Terminology

The literature on transmission processes between international financial markets has developed a terminology which is, unfortunately, not used in a coherent way. Therefore, we begin with a short introduction into the terminology and the literature specifically relevant in the context of our study.

3.2.1 Interdependence and Contagion

Generally, the terms stock market 'relations', 'linkages' and 'interdependence' are used synonymously to each other. Recent authors though, such as Forbes and Rigobon (2002), Corsetti et al. (2005), Billio and Caporin (2010), Baele and Inghelbrecht (2010) or Gebka and Karoglou (2012), subdivide stock market 'linkages' or 'relations' into 'interdependence' and 'contagion'. 'Interdependence' thereby stands for a state of 'continuous', 'normal' or 'tranquil-period' relation between markets. In this state, Kallberg and Pasquariello (2008) and Baele and Inghelbrecht (2010) assume market linkages to be driven by fundamentals. Measured stock market linkages can then be entirely explained by common observed factors due to real or financial linkages. Phenomena such as sudden expectation shifts or herding are excluded. However, high levels of comovement and some limited time-variation in measured linkages are well in line with the notion of 'interdependence'. This is acknowledged, for example, by Forbes and Rigobon (2002), Billio and Caporin (2010) and Baele and Inghelbrecht (2010), who state that fundamentals vary over time, too.

In contrast to that, the state of 'contagion' is characterized by strong and sudden changes in measured market linkages. To be more precise, by contagion we refer to a significant increase in comovement across markets after a shock. This definition goes back to Forbes and Rigobon (2002) and has also been employed, for example, by Caporale et al. (2005), Pesaran and Pick (2007), Baele and Inghelbrecht (2010) and Billio and Caporin (2010).

These studies consider contagion in the context of cross-market comovement in returns. The above definition is, however, sufficiently general to capture comovement in second moments of returns leading to what is known as volatility contagion. Such a more broad view on contagion has also been taken in the papers of Chakrabarti and Roll (2002), Chiang and Wang (2011) or Beirne et al. (2013).

One particular important aspect following from the work of Loretan and English (2000) and Forbes and Rigobon (2002) is that contagion measured by correlation in returns is potentially influenced by the presence of conditional heteroskedasticity in the return series. An immediate consequence of this important finding is that correlation-based identification of contagious events using unadjusted return data can lead to potentially wrong conclusions about the structural stability of market relations.

3.2.2 Volatility Spillovers

Following Weber and Strohsal (2012), financial economics offers at least two perspectives on volatility, which can straightforwardly be extended to the phenomenon of volatility transmission. The first one considers volatility transmission as the consequence of potentially (auto)correlated information flow. The second one regards volatility transmission as reflecting spillovers of uncertainty or valuation insecurity among market participants. Studies investigating these effects directly are Hamao et al. (1990), Lin et al. (1994), Baur and Jung (2006), Savva et al. (2009) or Dimpfl and Jung (2012). Typically, these authors find significant and substantial cross-market volatility spillovers. Further, they often find a dominant role of the US market as a source for volatility transmission.

Most closely related to the approach taken here are studies considering the consequences of important events, threshold- or regime-dependence and structural breaks. Employing dummy variables and various sample splits, e.g. Theodossiou et al. (1997) and Climent and Meneu (2003) investigate stock market spillovers and the consequences of the Asian crisis in 1997. Similarly, Gebka and Serwa (2006) study breaks in spillovers between the US and South East Asian stock markets in 1997. Employing a threshold vector autoregressive model with a calm and turmoil state, they find strong evidence for breaks in causality patterns and contagion. Regime-dependence is taken up by Ramchand and Susmel (1998) and Bialkowski et al. (2006). These authors estimate Markov switching models. Further Gebka and Karoglou (2012) employ batteries of structural break tests to analyze breaks in financial market linkages and to identify potential break dates on a purely data-driven basis.

Recently, though, beginning with Ewing and Malik (2005), a strand of literature has developed, which is specifically concerned with the consequences of structural breaks in volatilities. Huang (2012), for example, employs the Iterated Cumulative Sums of Squares (ICSS) algorithm developed by Inclan and Tiao (1994) within their GARCH model. Using weekly futures data, they analyze stock market relations between the US, UK and Japan from 1989 to 2006. They find structural changes in variance not to occur simultaneously in the different markets. Moreover, they find measured volatility spillovers to be much weaker or even to disappear after controlling for structural change in volatilities. Not taking structural change into account, they reason, can lead to a significant overestimation of volatility transmission. Similar conclusions, based on weekly data are drawn in Ewing and Malik (2005) and Miralles-Marcelo et al. (2008). Note, however, that none of these authors uses intra-daily data such as we do.

3.3 Empirical Framework

This section starts with a brief description of our dataset. We then move on to explain the framework for our computation of non-overlapping realized volatilities which enables us to conduct Granger causality inference and to treat volatility as an observed time series. We conclude this section by describing our empirical modeling framework.

3.3.1 Data

For each of the three different markets analyzed, we use stock index data sampled at the five-minute frequency. For Hong Kong we choose the Hang Seng Index (HSI), provided directly by the Hang Seng Indexes Company. For Europe we choose the Euro Stoxx 50 (ESTX) from Stoxx Limited in Zürich. For the United States we choose the S&P 500 (S&P) from Standard and Poor's in New York. The latter two series have been provided by Olsen Financial Technologies. All three series contain free-float capitalization weighted price indexes, representing major and highly liquid financial markets in three different parts of the world. The Euro Stoxx 50 and the S&P 500 are leading stock market indicators in Europe and the US, the Hang Seng Index is one of the most closely monitored stock market indexes in Asia. The sample reaches from 03.01.2000 to 30.9.2011. However, as customary in the literature, we only take common trading days into account. Holidays and weekends are thus excluded. Overall, we consider 2700 trading days.

3.3.2 Non-Overlapping Realized Volatilities

Realized volatility is an error-free measure for the volatility in a given market if price jumps and market microstructure noise are absent. This has been shown by various authors - foremost Andersen et al. (2001) and Barndorff-Nielsen and Shephard (2002). For our empirical application, this is an attractive feature. Following e.g. Andersen et al. (2006) we can treat volatility as directly observed. As a measure for the logarithmized realized volatility in a single market for trading day t, we use

$$ln(\sigma_t) = ln\sqrt{\sum_{j=1}^{M} r_{t,j}^2}\,. \tag{3.1}$$

I.e., we compute daily realized volatilities for each of our markets by summing up the M squared intra-day log returns ($r_{t,j}^2$). Following Andersen et al. (2010), we choose to use data on a five-minute frequency. Empirically, this frequency has been shown to be most adequate to solve the trade-off between bias and variance in the realized volatility estimator.[2] Finally, we log-transform our series to improve their statistical properties, as suggested by Andersen et al. (2003).

An important feature of our study is the consideration of non-overlapping trading times and volatility measures. To achieve this, we do not use intra-day returns over

[2]The bias arises from market microstructure noise, for example induced by non-synchronous trading. The volatility rises as a consequence of discretization if the frequency is lowered.

the full trading times of our markets, as it is done typically in other studies. We only compute them over the non-overlapping time spans, as illustrated in Figure 3.1 and elaborated on below.

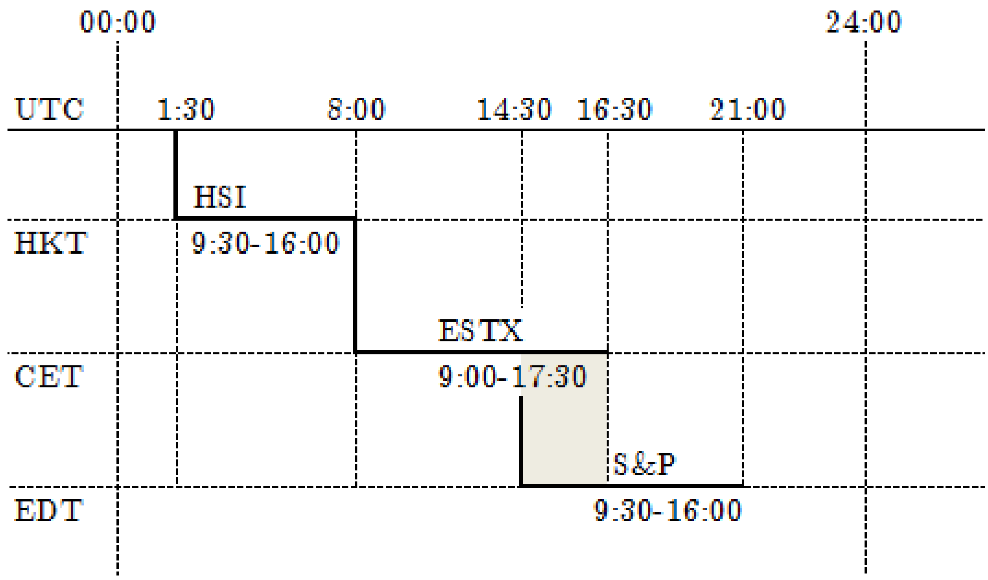


FIGURE 3.1: *Trading times in the three markets.*

Notes: Winter time both in Europe and the US in 2011, UTC is Universal Time Coordinated, HKT is Hong Kong Time, CET is Central European Time, EDT is Eastern Daylight Time.

Figure 3.1 illustrates the opening and closing times in the three markets analyzed, corresponding to a typical trading day during winter time, both in Europe and the United States. Time is given in Universal Time Coordinated (UTC) as well as the respective local times and refers to a date after the change of trading times in Hong Kong on 07.03.2011, when continuous trading was shifted to begin at 9:30 Hong Kong local time. Trading on a new day starts at 1:30 UTC in Hong Kong. During winter time there is no overlap with trading in the European market which opens at 8:00 UTC. However, during summer time, there is a one hour overlap, which we take into account by taking 7:00 UTC as a proxy for market closing in Hong Kong. The Euro Stoxx 50 includes stocks that are traded until 16:30 UTC in winter. However, trading in the US already starts at 14:30 UTC, leading to a two hour overlap (depicted by the grey shaded area). To take this into account, we use 14:30 UTC as a proxy for market closing in Europe. For summer time we proceed analogously, using 13:30 UTC as the closing proxy for Europe. For the S&P 500 intra-day returns we use the entire trading day, as neither in winter, nor in summer any overlap with trading in Hong Kong occurs.

An additional aspect that we take into account is the problem of stale quotes in index opening prices. The computation of the three stock indexes starts immediately after the opening on a new trading day. Yet, for some stocks it takes up to several minutes until the first transaction on a new trading day is recorded. Until then, those stocks enter the index computation with their previous day close prices - so called stale quotes (see Hang Seng Indexes Company Limited (2012), Stoxx Limited (2011) and S&P Dow Jones Indices LLC (2012)). Having investigated this issue in an extensive separate analysis, we decide to begin with the computation of our realized volatilities three minutes after market opening. Additionally, we respect for non-synchronous clock changes in Europe and the US and take changes in trading times into account. Details on these changes are given in Table 3.1.

TABLE 3.1: *Trading times.*

Hang Seng Index	
03.01.2000 to 04.03.2011	10:00-12:30/14:30-16:00
07.03.2011 to 02.03.2012	9:30-12:00/13:30-16:00
05.03.2012 to present	9:30-12:00/13:00-16:00
Euro Stoxx 50	
03.01.2000 to 01.06.2000	9:00-17:30
02.06.2000 to 31.10.2003	9:00-20:00
03.11.2003 to present	9:00-17:30
S&P 500	
03.01.2000 to present	9:30 - 16:00

Notes: In local times.

The summary statistics of the log-realized volatility series that we obtain for each of our markets are provided in Table 3.2. All time series exhibit characteristics that have been reported elsewhere in the literature. Note, that the means and medians of the series are negative due to logarithmization. The standard deviations of the three series are comparable across the different markets. Joint skewness and kurtosis tests for the single series reject standard normality in all three cases. However, mainly the positive skewness drives this result. The kurtosis values being close to three is quite remarkable, given that our sample period contains data from the recent financial crisis.

TABLE 3.2: *Descriptive statistics: Log-realized volatilities.*

Sample	01/2000 to 09/2011		
Market	HSI	ESTX	S&P
Obs.	2700	2700	2700
Mean	−0.240	−0.289	−0.252
Median	−0.272	−0.308	−0.284
Minimum	−1.407	−1.819	−1.641
Maximum	1.883	2.418	2.256
St. Dev.	0.445	0.521	0.508
Skewness	0.546	0.348	0.563
Kurtosis	3.820	3.188	3.632
Normality test	159.180	55.340	152.930
	(0.000)	(0.000)	(0.000)
Sample correlations			
HSI_t	1	-	-
$ESTX_t$	0.440	1	-
$S\&P_t$	0.575	0.784	1
HSI_{t-1}	0.755	0.413	0.555
$ESTX_{t-1}$	0.418	0.819	0.713
$S\&P_{t-1}$	0.570	0.756	0.852

Notes: Normality tests according to D'Agostino, Belanger and D'Agostino Jr. (1990). P-values given in parentheses.

3.3.3 Heterogeneous Autoregressive Distributed Lag Model

Based on our definition of intra-day realized volatilities, volatility can only transmit from east to west in a chronological order. We use this fact directly to formulate three dynamic models in the spirit of the Autoregressive Distributed Lag (ADL) approach. Each model enables us to conduct Granger causality inference on volatility transmission and to obtain dynamically complete specifications. This approach does not require us to impose any restrictions, nor to limit ourselves to reduced form models, as it would be the case in a multivariate vector autoregressive framework. Moreover, we are able to conduct our estimations for each market separately using the Ordinary Least Squares (OLS) method.

Specifically, we have one $ADL(p,q_1,q_2)$ model for each market, where p denotes the number of lags of the domestic market and q_1 and q_2 are the numbers of lags of the two preceding foreign markets. The volatility persistence of the domestic market is then captured by the coefficients for its own lags, whereas cross-market volatility spillovers are captured by the parameters corresponding to the lagged foreign volatilities. The equations corresponding to the three markets are as follows:

$$
\begin{aligned}
HSI_t &= \alpha_{0,HSI} \\
&+ \alpha_{1,HSI} HSI_{t-1} + ... + \alpha_{p,HSI} HSI_{t-p} \\
&+ \beta_{1,HSI} ESTX_{t-1} + ... + \beta_{q_1,HSI} ESTX_{t-q_1} \\
&+ \gamma_{1,HSI} S\&P_{t-1} + ... + \gamma_{q_2,HSI} S\&P_{t-q_2} \\
&+ \epsilon_{HSI,t}
\end{aligned} \tag{3.2}
$$

$$
\begin{aligned}
ESTX_t &= \beta_{0,ESTX} \\
&+ \alpha_{1,ESTX} HSI_t + \alpha_{2,ESTX} HSI_{t-1} + ... + \alpha_{q_1,ESTX} HSI_{t-q_1} \\
&+ \beta_{1,ESTX} ESTX_{t-1} + ... + \beta_{p,ESTX} ESTX_{t-p} \\
&+ \gamma_{1,ESTX} S\&P_{t-1} + ... + \gamma_{q_2,ESTX} S\&P_{t-q_2} \\
&+ \epsilon_{ESTX,t}
\end{aligned} \tag{3.3}
$$

$$
\begin{aligned}
S\&P_t &= \gamma_{0,S\&P} \\
&+ \alpha_{1,S\&P} HSI_t + \alpha_{2,S\&P} HSI_{t-1} + ... + \alpha_{q_1,S\&P} HSI_{t-q_1} \\
&+ \beta_{1,S\&P} ESTX_t + \beta_{2,S\&P} ESTX_{t-1} + ... + \beta_{p,S\&P} ESTX_{t-p} \\
&+ \gamma_{1,S\&P} S\&P_{t-1} + ... + \gamma_{q_2,S\&P} S\&P_{t-q_2} \\
&+ \epsilon_{S\&P,t} \, ,
\end{aligned} \tag{3.4}
$$

with $\epsilon_{HSI,t}$, $\epsilon_{ESTX,t}$ and $\epsilon_{S\&P,t}$ assumed to be serially independent mean zero volatility innovations. Note that by construction, we do not include volatility spillovers from day t in Equation (3.2), as the Hong Kong market is the first market to trade on a new day. Past trading in foreign markets can hence only exert a Granger causal effect up to day $t-1$ at the latest. In the Equation (3.3), for the Euro Stoxx 50, by contrast, the directly preceding trading in Hong Kong on day t has to be considered ($\alpha_{1,ESTX} HSI_t$). In Equation (3.4), we analogously include and $\alpha_{1,S\&P} HSI_t$ and $\beta_{1,S\&P} ESTX_t$ because both markets precede trading in the US market on day t, too. The selection of the number of lags q, p_1 and p_2 in the three equations could in principle be based on information criteria. Moreover, non-significant lags could be eliminated from the estimated regressions in order to provide parsimonious model specifications.

However, previous studies such as Andersen et al. (2001), Andersen et al. (2003) or Choi et al. (2010) have documented strong persistence in (log)-realized volatilities. We therefore anticipate even the most parsimonious model versions still to contain a high number of parameters to be estimated. To circumvent this problem, we propose to use the framework of the Heterogeneous Autoregressive model of Realized Volatility (HAR-RV) according to Corsi (2009). This approach considers volatility components realized over different time horizons instead of the whole range of lagged realized volatilities to capture the persistence in volatility. Corsi (2009)'s generic notation for realized volatilities without cross-market interactions has the following form:

$$RV_t^{(d)} = c + \beta^{(d)} RV_{t-1}^{(d)} + \beta^{(w)} RV_{t-1}^{(w)} + \beta^{(m)} RV_{t-1}^{(m)} + \omega_t \tag{3.5}$$

where ω_t is a serially independent zero mean volatility innovation and $RV_t^{(d)}$, $RV_{t-1}^{(d)}, RV_{t-1}^{(w)}, RV_{t-1}^{(m)}$ are realized volatilities over daily, weekly and monthly time horizons, respectively. The weekly volatility component $RV_{t-1}^{(w)}$, for example, is computed in the following way:

$$RV_t^{(w)} = \frac{1}{5}(RV_t^{(d)} + RV_{t-1}^{(d)} + ... + RV_{t-4}^{(d)}) \tag{3.6}$$

The monthly component can be computed analogously over 22 trading days.

Implementing this concept into our specific context, we rewrite Equations (3.2) to (3.4) and use the corresponding weekly and monthly volatility components instead of the respective lags from one to p, q_1 and q_2. We denote the resulting generic model the Heterogeneous Autoregressive Distributed Lag model (HAR-DL). The number of parameters to estimate is reduced when applying this model to the single equations of our markets. This is attractive both in testing for breaks in volatility transmission and conducting rolling window estimations in Section 3.4. For the three markets under study here, the resulting regression equations have an HAR-DL form as follows:

$$\begin{aligned}
HSI_t^{(d)} &= \alpha_{0,HSI} \\
&+ \alpha_{1,HSI} HSI_{t-1}^{(d)} + \alpha_{2,HSI} HSI_{t-1}^{(w)} + \alpha_{3,HSI} HSI_{t-1}^{(m)} \\
&+ \beta_{1,HSI} ESTX_{t-1}^{(d)} + \beta_{2,HSI} ESTX_{t-1}^{(w)} + \beta_{3,HSI} ESTX_{t-1}^{(m)} \\
&+ \gamma_{1,HSI} S\&P_{t-1}^{(d)} + \gamma_{2,HSI} S\&P_{t-1}^{(w)} + \gamma_{3,HSI} S\&P_{t-1}^{(m)} \\
&+ v_{HSI,t}
\end{aligned} \tag{3.7}$$

$$\begin{aligned}
ESTX_t^{(d)} &= \beta_{0,ESTX} + \alpha_{1,ESTX} HSI_t^{(d)} \\
&+ \alpha_{2,ESTX} HSI_{t-1}^{(d)} + \alpha_{3,ESTX} HSI_{t-1}^{(w)} + \alpha_{4,ESTX} HSI_{t-1}^{(m)} \\
&+ \beta_{1,ESTX} ESTX_{t-1}^{(d)} + \beta_{2,ESTX} ESTX_{t-1}^{(w)} + \beta_{3,ESTX} ESTX_{t-1}^{(m)} \\
&+ \gamma_{1,ESTX} S\&P_{t-1}^{(d)} + \gamma_{2,ESTX} S\&P_{t-1}^{(w)} + \gamma_{3,ESTX} S\&P_{t-1}^{(m)} \\
&+ v_{ESTX,t}
\end{aligned} \tag{3.8}$$

$$\begin{aligned}
S\&P_t^{(d)} &= \gamma_{0,S\&P} + \alpha_{1,S\&P} HSI_t^{(d)} + \beta_{1,S\&P} ESTX_t^{(d)} \\
&+ \alpha_{2,S\&P} HSI_{t-1}^{(d)} + \alpha_{3,S\&P} HSI_{t-1}^{(w)} + \alpha_{4,S\&P} HSI_{t-1}^{(m)} \\
&+ \beta_{2,S\&P} ESTX_{t-1}^{(d)} + \beta_{3,S\&P} ESTX_{t-1}^{(w)} + \beta_{4,S\&P} ESTX_{t-1}^{(m)} \\
&+ \gamma_{1,S\&P} S\&P_{t-1}^{(d)} + \gamma_{2,S\&P} S\&P_{t-1}^{(w)} + \gamma_{3,S\&P} S\&P_{t-1}^{(m)} \\
&+ v_{S\&P,t}\,.
\end{aligned} \tag{3.9}$$

Again $v_{HSI,t}$, $v_{ESTX,t}$, $v_{S\&P,t}$ are assumed to be serially independent zero mean volatility innovations. Subsequently, we refer to Equation (3.7) as the 'HSI-Equation', Equation (3.8) as the 'ESTX-Equation' and Equation (3.9) as the 'S&P-Equation'.

3.4 Empirical Results

In this section we first present empirical results for our total sample ranging from 01/2000 to 09/2011. These results are supposed to reflect volatility dependencies over the long term perspective of more than a decade. However, motivated by the presence of the financial crisis of 2007 and various other important events in our sample, we expect the structural stability of volatility transmission to be questionable. Therefore, we subsequently conduct tests on breaks in linear regression relations and perform rolling window estimations to gain deeper insights to investigate this hypothesis.

3.4.1 Evidence for the Total Sample

In this subsection we present OLS estimation results for the three HAR-DL models presented in the Equations (3.7) to (3.9). Our particular focus is on volatility spillovers from the two directly preceding foreign markets. These are expected to carry the most relevant information as compared to further lagged foreign market spillovers. For the European market, for example, this amounts to particularly taking volatility spillovers from $HSI_t^{(d)}$ and $S\&P_{t-1}^{(d)}$ into account.

Our estimation results are displayed in Table 3.3. For each of the three markets we find the coefficients for the domestic weekly and monthly volatility components to be positive and statistically different from zero. By contrast, the coefficients for weekly and monthly volatility components from foreign markets tend to be small and mostly not statistically significantly different from zero.[3]
Most importantly, though, for volatility spillovers from foreign markets, we find several large statistically significant coefficients. Particularly, volatility from chronologically directly preceding foreign markets tend to increase volatility in domestic mar-

[3]Note that in contrast to daily realized volatilities, for weekly and monthly volatility components collinearity is strongly pronounced. We therefore do not put too much weight on significant volatility spillovers at these components.

kets. The Hong Kong market appears to be particularly susceptible to volatility from directly preceding trading in the US. Volatility spillovers from Europe, however, are small and not statistically different from zero. Vice versa, however, the volatility spillover effect from directly preceding trading in Hong Kong to Europe is positive and statistically significantly different from zero. Moreover, despite the fact that the Hong Kong market is the directly preceding market, there is a strongly pronounced positive statistically significant effect from previous day trading in the US to Europe. Finally, concerning the US market, we likewise find evidence for a strong positive statistically significant volatility spillover from directly preceding trading in Europe. By contrast, the positive spillover from Hong Kong is significant, but only small. Overall, we find our HAR-type models to capture the volatility dynamics very well. All models are dynamically complete, leading to residuals statistically not distinguishable from white noise.

3.4.2 Structural Stability and Time-Varying Spillovers

The estimation results from above give useful overall approximations on volatility transmission in our total sample. However, including various important events such as the financial crisis of 2007, it appears doubtful that the linear relations, as proposed in the total regression results, remain stable over the whole sample period. We therefore use the standard test for breaks in linear relations due to Andrews (1993), Andrews and Ploberger (1994) and Zeileis et al. (2002). For each of our three regression Equations (3.7) to (3.9), we test the null hypothesis of no structural break versus the alternative of a single parameter shift. With the potential break dates being unknown, we compute the following F-statistic according to Andrews (1993) for all potential break dates and in each single market separately:

$$F_t = \frac{\widehat{u}^T\widehat{u} - \widehat{e}_t^T\widehat{e}_t}{\widehat{e}_t^T\widehat{e}_t/(n-2k)} \tag{3.10}$$

TABLE 3.3: *HAR-DL models: Evidence from 01/2000 to 09/2011.*

HSI-Equation			ESTX-Equation			S&P-Equation		
$HSI_t^{(d)}$	.		$HSI_t^{(d)}$	**0.1386**	***	$HSI_t^{(d)}$	**0.0959**	***
	(.)			**(0.000)**			**(0.000)**	
$HSI_{t-1}^{(d)}$	0.1677	***	$HSI_{t-1}^{(d)}$	−0.0319		$HSI_{t-1}^{(d)}$	0.0689	***
	(0.000)			(0.188)			(0.001)	
$HSI_{t-1}^{(w)}$	0.3564	***	$HSI_{t-1}^{(w)}$	0.0205		$HSI_{t-1}^{(w)}$	−0.1251	***
	(0.000)			(0.651)			(0.001)	
$HSI_{t-1}^{(m)}$	0.3940	***	$HSI_{t-1}^{(m)}$	−0.1438	***	$HSI_{t-1}^{(m)}$	0.0103	
	(0.000)			(0.001)			(0.780)	
$ESTX_t^{(d)}$	.		$ESTX_t^{(d)}$	.	***	$ESTX_t^{(d)}$	**0.3675**	***
	(.)			(.)			**(0.000)**	
$ESTX_{t-1}^{(d)}$	**0.0017**		$ESTX_{t-1}^{(d)}$	0.1945	***	$ESTX_{t-1}^{(d)}$	−0.0705	***
	(0.942)			(0.000)			(0.001)	
$ESTX_{t-1}^{(w)}$	−0.0091		$ESTX_{t-1}^{(w)}$	0.3872	***	$ESTX_{t-1}^{(w)}$	−0.0590	
	(0.834)			(0.000)			(0.132)	
$ESTX_{t-1}^{(m)}$	−0.0337		$ESTX_{t-1}^{(m)}$	0.3153	***	$ESTX_{t-1}^{(m)}$	−0.1584	***
	(0.436)			(0.000)			(0.000)	
$S\&P_{t-1}^{(d)}$	**0.1474**	***	$S\&P_{t-1}^{(d)}$	**0.3176**	***	$S\&P_{t-1}^{(d)}$	0.2721	***
	(0.000)			**(0.000)**			(0.000)	
$S\&P_{t-1}^{(w)}$	0.0278		$S\&P_{t-1}^{(w)}$	−0.1145	**	$S\&P_{t-1}^{(w)}$	0.3651	***
	(0.551)			(0.017)			(0.000)	
$S\&P_{t-1}^{(m)}$	−0.0940	**	$S\&P_{t-1}^{(m)}$	−0.1156	**	$S\&P_{t-1}^{(m)}$	0.2251	***
	0.048			(0.018)			(0.000)	
Const	−0.0115	*	*Const*	−0.0110	*	*Const*	0.0000	
	(0.065)			(0.088)			(0.993)	

*Notes: *** Significance at the 1% level. ** Significance at the 5% level. * Significance at the 10% level. P-values given in parentheses.*

where $\widehat{e_t} = (\widehat{u}_{<t}, \widehat{u}_{>t})^T$ are the residuals from the model in which the coefficients are estimated separately for subsamples before and after potential break dates t, $\widehat{u}$ denote the residuals from the model with the parameters estimated over the total sample, n denotes the total sample size, k are the degrees of freedom and the potential break dates t are given by the interval $[(0.075 \cdot n); (n - 0.075 \cdot n)]$.

The results obtained from applying this procedure to our log-realized volatility series are depicted in Figure 3.2. The boundaries are computed in such a way that the probability for the supremum of the F-statistic to exceed them is $\alpha = 5\%$. As is evident from the Figure, the F-statistics move across the boundaries in all three markets. We therefore reject the null hypothesis of no structural change in each single case. Overall, we hence conclude that our HAR-DL models are not structurally stable over the whole sample period, particularly not during the financial crisis of 2007.

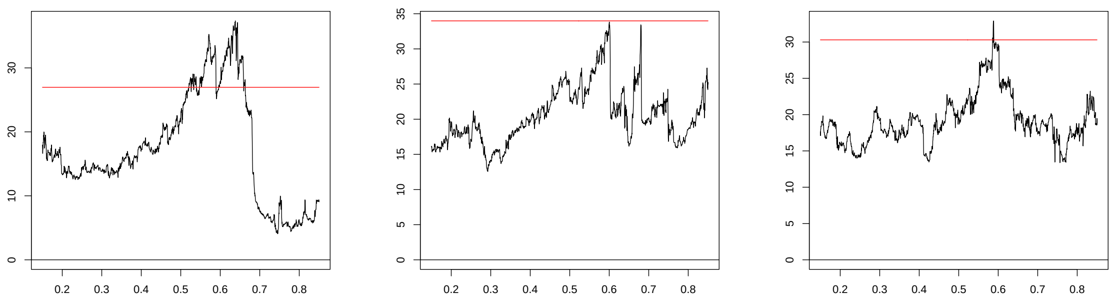


FIGURE 3.2: *Tests for breaks in linear relations I.*

Notes: HAR-DL models with log-realized volatilities. HSI-Equation (left), ESTX-Equation (middle), S&P-Equation (right). F-Statistics (jagged, black), boundaries for $\alpha = 5\%$ (upper, red lines).

However, to gain an even deeper insight into parameter changes, we conduct rolling window estimations. To avoid collinearity issues and to follow the principle of parsimony, we proceed by taking only those coefficients into account, that are statistically significant at the 1% level in Table 3.3. However, we always retain the volatility of two directly preceding foreign markets in the regression equations. We then estimate the three equations for our different markets by OLS, rolling through our total sample from the beginning to its end. Setting the window size fixed and equal to 250 days, our volatility spillovers at time t then denote the point estimates for the window $t - 250$. Starting from the beginning of our sample, we provide rolling spillover estimates from the 250th observation onwards. We hence conduct 2450 regressions with corresponding 2450 spillover estimates for each of our three markets and depict the results graphically. The window length of 250 days is approximately equivalent to one trading year. In the course of robustness checking, we try out different window sizes between 100 and 500 days. We expect two opposing effects. On the one hand, spillover effects being statistically significant for short time spans, should tend to be detected with small window sizes. On the other hand, the power of the significance tests should increase with bigger window sizes. In practice, however, we find these conflicting effects to balance themselves so that our conclusions are virtually the same, no matter which window size between 100 and 500 we use. Concerning the standard errors for the rolling regression estimates, we decide to use heteroskedasticity and autocorrelation-consistent ones, according to Newey and West (1987).

The results for the rolling estimations are depicted in Figure 3.3. The graphs depict the corresponding 250 days moving-window spillover point estimates together with their pointwise 95%-confidence bands. The total sample spillover estimates are represented by the continuous lines. From the course of these spillovers, it is apparent, that already before the financial crisis of 2007, the volatility spillover estimates vary around their long term estimates. The patterns are hardly associable with external events. However, with the beginning of the financial crisis of 2007 several strong and sudden changes in spillovers occur, with both confidence bands moving well above the estimated total sample spillover estimates. In the HSI-Equation, depicted in the first column of Figure 3.3, a sudden upwards shift in the volatility spillover from $S\&P_{t-1}^{(d)}$ occurs. Similarly, in the second and third column of Figure 3.3, the spillover from $S\&P_{t-1}^{(d)}$ in the ESTX-Equation and the spillover from $ESTX_t^{(d)}$ in the S&P-Equation suddenly move upwards. Overall, particularly volatility spillovers from the US market to the other two markets and the spillover from the European to the US market appear to increase. The Hong Kong market is susceptible to US volatility, but only plays a minor role as an origin of volatility.[4]

Taken as a whole, the results suggest a pronounced strengthening of market to market volatility transmission only during the financial crisis of 2007. Considering our

[4]Even though volatility persistence is not in the focus of this study, note that we only find very little fluctuations in weekly and monthly volatility components both from domestic and foreign markets.

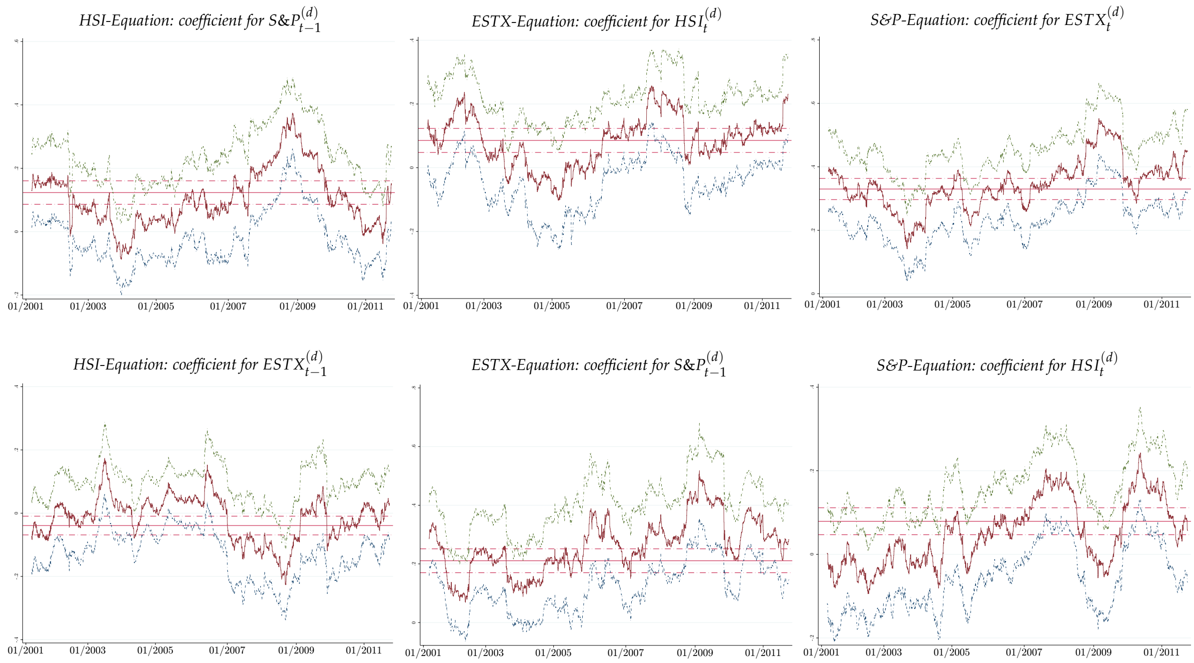


FIGURE 3.3: *HAR-DL models with log-realized volatilities: Time-varying volatility spillovers.*

Notes: First line: Chronologically directly preceding markets. Second line: Chronologically secondly preceding markets. Horizontal lines: Full sample spillovers (continuous) with 95% confidence bands (dotted). Jagged lines: 250 days rolling windows spillovers with 95% confidence bands. Plotted spillover at time t: Estimate for the subperiod $t-250$ to t. Graphs for further lags: Available upon request. Standard errors: HAC.

specific framework, the results suggest an increased synchronization in chronologically succeeding realized volatilities in our markets analyzed during the financial crisis. The strong and sudden character of the changes in volatility transmission is well in line with the notion of contagion, as outlined in Section 3.2. Taking the viewpoint of volatility as reflecting information flow, the results suggests, that the relevance of information flow from preceding foreign markets for domestic markets might have changed suddenly during the crisis. Information arising in the US, for example, seems to have had a stronger impact during the crisis than before. Taking the perspective of volatility as reflecting market participants' uncertainty, the results suggest that compared to the period before the crisis, uncertainty has been transmitted in a disproportionate way across the markets.

3.5 Economic Implications: Contagion or mere Interdependence?

In the previous section, we have uncovered strong time-variation and structural breaks in volatility transmission during the financial crisis of 2007. The results suggest a strong and sudden increase in the synchronization of volatilities across chronologically succeeding markets. However, as outlined in Section 3.2.2, the literature suggests, that structural breaks in the means of our volatility series might affect our results. Further, as outlined in Section 3.2.1, Forbes and Rigobon (2002) find conditional heteroskedasticity to play a critical role for potentially misdiagnosed contagion in the context of stock market returns. An analogous problem, however, might occur in regressions based on realized volatilities. In order to preclude any misdiagnosed volatility contagion, we assess the impact of both structural breaks in means and conditional heteroskedasticity in realized volatilities in the following.

3.5.1 The Impact of Structural Breaks in the Mean

From a visual inspection of our logarithmized realized volatility series, depicted in Figure 3.4, together with the rolling regression results from Figure 3.3, we find the episodes of extraordinarily strong spillovers and potential contagion to coincide with periods of particularly high realized volatilities. In a first step, we therefore investigate the role of structural breaks in the means of our realized volatilities. As mentioned in Section 3.2.2, the relation between spillover effects and structural breaks in volatilities, has up to now only been analyzed within GARCH-type models. Generally, structural breaks have been investigated foremost in the context of long memory models for volatility (see the ongoing discussion lead by Granger and Ding (1996), Granger and Hyung (2004) or Choi and Zivot (2007)). Relating to high frequency data and realized volatilities, however, suitable studies are still rare. Examples for studies are Liu and Maheu (2008) and Choi et al. (2010). Using exchange rate data, Choi et al. (2010) employ the same econometric strategy as we do. They conduct the break search procedure according to Bai and Perron (1998) and Bai and Perron (2003), which is suited to detect multiple breaks with unknown break dates. They find two to five breaks in their two year and a half exchange rate series for Deutsche Mark/Dollar and Yen/Dollar. However, they demonstrate by simulation that absent structural breaks there is always some positive association between long memory and the number of breaks detected by their method. Hence not all of their breaks identified truly constitute structural breaks in a strict sense.

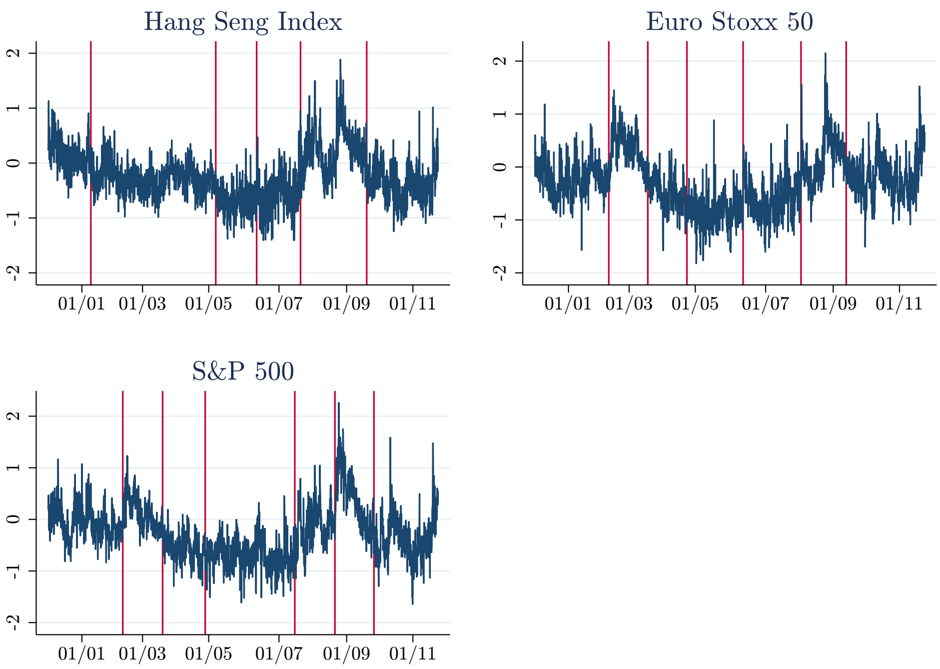


FIGURE 3.4: *Log-realized volatilities with structural break dates according to Table 3.4.*

The results presented in Table 3.4 suggest that structural breaks in the means of the realized volatility series used here are a concern, too. The null hypothesis of no structural breaks against the alternative of an unknown number of structural breaks is clearly rejected. All test statistics are above their critical values at common levels of significance. As proposed by Bai and Perron (2003), we use the Bayesian information criterion (BIC) to condense the information given by the tests. This criterion is most appropriate in our case, as structural breaks have to be expected a priori. Indeed the BIC suggests five breaks for the Hong Kong series, six breaks for the ESTX series and six breaks for the S&P series. To some extent, this high number of structural breaks reflects the high level of sensitivity that we chose for our tests. We set the the trimming parameter to 10% which results in a minimum length of a segment of 270 days. This length is close to the 250 day window from our rolling regressions and allows for 8 structural breaks detected in every single series at the maximum.

Concerning the dates of our structural breaks detected, only a few of them appear to

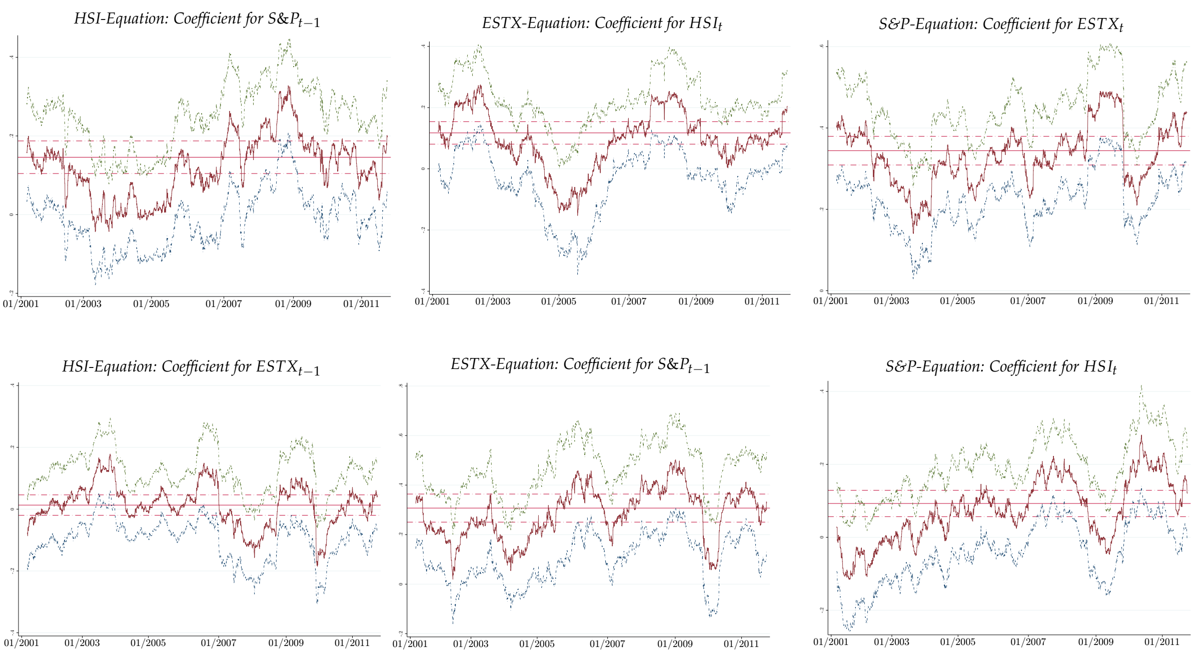


FIGURE 3.5: *HAR-DL models with demeaned log-realized volatilities: Time-varying spillovers.*

Notes: First line: Chronologically directly preceding markets. Second line: Chronologically secondly preceding markets. Horizontal lines: Full sample spillovers (continuous) with 95% confidence bands (dotted). Jagged lines: 250 days rolling windows spillovers with 95% confidence bands. Plotted spillover at time t: Estimate for the subperiod $t-250$ to t. Graphs for further lags: Available upon request. Standard errors: HAC.

be approximately synchronous across the different markets. This is consistent with the findings of Ewing and Malik (2005) and Huang (2012), mentioned in Section 3.2.2, who also find non-synchronous breaks in volatilities within their GARCH-type approaches. To conduct sample splits according to synchronous break dates and to assess differences in volatility spillovers across the resulting subsamples is hence not feasible. However, to assess the impact of structural breaks on volatility spillovers, we follow a different strategy, in line with Choi et al. (2010). In a first step, we demean the single realized volatility series. However, we do not use the means from the total samples, but the means from the subsamples splitted according to the break dates presented in Table 3.4. In a second step, we use the piecewisely demeaned series to estimate three separate HAR-DL models for our different markets. Again, we follow the principle of parsimony by first estimating models for the total samples, eliminating the lags with insignificant coefficients on the 1% level, except of those from the two directly preceding foreign markets. Then we proceed by estimating the models over 250 days rolling windows. The results are depicted in Figure 3.5. Compared to the pattern of the volatility spillovers depicted in Figure 3.3, we find slight reductions of our volatility spillovers during potential episodes of contagion. However, the overall pattern is very similar to the one before. Again, in parts the changes in volatility spillovers are so pronounced that both confidence bands shift above the long term spillover estimates. We hence conclude that structural breaks in the means of our realized volatilities are only able to explain a minor part of the shifts in volatility spillovers measured during the crisis.

3.5.2 The Role of Conditional Heteroskedasticity

The starting point for the investigation in this subsection is again the graphical inspection of the log-realized volatility series. In addition to potential mean shifts, Figure 3.4 reveals that the realized volatilities appear to fluctuate with non-constant rates over time. This motivates us to take the volatility of the realized volatility estimators into account. Following our reasoning on contagion, we thereby aim to disentangle two different effects. The first one is a genuine increase in the synchronization

TABLE 3.4: *Structural breaks in the log-realized volatilities.*

Market			Specifications				
	$z=1$	$q=1$	$p=0$	$h=270$	$M=8$		
			Tests				
	Sup$F_t(1)$	Sup$F_t(2)$	Sup$F_t(3)$	Sup$F_t(4)$	Sup$F_t(5)$	Sup$F_t(6)$	
HSI	159.94	100.79	202.31	214.59	210.99	147.08	
ESTX	82.48	245.96	204.04	161.04	142.00	169.29	
S&P	74.11	268.30	160.01	148.70	128.56	114.75	
	Sup$F_t(7)$	Sup$F_t(8)$	$UDmax$	$WDmax$			
HSI	154.27	131.96	214.59	214.59			
ESTX	145.42	118.94	245.96	245.96			
S&P	99.40	84.76	268.30	268.30			
	Sup$F_t(2\|1)$	Sup$F_t(3\|2)$	Sup$F_t(4\|3)$	Sup$F_t(5\|4)$	Sup$F_t(6\|5)$	Sup$F_t(7\|6)$	
HSI	79.98	303.26	194.54	9.30	8.38	0.00	
ESTX	236.55	40.14	28.62	28.62	44.64	0.10	
S&P	121.12	41.99	14.65	25.33	26.62	0.78	
			Number of breaks selected				
		Sequential		LWZ		BIC	
HSI		4		4		5	
ESTX		6		6		6	
S&P		5		5		6	
			Break dates according to BIC.				
HSI	18.04.01		04.03.05	15.05.06	15.08.07	21.08.09	
ESTX	24.05.02	22.07.03	15.09.04	11.05.06	15.01.08	8.06.09	
S&P	31.05.02	06.08.03	05.11.04	18.06.07	27.08.08	6.11.09	
Mean realized volatilities according to subsamples proposed by break dates given above.							
HSI	0.1327	−0.2797	−0.7007	−0.5846	0.2640	−0.3834	
ESTX	−0.2031	0.3472	−0.5150	−0.8776	−0.6187	0.1852	−0.1842
S&P	−0.0679	0.1288	−0.5487	−0.7101	−0.0989	0.3842	−0.3496

Notes: According to Bai and Perron (2003) the BIC criterion has to be preferred under the presence of multiple breaks, the LWZ by contrast under H_0: No breaks.
M: Maximum number of breaks allowed.
*h: Minimum length of a segment (0.1*sample size).*
z: Matrix of regressors whose coefficients are allowed to change.
q: Number of regressors z.
x: Matrix of regressors with coefficients fixed across regimes.
p: Number of regressors x.
Sup$F_t(l)$: F statistic for H_0: No str. breaks vs. H_1: Arbitrary nr. of breaks.
Sup$F_t(l+1|l:)$: Sequential test, H_0: No breaks vs. H_1: $l+1$ breaks.
$UDmax$: Double maximum statistic ($max_{1\leq l\leq M} supF_T(l)$).
$WDmax$: Weighted double maximum statistic ($max_{1\leq l\leq M} w_l supF_T(l)$).

of chronologically succeeding volatilities. This effect is truly consistent with the notion of contagion and implies a de facto break in cross-market volatility transmission. Taking the volatility of the realized volatilities into account, this effect should still be detectable. The second effect, however, is a positive association of measured spillover effects with the conditional volatility of the volatility process itself. This effect should not be detectable after taking the volatility of the realized volatilities into account. Further, such an effect is not in line with the notion of contagion. It indicates that previously measured shifts in volatility spillovers are an artefact of a measurement issue and not the consequence of genuine structural breaks in the processes of volatility transmission.

In order to achieve this goal mentioned above, we standardize our non-logarithmized realized volatilities with consistent estimators for the volatilities of the realized volatilities. The estimators that we use were introduced by Corsi et al. (2008):

$$\sqrt{\frac{RQ_{i,t}}{2M\sigma_{i,t}}} = \sqrt{\frac{\sum_{j=1}^{M} r_{i,t,j}^{4}}{6\sum_{j=1}^{M} r_{i,t,j}^{2}}} \tag{3.11}$$

where $RQ_{i,t}$ and M stand for the realized quarticity for market i and the number of intra-day returns on day t. The realized quarticity, or fourth power variation, as shown in Corsi et al. (2008), is a consistent estimator for the integrated quarticity:

$$RQ_t = \frac{M}{3}\sum_{j=1}^{M} r_{i,t,j}^{4} \xrightarrow{p} \int_{t-1}^{t} \sigma^4(s)ds\,. \tag{3.12}$$

Table 3.5 depicts the descriptive statistics for the series obtained by standardizing the realized volatility series for the three markets with their corresponding square root of the realized quarticity. It is evident from this table that the resulting quantities have favorable statistical properties. Further, from auxiliary graphical inspections, we find the series to fluctuate regularly around their long term means.

TABLE 3.5: *Descriptive statistics: Standardized realized volatilities.*

Sample	01/2000 to 09/2011		
Market	HSI	ESTX	S&P
Obs.	2700	2700	2700
Mean	8.042	9.795	10.778
Median	8.185	10.099	11.007
Minimum	2.963	2.791	3.359
Maximum	12.513	15.200	15.324
St. Dev.	1.575	2.095	1.794
Skewness	−0.380	−0.582	−0.703
Kurtosis	2.936	3.061	3.616
N. test χ^2	61.59	133.47	210.18
	(0.0000)	(0.0000)	(0.0000)
Sample correlations			
HSI	1	-	-
ESTX	0.006	1	-
S&P	0.010	0.093	1
HSI_{t-1}	0.163	0.017	0.014
ESTX_{t-1}	−0.018	0.070	0.043
$\text{S\&P}_{t-1}$	−0.001	0.026	0.073

Notes: Normality tests according to D'Agostino, Belanger and D'Agostino Jr. (1990). P-values given in parentheses.

Analogous to previous steps in our analysis, we proceed by estimating the models from Equations (3.7) to (3.9), this time using our standardized realized volatility quantities. Again, we first conduct the estimations with our total sample. Then we keep the lags for the two chronologically directly preceding foreign markets and eliminate all other lags with insignificant coefficients in the total sample regressions.

The results, depicted in Figure 3.6, now reveal a very different picture than before. Apart from a few non-systematic exceptions, the confidence bands for the estimated volatility spillovers do not cross their total sample estimates anymore. Particularly, the pronounced shifts in volatility transmission during the financial crisis of 2007 do not seem to occur anymore. Further, all volatility spillovers are strongly reduced as compared to those presented in Section 3.4.1 and 3.4.2. Most coefficients are now no more statistically significantly different from zero over long time spans. Conditional heteroskedasticity hence plays an important role for the measured time-variation in volatility spillovers. Additionally, tests on breaks in linear regression relations, anal-

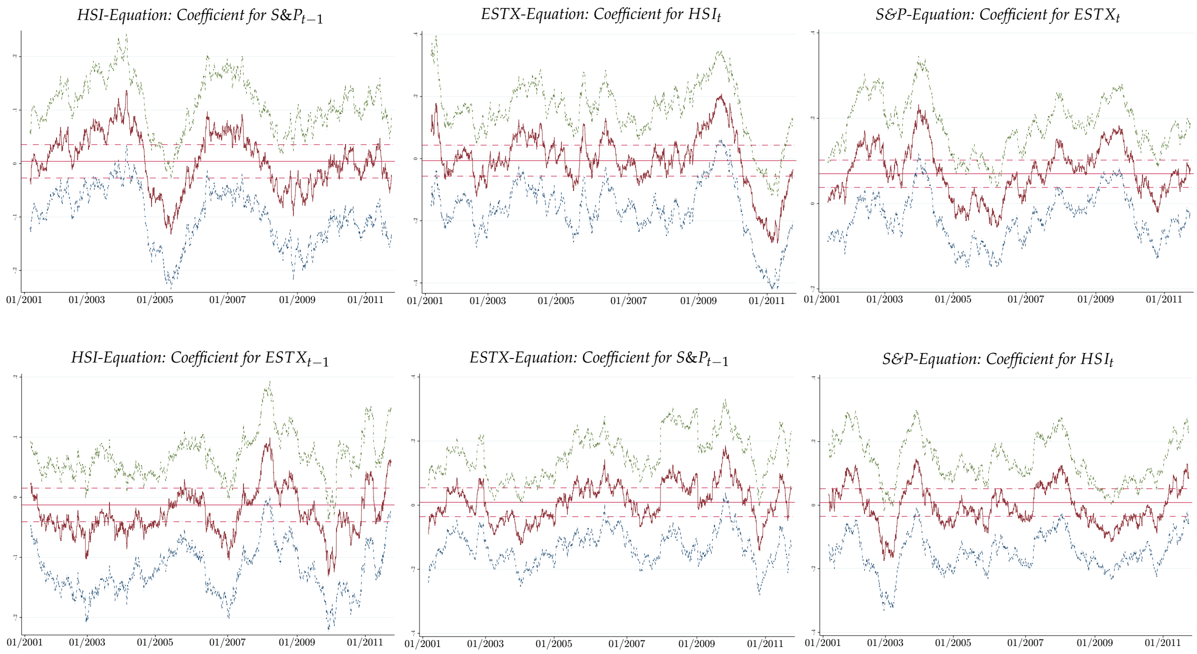


FIGURE 3.6: *HAR-DL models with stand. realized volatilities: Time-varying spillovers.*

Notes: First line: Chronologically directly preceding markets. Second line: Chronologically secondly preceding markets. Horizontal lines: Full sample spillovers (continuous) with 95% confidence bands (dotted). Jagged lines: 250 days rolling windows spillovers with 95% confidence bands. Plotted spillover at time t: Estimate for the subperiod $t-250$ to t. Graphs for further lags: Available upon request. Standard errors: HAC.

ogous to those in Section 3.4.2, but now with the standardized realized volatilities, show that the F-statistics remain below their critical boundaries (see Figure 3.7). This suggests the stability of our HAR-DL models for the standardized realized volatilities over the whole sample period.

Further, using index data, we assume price jumps not to be as frequent as typically observed with single stock data. According to Andersen et al. (2010) we expect jumps only to have a slight impact on our computed standardized quantities. The is due to the fact that jumps inflate both the returns (numerator) and the volatility (denom-

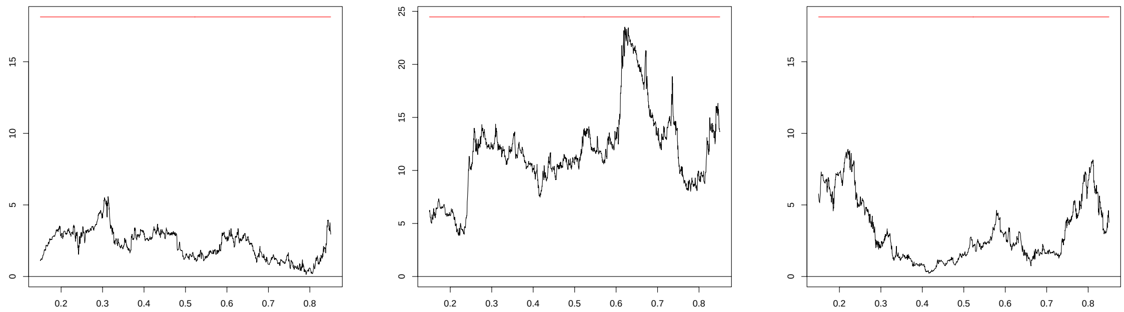


FIGURE 3.7: *Tests for breaks in linear relations II.*

Notes: HAR-DL models with stand. realized volatilities. HSI-Equation (left), ESTX-Equation (middle), S&P-Equation (right). F-Statistics (jagged, black), boundaries for $\alpha = 5\%$ (upper, red lines).

inator). They hence tend to self-standardize. However, for matters of robustness checking, we additionally compute standardized realized volatility quantities using the jump-robust estimator for the realized tri-power quarticity ($RTQT_t$) according to Andersen et al. (2007):

$$\sqrt{\frac{RTQ_{i,t}}{2M\sigma_{i,t}}} = \sqrt{\frac{\Gamma(1/2)^3 \sum\limits_{j=3}^{M} |r_{i,t,j}|^{4/3}|r_{i,t,j-1}|^{4/3}|r_{i,t,j-2}|^{4/3}}{8\Gamma(7/6) \sum\limits_{j=1}^{M} r_{i,t,j}^2}} \tag{3.13}$$

where $\Gamma(.)$ denotes the gamma-function, $\Gamma(x) = \int_0^\infty t^{x-1}e^{-t}dt$. The results based on estimations with these quantities even strengthen our conclusions from before: Now we find no more exceptions from the total sample volatility spillover estimates. All confidence bands enclose the long term volatility spillover estimates. Further, virtually all of them are equal to zero.[5]

Overall, we hence conclude conditional heteroskedasticity, the volatility in volatility, to be the main driver behind our measured shifts in volatility transmission. The

[5]Graphics not provided for sake of brevity, but available upon request.

results argue strongly against the notion of contagion in the sense of a strong and sudden increase in the synchronization of chronologically succeeding volatilities. After taking conditional heteroskedasticity into account, a synchronization during the crisis period cannot be observed anymore. A structural break in market relations does not seem to have occurred in a strict sense. Indeed, these conclusions are similar in spirit to those from the literature following Forbes and Rigobon (2002).

Further, again taking the perspectives of uncertainty and information flow, the results argue against irrational phenomena such as a disproportionate spreading of uncertainty and against sudden changes in information processing, as first proposed in Section 3.4.2. The standardized realized volatility series can be seen as reflecting stable uncertainty or information flow regimes. Not finding any linear association between the markets' volatilities under these circumstances is remarkable from an economic point of view.

This empirical finding, however, can be rationalized. Assuming that the intra-daily price processes in our three chronologically succeeding markets evolve independently from each other and with an equal variance σ_i^2 each, the expected realized variance is equal to the number of intra-daily returns times the constant variance of the intra-day returns for each market ($E[r_{m,i}^2] = m \cdot \sigma_i^2$). The expected realized variances and volatilities are hence constant in all three markets. As the correlation between constant quantities must be zero, a regression of the resulting realized volatilities onto each other cannot lead to significant results under these specific circumstances. Additionally to what is stated above, our empirical results hence suggest that the price processes in our three chronologically succeeding markets evolve independently from each other. After respecting for conditional heteroskedasticity (and jumps), the results match theoretical considerations.

3.6 Conclusion

This study seeks to shed new light on the process of volatility transmission between international stock markets. We take a unique long term view, using data from January 2000 up to September 2011. In particular, we analyze the structural stability of volatility spillovers from the chronologically preceding trading in foreign markets into domestic markets. Based on three series of logarithmized realized volatilities, computed on the basis of intra-daily data from the Hang Seng Index, the Euro Stoxx 50 and the S&P 500 index, we find the dynamics of volatility spillovers to be unstable and highly time-varying. The rolling window estimations of our HAR-DL models further reveal particular strong and sudden upwards shifts in volatility spillovers in all markets, solely during the financial crisis of 2007. At first sight, these upwards shifts in volatility spillovers seem to be in line with the notion of contagion according to Forbes and Rigobon (2002). They suggest significantly strengthened market relations during the financial crisis of 2007, in particular a strong and sudden increase in the synchronization of chronologically succeeding volatilities.

To preclude any misdiagnosed contagion, however, we investigate the role of structural breaks and conditional heteroskedasticity in the realized volatilities. As for the structural breaks, we find those only to have a minor impact on measured volatility spillovers. Concerning conditional heteroskedasticity, though, we find a strong impact on volatility spillovers. After taking the volatility of the volatilities into account, by using appropriately standardized realized volatilities for our estimations, we find the effects consistent with contagion to be no more detectable. Further, the dimensions and statistical significances of the volatility spillovers decrease strongly. On the one hand this indicates, that conditional heteroskedasticity is likewise highly relevant in measuring cross-market dependencies in realized volatilities. Spillover studies following the tradition of Hamao et al. (1990), Lin et al. (1994) and Susmel and Engle (1994) are fundamentally affected by this problem. On the other hand, this indicates that cross-market linkages in volatilities are far more stable than previously assumed. Measured strong and sudden shifts in volatility transmission turn out to be due to a heightened level of fluctuations in the realized volatilities and not due to a strengthened cross-market synchronization in chronologically succeeding volatilities. The overall conclusion hence argues strongly against fundamental breaks in market relations and effects consistent with contagion. Hence regarding time-varying volatility spillovers it applies: No contagion, only interdependence.

Chapter 4

Spillovers from the US to Stock Markets in Asia: A Quantile Regression Approach

This paper analyzes return spillovers from the US to stock markets in Asia by means of quantile regressions. Traditional studies consider spillovers as effects of foreign returns onto the conditional means of chronologically succeeding domestic markets' returns. We, by contrast, study the full range of quantiles of the conditional distribution of the domestic markets' returns. This enables us to document the detailed structure of spillovers across return quantiles. Generally, we find spillovers from the US to Asia to be negative. Specifically, however, we reveal an asymmetric structure of spillovers with an increasing negative magnitude from lower to upper return quantiles. Theoretically, this pattern is consistent with an asymmetric overreaction of traders in Asia to news from the US market. Extensions from the baseline model further suggest the presence of contagion throughout the financial crisis of 2007-08 as well as of calm-down effects over weekends. [1]

[1]This article is printed with kind permission of Routledge Taylor & Francis. It has been originally published as *Maderitsch R. (2015). Spillovers from the USA to stock markets in Asia: a quantile regression approach. Applied Economics. Doi:10.1080/00036846.2015.1034839.*

4.1 Introduction

The aim of this study is to provide new evidence on return spillovers from the US stock market to chronologically subsequently trading stock markets in Asia. Specifically, we show that quantile regression techniques yield important new insights into the particular structure of spillovers throughout different return quantiles. Taking a long-term view, we analyze a sample from January 1990 to January 2014. To represent the US market, we use daily return data for the S&P 500 Index. For the Asian stock markets, we use intra daily return data for the constituent stocks of the Hang Seng Index (Hong Kong), the Nikkei 225 Index (Japan), the Kospi 50 Index (Korea), the Straits Times Index (Singapore), the SSE 50 Index (China mainland) and the FTSE TWSE Taiwan 50 Index (Taiwan).

In analyzing cross-market return spillovers, we closely follow studies such as Hamao et al. (1990), Susmel and Engle (1994), Lin et al. (1994), Baur and Jung (2006) or Dimpfl and Jung (2012). These authors define return spillovers as effects of the conditional means of foreign stock returns onto the conditional means of non-overlapping returns in chronologically succeeding markets. Analyzing spillovers by means of linear regression models, these studies are confined to the analysis of spillovers in the conditional means of the stock return series. Using non-linear econometric techniques, however, we are able to broaden the perspective. Quantile regressions, first introduced by Koenker and Bassett (1978), enable us to investigate spillovers across all conditional quantiles of the stock returns' distributions. Specifically, they allow us to describe the structure and degree of spillovers, building upon the approach of Baur (2013). As they permit us to analyze potential asymmetries in spillovers, we are able to investigate differences in spillovers across returns of positive and negative sign.

Moreover, extensions of the baseline model allow us to asses the impact of the financial crisis of 2007-08. As the financial crisis had its origin in the United States and then spread to the rest of the world,[2] the transmission of return shocks from the US to Asia might have been affected, too. Taking the perspective of an 'Asia investor', we further demonstrate the significance and universality of our results by re-estimating the models based on portfolio returns, constructed from all constituent stocks of the stock indexes considered. In addition, motivated by the idea that traders' information processing time might have an effect on spillovers, we test for potential weekday effects in spillovers, in particular a calm-down effect over weekends.

The relevance of our study is given with respect to the literature on cross-market information transmission and informational efficiency. International asset pricing models and the (strong-form) efficient market hypothesis (EMH) suggest that neither linear nor non-linear return spillovers should exist. In informationally efficient markets, information generated in chronologically preceding markets should not contain predictive power for chronologically succeeding markets' returns. Theoretically, information generated in previously trading markets should be fully incorporated into the succeeding markets' opening prices. Despite this, previous studies on stock return spillovers, such as those mentioned above, provide convincing evidence that statistically significant spillovers do exist - at least across some markets. Typically, however, the effects are found to be only of a weak magnitude.

From an economic point of view, various competing explanations for significant return spillovers have been put forward. One line of reasoning, that can be aligned with rational expectations, claims the existence of partial price adjustment according to, for example, Kyle (1985) or Admati and Pfleiderer (1988). The incorporation of information into opening prices is hence potentially delayed due to traders' strategic considerations. If they are uncertain, regarding the informational content of stock price movements in preceding markets, they exert their (private) information only gradually.

[2]For more details see e.g. Johansson (2011).

Alternatively, psychological reasons come into consideration. According to this approach, spillovers are driven by traders' irrational behavior. Fung et al. (2000) and Fung et al. (2010), for example, argue that market participants have a tendency to overreact to movements in chronologically preceding markets. In particular, this might be the case if uncertainty is high and when traders only have little time to process information. Statistically significant spillovers then result from 'falsely' set opening prices. This 'mispricing theory' implies a clear violation of any form of the EMH. The rational expectations explanation, however, is consistent, at least with weak form market efficiency.

The remainder of this paper is structured as follows. We first introduce the data and institutional framework in Section 4.2. Then we present the empirical framework in Section 4.3, before we provide the results of the empirical analysis in Section 4.4. After that, we present robustness checks in Section 4.5 and elaborate on the economic implications of our results in Section 4.6. Section 4.7 concludes.

4.2 Data and Institutional Framework

An important condition for appropriate Granger causality inference on stock return spillovers is that the returns of subsequently trading markets do not overlap. We therefore consider daily (close-to-close) returns for the US stock market (S&P 500 Index) on day t as well as intra daily returns for various stocks in Asia on day t+1.[3] Specifically, we consider intra daily (open-to-close) returns for stocks contained in six of the largest, in terms of market capitalization, and most closely monitored stock market indexes in Asia — the Nikkei 225 Index (Japan), the Kospi 50 Index (Korea), the Straits Times Index (Singapore), the FTSE TWSE Taiwan 50 Index (Taiwan), the Hang Seng Index (Hong Kong) and the SSE Composite Index (China mainland). We

[3]Note that the time distance between market closing in the US on day t and market opening in Asia on day t+1 is very small. As no other important markets trade in between, we do not expect any distortions of our results.

retrieve all required prices from Thomson Reuters Datastream. As convention in the literature, we compute the returns as percentage close-to-close and open-to-close logarithmized price differences. All prices stem from the regular trading hours. Table 4.1 presents descriptive statistics for the resulting series. Table 4.2 summarizes the considered markets' trading hours in local times as well as in Universal Time Coordinated (UTC).

TABLE 4.1: *Descriptive statistics.*

US market	S&P 500 Index	Asian markets' index constituents	Nikkei 225 Index	Kospi 50 Index
Sample	01/1990-01/2014	Sample	12/1993-01/2014	01/1990-01/2014
Nr. of obs.	6274	Maximum nr. of observations	5687	5913
Skewness	-0.2377	Median nr. of observations	5687	4264
Kurtosis	12.0364	Minimum nr. of observations	1000	1000
Average return	0.0263	Average return	-0.0607	0.0015
Return st. dev.	1.1357	Average return st. dev.	1.9573	2.5553
Minimum	-9.4695	Minimum	-39.7302	-29.9902
5% quantile	-1.7480	Average 5% quantile	-0.1260	-0.1724
Median	0.0216	Average median	-0.0611	0.0130
95% quantile	1.6638	Average 95% quantile	0.0022	0.1248
Maximum	10.9572	Maximum	32.7213	26.5620
Asian markets' index constituents	Straits Times Index	FTSE TWSE 50 Index	Hang Seng Index	SSE Composite Index
Sample	01/1990-01/2014	01/1990-01/2014	06/1994-01/2014	03/1993-01/2014
Maximum nr. of observations	5980	5975	4840	4806
Median nr. of observations	4486	4895	4541	2396
Minimum nr. of observations	1000	1000	1000	1000
Average return	0.0098	-0.1317	-0.0435	0.0997
Average return st. dev.	2.0726	2.0936	2.1904	2.4433
Minimum	-35.6675	-13.8999	-57.6911	-22.6313
Average 5% quantile	-0.0876	-0.2969	-0.1440	-0.0321
Average median	-0.0035	-0.1347	-0.0400	0.0836
Average 95% quantile	0.2118	0.0529	0.0425	0.2840
Maximum	62.8711	20.0671	51.0826	33.3245

TABLE 4.2: *Trading hours.*

Market	Stock index	Nr. of constituents	Index dissemination times	
			Local time	UTC
United States	S&P 500	500	9:30-16:00	13:30/14:30-20:00/21:00
Japan	Nikkei 225 Index	225	9:00-11:00/12:30-15:00	0:00-2:00/3:30-6:00
Korea	Kospi 50 Index	50	9:00-15:00	0:00-6:00
Singapore	Straits Times Index	30	9:00-17:00	1:00-9:00
Taiwan	FTSE TWSE 50 Index	50	9:00-13:30	1:00-5:30
Hong Kong	Hang Seng Index	45	9:30-12:00/13:00-16:00	1:30-4:00/5:00-8:00
China (mainland)	SSE 50 Index	50	9:30-15:00	1:30-7:00

Notes: Regular trading hours as of April 2014. Minor changes in trading hours occurred over time. Overlaps between Asian and US trading hours did not occur throughout the whole sample period.

4.3 Empirical Framework

4.3.1 The Quantile Spillover Model

In Ordinary Least Squares regressions, the focus is typically on the estimation of the conditional mean of a dependent variable y, given the explanatory variable(s) x. In the context of spillover studies, x typically denotes a (set of) foreign market return(s), whereas y contains the domestic market's returns. The resulting slope-coefficient(s) β is (are) considered as the spillover effect(s). Quantile regression techniques, as introduced by Koenker and Bassett (1978), however, allow to model the dependence of specific conditional quantiles of the dependent variable y, given the explanatory variable(s) x. They hence provide a more detailed description of the tails of the distribution of the dependent variable y and provide more flexibility in modeling data with heterogeneous conditional distributions. This is of particular importance in our context of financial return data. As conditional heteroskedasticity is a common feature of stock returns, it is important that the regressions' error term variances are allowed to vary over time. In quantile regressions this is unproblematic as no assumptions about the error distributions and their variance structures are required. Further, skewness and leptokurtosis are allowed, with the quantile regressions' inherent robustness to outliers as another useful feature.[4]

We use the following quantile spillover model as our baseline specification:[5]

$$Q_{r_{ASIA,i,t+1}}(\tau|X) = \alpha_i(\tau) + \beta_i(\tau) r_{US,t}, \tag{4.1}$$

[4]For more detailed information on the properties of quantile regression, the interested reader is referred to Koenker and Bassett (1978), Koenker and Bassett (1982), Furno (2004), Koenker and Xiao (2006) or Baur et al. (2012).

[5]Comprehensive robustness checks are presented in Section 4.5.

where X generally denotes the regressor matrix, here containing $r_{US,t}$, the close-to-close return of the S&P 500 Index on day t and $Q_{r_{ASIA,i,t+1}}(\tau|X)$ is the day t+1 τth quantile of the open-to-close return of stock i, contained in one of the above-mentioned Asian stock indexes[6] conditional on the US market close-to-close return on day t. $\alpha_i(\tau)$ and $\beta_i(\tau)$ are the quantile-specific parameters. $\beta_i(\tau)$, the dependence parameter, is of central interest to us. We interpret it as the quantile-specific spillover parameter and contrast it to the spillover parameter, resulting from a common Ordinary Least Squares (OLS) framework $y_i = \alpha_i + X\beta_i + u_i$, with y_i as the domestic market's return, u_i as an error term, α_i as a constant and β_i as the spillover parameter.

In addition to the baseline specification, we consider three model extensions. Firstly, we assess the impact of the financial crisis of 2007-08 on the quantile-specific spillovers:

$$Q_{r_{ASIA,i,t+1}}(\tau|X) = \alpha_i(\tau) + \beta_i(\tau) r_{US,t} + \gamma_i(\tau) r_{US,t} D_{Crisis}, \tag{4.2}$$

where D_{Crisis} is a dummy, interacted with the S&P 500 returns $r_{US,t}$. D_{Crisis} is equal to zero in tranquil (no crisis) times, and equal to one during the financial crisis of 2007-08.

In accordance with popular time lines on the financial crisis, such as provided by the Federal Reserve Board of St. Louis (2010) or Guillen (2009), we use August 2007 to December 2008 as the crisis period. If the financial crisis had a significant impact, then spillovers during the financial crisis ($\beta_i(\tau) + \gamma_i(\tau)$) should differ significantly from spillovers in tranquil times ($\beta_i(\tau)$).

Theoretically, crisis-related differences in spillovers are consistent with the notion of

[6] Stock i is either contained in the Nikkei 225 Index, the Kospi 50 Index, the Straits Times Index, the FTSE TWSE Taiwan 50 Index, the Hang Seng Index or the SSE Composite Index. There are no cross-listings of any stocks.

contagion. In its broadest sense, contagion is defined as a strong and sudden increase in cross-market linkages after a shock (see e.g. Forbes and Rigobon (2002), Pesaran and Pick (2007) or Baele and Inghelbrecht (2010)).

In the second model extension, we test for significance and draw conclusions on the universality of our results. Instead of using single Asian stocks' returns, we re-estimate both the baseline model and the first extended model, using returns from an equally weighted Asia portfolio. For the construction of this portfolio, we use all constituent stocks, contained in the six different indexes outlined above.

The third model extension allows us to test for the presence of weekday effects, in particular for differences in spillovers following weekends. Economically, the idea is that if investors' time to process information has an impact, spillovers after weekends might differ, as there time to process information is longer than on other days of the week. The third model extension has the following form:

$$Q_{r_{ASIA,i,t+1}}(\tau|X) = \alpha_i(\tau) + \beta_i(\tau) r_{US,t} + \delta_i(\tau) r_{US,t} D_{Weekend}, \tag{4.3}$$

where now the dummy $D_{Weekend}$ interacts with the S&P 500 returns $r_{US,t}$. Specifically, $D_{Weekend}$ is equal to zero for days from Tuesday to Friday and equal to one on Mondays. The weekend effect is then captured by $\beta_i(\tau) + \delta_i(\tau)$, where $\beta_i(\tau)$ denotes spillovers on other days of the week. If markets calm down over the weekend, then $\beta_i(\tau) + \delta_i(\tau)$ should be closer to zero than $\beta_i(\tau)$.

4.3.2 The Structure and Degree of Spillovers

To describe the particular pattern of the spillovers revealed by our estimations, we resort to Baur (2013), who introduces the concept of the so called structure and degree of dependence into the quantile regression framework. Bringing this concept forward to our particular context, we adopt the term 'structure and degree of spillovers'. In particular, we obtain the stock market-specific degree of spillovers by averaging the conditional $\hat{\beta}_i$'s over all quantiles and all stocks, contained in the respective index. In case of the extension with the Asia portfolio, we use all stocks available. Analogously, we compute sequences of the (average) conditional $\hat{\beta}_i$'s across all different quantiles to obtain the corresponding structures of spillovers.

Figure 4.1 depicts different simulated structures and degrees of spillovers for the purpose of illustration. The zero line corresponds to the theoretical case of no dependence between foreign and domestic market returns. It is consistent with (strict form) market efficiency. Spillovers are equal to zero across all quantiles and the structure and the degree of spillovers coincide with each other. In the first (second) quadrant, however, positive spillovers denote a positive dependence of negative (positive) domestic returns, conditional on the previously trading foreign market's returns. In the third (fourth) quadrant, negative spillovers correspond to a negative dependence of negative (positive) domestic returns, conditional on previously trading foreign markets' returns. The dashed two lines correspond to positive and negative spillovers. As in both cases the structure of spillovers is constant (straight line), the structure and the degree of spillovers again coincide with each other.

By contrast, the S-shaped blue and green curve demonstrate increasing and decreasing spillovers across quantiles. Despite the increases and decreases, however, the overall degree of spillovers is zero in both cases. The blue curve is particularly interesting. It broadly corresponds to the pattern revealed by Baur et al. (2012). They estimate various quantile autoregressive models, using close-to-close stock returns. As their results are based on a long-term sample, comprising 600 stocks, we regard this particular pattern as a benchmark structure of dependence to compare our results with. In principle, however, also the U-shaped structures, implied by the (blue and green) curves, are interesting. They imply symmetric structures of spillovers.[7]

[7] For further possible structures of dependence, see Baur (2013).

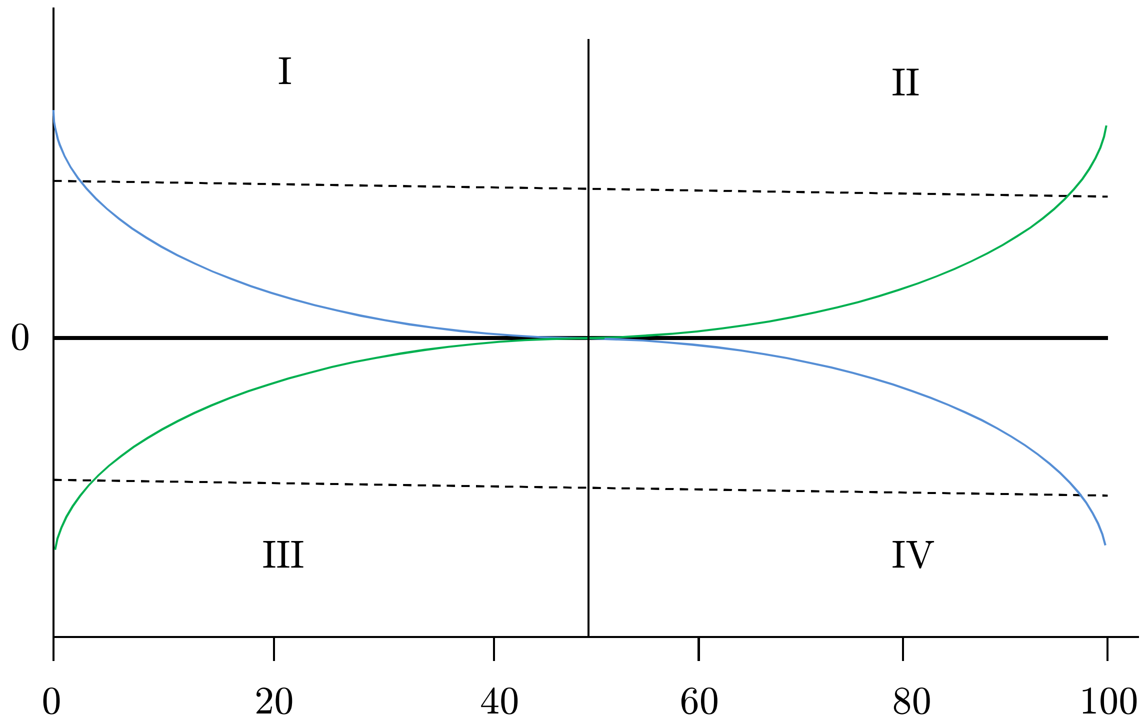


FIGURE 4.1: *Simulated structures and degrees of spillovers.*

Notes: Vertical axis: Spillovers. Horizontal axis: Quantiles in percent.

4.4 Empirical Results

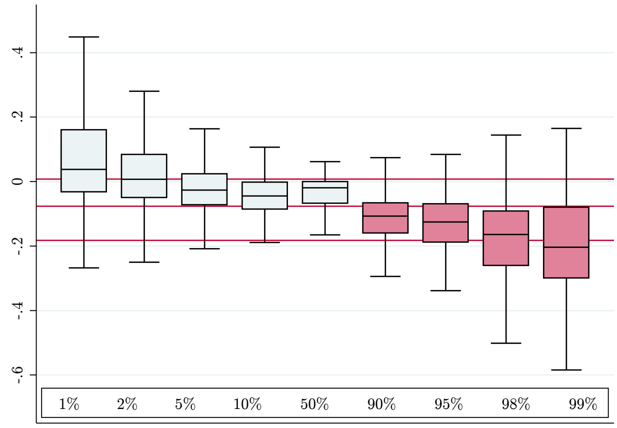
4.4.1 Baseline Quantile Spillover Model

The estimated quantile-specific $\hat{\beta}_i$ spillover parameters for the stocks contained in the corresponding Asian stock indexes are summarized in Figure 4.2. The boxplots reveal substantial additional information to the OLS-estimates. Generally, the spillover parameters $\hat{\beta}_i$ tend to be negative. However, apart from a few exceptions, such as in the Japanese market, the median $\hat{\beta}_i$'s are all located below zero. In particular, this is apparent for the upper return quantiles. There, even the 75% quantiles are located below zero in all six different markets (see boxes in red). Overall, negative spillovers tend to be relatively more pronounced for upper return quantiles.

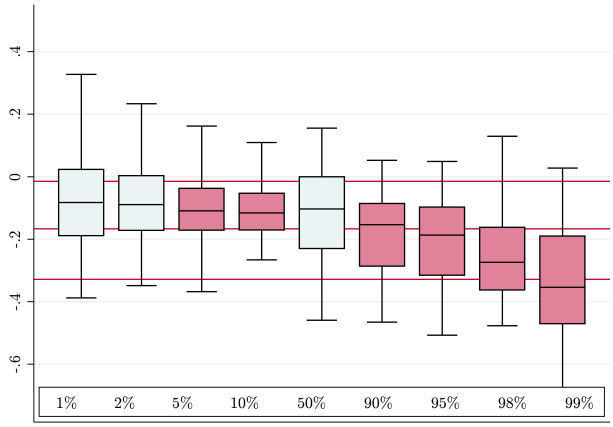
The resulting structures and degrees of spillovers are depicted in Figure 4.3. The green lines show that the degree of spillovers is negative in all six different markets. The Nikkei 225 Index, the Straits Times Index and the Hang Seng Index exhibit similar, rather moderate negative degrees of spillovers. In case of the FTSE TWSE Taiwan 50 Index, the Kospi 50 Index and the SSE Composite Index, however, the negative degree of spillovers is relatively more pronounced.

The blue lines depict the market-specific structures of the spillovers, the averages of the estimated stock index constituents' $\hat{\beta}_i$'s over all quantiles.[8] As clearly apparent in all six graphs, there is important additional information, hidden by the degree of spillovers and the OLS-spillover coefficients (see again Figure 4.2). The shape of the blue lines reveals that the spillovers' structures are not constant, as to be expected under strict form market efficiency. Rather, the negative spillovers tend to be increasingly pronounced from central to upper return quantiles, i.e. from positive to negative returns. This general pattern is obvious in all six different markets. However, it appears most pronounced in case of the FTSE TWSE Taiwan 50 and the SSE Composite Index. Moreover, around the central quantiles, the slight peaks in the lines indicate that spillovers tend to be particularly weak in case of small returns. This pattern is most pronounced in case of the Nikkei 225, the Straits Times and the Hang Seng Index.

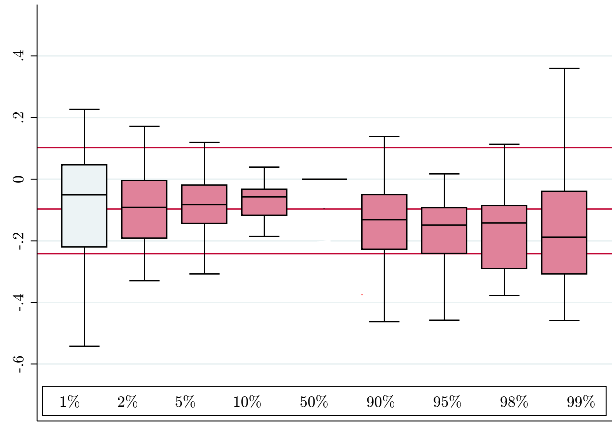
[8] Note that basing the structure of the spillovers on the median $\hat{\beta}_i$'s (red lines) leaves the conclusions virtually unchanged.



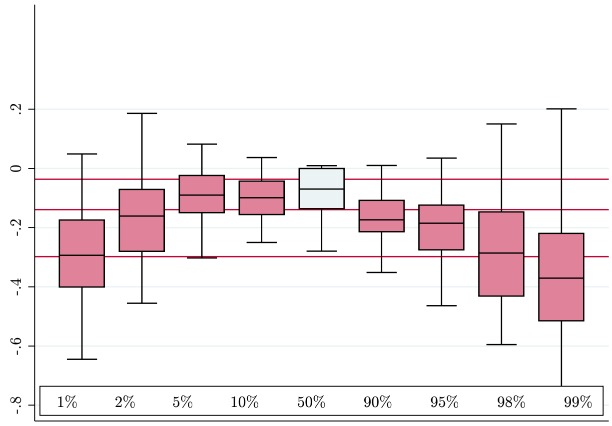
(A) *Nikkei 225 Index constituent stocks.*



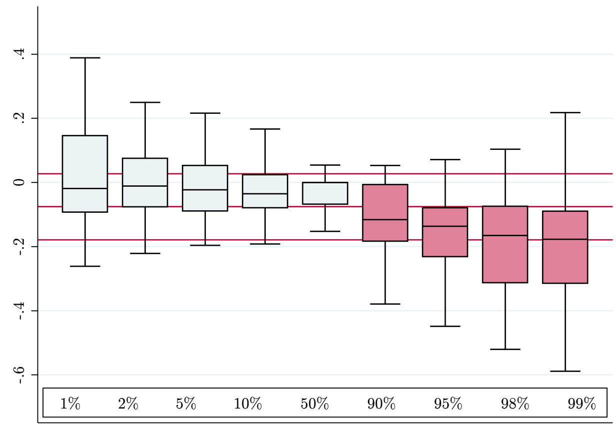
(B) *Kospi 50 Index constituent stocks.*



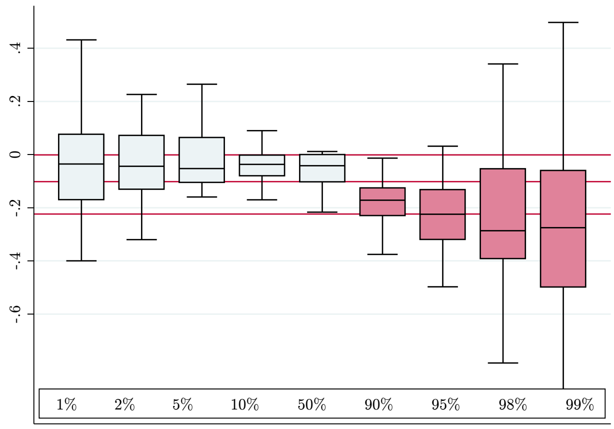
(C) *Straits Times Index constituent stocks.*



(D) *FTSE TWSE Taiwan 50 Index constituent stocks.*



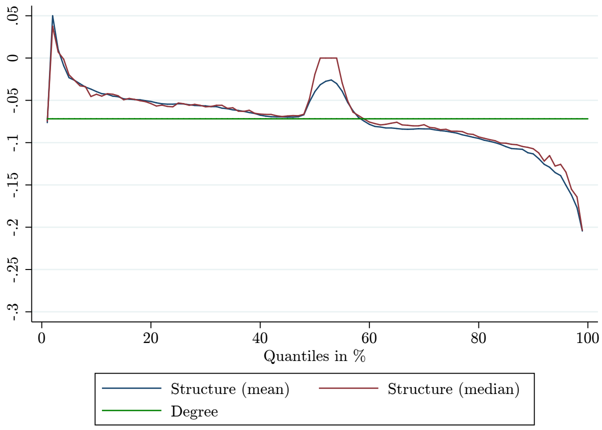
(E) *Hang Seng Index constituent stocks.*



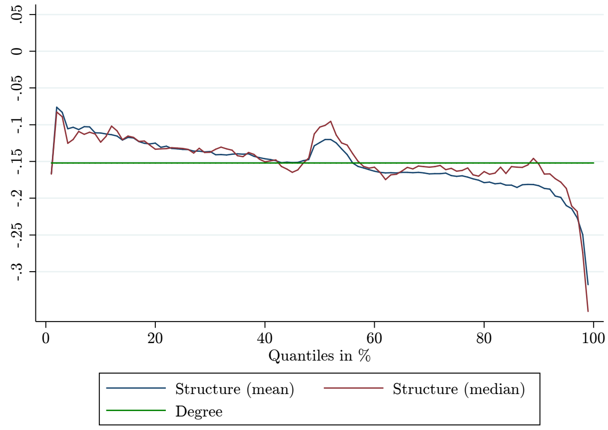
(F) *SSE Composite Index constituent stocks.*

FIGURE 4.2: *Boxplots for quantile-specific $\hat{\beta}_i$'s: Total sample (baseline specification).*

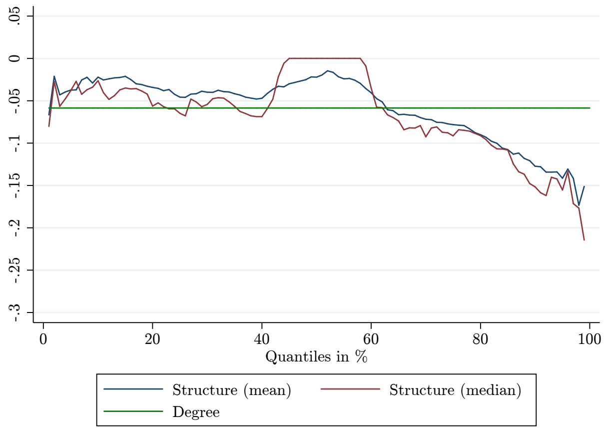
Notes: Boxplot of the $\beta_i\hat{(\tau)}$ parameters for the 1%, 2%, 5%, 10%, 50%, 90%, 95%, 98& and 99% quantiles. The red lines correspond to the respective average OLS estimates together with their 5% and 95% quantiles. Boxes given in red if 75% quantile below zero. Y-axes: Degree of dependence. X-axes: Quantiles in percent.



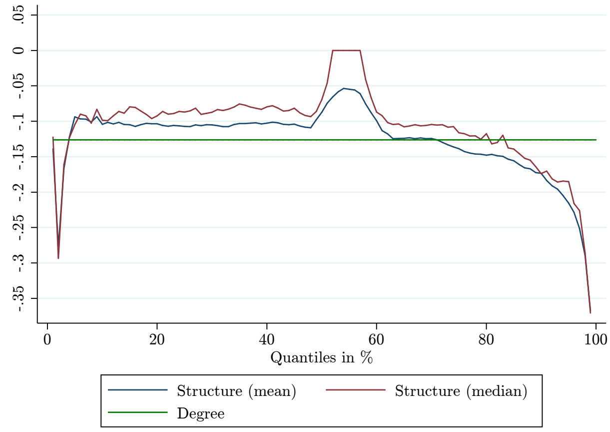
(A) *Nikkei 225 Index constituent stocks.*



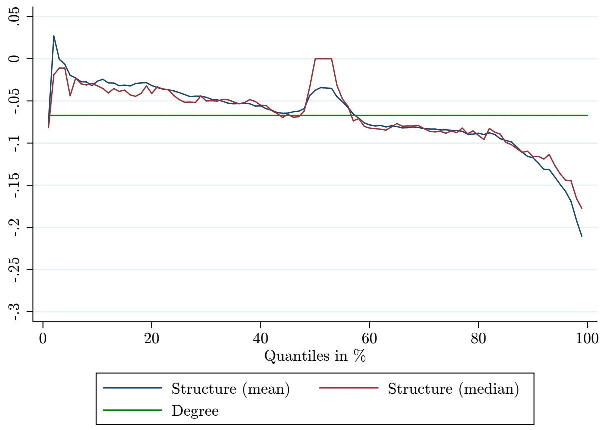
(B) *Kospi 50 Index constituent stocks.*



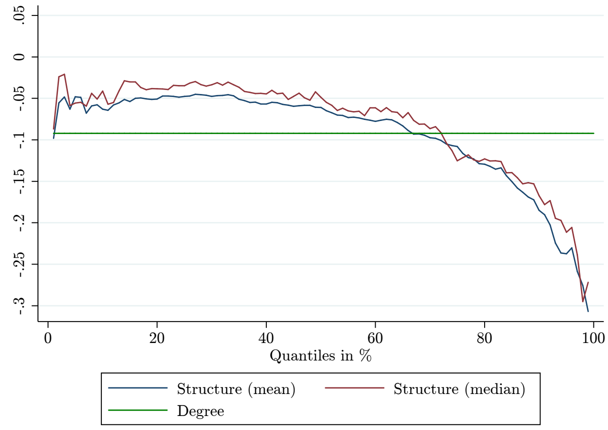
(C) *Straits Times Index constituent stocks.*



(D) *FTSE TWSE Taiwan 50 Index constituent stocks.*



(E) *Hang Seng Index constituent stocks.*



(F) *SSE Composite Index constituent stocks.*

FIGURE 4.3: *Structure and degree of spillovers: Total sample (baseline specification).*

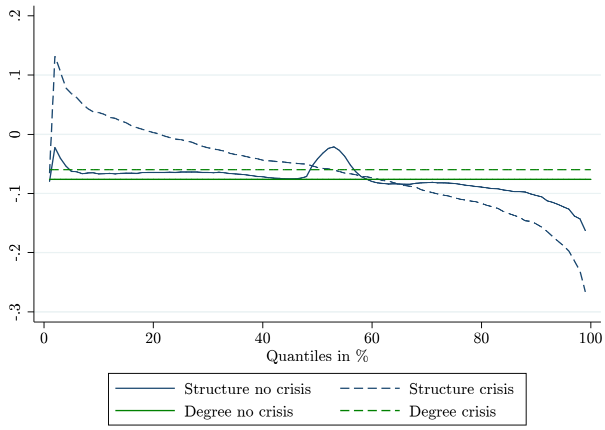
Notes: Quantile-specific mean $\hat{\beta}_i$'s given in blue. Quantile-specific median $\hat{\beta}_i$'s given in red. Degree of the dependence (overall mean $\hat{\beta}_i{}'s$) given in green. Y-axes: Degree of dependence. X-axes: Quantiles in percent.

4.4.2 Extension I: Impact of the Financial Crisis of 2007-08

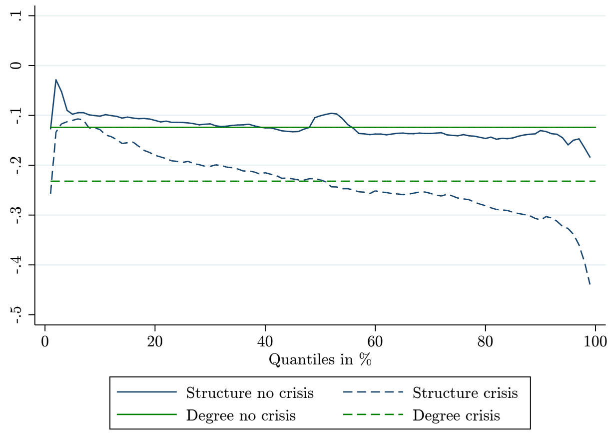
Figure 4.4 depicts the estimation results for the first model extension. The solid green lines denote the degrees of spillovers over the tranquil (no crisis) period (average $\hat{\beta}_i$'s across all quantiles and stocks in the respective markets). The dashed green lines show the degrees of spillovers over the period of the financial crisis (average $\hat{\beta}_i + \hat{\gamma}_i$ across all quantiles and stocks in the corresponding market). Most apparently, the degree of spillovers tends to become more pronounced during the financial crisis, except in the case of the Nikkei 225 Index. The strongest changes of the degree of spillovers are apparent for the Kospi 50 Index, the Straits Times Index and the SSE Composite Index.

More detailed insights, however, are apparent from the blue lines. The solid lines depict the structure of the spillovers in the tranquil (no crisis) period (sequence of $\hat{\hat{\beta}}_i(\tau)$). The dashed lines denote the spillovers during the financial crisis 2007-08 (sequence of $\hat{\hat{\beta}}_i(\tau) + \hat{\hat{\gamma}}_i(\tau)$). In all five markets, changes in the structure of spillovers are apparent throughout the financial crisis. Most notable is that the negative spillovers in the right tails (positive returns) tend to become more pronounced in all markets. For the left tails (negative) returns, however, changes in spillovers tend to be smaller. In particular, shifts in the structure of the spillovers are apparent for the Nikkei 225 Index, the Kospi 50 Index, the Straits Times Index and the Hang Seng Index, where the asymmetry tends to become more pronounced.

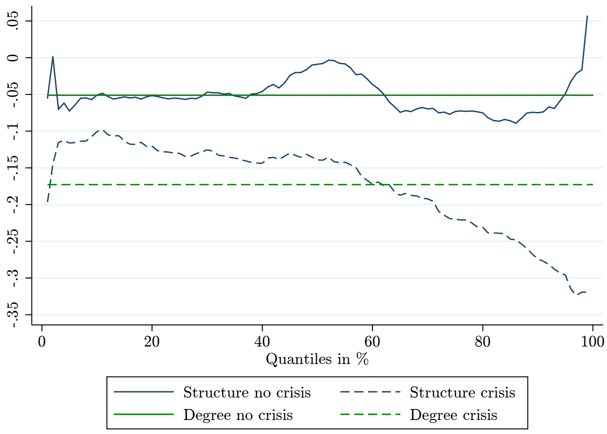
Furthermore, rather minor differences between the structure of spillovers from the tranquil period and the baseline model estimations are apparent (see again Figure 4.3). The fundamental pattern, revealed by the baseline model, is hence only marginally driven by the presence of the financial crisis in the sample period.



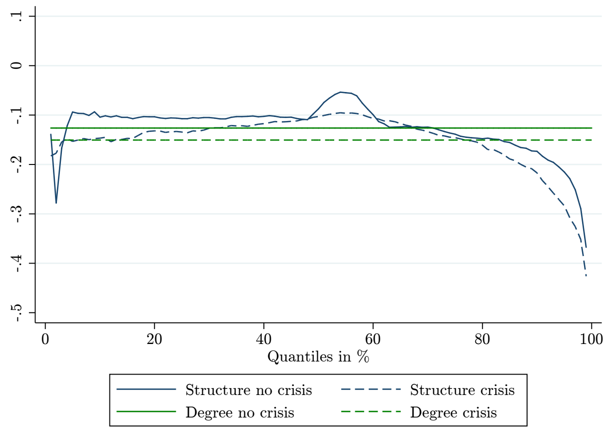
(A) *Nikkei 225 Index constituent stocks.*



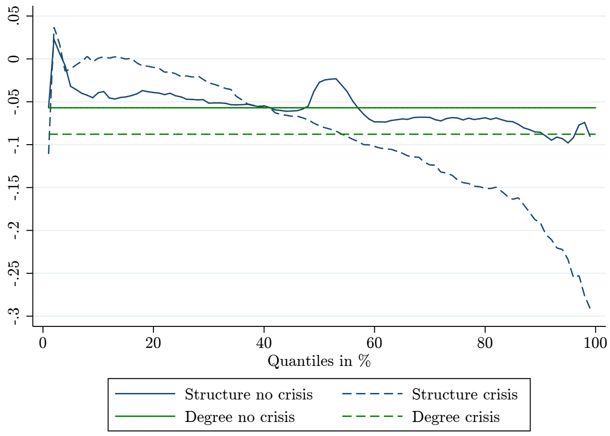
(B) *Kospi 50 Index constituent stocks.*



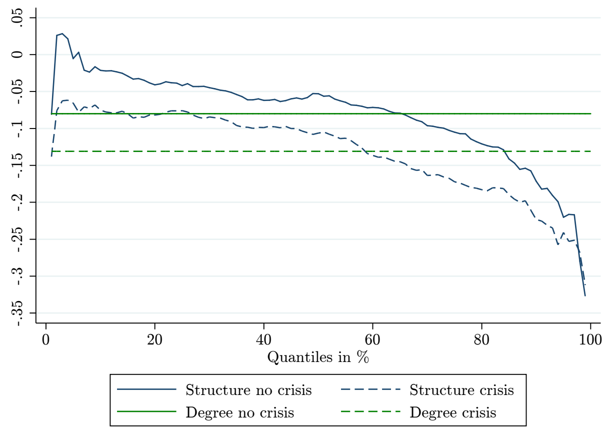
(C) *Straits Times Index constituent stocks.*



(D) *FTSE TWSE Taiwan 50 Index constituent stocks.*



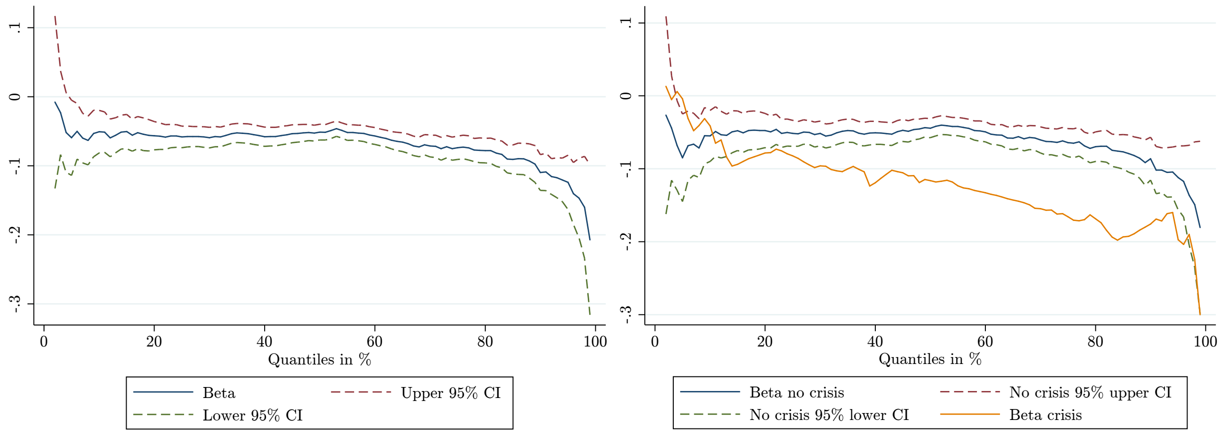
(E) *Hang Seng Index constituent stocks.*



(F) *SSE Composite Index constituent stocks.*

FIGURE 4.4: *Structure and degree of spillovers: Impact of the financial crisis of 2007-08 (extension I).*

Notes: Quantile-specific mean $\hat{\beta}_i$'s given in blue. Quantile-specific median $\hat{\beta}_i$'s given in red. Degree of the dependence (overall mean $\hat{\beta}_i^{\prime}$s) given in green. Y-axes: Degree of dependence. X-axes: Quantiles in percent.



(A) *Asia Portfolio.* (B) *Asia Portfolio extended.*

FIGURE 4.5: *Asia portfolio (extension II).*

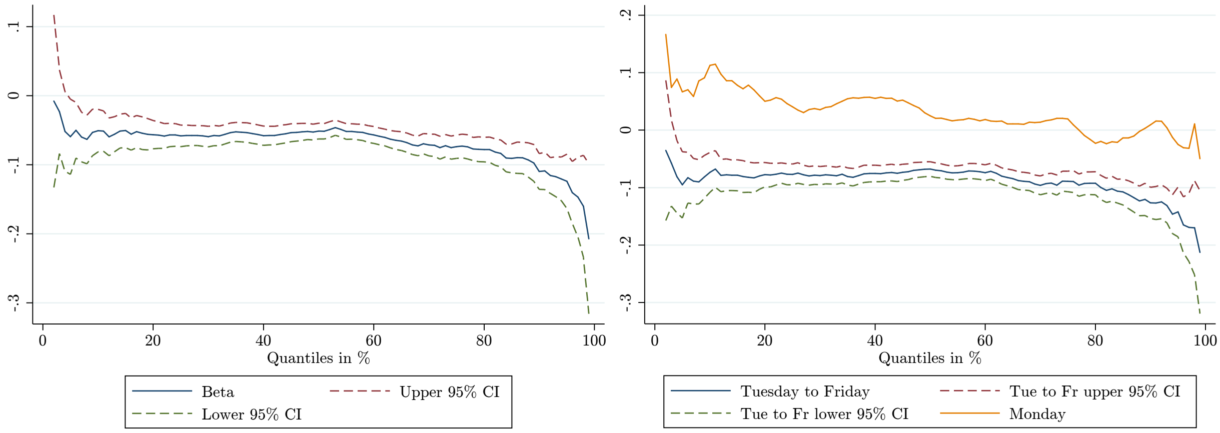
Notes: The quantile-specific $\hat{\beta}$'s are given in blue. The corresponding dashed 95% confidence bands are given in red and green. In (A) they correspond to the total sample spillovers. In (B) they refer to the tranquil period spillovers, whereas the crisis-specific spillovers are depicted in yellow. The confidence bands are based on asymptotic standard errors, estimated using a block-bootstrap robust to heteroskedasticity and autocorrelation of unknown form. We use a fixed length of 25 observations and 600 replications. Y-axes: Degree of dependence. X-axes: Quantiles in percent.

4.4.3 Extension II: Asia Portfolio

Figure 4.5(A) depicts the results from re-estimating both the baseline and the extended model, using the returns from the Asia portfolio.[9] The same fundamental structure of spillovers as in Figure 4.3 is apparent. Overall, spillovers are negative and significantly different from zero. They tend to become more pronounced from lower to upper return quantiles. In addition, as apparent in Figure 4.5(B), spillovers for the Asia portfolio are significantly affected by the financial crisis. Over the crisis period, particularly the upper return quantiles tend to exhibit stronger negative spillovers.

[9]Note that to avoid a potential over-representation of the Japanese stock market due to the strong weight of the Nikkei 225 Index in the Asia portfolio, we also consider using only the 50 stocks of the Nikkei 225 Index with the highest market capitalization. The results, however, remain virtually unchanged.

4.4.4 Extension III: Weekend Effect



(A) *Asia Portfolio.* (B) *Weekend effect.*

FIGURE 4.6: *Weekend effect (extension III).*

Notes: The quantile-specific $\hat{\beta}$'s are given in blue. The corresponding dashed 95% confidence bands are given in red and green. In (A) they correspond to the total sample spillovers. In (B) they refer to the Tuesday to Friday spillovers, whereas the Monday-specific spillovers are depicted in yellow. The confidence bands are based on asymptotic standard errors, estimated using a block-bootstrap robust to heteroskedasticity and autocorrelation of unknown form. We use a fixed length of 25 observations and 600 replications. Y-axes: Degree of dependence. X-axes: Quantiles in percent.

Estimating the third model extension for all six markets, we find the results to be very similar across the markets. The degree of spillovers after weekends is broadly between 0.15 and 0.2 points higher, compared to other days of the week. We report the estimation results for the Asia portfolio, however, the results for the single markets are available upon request. Figure 4.6(B) illustrates the significant differences in spillovers after weekends, compared to other days of the week. In particular, it reveals, that spillovers on Mondays appear to be close to zero and slightly positive over most quantiles. Spillovers for the rest of the week, however, are only slightly smaller than those revealed by the total sample estimations, depicted in Figure 4.6(A). Experimenting with different model specifications in which we link the dummy variable to other days of the week, we find this pattern to be highly distinct. There is no other weekday for which comparable changes in spillovers can be detected.

4.5 Robustness Checks

In order to robustify our conclusions, we conduct various different sample splits across time. However, the fundamental spillover patterns remain remarkably stable. The same holds if we include the dummy variables themselves in the two model extensions. The estimated spillover effects remain virtually unchanged. Further, we consider additional model extensions. In particular, we estimate augmented models, including lagged open-to-open and open-to-close returns for Asian stocks as well as (lagged) US market close-to-close and open-to-close returns. The structure of spillovers, however, remains virtually unaffected. The degree of dependence for additional variables is generally close to zero and the structure of dependence is relatively constant.

Further, estimating quantile autoregressive models according to Baur et al. (2012), we find the dependence patterns for the Asian intra-day stock returns to be generally very similar to the benchmark pattern, reported by Baur et al. (2012). Without including other markets, we find that lower return quantiles tend to exhibit positive dependence, whereas upper return quantiles tend to exhibit negative dependence on past returns.

Moreover, similarly as Baur et al. (2012), we also experiment with extended models in which we consider the size of the previous day's US market return as well as the sign of the previous day's US market return. As Baur et al. (2012), we find the particular patterns that we reveal to be strongly driven by extreme lagged and negative US returns. In particular the negative returns strongly drive the overall structure of spillovers.

Furthermore, we consider the particular opening and closing mechanisms in the different Asian markets as well as the time distances between market closing in the US and market opening in the respective local stock markets in Asia. The graphs in Figures 4.2 and 4.3 are sorted according to the opening times in UTC, given in Table 4.2.

A particular pattern, however, is not apparent.[10] Similar conclusions apply with respect to differences in trading mechanisms. Minor differences in these mechanisms exist. For example the Shanghai and the Hong Kong stock exchange do not use call auctions at market closing (see Comerton-Forde and Rydge (2006) for details). However, we do not find particular differences between these and other markets' spillover estimates. Further, using opening prices from the beginning of the regular, continuous trading hours, we are able to exclude the presence of adverse market microstructure effects such as potentially arising from non-synchronous trading.

4.6 Economic Implications

As a first important result, we are able to confirm that negative return spillovers from the US to stock markets in Asia actually constitute market-wide phenomena. In contrast to, for example Fung et al. (2010) or Dimpfl and Jung (2012), who report negative spillovers from the US to individual futures markets in Asia, we use data on constituent stocks of the respective indexes. This allows us to draw broader conclusions. Analyzing data from January 1990 up to January 2014, we are able to verify the presence of negative spillovers over a much longer time period than previous authors.[11]

Further, the fact that spillovers detected by our study exclusively have negative signs, points into the direction of psychologically grounded explanations, as suggested by Fung et al. (2010). These authors conduct various robustness checks to preclude any other, for example, liquidity-, bid-ask-spread or risk-related explanations. Finally, they come to the conclusion that negative spillovers have to be seen as price reversals,

[10]Note again, that we also consider a portfolio consisting of only 50 Japanese stocks to exclude any false conclusions due to the large number of constituents of the Nikkei 225 Index.

[11]Note that Dimpfl and Jung (2012) find weak negative spillovers from S&P 500 Future intra-day returns to Nikkei 225 Future intra-day returns between July 2002 and May 2006. Fung et al. (2010) report similar effects from S&P 500 Index close-to-close returns to intra-daily index future returns in Japan, Korea, Hong Kong, Singapore and Taiwan between January 1996 and December 2003.

following an overreaction phenomenon at market opening. Specifically, they state that negative (positive) price reversals occur after positive (negative) foreign market returns if opening prices are too high (low), compared to efficient opening prices. Negative spillovers are hence to be seen a result of intra daily corrections of traders' overoptimism and -pessimism at market opening.

Partial price adjustment in the sense of Kyle (1985) or Admati and Pfleiderer (1988), by contrast, implies that traders incorporate their (private) information into prices in a potentially slow and delayed fashion.[12] Consequently, if compared to the efficient opening price, the effective opening price is, too low (high) after positive (negative) foreign market returns, then this tends to induce positive spillovers. However, as positive spillovers are excluded by our results, we can rule out partial price adjustment as a potential cause of significant spillovers.

The view that our results support the overreaction hypothesis is further strengthened by the fundamentally asymmetric structure of spillovers that we detect. In particular, the negative spillovers from the US tend to be more pronounced for (large) positive than for (large) negative returns in Asia. This essentially implies that positive price reversals tend to depend more strongly on the magnitude of previous day US returns than negative ones. In terms of overreaction, the correction of overpessimism at market opening hence seems to depend more strongly on the US market's returns than the correction of overoptimism. This, in turn, supports the assertion that overpessimism as a reaction to negative news is more widespread than overoptimism as a reaction to positive news. Overall, traders in Asia appear to be more (over-) sensitive to negative, than to positive news from the US. In particular, this pattern appears pronounced in case of the FTSE Taiwan 50 Index, the Kospi 50 Index and the SSE Composite Index, where not only the negative degrees of the spillovers, but also the asymmetries in the structures of the spillovers are relatively strong. Economically,

[12] If traders do not act strategically, then this can also be considered as psychologically grounded 'underreaction'.

this might point to the presence of extraordinarily oversensitive traders in these stock markets.

During the financial crisis of 2007-08, the above-mentioned patterns tend to become even more pronounced. Economically, this might support the idea that Asian traders' sensitivity to US news might have increased during the crisis. The negative degree of the spillovers becomes stronger in all markets. Particularly strong increases in the asymmetries in the structures of the spillovers are apparent for the indexes with relatively little asymmetries over the total sample period – the Nikkei 225, the Straits Times and the Hang Seng Index. A mere increase in the dimension of shocks from the US market would not necessarily have altered the spillover estimates. The factual strengthening of the estimated spillovers, however, suggests that not only stronger shocks, but also a higher sensitivity to US market returns was apparent during the crisis. Theoretically, such an amplified shock-transmission is consistent with the notion of contagion in the sense of strengthening cross-market linkages during a crisis.

The significance of the weekend effect further provides evidence for the presence of a calm-down effect. Economically, this finding might support the idea that the more time traders have to process information from chronologically preceding markets, the better they might do at assessing foreign markets' returns information content. Similarly, however, one might argue that returns generated in previously trading markets receive less attention, the more time passes between the preceding market's closing and the succeeding market's opening. Any way, potentially more information, accumulating over the weekend, does not tend to increase overreaction. Rather, the slight positive spillovers, in particular for the lower quantiles, provide weak evidence for partial price adjustment.

From a theoretical point of view, our findings are well in line with behavioral finance theory. Phenomena such as differing reactions to positive and negative news, overreaction to (dramatic) news or a tendency to overweight recent information are well-established, at least since the fundamental contributions of De Bondt and Thaler

(1985), Barberis et al. (1998), Kant et al. (1998) etc. Interestingly, there is also a strand of the literature, concerned with particular behavioral anomalies in Asia. As Kim and Nofsinger (2008) point out, Asian markets tend to be differently affected by behavioral biases than, for example, European or US stock markets. Unfortunately, however, there is virtually no literature, explicitly considering cross-market return spillovers. Most closely related might be the literature on stock return autocorrelation.[13] In this context, Baur et al. (2012) point out, that asymmetric autocorrelation patterns are not necessarily inconsistent with rational behaviour. Veronesi (1999), for example, provides an intertemporal model in which overreaction to bad news in good times (right tail) and underreaction to good news in bad times (left tail) is compatible with rational expectations. Further, for example, the Uncertain Information Hypothesis according to Brown et al. (1988), provides a risk-related explanation for stronger price reactions to bad than to good news. These approaches might not directly apply to our particular context. An examination of the deeper causes for negative spillovers is beyond the scope of this paper. Overall, we hence conclude that our results strongly support the presence of psychologically grounded overreaction. At the same time, however, we do not want to categorically rule out other explanations, potentially consistent with rational expectations.

4.7 Conclusion

This paper provides new insights into the detailed structure and degree of spillovers from the US stock market to intra daily stock returns in Asia. Using quantile regression techniques, we reveal an asymmetric structure of spillovers from the US to stock markets in Hong Kong, Japan, Korea, Singapore, Shanghai and Taiwan. Specifically, we find spillovers from the US to be generally weak around central return quantiles. For lower and upper return quantiles, however, we find that spillovers tend to be

[13] A recent overview for potential sources of stock return autocorrelation is given by Amini et al. (2013).

negative. For the latter, negative spillovers tend to be distinctively more pronounced than for lower quantiles. This pattern is relatively universal across markets with only slight differences across markets. Theoretically, it is consistent with the presence of an asymmetric overreaction phenomenon. Moreover, we detect strengthening spillovers from the US during the financial crisis of 2007-08. The effects are consistent with the presence of contagion. The fact that spillovers tend to be substantially weaker after weekends, further suggests the presence of calm-down effects over weekends and the importance of the length of the time period that traders have to process information generated in foreign markets.

Chapter 5

24-Hour Realized Volatilities and Transatlantic Volatility Interdependence

This paper proposes an innovative econometric approach for the computation of 24-hour realized volatilities across stock markets in Europe and the US. In particular, we deal with the problem of non-synchronous trading hours and intermittent high-frequency data during overnight non-trading periods. Using high-frequency data for the Euro Stoxx 50 and the S&P 500 Index between 2003 and 2011, we combine squared overnight returns and realized daytime variances to obtain synchronous 24-hour realized volatilities for both markets. Specifically, we use a piece-wise weighting procedure for daytime and overnight information to take structural breaks in the relation between the two into account. To demonstrate the new possibilities that our approach opens up, we use the new 24-hour volatilities to estimate a bivariate extension of Corsi et al. (2008)'s HAR-GARCH model. The results suggest that the contemporaneous transatlantic volatility interdependence is remarkably stable over the sample period.

5.1 Introduction

This paper considers the problem of intermittent high-frequency data and non-synchronous trading hours in the context of realized volatility interdependence across stock markets in Europe and the US. In particular, we propose a new approach for the computation of synchronous 24-hour realized volatilities, using eight years of high-frequency data for the Euro Stoxx 50 (ESTX) and the S&P 500 (S&P) Index.

Understanding cross-market volatility interdependence is of utmost importance for international policy makers and investors. In terms of risk, the extent of cross-market information transmission has a direct impact on the speed and severity of (financial) crises propagation and the benefits of international portfolio diversification. Using realized volatilities in modeling cross-market volatility interdependence is beneficial. The realized volatility is known to suffer from less noise than other volatility proxies and it permits to treat daily return variability as observed - despite the otherwise fundamentally latent character of volatility. As Andersen and Bollerslev (1998), Andersen et al. (2001) and Barndorff-Nielsen and Shephard (2002) have shown, under certain conditions, the realized volatility can be estimated from approximately continuously sampled intra day returns. It then consistently approximates the integrated variance – the theoretically 'true' intra daily price variation.

In modeling the interdependence of (realized) volatilities across international stock markets, however, two important problems arise. Firstly, approximately continuously sampled prices are only available over active trading hours. Realized volatilities based on prices from these particular hours hence do not represent the full 24 hours. The latent 'true' volatility, however, spans over the whole day. The information flow in international financial markets can be considered as continuous, potentially affecting overnight non-trading periods, too. The importance of information arising during non-trading periods is acknowledged since early contributions such as Lockwood and Linn (1990) or Stoll and Whaley (1990). Recently, however, it has been reconsidered in the context of realized volatility, for example, by Hansen and Lunde (2005), Taylor (2007) or Ahoniemi and Lanne (2013). Unfortunately, as Ahoniemi and Lanne (2013) state, no consensus has emerged on how to optimally treat overnight information in the context of realized volatility estimation.

Secondly, if trading hours across stock markets around the globe overlap, then typically only over short time periods. Trading in stock markets in Europe and the US, for example, is characterized by a short overlap in the early afternoon. Estimating multivariate volatility models based on conventional realized volatilities, computed over active trading hours, might be misleading. Similarly as in the case of return correlations over non-synchronous time periods, the results are potentially biased.[1]

Regarding the first problem, Christoffersen (2012) only recently provides a first overview on different possibilities, how overnight information can be treated in estimating realized volatilities. According to him, alternatives to ignoring overnight information are adding squared overnight returns to the realized variances over active trading hours, scaling up realized volatilities over active trading hours or finding optimal weights to combine realized variances from active trading hours and squared overnight returns. The latter, most sophisticated, approach goes back to Hansen and Lunde (2005).[2] The benefits of this approach are emphasized by Ahoniemi and Lanne (2013) who find the realized volatility of the S&P 500 Index to become more precise if is used. Motivated by their findings, we follow this approach, too.

An unresolved issue, however, is how Hansen and Lunde (2005)'s weighting technique can be used over longer time periods.[3] As the authors show, a critical assump-

[1] In case of non-synchronous returns and positive correlation, the true correlation is underestimated. For extensive documentations of this problem, see Martens and Poon (2001) or Schotman and Zalewska (2006).

[2] Note that we focus on the realized volatility, whereas Hansen and Lunde (2005) actually focus on realized variances. However, the realized variance and the realized volatility are closely related. The latter can be obtained from extracting the square root of the realized variance. In the following, we use RV to denote the realized volatility and $RVAR$ to denote the realized variance.

[3] So far, the literature has been confined to the analysis of short time periods. Hansen and Lunde (2005), for example, consider a sample from January 2001 to December 2004, whereas Masuda and Morimoto (2012) use a sample from January 2004 to November 2006.

tion for the consistent estimation of 24-hour realized variances (and volatilities), is the conditional proportionality between squared overnight returns and the realized variances over active trading hours. However, in particular over longer samples, including periods such as the financial crisis of 2007-08, the validity of this assumption is questionable. To solve this problem, we consider a piece-wise weight determination procedure, taking structural breaks in the relation between squared overnight returns and realized volatilities over active trading hours into account.

Concerning the second problem, no satisfactory solution has emerged so far. Some authors try to circumvent non-synchronicity issues by resorting to low frequencies. Pesaran and Pesaran (2010), for example, compute weekly realized volatilities. Other authors, such as Dimpfl and Jung (2012) or Jung and Maderitsch (2014) use non-overlapping ralized volatilities to conduct Granger causality inference. Further authors, such as Bubák et al. (2011) use data from exactly overlapping time periods. Moreover, at the intra daily frequency, for example, Bauer and Vorkink (2011), Chiriac and Voev (2011) or Golosnoy et al. (2012) model the temporal interdependence between realized variances and covariances for stocks with common trading hours.

To close this gap in the literature, we show that Hansen and Lunde (2005)'s weighting technique can be adjusted in a way that synchronous 24-hour realized volatilities can be obtained, even if the markets analyzed are characterized by non-synchronous (but partly overlapping) trading hours. To highlight the new possibilities that our approach opens up for future research, we estimate a bivariate model of transatlantic volatility interdependence. In particular, we estimate a vector heterogeneous autoregressive multivariate generalized autoregressive conditional heteroskedasticity model of realized volatility (V-HAR-MGARCH).

The paper is structured as follows. We introduce our data and the particular institutional framework in Section 5.2. In Section 5.3 we present the baseline approach for the computation of 24-hour realized volatilities, according to Hansen and Lunde (2005). Then we show how we extend this approach for our particular purposes in

Section 5.4. Subsequently, we present the results of our model of transatlantic volatility interdependence in Section 5.5. We conclude in Section 5.6.

5.2 Data and Institutional Framework

We use five-minute high frequency time series from Olsen Financial Technologies. As representatives for the European and the US stock markets, we use data for the Euro Stoxx 50 and the S&P 500 Index. Both time series represent free-float capitalization weighted price indexes. Our sample reaches from September 2, 2003 to September 30, 2011. Excluding holidays and weekends and only taking common trading days into account, we have data on 1964 trading days at our disposal. The institutional framework that we consider is illustrated in Figure 5.1.

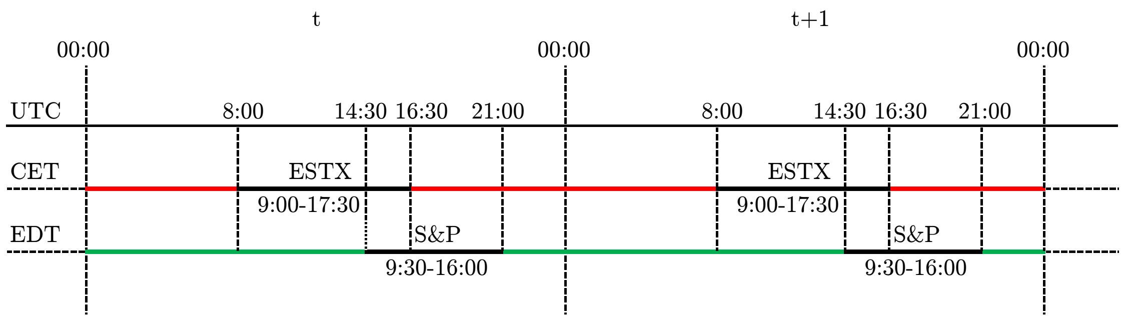


FIGURE 5.1: *Trading hours.*

Notes: Winter time both in Europe and the US. UTC is Universal Time Coordinated. CET is Central European Time. EDT is Eastern Daylight Time.

The vertical dashed lines show the particular stock market opening and closing times as well as the day changes at midnight. The times correspond to a typical trading day in winter both in Europe and the US.[4] They are given in Universal Time Coordinated (UTC) as well as the corresponding local times. The regular active trading hours are represented by black horizontal lines. The overnight non-trading periods are given

[4]One hour has to be subtracted from the winter trading times to obtain the trading times in summer. Note that we also take non-synchronous time-shifts in Europe and the US into account.

in red (European market) and green (US market). The European market opens at 8:00 UTC and closes at 16:30 UTC. The US market opens at 14:30 UTC and closes at 16:30 UTC. The resulting overlaps of the trading times are apparent between 14:30 UTC and 16:30 UTC.[5]

To obtain realized volatilities over the active trading hours, we proceed as common in the literature and follow i.a. Andersen et al. (2001), Barndorff-Nielsen and Shephard (2002), Andersen et al. (2010) and Masuda and Morimoto (2012). For every single trading day and each of our two markets, we sum up the M available squared five-minute intra day log-returns ($r^2_{t,j}$) to obtain the realized variances ($RVAR_t$) and then extract the square root to get the realized volatilities (RV_t):

$$RV_t = \sqrt{RVAR_t} = \sqrt{\sum_{j=1}^{M} r^2_{t,j}}, \tag{5.1}$$

where we use the five minute frequency due to the empirical finding that this frequency is typically most adequate to solve the trade-off between bias and variance in the realized volatility estimator.[6] The descriptive statistics are depicted in Table 5.1. In addition to the descriptive statistics for the realized volatilities, we present descriptive statistics for the log-transformed realized volatilities. The use of these volatilities is typically preferred in applied research as the log-transformed series are closer to normally distributed than the non-transformed series (see Andersen et al. (2003)). Further, we present the descriptive statistics for the overnight returns as well

[5] Note that these times were given throughout the whole sample period, apart from a short exception at the beginning of the sample period. From June 2, 2000 onwards, trading hours in Europe were extended until 19:00 UTC. However, as the trading volume was only small over this period, the extended trading hours were disestablished on October 31, 2003. We do not consider extended hours trading in October 2003.

[6] On the one hand, a bias might arise from market microstructure noise, for example, due to non-synchronous trading. On the other hand, the volatility rises as a consequence of discretization if the frequency is lowered.

as the squared overnight returns. To obtain the overnight returns, we compute close-to-open log-returns. All distributions have typical characteristics, as reported elsewhere in the literature. They are characterized by pronounced skewness and excess kurtosis.

TABLE 5.1: *Descriptive statistics: Daytime and overnight variances.*

S&P 500				
	Daytime *RV*	Log. daytime *RV*	Overnight returns	Squ. overnight returns
Obs.	1964	1964	1964	1964
Mean	0.8187	-0.3717	0.0126	0.4843
Median	0.6249	-0.4702	0.0326	0.0825
Minimum	0.1677	-1.7856	-6.9660	0.0000
Maximum	7.6048	2.0288	3.9173	48.5254
St. Dev.	0.6238	0.5385	0.6960	1.8087
Skewness	3.5336	0.9061	-0.9755	15.0493
Kurtosis	21.9901	4.0157	15.0175	332.6269
Euro Stoxx 50				
	Daytime *RV*	Log. daytime *RV*	Overnight returns	Squ. overnight returns
Obs.	1964	1964	1964	1964
Mean	0.9657	-0.1172	0.0251	0.7179
Median	0.7932	-0.2317	0.0581	0.1610
Minimum	0.1699	-1.7727	-10.3685	0.0000
Maximum	5.8941	1.7739	6.4079	107.5056
St. Dev.	0.6143	0.5083	0.8471	3.3132
Skewness	2.8049	0.5579	-1.1080	20.8352
Kurtosis	15.6393	3.3990	21.4534	592.0077

5.3 The 24-Hour Realized Volatility

The fundamental idea behind the approach of Hansen and Lunde (2005) is to determine the 24-hour realized variance ($RVAR_t^{HL}$) as an optimal linear combination of the overnight (close-to-open) squared return $r_{1,t}^2$ and the (open-to-close/daytime) realized variance $RVAR_{2,t}$. In case that the overnight period precedes the active trading period, the resulting whole-day realized variance is

$$RVAR_t^{HL}(\omega) \equiv \omega_1 r_{1,t}^2 + \omega_2 RVAR_{2,t}, \tag{5.2}$$

where the realized variance can be constructed e.g. as the sum of the squared intraday returns. The weights for the optimal combination, $\omega \equiv (\omega_1, \omega_2)$ are chosen such that the squared error is minimal. Specifically, this means that the squared difference between the whole-day realized variance $RVAR_t^{HL}(\omega)$ and its theoretical counterpart IV_t, the integrated variance, is minimized

$$\min_{\omega \in \Omega} E[RVAR_t^{HL}(\omega) - IV_t]^2, \tag{5.3}$$

where $\Omega \subset R^2$. Due to the latent character of IV_t, this equation cannot be evaluated directly. However, Hansen and Lunde (2005) demonstrate that the problem can be simplified by restricting the attention to conditionally unbiased estimators. More precisely, they show that the pseudo-objective function

$$\min_{\omega \in \Omega} var[RVAR_t^{HL}(\omega)] \tag{5.4}$$

can be solved empirically and that this solution is identical to the solution of Equation (5.2). The optimal unbiased linear estimator $RVAR_t^{HL}(\omega)$ then results from

$$\min_{\omega_1, \omega_2} \text{var}(\omega_1 r_{1,t}^2 + \omega_2 RVAR_{2,t}), \text{ s.t. } \omega_1 \mu_1 + \omega_2 \mu_2 = \mu_0, \tag{5.5}$$

where $\mu_0 \equiv E(IV_t)$, $\mu_1 \equiv E(r_{1,t}^2)$ and $\mu_2 \equiv E(RVAR_{2,t})$. The solution is given by

$$\omega_1^* \equiv (1-\varphi)\mu_0/\mu_1 \text{ and } \omega_2^* = \varphi\mu_0/\mu_2, \tag{5.6}$$

where the relative importance factor φ is defined as

$$\varphi = \frac{\mu_2^2\eta_1^2 - \mu_1\mu_2\eta_{12}}{\mu_2^2\eta_1^2 + \mu_1^2\eta_2^2 - 2\mu_1\mu_2\eta_{12}} \tag{5.7}$$

and $\eta_1^2 \equiv \text{var}(r_{1,t}^2)$, $\eta_2^2 \equiv \text{var}(RVAR_{2,t})$ and $\eta_{1,2} \equiv \text{cov}(r_{1,t}^2, RVAR_{2,t})$. If suitable regularity conditions, such as conditional proportionality between the daytime and overnight variance, are met, then $\mu_0, \mu_1, \mu_2, \eta_1, \eta_2$ and η_{12} can be estimated by inserting empirical sample averages. For further details, see Hansen and Lunde (2005).

5.4 Synchronous 24-Hour Realized Volatilities for the Stock Markets in Europe and the US

5.4.1 Adjusting the Approach of Hansen and Lunde (2005)

An application of Hansen and Lunde (2005)'s approach is, in principle, possible to both the Euro Stoxx 50 and the S&P 500 Index. However, using the approach in its original form, based on the close-to-close periods, given in Figure 5.1, would lead to non-synchronous 24-hour realized volatilities. Measuring cross-market volatility interdependence, based on these quantities could be misleading.

We therefore propose an alternative adjusted procedure to obtain exactly overlapping 24-hour volatilities. Figure 5.2 depicts again the trading times (in UTC) over two trading days. Additionally, it includes hypothetical price processes to illustrate the idea of price latency during overnight periods. The black lines refer to the active trading periods, whereas the red and the green lines refer to the overnight non-trading periods. As the information flow on international financial markets can be considered as continuous, the hypothetical price processes during these periods need to be taken into account to consistently estimate realized volatilities over the whole day.

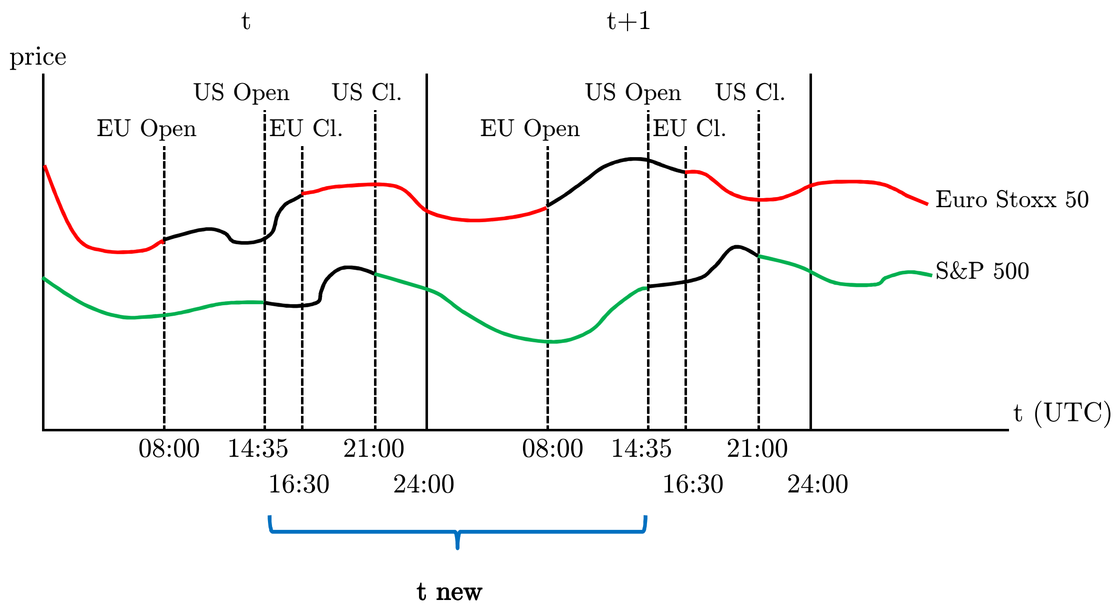


FIGURE 5.2: *Latent price processes.*

Notes: Winter time both in Europe and the US. UTC is Universal Time Coordinated. CET is Central European Time. EDT is Eastern Daylight Time. Active trading hours given in black. The overnight period in Europe is given in red. The overnight period in the US is given in green.

In our adjusted approach, we now redefine the day from 0:00 UTC to 24:00 UTC to 14:35 UTC to 14:35 UTC in winter time and 13:35 UTC to 13:35 UTC in summer time. The resulting new 24-hour period is highlighted by the blue horizontal brace in Figure 5.2. The time point 14:35 UTC (13:35 UTC) lies within the overlap of the trading hours of the stock exchanges in Europe and the US.

Using this particular time point essentially enables us to apply the approach of Hansen and Lunde (2005) to both markets simultaneously and to obtain realized variances over synchronous 24-hour periods. Further, it allows us to exploit the full information set available, apart from the 14:30 UTC (13:30 UTC) S&P 500 opening price that we exclude due to stale quotes, potentially contained in S&P 500 opening prices.[7]

For the US market, we compute the 24-hour realized variance ($RVAR^{HL}_{t,US}$) according to Equation 5.2. The only difference is that the order of the trading and non-trading period is now diametrically opposed:

$$RVAR^{HL}_{t,US}(\omega) \equiv \omega_1 RVAR_{1,t,US} + \omega_2 r^2_{2,t,US}, \tag{5.8}$$

where $RVAR_{1,t,US}$ is the realized variance of the active trading period and $r^2_{2,t,US}$ is the squared return over the overnight non-trading period.

For the European market, however, it is obvious in Figure 5.2 that now two different components of active trading lie within the newly defined day t. The first period refers to the time from the beginning of trading in the US until market closing in Europe (14:35 UTC to 16:30 UTC). The second period refers to the beginning of trading in Europe until market opening in the US (8:00 UTC to 14:35 UTC). Between these two components, there is the overnight non-trading period from market close to market open in Europe (16:30 UTC until 8:00 UTC). The minimization problem to obtain the realized variance for the European market ($RVAR^{HL}_{t,EU}$) hence takes the following form:

[7] Note that stale information is contained in index opening prices, if not all stocks are traded immediately at the beginning of a trading day. As nowadays most stocks tend to be traded very shortly after market opening, however, the economic implications of this problem become negligible after very short time (see e.g. Jung and Maderitsch (2014)).

$$\min_{\omega_{11},\omega_2,\omega_{12}} \operatorname{var}(\omega_{11} RVAR_{11,t,EU} + \omega_2 r^2_{2,t,EU} + \omega_{12} RVAR_{12,t,EU}),$$
$$\text{s.t. } \omega_{11}\mu_{11} + \omega_2\mu_2 + \omega_{12}\mu_{12} = \mu_0, \tag{5.9}$$

where $RVAR_{11,t,EU}$ refers to the realized variance component over the first period mentioned above, $r^2_{1,t,EU}$ is the squared return over the non-trading period and $RVAR_{12,t,EU}$ denotes the realized variance component over the second period mentioned above. Theoretically, hence three different weights need to be determined. In principle, this is feasible as long as the regularity conditions, mentioned in Hansen and Lunde (2005), are met (in particular the conditional proportionality between the three different volatility components). Masuda and Morimoto (2012), for example, estimate four weights over a relatively short sample period. Our particular sample period, however, is very long and contains the financial crisis of 2007 which makes the validity of the regularity conditions unlikely. Further, from a practical computational standpoint, there exists a more efficient way to proceed. Due to commutativity, the chronological order of the volatility components is immaterial. The minimization problem for the European market can be reduced to

$$\min_{\omega_1,\omega_2} \operatorname{var}(\omega_1 RVAR_{1,t,EU} + \omega_2 r^2_{2,t,EU}), \text{ s.t. } \omega_1\mu_1 + \omega_2\mu_2 = \mu_0, \tag{5.10}$$

so that now $\omega_1 RVAR_{11,t,EU} + \omega_2 r^2_{2,t,EU} + \omega_3 RVAR_{12,t,EU}$ is summarized as $\omega_1(RVAR_{11,t,EU} + RVAR_{12,t,EU}) + \omega_2 r^2_{2,t,EU}$ and only one weight for the realized variance from the active trading period has to be determined. Overall, we hence compute the realized variance for the European market as:

$$RVAR^{HL}_{t,EU}(\omega) \equiv \omega_1 RVAR_{1,t,EU} + \omega_2 r^2_{2,t,EU}. \tag{5.11}$$

5.4.2 Obtaining Weights for Overnight and Daytime Variance

To ensure the consistency of their estimated volatilities, Hansen and Lunde (2005) introduce important identifying assumptions and conduct various robustness checks. Further, they check the sensitivity of their results to outliers. We proceed analogously. Similarly as Hansen and Lunde (2005) we find the optimal weights to be sensitive to outliers as well. Therefore, we use a truncated dataset for the determination of the optimal weights. For the computation of the whole day volatilities we resort to the full sample again. However, in contrast to Hansen and Lunde (2005), who discard about 1% of their sample, we only discard about 0.5% of our sample.[8]

For consistency to be given, the following four identifying assumptions need to be fulfilled according to Hansen and Lunde (2005):

$$\begin{aligned}
&(i)\ \ E(IV_{1,t}|IV_t) = \delta_0 IV_t \\
&(ii)\ E(\delta_{b_1} RVAR_{1,t} - IV_{1,t}|IV_t) = 0 \\
&(iii)\, E(\delta_{b_2} r^2_{2,t} - IV_{2,t}|IV_t) = 0 \\
&(iv)\, \{RVAR_{1,t}\}, \{r_t\} \text{ and } \{r^2_t\} \text{ satisfy a law of large numbers as } n \to \infty,
\end{aligned} \tag{5.12}$$

where $E(.)$ refers to the conditional expectation, $IV_{t,1}$ and IV_t are the integrated variances over the active trading and the whole day periods, $\delta_{(.)}$ is a scalar and $RVAR_{1,t}$ is the realized variance over the active period.

[8]More precisely, we discard nine days from our 1964 days sample (the five days with the highest realized variances over the active trading periods and the 4 days with the highest overnight returns). Hansen and Lunde (2005) exclude 10 days in total from their 986 days total sample.

Due to its particular importance, we discuss condition (i) at this point. Further elaborations on assumptions (ii) to (iv) can be found in Appendix B.1. Condition (i) requires that the proportion of the integrated variance, occurring during the active trading period, is fix.[9] To test this assumption, Hansen and Lunde (2005) regress the logarithmized squared overnight returns on the logarithmized daytime realized variances over the total sample period as well as over subsamples of approximately two years length. Then they test if the estimated coefficients from the subsamples differ significantly from their total sample counterparts. We proceed in the same way and find the regression coefficients to be fairly stable over time for the European market, but not so for the US market.[10]

This ultimately motivates us to conduct structural break tests to identify subsamples over which the relation between the overnight and the daytime variances is structurally stable. In particular, we conduct tests for breaks in linear regression relations over time according to Andrews (1993), Andrews and Ploberger (1994) and Zeileis et al. (2002). For both markets, we formulate 'H_0: No structural break' versus 'H_1: One single parameter shift' in the relation between the logarithmized squared overnight returns and the daytime realized variances. As the potential break dates are unknown, we compute the following F-statistic due to Andrews (1993) for all potential break dates and each market:

$$F_t = \frac{\widehat{u}^T \widehat{u} - \widehat{e}_t T \widehat{e}_t}{\widehat{e}_t^T \widehat{e}_t / (n - 2k)}, \tag{5.13}$$

where $\widehat{e}_t = (\widehat{u}_{<t}, \widehat{u}_{>t})'$ are the residuals from the model with coefficients estimated separately from each other on subsamples before and after potential break dates t, $\widehat{u}$ are the residuals from the model estimated over the total sample, n is the sample size,

[9] However, different stochastic processes are possible. E.g. a relatively higher weekend variance is allowed as long as it is proportional to IV_t.

[10] Note that we follow a conservative approach, using the dataset which is not corrected for outliers.

k are the degrees of freedom and $[(0.075 \cdot n);(n - 0.075 \cdot n)]$ is the interval of potential break dates t. We first apply this test to the overall samples. After identifying a structural break, we proceed by splitting the sample based on the break date suggested by the previous test. Then we test for further breaks within the subsamples. We continue in this way until no more breaks are detectable within the subsamples anymore.[11] Overall, we find evidence for one structural break in the European market and three structural breaks in the US market. The particular time periods of the subsamples, suggested by the break tests, are presented in Table 5.2. As there is no more evidence for further structural breaks, we conclude that assumption (i) is fulfilled within these subsamples.

In addition, Table 5.2 depicts the averages of the daytime realized variances and the overnight squared returns as well as the averages of their sums and their ratios. Most notably, the ratios between the overnight and the daytime variances vary over time. During the financial crisis, significant increases both in daytime and overnight variances are apparent. In particular for the US market, the ratio is relatively small in the first two subsamples. Then it increases in the last two subsamples due to disproportionate increases in the overnight variances. The particularly large increase in the last subsample might be attributable to the European sovereign debt crisis. Important information might have been generated during the active trading period in Europe which in turn coincides with the US overnight non-trading period. The notion that overnight variance reflects information, generated during active trading in the respective foreign market, is further supported by the permanently higher overnight to daytime variance ratio in Europe. It might reflect the particular importance of trading in the US for the European market.

Moreover, Table 5.2 presents the variances of the squared overnight returns, the realized daytime variances, their ratios as well as their correlations. Most apparently, the ratio between the overnight and the daytime variance is predominantly smaller

[11] The graphical results for the F-statistics are depicted in Figure B1 in the Appendix. The boundaries are computed such that the probability that the supremum F-statistic exceeds them is $\alpha = 5\%$.

for the US than for the European market. Again, this might reflect the importance of information, generated in the US market. Further, the correlations between the daytime and the overnight variances appear to tend slightly upwards over the sample period.

TABLE 5.2: *(Sub-) samples suggested by structural break tests and empirical estimates of components.*

Subsample	$\hat{\mu}_1$	$\hat{\mu}_2$	$\hat{\mu}_0$	$\hat{\mu}_2/\hat{\mu}_1$	$\hat{\eta}_1^2$	$\hat{\eta}_2^2$	$\hat{\eta}_2^2/\hat{\eta}_1^2$	$\hat{\eta}_{12}/(\hat{\eta}_1\hat{\eta}_2)$
				Euro Stoxx 50				
02/09/03-23/01/09	0.9259	0.4910	1.4169	0.5303	1.8909	2.6035	1.3769	0.5597
26/01/09-29/09/11	1.7357	0.6734	2.4091	0.3880	1.6930	4.3951	2.5960	0.3112
				S&P 500				
02/09/03-27/10/04	0.3556	0.1150	0.4706	0.3233	0.0382	0.0350	0.9171	0.1048
28/10/04-13/11/06	0.2856	0.0747	0.3592	0.2633	0.0362	0.0170	0.4814	0.1250
14/11/06-30/04/08	0.7723	0.3066	1.0789	0.3970	0.8656	0.4157	0.4802	0.4693
02/05/08-29/09/11	1.6530	0.7601	2.4132	0.4570	7.7107	2.2713	0.2946	0.4504

Notes: $\hat{\mu}_1$*=daytime variance.* $\hat{\mu}_2$*=overnight variance.* $\hat{\mu}_0$*=sum of the daytime and the overnight variance.* $\hat{\eta}_1^2$*=variance of the daytime variance.* $\hat{\eta}_2^2$*=variance of the overnight variance.* $\hat{\eta}_{1,2}$*=covariance between the daytime and the overnight variance.*

$$\hat{\mu}_1 = \frac{1}{n}\sum_{t=1}^{n} RVAR_{1,t} \quad \hat{\mu}_2 = \frac{1}{n}\sum_{t=1}^{n} r_{2,t}^2 \quad \hat{\mu}_0 = \frac{1}{n}\sum_{t=1}^{n}(RVAR_{1,t} + r_{2,t}^2)$$

$$\hat{\eta}_1^2 = \frac{1}{n}\sum_{t=1}^{n}(RVAR_{1,t} - \hat{\mu}_1)^2 \quad \hat{\eta}_2^2 = \frac{1}{n}\sum_{t=1}^{n}(r_{2,t}^2 - \hat{\mu}_2)^2 \quad \hat{\eta}_{1,2} = \frac{1}{n}\sum_{t=1}^{n} RVAR_{1,t}(r_{2,t}^2 - \hat{\mu}_2).$$

5.4.3 The Resulting Quantities

Considering the results from the structural break tests, we decide to apply a piecewise weighting of overnight and daytime variances. In particular, we insert the empirical estimates of the components, as given in Table 5.2. The finally resulting weights are presented in Table 5.3.

Overall, our findings are consistent with Hansen and Lunde (2005). In particular, most of our computed weights for the daytime variance components (ω_1) are slightly above one. This induces an upscaling of the daytime variances. By contrast, most weights for the overnight variance components (ω_2) are smaller than one. These, compared to the daytime variances typically more noisy variances, are hence downscaled. The ratio between the overnight and daytime variance weight varies over time. A relative increase in the importance of the daytime component is apparent in the last subsample of each market. Again, the presence of the financial crisis and the European sovereign debt crisis seem to play a role. In case of the US market, the weight for the overnight variance even gets larger than one so that the daytime variance is slightly downscaled, whereas the overnight variance is slightly upscaled. Technically, this can be explained by a relative increase of the noisiness of the daytime variance, as indicated by its particularly large variance.

Applying these weights to the full sample data, we finally obtain the 24-hour realized volatilities as the square roots of the 24-hour realized variances. We provide descriptive statistics for the realized variances, the realized volatilities and their logarithmized counterparts in Table 5.4. Compared to their daytime counterparts, the new 24-hour quantities are considerably larger. Their statistical properties, however, remain relatively similar and hardly differ from what has been elsewhere reported in the literature (see again, for example, Andersen et al. (2001), Barndorff-Nielsen and Shephard (2002) and Andersen et al. (2010)). The realized variance and the realized volatility series are characterized by extreme excess kurtosis and strong positive skewness. The log-realized volatilities, however, are relatively closer to normally distributed.

TABLE 5.3: *Resulting weights together with their ratios.*

Market	Time span	$\hat{\varphi}$	$\hat{\omega}_1$	$\hat{\omega}_2$	$\hat{\omega}_2/\hat{\omega}_1$
Euro Stoxx 50	02/09/03-23/01/09	0.9436	1.4440	0.1626	0.1126
	26/01/09-29/09/11	0.8041	1.1161	0.7008	0.6279
S&P 500	02/09/03-27/10/04	0.9210	1.2229	0.3199	0.2615
	28/10/04-13/11/06	0.9085	1.1471	0.4400	0.3835
	14/11/06-30/04/08	0.9253	1.2924	0.2629	0.2035
	02/05/08-29/09/11	0.6524	0.9497	1.1103	1.1690

TABLE 5.4: *Descriptive statistics: 24-hour realized variances and volatilities.*

Market		24-hour *RVAR*	24-hour *RV*	24-hour log. *RV*
Euro Stoxx 50	Observations	1964	1964	1964
	Mean	1.9726	1.1726	0.0365
	Median	0.9378	0.9684	-0.0642
	Minimum	0.0438	0.2093	-3.1277
	Maximum	109.7824	10.4777	4.6985
	St. Dev.	4.5003	0.7732	1.0012
	Skewness	11.8960	3.6092	0.6527
	Kurtosis	218.1832	26.5872	3.7520
S&P 500	Observations	1964	1964	1964
	Mean	1.5341	0.9787	-0.2059
	Median	0.5276	0.7263	-0.3197
	Minimum	0.0324	0.1801	-1.7141
	Maximum	70.3543	8.3878	2.1268
	St. Dev.	3.8131	0.7636	0.5598
	Skewness	8.7835	3.3474	0.8723
	Kurtosis	114.2458	20.0390	3.7328

5.5 A Model of Transatlantic Volatility Interdependence

In order to demonstrate the new possibilities that our approach opens up, we use the newly computed realized volatilities to conduct a first-time investigation of contemporaneous transatlantic volatility interdependence over synchronous 24-hour periods. Following Bubák et al. (2011) and Souček and Todorova (2013), we estimate a bivariate extension of Corsi et al. (2008)'s HAR-GARCH model.

Specifically, we use an auxiliary vector heterogeneous autoregressive model of realized volatility (V-HAR) to model volatility persistence and cross-market volatility spillovers at the daily, weekly and the monthly time horizon. Based on the resulting residuals, we then estimate a time-varying conditional correlation (VCC) model according to Tse and Tsui (2002). We use this particular model to study the contemporaneous volatility interdependence as it does not require an indirect standardization-based calculation of the dynamic conditional correlation matrix. In contrast to Engle (2002)'s widely used dynamic conditional correlation (DCC) approach, the time-varying conditional correlation model formulates the conditional correlations explicitly as a weighted sum of past correlations.[12]

Apart from providing a visualization of the joint behavior of the realized volatilities, the time-varying conditional correlation model allows us to explicitly capture the so called volatility-of-volatility effect. According to Corsi et al. (2008), this effect describes the empirical phenomenon that when the realized volatility increases, typically the volatility of the realized volatility time series tends to increase as well.

In summary, our approach can be denoted as a vector heterogeneous autoregressive multivariate generalized autoregressive conditional heteroskedasticity (V-HAR-MGARCH) model of realized volatility.

[12]Note that the goal of this section is to provide an interesting new visualization of the joint behavior of the volatilities across the markets. A discussion of all critical aspects of DCC-type representations is beyond the scope of the paper. The interested reader, however, is referred to Bauwens et al. (2006), Aielli (2013) or Caporin and McAleer (2013).

In Corsi (2009)'s baseline HAR model, the key idea is to capture volatility, realized over different time intervals, allowing to analyze the news reactions of traders with heterogeneous time horizons.[13] Empirically, it has been shown that this model performs remarkably well in reproducing the realized volatility's empirical properties. In its simplest univariate form, the HAR model can be written as:

$$RV_t^{(d)} = \alpha + \beta^{(d)} RV_{t-1}^{(d)} + \gamma^{(w)} RV_{t-1}^{(w)} + \delta^{(m)} RV_{t-1}^{(m)} + \epsilon_t, \tag{5.14}$$

where ϵ_t is a serially independent zero mean innovation term and $RV_t^{(d)}$, $RV_{t-1}^{(d)}$, $RV_{t-1}^{(w)}$ and $RV_{t-1}^{(m)}$ are logarithmized realized volatilities over daily, weekly and monthly time horizons. Specifically, $RV_t^{(d)}$ is the daily and $RV_{t-1}^{(d)}$ is the lagged daily log-realized volatility. $RV_{t-1}^{(w)}$ is the lagged weekly log-realized volatility component, computed as $RV_{t-1}^{(w)} = \frac{1}{5}(RV_{t-1}^{(d)} + RV_{t-2}^{(d)} + ... + RV_{t-5}^{(d)})$. $RV_{t-1}^{(m)}$ denotes the lagged monthly log-realized volatility component. It is obtained as $RV_t^{(m)} = \frac{1}{22}(RV_{t-1}^{(d)} + RV_{t-1}^{(d)} + ... + RV_{t-22}^{(d)})$.

Extending this model to a vector autoregressive framework allows us to analyze Granger causal cross-market volatility spillovers in addition to the markets' dependencies on own past realized volatility components. Including foreign markets' volatility components, the V-HAR model takes the following form:

$$\boldsymbol{RV}_t^{(d)} = \boldsymbol{\alpha} + \boldsymbol{\beta}^{(d)} \boldsymbol{RV}_{t-1}^{(d)} + \boldsymbol{\gamma}^{(w)} \boldsymbol{RV}_{t-1}^{(w)} + \boldsymbol{\delta}^{(m)} \boldsymbol{RV}_{t-1}^{(m)} + \boldsymbol{\epsilon}_t, \tag{5.15}$$

where $\boldsymbol{RV}_t^{(.)}$ contains the US market's and the European market's log-realized volatility components over the daily, the weekly and the monthly time horizon. $\boldsymbol{\beta}^{(d)}, \boldsymbol{\gamma}^{(w)}$

[13] Short-term volatility, for example, might be unimportant for investors with long-term trading horizons, but not vice versa.

and $\delta^{(m)}$ contain the corresponding persistence and spillover coefficients. The persistence coefficients correspond to a market's own past realized volatility components, whereas the spillover coefficients refer to the foreign markets' past realized volatility components. $\boldsymbol{\epsilon}_t$ is a vector innovation term.

Using the time-varying conditional correlation approach according to Tse and Tsui (2002) , we then specify

$$\boldsymbol{\epsilon}_t = \boldsymbol{H}_t^{1/2}\boldsymbol{\nu}_t \tag{5.16}$$

$$\boldsymbol{H}_t = \boldsymbol{D}_t^{1/2}\boldsymbol{R}_t\boldsymbol{D}_t^{1/2} \tag{5.17}$$

$$\boldsymbol{R}_t = (1-\lambda_1-\lambda_2)\boldsymbol{R} + \lambda_1\boldsymbol{\Psi}_{t-1} + \lambda_2\boldsymbol{R}_{t-1}, \tag{5.18}$$

where $\boldsymbol{H}_t^{1/2}$ is the Cholesky factor of the time-varying conditional covariance matrix $\boldsymbol{H}_t$, $\boldsymbol{\nu}_t$ is a vector of independent and identically distributed innovations and $\boldsymbol{D}_t$ is a diagonal matrix of conditional variances in which the two diagonal elements $\sigma_{i,t}^2 \equiv (\sigma_{EU,t}^2, \sigma_{US,t}^2)$ evolve according to distinct univariate GARCH models of the form $\sigma_{i,t}^2 = c_i + \alpha_i\epsilon_{i,t-1}^2 + \beta_i\sigma_{i,t-1}^2$. $\boldsymbol{R}_t$ is the conditional correlation matrix to follow an autoregressive moving average type of analog. $\boldsymbol{R}$ contains the mean to which the dynamic process reverts. $\boldsymbol{\Psi}_t$ is the rolling estimator of the correlation matrix of the standardized residuals $\tilde{\epsilon}_{i,t} = \epsilon_{i,t}/\sigma_{i,t}$ and λ_1 and λ_2 are non-negative scalars that govern the dynamics of the conditional correlations.

The main interest of this section is on the contemporaneous volatility interdependence across the markets. At this point, however, we briefly discuss the estimation results of the auxiliary V-HAR model, presented in the first panel of Table 5.5. For the Euro Stoxx 50 Index, the lagged daily and weekly volatility components have the strongest Granger-causal impact on the daily realized volatilities. The magnitude of the measured effects decreases from the daily, to the weekly, to the monthly

TABLE 5.5: *Transatlantic volatility interdependence: Estimation results.*

PANEL I: Mean equations (V-HAR)				
Market	Euro Stoxx 50		S&P 500	
Domestic market	$\beta^{(d)}_{EU,t-1}$	0.3563 *** (0.000)	$\beta^{(d)}_{S\&P,t-1}$	0.1028 *** (0.001)
	$\gamma^{(w)}_{EU,t-1}$	0.3115 *** (0.000)	$\gamma^{(w)}_{S\&P,t-1}$	0.5070 *** (0.000)
	$\delta^{(m)}_{EU,t-1}$	0.1523 ** (0.016)	$\delta^{(m)}_{S\&P,t-1}$	0.3107 *** (0.000)
Foreign market	$\beta^{(d)}_{US,t-1}$	0.0252 (0.377)	$\beta^{(d)}_{EU,t-1}$	0.3677 *** (0.000)
	$\gamma^{(w)}_{S\&P,t-1}$	0.1129 ** (0.045)	$\gamma^{(w)}_{EU,t-1}$	-0.1274 ** (0.043)
	$\delta^{(m)}_{S\&P,t-1}$	-0.0206 (0.723)	$\delta^{(m)}_{EU,t-1}$	-0.1991 *** (0.002)
	α_{EU}	0.0290 *** (0.005)	α_{US}	-0.0158 (0.112)

PANEL II: Variance equations (MGARCH)				
Market	Euro Stoxx 50		S&P 500	
ARCH-coefficients	α_{EU}	0.0608***	α_{US}	0.0104***
		(0.000)		(0.002)
GARCH-coefficients	β_{EU}	0.8516***	β_{US}	0.9897***
		(0.000)		(0.000)
Adjustment coefficients	λ_1	0.0002	λ_2	0.9905***
		(0.939)		(0.000)
Log likelihood	27.3633			

*Notes: Significance at the 1% level: ***. Significance at the 5% level: **. Significance at the 10% level: *. P-values given in parentheses.*

volatility component. Spillovers from the US market, however, play a rather minor role. Only the weekly US-volatility component tends to exhibit a weak significant positive effect. In case of the US market, the 24-hour realized volatility appears to depend strongly on its own lagged volatility components. Surprisingly, however, the weekly volatility component exerts a relatively stronger impact than the daily and the monthly component.[14] Regarding spillovers from the European markets, particularly the daily component exhibits a strong positive effect, whereas the weekly and the monthly component each tend to have a moderate negative impact.

The results of the variance-equations are depicted in the second panel of Table 5.5. The ARCH- and GARCH-coefficients are statistically significant in both markets' equations. The comparatively larger ARCH-coefficient for the European market indicates a stronger reaction to short-run volatility shocks than in the US market. The relatively larger GARCH-coefficient for the US market points to a more pronounced persistence of the volatility of the volatility in the US market. Overall, the results support the importance of considering the volatility-of-volatility effect in the 24-hour realized volatilities.

The estimated adjustment coefficients λ_1 and λ_2 satisfy the non-negativity constraint ($\lambda_1 + \lambda_2 < 1$) with the sum of the coefficients being close to one. Testing $\lambda_1 = \lambda_2 = 0$ by a Wald test leads to a rejection of the null hypothesis of time-invariant conditional correlations under $\lambda_1 = \lambda_2 = 0$ at all common levels of significance.[15] The news parameter λ_1 is very small and statistically not significantly different from zero. A small dimension of this parameter ($\lambda_1 < 0.05$) is typical in the literature. In our case, however, the very small magnitude of λ_1 points to the presence of only very limited oscillations around the unconditional correlation level. λ_2, by contrast, is close to one

[14]Note, however, that after taking collinearity between the realized volatility components into account by estimating a model with orthogonalized volatility components according to Souček and Todorova (2013), we find the dependence on the daily volatility component to increase and the dependence on the monthly component to decrease. All other coefficients remain virtually unchanged.

[15]Note that under $\lambda_1 = \lambda_2 = 0$ the constant conditional correlation (CCC) model according to Bollerslev (1990) is nested in the varying conditional correlation model.

and differs statistically significantly from zero. The large dimension of this coefficient indicates a strong persistence in the dynamic conditional correlations. Despite the fact that we are able to reject the null hypothesis of the above-mentioned test, the insignificance of λ_1 might point to the presence of a limiting case with an only slightly time-varying correlation structure. As for a constant correlation structure, Bollerslev (1990)'s CCC model would be the optimal alternative, we estimate various CCC models in the course of robustness checks. Not surprisingly, however, we find only little time-variation in the constant correlation estimates across subsamples and only very small differences compared to the results of the time-varying conditional correlation model for the total sample.[16]

Figure 5.3 plots the evolution of the estimated conditional correlations over time. Most notably, it is obvious that the correlations do vary over time. A close look, however, reveals that the dynamic conditional correlations' fluctuate only within narrow limits, approximately between 0.526 and 0.534.

Further, associations between changes in the correlations and external events are hardly apparent. With the beginning of the financial crisis in 2007, for example, the correlations tend to rise. The correlation levels reached, however, are not particularly high in comparison to the past. Similar correlation levels are apparent, for example, around 2004 as well.

Overall, exceptional, potentially crisis-related changes in the correlations are not evident. From an econometric point of view, this points to the fact that constant conditional correlation models might be considered as well. From an economic point of view, however, the findings support the idea of a strong and relatively time-constant

[16]Note that in this context we also test the auxiliary V-HAR model for the presence of structural breaks in linear regression relations over time. At least for the US market, we find evidence for breaks at the beginning of the financial crisis of 2007 and the European sovereign debt crisis since 2008. Taking these breaks into account and re-estimating both time-varying and constant conditional correlation models, however, leaves the main results virtually unchanged. As the auxiliary model is not of central interest to us, we find it well justifiable to present the time-varying conditional correlations over the total sample period.

market integration in terms of volatilities. After taking volatility persistence, cross-market spillovers and the volatility-of-volatility effect into account, the contemporaneous transatlantic volatility interdependence appears to be remarkably stable over time.

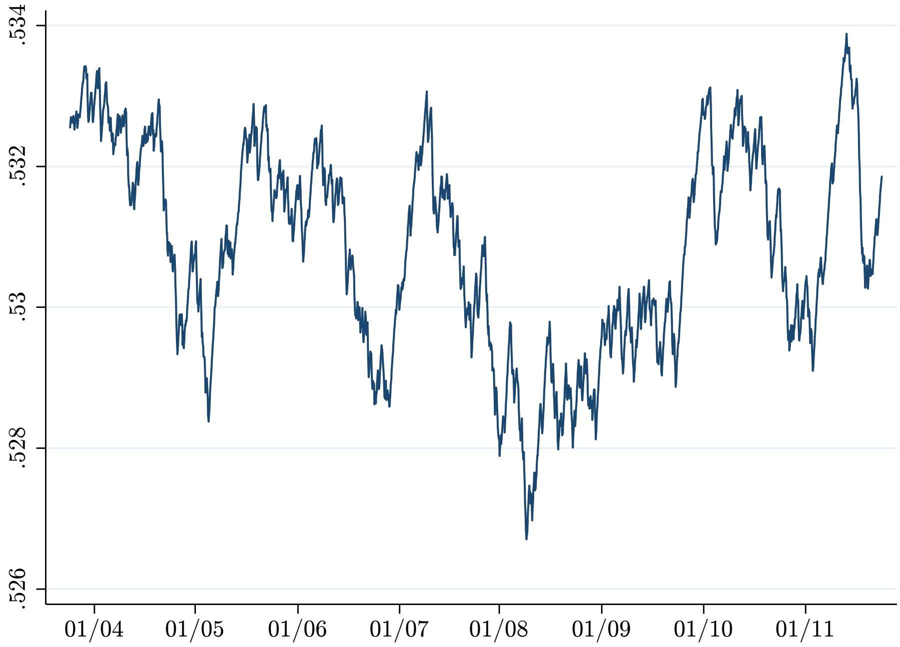


FIGURE 5.3: *Time-varying conditional correlation coefficients based on VCC-MGARCH model.*

5.6 Conclusion

This study introduces a new way to compute synchronous 24-hour realized volatilities for stock markets in Europe and the US. We deal with the problem of non-synchronous trading hours and a lack of high-frequency data during overnight non-trading periods for the Euro Stoxx 50 and the S&P 500 Index. In particular, we optimally combine squared overnight returns and realized daytime variances to estimate realized volatilities over synchronous 24-hour periods. As we find the relation between volatility over daytime and overnight periods to be unstable over time, we use a piece-wise weighting procedure based on structural break tests. The finally resulting 24-hour realized volatilities are characterized by typical distributional properties of realized volatilities. Their dimensions, however, differ considerably from their counterparts, computed only over the active trading hours.

To demonstrate the potential of or approach in the context of modeling cross-market volatility interdependence, we finally estimate a bivariate extension of Corsi et al. (2008)'s HAR-GARCH model. For the first time, this model allows us to investigate the contemporaneous transatlantic volatility interdependence over synchronous 24-hour periods. The estimation results indicate a high degree of integration between the markets' volatilities. In particular, they point to the presence of cross-market spillovers in addition to a strong persistence in the markets' 24-hour realized volatilities. Most apparently, however, our analysis reveals that the contemporaneous transatlantic volatility linkages are remarkably stable over time.

B Appendix

B.1 Further Identifying Assumptions

As Hansen and Lunde (2005) state, the assumptions given in Equation 5.10 imply $RVAR_{1,t} = c_1 IV_t(1 + \epsilon_t)$ and $r^2_{2,t} = c_2 IV_t(1 + v_t)$ with the error terms ϵ_t and v_t satisfying $E(\epsilon_t|IV_t) = E(v_t|IV_t) = 0$. To test these two conditional moment conditions, they employ kitchen sink regressions. More precisely, they estimate $\log(r^2_{2,t}/RVAR_{1,t}) = \alpha + \beta Z_t + u_t$ and conduct an F-test with $'H_0 : \beta = 0'$. Z_t thereby stands for instrument variables which need to be uncorrelated with ϵ_t and v_t, but strongly correlated with IV_t. As volatility persistence is an empirically well known phenomenon, Hansen and Lunde (2005) use $\log(RVAR_{1,t-1})$ as a strong instrument. Further, they employ dummies, $D_{Mon,t}, D_{Tue,t}, D_{Wed,t}, D_{Thu,t}$ and $D_{Fri,t}$ to test for the presence of weekday effects.[17] Concerning both the European and the US market, we conduct analogous tests based on the total sample as well as various subsamples. Overall, we find virtually no evidence against H_0. Generally, $E(e_t|IV_t) = E(v_t|IV_t) = 0$ tends to hold well.

Moreover, according to assumption (ii), the conditional bias of $RVAR_{1,t}$ must be proportional to $IV_{1,t}$. In our case, using pre-filtered five-minute data, this assumption should not be of concern.[18] Anyway, Hansen and Lunde (2005) propose to evaluate the conditional unbiasedness, $E[RVAR_t(\omega)|IV_t] = IV_t$ by splitting their sample and checking for anomalies. As an instrument for the unobserved variable IV_t, they use quantiles of the previous day daytime realized variances ($RVAR_{1,t-1}$) as these are expected to be uncorrelated with day t specific measurement errors. We proceed analogously, first again use the weekday dummies $D_{j,t}$ with $j = Mon, ..., Fri$ and then define $Q_{j,t} \equiv 1_{\{RVAR_{1,t-1} \in I_j\}}$ with $j = 1, ..., 4$ and $t = 1, ..., n$, where I_1, I_2, I_3 and I_4 subdivide the $RVAR_{1,t-1}$ observations into their empirical quartiles. Secondly, we compute the empirical ratios

$$\text{(B.1)} \qquad \frac{\sum_{t=1}^{n} RVAR_t Q_{j,t}}{\sum_{t=1}^{n} (RVAR_{1,t} + r_{2,t}^2) Q_{j,t}} \quad \text{and} \quad \frac{\sum_{t=1}^{n} RVAR_t D_{j,t}}{\sum_{t=1}^{n} (RVAR_{2,t} + r_{1,t}^2) D_{j,t}}$$

to implicitly check the identities $E(RVAR_t|Q_{j,t}) = E(IV_t|Q_{j,t})$ for $j = 1, ..., 4$ and $E(RVAR_t|D_{j,t}) = E(IV_t|D_{j,t})$ for $j = Mon, ..., Fri$. As obvious in Table B1, the resulting ratios are all close to one. There is hence virtually no evidence for a systematic measurement error in our measure $RVAR_t$. Moreover, we conduct again kitchen sink regressions based on $\log[RVAR_t/(RVAR_{1,t} + r_{2,t}^2)] = \alpha + \beta' Z_t + u_t$, using the same instrument variables as in the first kitchen sink regressions. Using heteroskedasticity robust p-values we are not able to reject $'H_0 : \beta = 0'$ in a single case.[19]

[17]Hence: $Z_t \equiv (log(RVAR_{2,t-1}, D_{Mon,t}, D_{Tue,t}, D_{Wed,t}, D_{Thu,t}))'$.

[18]Note, however, that even if our realized volatility estimator was biased, then this would only be problematic if the bias was not proportional to IV_t. Experimenting with volatility signature plots, however, we do not find evidence for the presence of considerable market microstructure noise.

[19]Detailed results are available upon request.

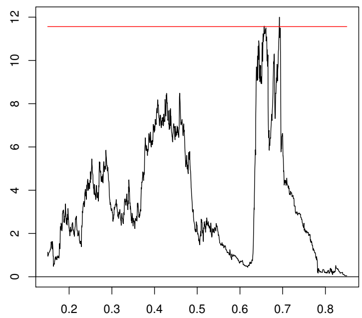
Assumptions (iii) and (iv) are not discussed in detail in Hansen and Lunde (2005). However, we believe that it is fair to assume that both conditions are met in our case. Even though the squared overnight return is a noisy variance estimator, the proportionality to the realized variance over the overnight period is plausible. Further, as our (sub-) sample sizes are sufficiently large, we expect (iv) to be uncritical as well. Overall, we hence conclude that the piece-wise weight determination procedure is justifiable and that all assumptions of Hansen and Lunde (2005) are sufficiently met in the respective subsamples.

TABLE B1: *Conditional unbiasedness.*

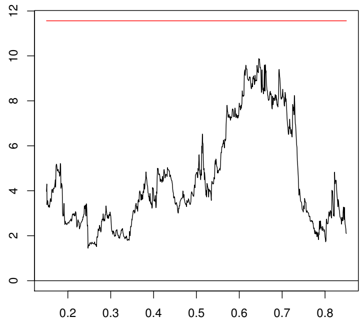
	q1	q2	q3	q4	Mon	Tue	Wed	Thu	Fri
Euro Stoxx 50	0.94	0.96	0.99	0.97	0.91	1.00	0.99	0.99	0.99
S&P 500	0.96	1.00	1.00	1.00	1.02	0.97	0.99	1.01	1.00

Notes: Bias ratios defined according to Equation (B.1).
q1, q2, q3 and q4 refer to the empirical quartiles of $RVAR_{2,t}$.
Mon, Tue, Wed, Thu, Fr refer to $RVAR_{2,t}$ *according to weekdays.*

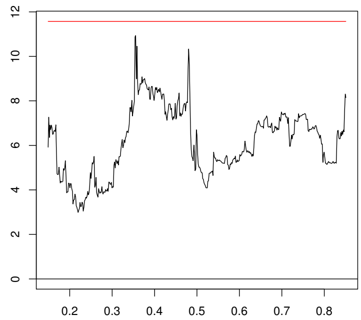
B.2 Structural Break Tests



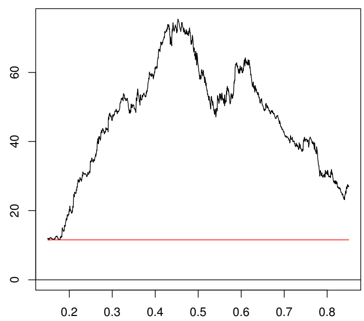
Euro Stoxx 50 (09/03-09/11)



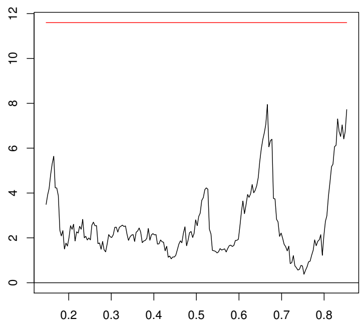
Euro Stoxx 50 (09/03-07/07)



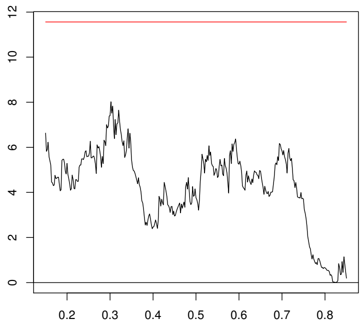
Euro Stoxx 50 (08/07-09/11)



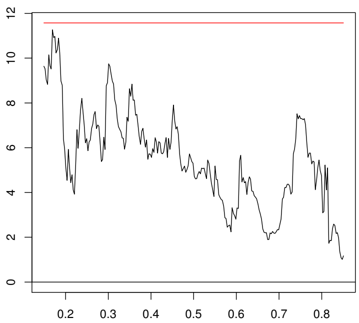
S&P 500 (02/09/03-29/09/11)



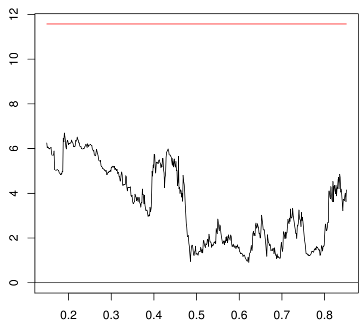
S&P 500 (02/09/03-27/10/04)



S&P 500 (28/10/04-13/11/06)



S&P 500 (14/11/06-30/04/08)



S&P 500 (02/05/08-29/09/11)

FIGURE B1: *Structural break tests.*

F-statistics given in black. Boundaries for $\alpha = 5\%$ *given in red.*

Chapter 6

Conclusion

This thesis provides a differentiated picture of the dynamics and interdependence of returns and (realized) volatilities across international financial markets. In particular, it presents new evidence on the time- and state-dependence of information processing against the background of the financial crisis of 2007. The main findings of its four different long-term studies are given in the respective chapter conclusions.

Before providing a synthesis, the following presents a short summary of highlights of each study with respect to the research questions addressed in the introduction:

1. **Time- and state-dependence of return spillovers and informational efficiency**

   We detect short-lived weak significant spillovers and return autocorrelations. To this effect, our threshold model estimations indicate that it is important whether markets are in a high- or low-volatility state. Overall, however, our results point to a high level of informational efficiency. The process of information transmission is remarkably stable – despite the presence of the financial crisis of 2007 in the sample period.

2. **Structural breaks in volatility spillovers and contagion**

   We find the dynamics of volatility spillovers to be characterized by pronounced time-variation and structural breaks. Significant upwards shifts in volatility spillovers are a distinct feature of the financial crisis of 2007. However, these effects should not to be interpreted as evidence of contagion in the sense of fundamental breaks in market linkages. In fact, we show that they are a consequence of conditional heteroskedasticity in realized volatilities and hence an expression of mere interdependence.

3. **Quantile regressions and return spillovers from the US to Asia**

   We find spillovers from the US stock market to be negative and statistically significant throughout various stock markets in Asia. We reveal that the spillovers' negative magnitude tends to increase from lower to upper return quantiles. Moreover, we find the transmission of shocks from the US to increase slightly during the financial crisis of 2007. From an economic perspective, our findings point to the presence of an overreaction phenomenon at market opening in Asia.

4. **24-hour realized volatilities and transatlantic volatility interdependence**

   We show that Hansen and Lunde (2005)'s approach of combining squared overnight returns and realized daytime variances can be extended to obtain synchronous 24-hour realized volatilities for stock markets in Europe and the US. Using such 24-hour volatilities to estimate an econometric model of transatlantic volatility interdependence, we show that the contemporaneous volatility interdependence between the markets varies only marginally over time.

The common feature of all chapters is the analysis of cross-market linkages, either in returns or (realized) volatilities. Chapter 3 and 5 highlight the stability of cross-market volatility linkages and the importance of taking measurement issues into account. Chapter 2 and 4 reveal evidence for weak and mostly short-lived potential deviations from informational efficiency. Overall, however, the fundamental linkages between the markets appear to be remarkably stable and well characterized by informational efficiency. Far-reaching permanent shifts in response to the financial crisis of 2007 are not apparent.

A limitation of the empirical analyses might be that an exact clarification of the deeper underlying reasons for what we denote as 'potential deviations from informational efficiency' remains, to a certain degree, beyond the scope of this thesis. Perfect informational efficiency might be an unrealistic ideal. The absence of sufficient data and the complexity of, for example, investigating potential arbitrage opportunities, make it difficult to give definitive statements. Further, risk-related and behavioral explanations for potential informational inefficiencies are hardly established in the context of cross-market information transmission. We therefore remain conservative and emphasize that our results should rather be seen as providing information on relative than on absolute informational efficiency (see e.g. Lo (2007) or Malkiel (2011)).

Moreover, studies such as Hamao et al. (1990) or King and Wadhwani (1990) already state that significant volatility spillovers might indeed exist in informationally efficient markets. We share this view and argue that volatility spillovers might even vary over time. What we question, however, is the compatibility of market efficiency with strong and sudden changes in volatility spillovers. Apart from irrational phenomena, we do not find plausible theoretical reasons why markets should become abruptly more susceptible to foreign markets' information flow or uncertainty. In a strict sense though, the theoretical basis for these considerations is not very comprehensive. The literature that explicitly considers shifts in volatility spillovers and contagion is still limited.

In the future, the use of ever more (high-frequency) data and sophisticated econometric techniques should shed light onto further issues opened up by this thesis. Apart from the field of volatility spillovers and contagion, it appears very promising to us to closely investigate the distinct features of stock markets in Asia. As Kim and Nofsinger (2008) point out, these markets appear to be characterized by various interesting empirical phenomena that can hardly be explained by classic financial market theory.

Put into a broader perspective, our findings are well in line with a strand of literature on financial crises that emphasizes the stability of fundamental economic principles and the importance of historically repeating patterns (see e.g. Reinhart and Rogoff (2009) and the literature mentioned therein). Further, our results support the view that financial crises do not spread indiscriminately across countries and that financial market interdependence per se does not play an important role. Similarly, for example, Bekaert et al. (2014) find contagion from the US to be relatively unimportant for the propagation of the financial crisis of 2007. Rather, they emphasize the importance of country-specific characteristics. Instead of reacting overly to developments in the US market, they suggest that traders paid more attention to local policies and fundamentals, thus reassessing the local markets' vulnerabilities in the course of a 'wake-up-call'.

Going back to the quotation given in the introduction, our results provide only little evidence supporting the idea that market participants process foreign market information irrationally different in times of crises. The fundamental process of information transmission appears to be remarkably stable. The hypothesis that market efficiency does not adequately underpin financial market linkages any more cannot be confirmed. From an empirical standpoint, informational efficiency still appears to be an excellent starting point for various kinds of investigations. From a policy perspective we cannot overemphasize the importance of this concept and can only warn of hasty conclusions, in particular in the context of financial market regulation. All that remains to be said is that we concur with the following statement of Malkiel (2011):

[...] reports of death of EMH are greatly exaggerated.

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