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The Impact of the Financial Crisis on  
Transatlantic Information Flows:  
an Intraday Analysis

by

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# The impact of the financial crisis on transatlantic information flows: an intraday analysis

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## Abstract

We use intraday stock index return data from both sides of the Atlantic during overlapping trading hours to analyze the dynamic interactions between European and US stock markets. We are particularly interested in differences of information transmission before, during, and after the financial crisis of 2007 to 2009. Our analysis draws on the concept of Rényi transfer entropy to allow for a flexible and model-free empirical assessment of linear as well as non-linear market dependencies. Thereby the importance of extreme (tail) observations of the return distributions is highlighted. The results show significant bi-directional information transfer between the US and the European markets with a dominant flow from the US market. During the crisis dynamic interactions increase. At the same time information flows from European markets increase. The US market does not entirely regain its leading role in the after crisis period.

*Keywords:* Stock market indices; information flows; financial crisis; Rényi transfer entropy; transatlantic information transmission

*JEL classification:* C58, G14, G15

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# 1 Introduction

Several research papers have dealt with equity market linkages in recent years. Bonfiglioli and Favero (2005), for instance, examine the long-term and short-term interdependencies between the US and the German stock market. They find evidence for contagion in the short-term dynamics, but no long-term interdependencies. By contrast, Forbes and Rigobon (2002) document no contagion, but interdependence in their analysis of stock market linkages during the recent crisis. International equity markets and their interactions are also the subject of a study by Bessler and Yang (2003) who support the role of the US market as a leader among the world's major stock markets.

We contribute to this vast and growing literature in various ways. First, we use high frequency intraday stock index data and focus on trading times when both European and US stock markets are open simultaneously. Second, we use Rényi transfer entropy, a model-free methodology which allows for great flexibility in measuring information flows. And third, we perform an in-depth analysis of the financial crisis, tracking the varying strength of information transmission before, during and after the financial crisis, broken down to a monthly analysis.

A major characteristic of European and US stock markets is their partially overlapping trading hours: When the stock market in New York opens at 9.30 a.m. ET, markets in Europe have already been trading for 5 hours. However, when those markets close (e.g. Frankfurt at 5 pm CET), trading still continues in the USA. Information transmission during these overlapping hours is in the focus of this article. The overlapping trading period is particularly interesting as it is the only time where information can be processed simultaneously. Information that is created before or after that period can only be processed by the US or the European markets, respectively, with delay. Considering the increasing availability of high frequency intraday data, it is surprising that most studies are based on daily (Bessler and Yang, 2003; Forbes and Rigobon, 2002) or even monthly data (Bonfiglioli and Favero, 2005). Daily data are particularly difficult to analyze due to the non-synchronicity of closing or opening prices. The analysis by Flad and

Jung (2008) is one of the very few that uses high frequency data to study the linkages of the US and the German stock markets during overlapping trading hours. Based on the cointegration methodology, these authors find a distinct leadership role of the DJIA in the price discovery process during the period of simultaneous trading.

In contrast to the study of Flad and Jung (2008), we do not depend on the existence of cointegration between stock market indices, whose economic plausibility and empirical support have been questioned in recent studies (compare Dimpfl, 2013). Instead, our analysis uses the concept of Rényi transfer entropy, which is a flexible non-parametric method that accounts for linear as well as non-linear dependencies (Schreiber, 2000). In particular, we do not need to rely on a specific (time series) model to estimate a dependence measure like correlation, Granger causality, or Hasbrouck (1995) information shares. The latter information measure is based on a microstructure model which allows for a direct interpretation of the common stochastic trend as the efficient price and the derivation of information shares as contributions to the variance of the efficient price innovations. This, however, comes at the cost of a rather limited applicability: the time series have to be cointegrated. Using Rényi transfer entropy instead, we exploit the empirical distribution of the data using a completely model-free measure which is based on information theory. The benefit is the unrestricted applicability of this measure. However, we lose the direct microstructure interpretation and, thus measure information flows rather than contributions to price discovery. The link between the two measures is information: the innovations in the microstructure model are generally interpreted as information flowing into the efficient price while in the entropy context we measure an information exchange between the two time series in the spirit of a general form of Granger causality.

The concept of Rényi transfer entropy is similar to the more common Shannon transfer entropy. Both measures are non-parametric and based on the Kullback-Leibler distance between probability distributions. Rényi transfer entropy, however, additionally allows to focus on specific parts of a distribution, such as center or tail observations. When dealing with financial

return data, which generally exhibit fat-tailed, non-normal empirical distributions, this feature is of special interest. It allows us to focus on tail events which are assumed to be more informative than observations located in the center of the distribution. This is particularly true for high frequency returns which are to a large extent extremely close to zero..

In spite of this appealing feature there are only few studies that measure dependencies of financial time series by means of transfer entropy. Jizba et al. (2012) use Rényi transfer entropy to quantify information flows between stock indices. Marschinski and Kantz (2002) and Kwon and Yang (2008) apply the Shannon transfer entropy in the same context. Dimpfl and Peter (2013) analyze information transfer between credit derivative and bond markets based on the Shannon transfer entropy as well.

From a methodological point of view, the study most closely related to ours is the one of Jizba et al. (2012). While these authors use high frequency data for only one and a half years, we examine a considerably longer data series which enables us to cover tranquil as well as crisis periods. Furthermore, we also address statistical significance of the Rényi transfer entropy measure based on the bootstrap method proposed by Dimpfl and Peter (2013).

Our results show significant bi-directional information flows at a one-minute frequency between major European stock market indices (namely DAX, CAC40 and FTSE) and the S&P 500 before the crisis. During the crisis period the strength of information transmission peaks. In the post-crisis period the magnitude is reduced again, but it remains on a higher level as compared to the pre-crisis period. In addition we show that information flows measured by the Rényi transfer entropy are the higher the more the tails of the distributions are accentuated. This supports the notion that tail observations of the empirical return distribution are more informative than observations in the center.

We proceed as follows. Section 2 introduces transfer entropy in general and the Rényi transfer entropy. Section 3 discusses institutional features and describes the data. Section 4 presents the empirical results and Section 5 concludes.

## 2 Measuring Information Flows using Rényi Transfer Entropy

In order to illustrate the concept of Rényi transfer entropy we start by introducing the Shannon entropy. Shannon entropy is a general measure for the uncertainty associated with draws from a specific probability distribution. Its most important application is found in the context of information theory to quantify the information content of a message (compare Shannon, 1948). Consider a discrete random variable  $J$  with probability distribution  $p(j)$ , where  $j$  denotes possible outcomes or (in terms of information theory) possible symbols of  $J$ . Hartley (1928) defines the amount of information that is gained when observing one specific symbol  $j$  of  $p(j)$  by  $\log_2(1/p(j))$ . Due to the base 2 logarithm, the measurement units are *bits*.

Based on this definition, the Shannon entropy of  $p(j)$  is given by

$$H_J = - \sum_j p(j) \times \log_2 p(j) .$$

It is a measure for uncertainty that reaches its maximum for an equally distributed variable (e.g. tossing a fair coin which has equal outcome probabilities). Uncertainty and, thus, the Shannon entropy measure are the lower the more the probabilities for observing a specific symbol differ from each other (e.g. if the coin was not fair).

Shannon entropy itself is a univariate measure. It is extended to the bivariate case by the concept of mutual information. Mutual information is a symmetric measure based on the Kullback-Leibler distance, a measure for the difference between two probability distributions (see Kullback and Leibler, 1951). Mutual information accounts for any form of statistical dependency. Assume that  $I$  and  $J$  are two discrete random variables with marginal probability distributions  $p(i)$  and  $p(j)$  and joint probability distribution  $p_{IJ}(i, j)$ . Mutual information of these two processes is given by

$$M_{IJ} = \sum_{i,j} p_{IJ}(i, j) \times \log \frac{p_{IJ}(i, j)}{p(i)p(j)}$$

where the summation runs over all possible values  $i$  and  $j$ . Mutual information quantifies the reduction in uncertainty compared to the case where both processes are independent. Independence implies that the joint distribution is given by the product of the marginal distributions,  $p_{IJ}(i, j) = p(i)p(j)$ , in which case mutual information would be zero. In other words, mutual information quantifies the usefulness of knowing one process when predicting outcomes of the other process.

Quantifying information flows in a finance context, however, requires time series properties and an asymmetric measure. Schreiber (2000) introduces a dynamic structure to mutual information by considering transition probabilities. Let  $I$  be a stationary Markov process of order  $k$ . The probability to observe  $I$  at time  $t + 1$  in state  $i$  conditional on the  $k$  previous observations is  $p(i_{t+1}|i_t, \dots, i_{t-k+1}) = p(i_{t+1}|i_t, \dots, i_{t-k})$ . For the bivariate case, Schreiber (2000) proposes to measure information flow from process  $J$  to process  $I$  by quantifying the deviation from the generalized Markov property  $p(i_{t+1}|i_t^{(k)}) = p(i_{t+1}|i_t^{(k)}, j_t^{(l)})$  based on the Kullback-Leibler distance and derives the formula for *transfer entropy* as

$$T_{J \rightarrow I}(k, l) = \sum_{i, j} p(i_{t+1}, i_t^{(k)}, j_t^{(l)}) \times \log \frac{p(i_{t+1}|i_t^{(k)}, j_t^{(l)})}{p(i_{t+1}|i_t^{(k)})}. \quad (1)$$

From the formula in Equation (1) it is evident that transfer entropy is an asymmetric measure. Equation (1) measures the information flow from process  $J$  to process  $I$ . In other words, Shannon transfer entropy quantifies the additional information about the future value of  $I$  that is gained by observing past values of  $J$ , assuming that the history of  $I$  is known. The information flow in the opposite direction,  $T_{I \rightarrow J}(l, k)$  can be calculated analogously.

As proposed by Jizba et al. (2012), transfer entropy can also be based on Rényi entropy rather than Shannon entropy. Rényi entropy as introduced by Rényi (1970) depends on a weighting parameter  $q$  which emphasizes different possible outcomes of  $J$ :

$$H_J^q = \frac{1}{1-q} \log \sum_j p^q(j)$$

with  $q > 0$ . It is easy to show that for  $q \rightarrow 1$  Rényi entropy converges to the Shannon entropy. For  $0 < q < 1$ , the more improbable events, i.e. the tail events are more accentuated, while for  $q > 1$  the more probable (center) observations receive more weight. Thus, Rényi entropy allows a more differentiated analysis, as depending on the parameter  $q$  different areas of a distribution can be emphasized. This is of particular interest in the context of financial data where special features of distributions, such as fat tails and tail dependence play a crucial role (Longin and Solnik, 2001; Grammig and Peter, 2013).

Using the escort distribution<sup>1</sup>  $\phi_q(j) = \frac{p^q(j)}{\sum_j p^q(j)}$  with  $q > 0$  to normalize the weighted distributions, Jizba et al. (2012) derive the Rényi transfer entropy as

$$\text{RT}_{J \rightarrow I}(k, l) = \frac{1}{1 - q} \log \frac{\sum_i \phi_q(i_t^{(k)}) \text{P}^q(i_{t+1} | i_t^{(k)})}{\sum_{i,j} \phi_q(i_t^{(k)}, j_t^{(l)}) \text{P}^q(i_{t+1} | i_t^{(k)}, j_t^{(l)})} . \quad (2)$$

Again,  $\text{RT}_{J \rightarrow I}(k, l)$  measures the information flow from process  $J$  to  $I$ . The inverse direction  $\text{RT}_{I \rightarrow J}(l, k)$  is defined analogously.

In contrast to the Shannon transfer entropy, a measure  $\text{RT}_{J \rightarrow I}(k, l) = 0$  does not mean that the processes  $I$  and  $J$  are independent as the obtained value of zero only holds for the particular value of  $q$  used for calculation. Furthermore, Rényi transfer entropy can become negative. For the Shannon-based measure an extra knowledge of past values of  $J$  can never increase uncertainty for future values of  $I$ . The worst case is that it does not add any information, i.e. does not lead to any uncertainty reduction, leaving the measure unchanged. In case of the Rényi entropy based measure, however, negative estimates can occur as past values of  $J$  might increase the probability of a future tail event of  $I$ . In other words, observing  $J$  might imply greater exposure to risk of  $I$  than would have been expected by observing  $I$  alone (cf the discussion in Jizba et al., 2012). It is generally assumed that extreme (tail) events are more informative than the median observation (see Rocco (2012) for an overview of extreme value theory and the literature cited therein). This renders Rényi transfer entropy a most appealing tool to analyze information flows between financial time series.

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<sup>1</sup>For details on the escort distribution see Beck and Schögl (1993), ch. 9.



### 3 Stock market data

In our analysis we use one minute index value observations of the S&P 500, the DAX, the CAC40 and the FTSE index. The data are obtained from Tick Data, Inc. The sample of the DAX and the S&P 500 covers the period July 1, 2003 to April 30, 2010. For the FTSE and the CAC40, the sample period is shorter, starting in July 2006 only. Returns are computed as first differences of the index values in logarithms. Days on which at least one market was closed are omitted from the sample.

The sample is restricted to the period where the US and the European stock markets are both open for continuous trading. The New York Stock Exchange (NYSE) opens at 9.30 am ET which corresponds to 3.30 pm CET and 2.30 pm BST. The European stock markets in consideration all close at the same time: Deutsche Börse Frankfurt and Euronext Paris at 5.30 pm CET and London Stock Exchange at 4.30 pm BST. Opening or closing auctions are not considered. We thus generally have an overlap of 2 hours and 120 index or 119 return observations per day. During the switch from daylight-saving time to standard time and vice versa the overlap may extend to three hours. For these days we will use all available 180 index observations to calculate returns.

In Table 1 we present summary statistics of the return series during overlapping trading hours. The data exhibit the usual properties of return time series, in particular skewness and excess kurtosis. As expected, skewness is negative for the European stock indices. For the S&P 500, however, we observe a positive and rather large skewness value. This result is due to the restriction of the dataset to the first two hours in the morning trading at the NYSE<sup>2</sup>.

For the definition of the crisis period we follow Bai and Collin-Dufresne (2011) and the Bank of International Settlements report by Filardo et al. (2010). They specify the period July 1, 2007 to September 30, 2009 as the crisis period. What is labeled “Phase 1” in Filardo et al. (2010) is 15 days shorter, ending mid-September 2010. Our results are qualitatively

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<sup>2</sup>For S&P 500 returns of the entire trading day skewness is also negative (-0.5716).

Table 1: The table presents descriptive statistics for the S&P 500, DAX, FTSE and CAC40 returns for the full sample period.

	S&P 500	DAX	FTSE	CAC40
Min	-0.0167	-0.0121	-0.088	-0.093
5% quantile	-0.0008	-0.0009	-0.0012	-0.001
Mean	0	0	0	0
Median	0	0	0	0
95% quantile	0.0008	0.0009	0.0011	0.001
Max	0.0125	0.0096	0.0796	0.0887
standard deviation	0.0006	0.0006	0.0015	0.0013
skewness	5.063	-0.1594	-2.2415	-1.8197
kurtosis	908.13	17.51	720.74	852.40

robust to this alteration. Table 2 reports the number of observations and the corresponding number of trading days for the full sample period as well as the pre-crisis, crisis, and post-crisis periods.

Table 2: The table presents the number of observations and the number of trading days for the full sample and the split samples. The datasets are composed of the S&P 500 and the respective European stock market index in column 1.

Dataset	number of	full	range	before	during	after
DAX	observations	208578	July 1, 2003 to	118474	71454	18650
	days	1690	April 30, 2010	992	556	142
FTSE	observations	117379	July 3, 2006 to	30234	69085	18060
	days	949	April 30, 2010	247	559	143
CAC40	observations	116309	July 3, 2006 to	29874	68596	17839
	days	941	April 30, 2010	244	555	142

In order to calculate Rényi transfer entropy we need to recode the sample. We propose to use three bins and divide the return data along the 5% and 95% quantiles (denoted as  $q_{[0.05]}^r$  and  $q_{[0.95]}^r$ , respectively) of the corresponding return distribution of the full data set. The symbolic encoding

$$S_t = \begin{cases} A & \text{for } r_t \leq q_{[0.05]}^r \\ B & \text{for } q_{[0.05]}^r < r_t < q_{[0.95]}^r \\ C & \text{for } r_t \geq q_{[0.95]}^r \end{cases}$$

replaces each value in the observed return time series  $r_t$  by a corresponding symbol ( $A$ ,  $B$ ,  $C$ ). The choice of the quantiles is motivated by the distribution of the data which is depicted in the density plots presented in Figure 1 which are generated using the Epanechnikov kernel. The bandwidth is chosen according to the 'rule of thumb' proposed by Silverman (1986). The graphs compare the empirical distribution of the return data (solid line) to a normal distribution with the same mean and standard deviation (dotted line; see Table 1). As can be seen, all time series are peaked and exhibit heavy tails.

The choice of the quantiles used to recode the data balances two aspects. First, moving further into the tails and thus dividing the data, for example, along the 1% and 99% quantile, leads to a very thin occupation of the extreme bins  $A$  and  $C$ . This may result in missing observations when counting the conditional frequencies. On the other hand, it is undesirable to move further to the center of the distribution (and divide the data, for example, along the 10% and 90% quantile) as this would dilute the information contained in the extreme observations. Using a 5% quantile to identify (extreme) tail events seems to be a general consensus in the literature (see also Bae et al., 2003).

To calculate the transfer entropy we set the block lengths to  $l = k = 5$  in Equation (2). Lag length selection is based on the mutual information criterion; for details refer to Dimpfl and Peter (2013). The estimation is re-initialized every day, which ensures that the blocks do not contain returns from two different trading days.

As we have a rather large sample, even when splitting it into the three sub-periods, the small sample bias that is generally encountered when estimating transfer entropies is not an issue in our application. Therefore, we do not calculate effective transfer entropies as advocated by Jizba et al. (2012) when we analyze the long samples. Only when we move on to the monthly analysis, effective transfer entropies will be used. Tests for significance are based on a bootstrap of the underlying Markov process under the null hypothesis that the two time series are independent as proposed by Dimpfl and Peter (2013).

## 4 Information flows between stock indices: What happened during the crisis period

In order to shed light on the transatlantic information flows during overlapping trading hours, we will first present the estimation results based on the full sample and the three sub-periods defined in Section 3 to obtain an overview of the information transmission. Subsequently, we perform a monthly analysis to get more insight into the time variability of the flows, in particular during the period of the financial crisis.

Tables 3 to 5 present our estimation results together with  $p$ -values for the full sample as well as the pre-crisis, crisis and post-crisis periods. We distinguish four different choices of the accentuating parameter  $q$ , namely 0.1, 0.2, 0.5 and 0.8. Table 3 shows the estimated Rényi transfer entropies for the S&P 500 and the DAX. For the entire sample period, we observe highly significant information transmission in both directions. The transmission strength (the order of magnitude of the estimates) in the full sample is basically balanced, that means that no market clearly dominates. This result holds for all choices of  $q$ .

The pre-crisis period shows a distinctively higher information flow from the S&P 500 to the DAX than in the opposite direction. For example for  $q = 0.1$ , the Rényi transfer entropy estimate of the flow from the S&P 500 to the DAX is 27% higher than the reverse flow from the DAX to the S&P 500. Even though our pre-crisis sample is longer than that of Flad and Jung (2008), our results are in line with their finding of US dominance in the information flows. During the crisis period the picture is altered: First, the information flow intensity increases considerably; the difference between pre-crisis and crisis estimates is also statistically significant. For values of  $q$  lower than 0.5 the measures almost double in magnitude. For  $q = 0.8$  the magnitude increases even by factor 10. After the crisis the transmission strength returns to its pre-crisis level, but the slight dominance of the S&P 500 is not restored. Again, this change is statistically significant. It seems that the estimates for the whole sample period are mainly driven by the crisis. The magnitude of the information flows in both directions corresponds to the one observed

Table 3: The table presents the Rényi transfer entropy estimates for the DAX/S&P 500 index pair for the weights  $q$  given in column 1 using the full sample (columns 2-3) or the split samples (columns 4-9).  $p$ -values are based on a bootstrap distribution and provided in parentheses.  $\rightarrow$  indicates the direction of the information flow (from $\rightarrow$ to).

$q$	full sample		before crisis		crisis		after crisis	
	SP $\rightarrow$ DAX	DAX $\rightarrow$ SP	SP $\rightarrow$ DAX	DAX $\rightarrow$ SP	SP $\rightarrow$ DAX	DAX $\rightarrow$ SP	SP $\rightarrow$ DAX	DAX $\rightarrow$ SP
0.1	1.006 ( $<0.001$ )	1.037 ( $<0.001$ )	0.653 ( $<0.001$ )	0.513 ( $<0.001$ )	1.052 ( $<0.001$ )	1.064 ( $<0.001$ )	0.625 ( $<0.001$ )	0.632 ( $<0.001$ )
0.2	0.936 ( $<0.001$ )	0.973 ( $<0.001$ )	0.603 ( $<0.001$ )	0.493 ( $<0.001$ )	0.996 ( $<0.001$ )	1.009 ( $<0.001$ )	0.606 ( $<0.001$ )	0.618 ( $<0.001$ )
0.5	0.619 ( $<0.001$ )	0.667 ( $<0.001$ )	0.319 ( $<0.001$ )	0.265 ( $<0.001$ )	0.764 ( $<0.001$ )	0.778 ( $<0.001$ )	0.457 ( $<0.001$ )	0.469 ( $<0.001$ )
0.8	0.193 ( $<0.001$ )	0.213 ( $<0.001$ )	0.048 ( $<0.001$ )	0.030 ( $0.001$ )	0.413 ( $<0.001$ )	0.429 ( $<0.001$ )	0.189 ( $<0.001$ )	0.190 ( $<0.001$ )

Table 4: The table presents the Rényi transfer entropy estimates for the CAC40/S&P 500 index pair for the weights  $q$  given in column 1 using the full sample (columns 2-3) or the split samples (columns 4-9).  $p$ -values are based on a bootstrap distribution and provided in parentheses.  $\rightarrow$  indicates the direction of the information flow (from $\rightarrow$ to).

$q$	full sample		before crisis		crisis		after crisis	
	SP $\rightarrow$ CAC	CAC $\rightarrow$ SP	SP $\rightarrow$ CAC	CAC $\rightarrow$ SP	SP $\rightarrow$ CAC	CAC $\rightarrow$ SP	SP $\rightarrow$ CAC	CAC $\rightarrow$ SP
0.1	1.012	1.027	0.361	0.336	1.025	1.038	0.486	0.436
	(<0.001)	(<0.001)	(<0.001)	(0.007)	(<0.001)	(<0.001)	(<0.001)	(0.002)
0.2	0.942	0.958	0.353	0.327	0.960	0.973	0.471	0.431
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
0.5	0.624	0.646	0.201	0.181	0.681	0.699	0.325	0.312
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
0.8	0.201	0.207	0.029	0.025	0.294	0.303	0.093	0.091
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)

Table 5: The table presents the Rényi transfer entropy estimates for the FTSE/S&P 500 index pair for the weights  $q$  given in column 1 using the full sample (columns 2-3) or the split samples (columns 4-9).  $p$ -values are based on a bootstrap distribution and provided in parentheses.  $\rightarrow$  indicates the direction of the information flow (from $\rightarrow$ to).

$q$	full sample		before crisis		crisis		after crisis	
	SP $\rightarrow$ FTSE	FTSE $\rightarrow$ SP	SP $\rightarrow$ FTSE	FTSE $\rightarrow$ SP	SP $\rightarrow$ FTSE	FTSE $\rightarrow$ SP	SP $\rightarrow$ FTSE	FTSE $\rightarrow$ SP
0.1	1.006 ( $<0.001$ )	0.9969 ( $<0.001$ )	0.292 (0.165)	0.347 ( $<0.001$ )	1.011 ( $<0.001$ )	1.006 ( $<0.001$ )	0.459 (0.001)	0.471 ( $<0.001$ )
0.2	0.939 ( $<0.001$ )	0.930 ( $<0.001$ )	0.290 (0.032)	0.328 ( $<0.001$ )	0.948 ( $<0.001$ )	0.944 ( $<0.001$ )	0.446 ( $<0.001$ )	0.457 ( $<0.001$ )
0.5	0.630 ( $<0.001$ )	0.630 ( $<0.001$ )	0.155 ( $<0.001$ )	0.168 ( $<0.001$ )	0.679 ( $<0.001$ )	0.682 ( $<0.001$ )	0.302 ( $<0.001$ )	0.313 ( $<0.001$ )
0.8	0.201 ( $<0.001$ )	0.209 ( $<0.001$ )	0.021 ( $<0.001$ )	0.024 ( $<0.001$ )	0.297 ( $<0.001$ )	0.307 ( $<0.001$ )	0.078 ( $<0.001$ )	0.090 ( $<0.001$ )

during the crisis period.

The described patterns hold for the different values of  $q$ . Choosing  $0 < q < 1$  accentuates the dependencies in the tails between the two return distributions. As  $q$  goes to zero, the weight placed on the transition probabilities of the tails increases. This results in increasing measures of the Rényi transfer entropy when  $q$  is lowered from 0.8 to 0.1 as can be seen from Table 3. This supports the notion that it is actually tail events rather than observations in the center that matter when it comes to information transfer. Using Rényi transfer entropy which enables us to emphasize different areas of distributions therefore provides a more accurate measurement of information flows.

Table 4 shows the Rényi transfer entropy estimates for S&P 500 and CAC40. Again, all estimates are significant on the 1% significance level for all considered values of  $q$ . The interpretation of the results is qualitatively similar to the one of S&P 500 and DAX. We observe significant bidirectional information flows that decrease as  $q$  approaches 1. The order of magnitude for the full sample period is virtually identical to the one observed for the DAX and S&P flows. Also, estimates using the whole sample period seem to be driven by the crisis period, as the information transmission strengthens during the crisis.

We find that during the period until June 2007 the dominance of the US information flow is not as strong as for the DAX. During the crisis period the strength of the information flows in both directions is virtually identical. Furthermore, the post-crisis period is marked by a higher level of information transmission than the pre-crisis period. We also find a slight dominance of the US market, but the difference is not very pronounced.

Table 5 holds the estimates for S&P 500 and FTSE. Here, all but two estimates are statistically significant on the 1% significance level. For the FTSE we find the dominant direction to be the one to the US in the pre-crisis period. When  $q = 0.1$ , the transmission channel from the S&P 500 to the FTSE is not even statistically significant. This changes during the crisis where there is a marginally greater information flow from the USA to the UK than vice versa. After September 2009 the information flow does



not completely return to its pre-crisis level, but remains on a higher level than before the crisis. Again, the information flows are now more equal than before the crisis which suggests that a) the financial crisis strengthened the informational links between the US and European indices and b) information transmission has permanently increased.

We conduct a number of robustness checks in order to examine the sensitivity of our results with respect to the sampling frequency and the quantiles used for recoding the data. We first alter the sampling frequency for the specification reported above using 2 and 5 minute returns. Subsequently, we repeat the analysis with data sampled at all frequencies (1, 2 and 5 minutes) using the 6th and 94th quantile, the 4th and 96th quantile and the 10th and 90th quantile for recoding the return data.<sup>3</sup>

For the lower sampling frequencies of 2 and 5 minutes we observe a lower estimated strength of information flows. This is most probably due to the high speed of information transmission. Sampling the data at 2 or even 5 minute intervals disregards a large part of the information flow that takes place within this interval. Furthermore, the number of daily available observations is greatly reduced (from 119 one-minute-observations to 23 five-minute-observations) which impacts on statistical significance of the estimates.

The conclusions drawn from the entropy estimates are robust with respect to small changes to the quantiles used for recoding the data (6th and 94th or the 4th and 96th quantile). For the 10th and 90th quantile, however, we generally observe smaller estimates, i.e. a lower level of information transmission. Using the 10th and 90th quantile for recoding means that we increase the number of tail observations, i.e. observations that have been part of the center bin before now move into the tails and are classified as "extreme" observations. This obviously leads to an increased amount of noise in the tails as possibly uninformative observations are classified as extreme (and potentially informative) observations. The pattern across time, however, still holds. We observe higher information flow during the crisis than before or after. The information flow is generally weaker before the crisis where we

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<sup>3</sup>Detailed results are available upon request.

have a slightly larger flow from the US market to the European market for CAC40 and FTSE. After the crisis, the flows are more equal.

We conclude from these additional analyses that generally our results are robust with respect to the choice of the sampling frequency and the quantiles used for recoding. In general, the additional estimations support the main conclusions drawn in the empirical analysis. The effects when altering the modeling parameters are as expected. A lower sampling frequency leads to a slight decrease in the order of magnitude of the estimates and to less precision. Enlarging the tail bins also leads to lower Rényi transfer entropy estimates as the discriminatory power between informative tail events and uninformative center events is reduced.

To provide a more detailed picture about the development of the information flows, in particular during the crisis period, we calculate the Rényi transfer entropy on a monthly basis. As the number of observations is reduced significantly, we now report bias-adjusted estimates or effective Rényi transfer entropies, calculated as in Marschinski and Kantz (2002). The results are graphically displayed in Figures 2 (DAX), 3 (CAC40) and 4 (FTSE).

In general, the main finding that information flows increase during the crisis period and then level off slightly, is confirmed by the monthly estimates for all three market pairs. In the graphics, the yellow shaded area depicts the crisis period as defined by Bai and Collin-Dufresne (2011). As can be seen, the RTE measures start to rise in early 2007. This corresponds to the time when Bear Stearns got into trouble until finally the US housing market crashed approximately mid-June 2007 which marks the beginning of the crisis. The rise of the RTE measure then gets steeper in the beginning of 2008. January 2008 saw the “Black Monday” where, for example, the DAX lost approximately 7.5%. This led to the US Federal Reserve Bank lowering interest rates in two steps within a week by 125 base points. There is a small peak in the RTE measures in March 2008 which coincides with the break down of Bear Sterns. In September 2008 when Lehman Brothers collapsed and Fannie Mae and Freddie Mac went into government control (indicated by the dashed vertical line), we observe a distinct jump in the RTE measure for all quantiles. The jump is most pronounced for  $q = 0.8$ . For weights

$q = 0.1, 0.2, 0.5$  the peak in September 2008 is really a peak, after which the RTE returns to its previous level. Only for  $q = 0.8$  the magnitude of the RTE does not return immediately to its previous level. After the crisis, RTE generally remains on an elevated level.

Before the financial crisis and even in the early crisis period we observe that the information flow from the S&P 500 to the DAX or the CAC40 was dominating. In Figures 2 and 3 the solid line lies clearly above the dashed line until September 2008. For the FTSE, depicted in Figure 4, the difference is negligible. Then, during the crisis period, the level of the information flow from the US market matches the one to the US market. As major crisis events happened on both sides of the Atlantic, this finding is not surprising. However, in the after-crisis period, the information flows in both directions are still similar for the FTSE and the DAX sample which suggests that the US market has lost some of its importance during the crisis. Another explanation could be the ongoing Euro crisis which generates information of world wide importance in Europe and then translates into the US market. For the CAC40 we observe that the US market retains its informational leadership role the entire time. This becomes more evident from Figure 3 than from Table 4.

Overall, the analysis of information flows between European and US stock markets reveals that before the financial crisis, the US market played a dominant role: the information flow from the US to Europe was greater than the one in the other direction. This is in line with findings of Flad and Jung (2008). However, during the financial crisis the information flows became more conform. The similar strength of the information flow is conserved after the financial crisis for Germany and the UK. The French market, however, seems to be more susceptible to US information and the information flow into France is greater than in the other direction.

## 5 Conclusion

We investigate the information flows between European and US stock markets during overlapping trading hours with a particular focus on the recent

financial crisis period. We employ Rényi transfer entropy as it is a flexible measure which captures asymmetries and non-linearity in the transmission process.

Our results indicate that the flow of information across the Atlantic has dramatically increased during the financial crisis. We find elevated levels of the Rényi transfer entropy as soon as the crisis begins. After the crisis, the information flow is slightly reduced, but remains at a higher level as compared to the pre-crisis period. We find partial support for the dominating role of the US market before the crisis. However, the interplay between the US and the German and the US and the UK markets becomes more equal during and after the financial crisis. Only for the French market the US leadership is visible throughout the entire time we investigate. This means that information processing today takes place simultaneously at the European and the US stock exchanges and that in general, information flows between the different markets are of similar strengths. The finding that the relationship is not stable over time is in line with the literature which documents changing co-movement and information transmission between stock markets (see *inter alia* Brooks and Del Negro, 2004; Rua and Nunes, 2009).

Focusing on the crisis period in more detail reveals that information like the collapse of Lehman Brothers has a serious impact on all markets as the information flow increases dramatically. This shows that major events provoke feedback effects and information cascades which may, as in the Lehman case, lead to a significant downturn of the markets. In this respect our article supports findings of contagion and spillovers between financial markets (see *inter alia* Longstaff, 2010; Aloui et al., 2011), in particular during times of market turmoil.

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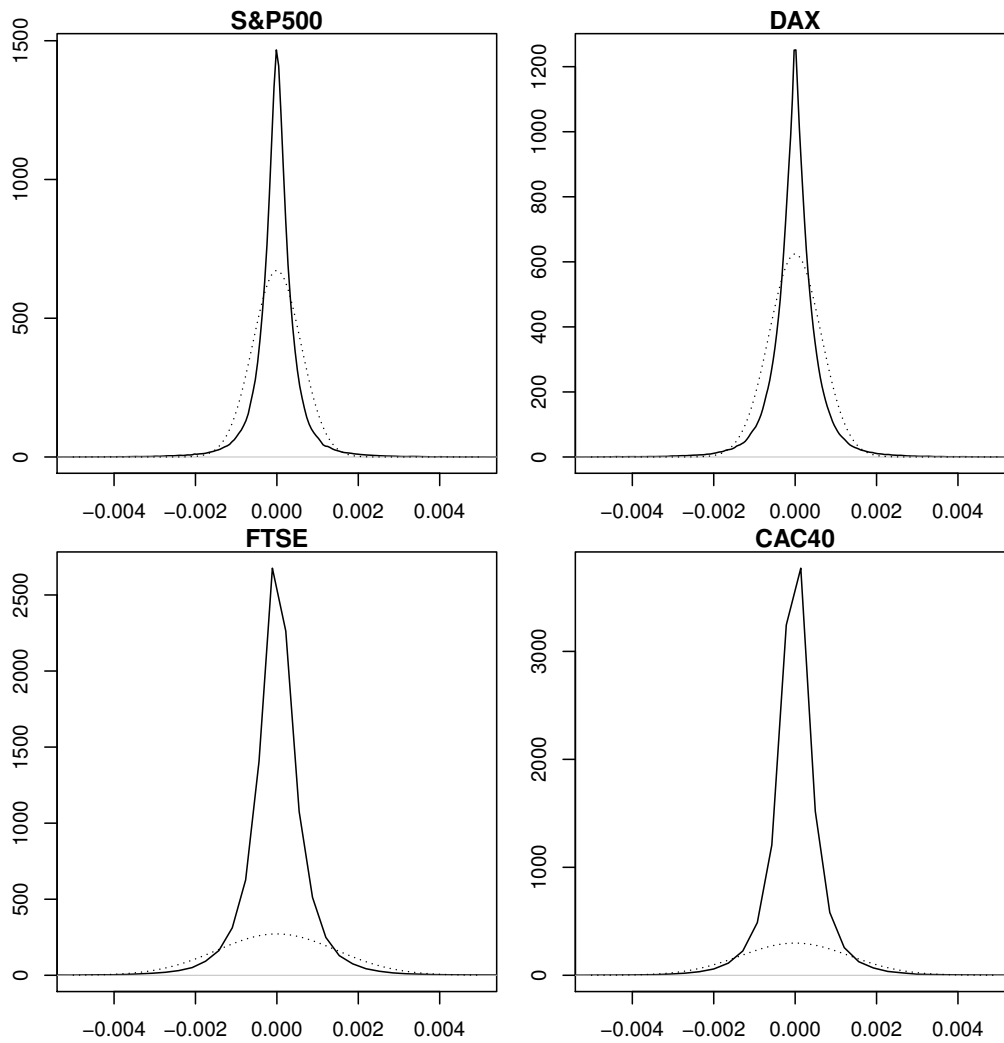


Figure 1: Return density plots. The figure presents density plots of S&P 500, DAX, FTSE and CAC40 one minute returns for overlapping trading hours using the Epanechnikov kernel (solid line). The dotted line is a normal distribution configured with the mean and standard deviation of the respective return series (see Table 1).



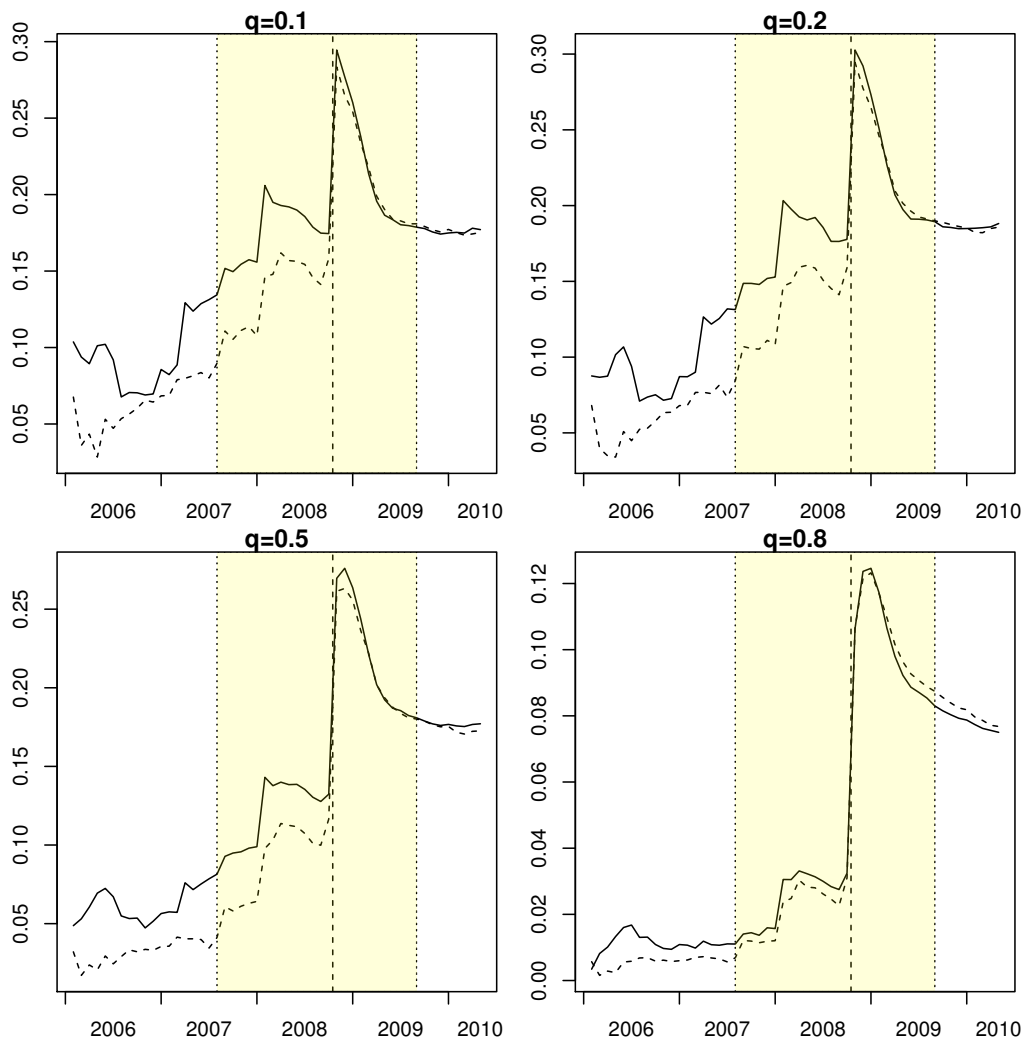


Figure 2: Monthly RTE of DAX and S&P 500. The figure displays monthly Rényi transfer entropy estimates for DAX and S&P 500 for four different weighting values  $q$ . The solid line presents the information flow from the S&P 500 to the DAX, the dashed line presents the information flow from the DAX to the S&P 500. The dashed vertical line depicts September 2008, the yellow shaded area highlights the crisis period as defined by Bai and Collin-Dufresne (2011).

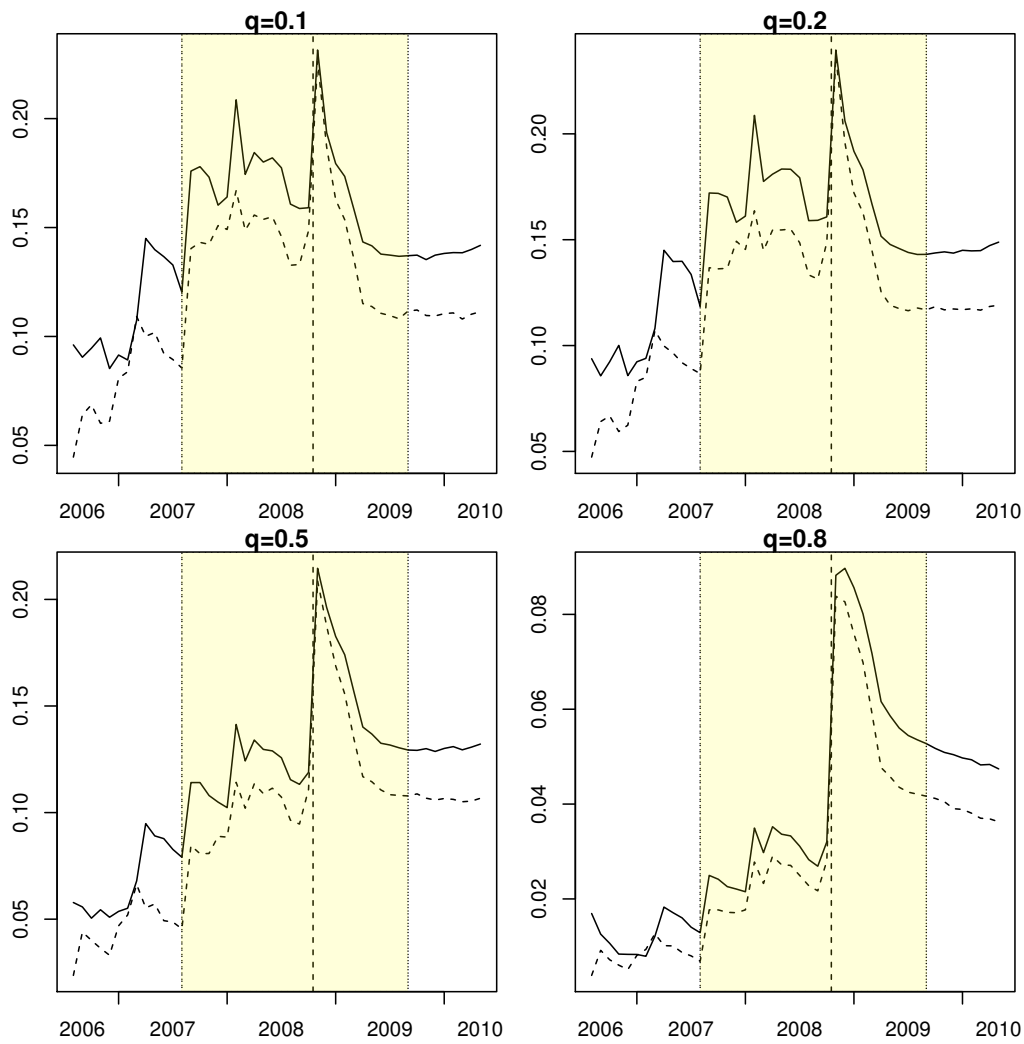


Figure 3: Monthly RTE of CAC40 and S&P 500. The figure displays monthly Rényi transfer entropy estimates for CAC40 and S&P 500 for four different weighting values  $q$ . The solid line presents the information flow from the S&P 500 to the CAC40, the dashed line presents the information flow from the CAC40 to the S&P 500. The dashed vertical line depicts September 2008, the yellow shaded area highlights the crisis period as defined by Bai and Collin-Dufresne (2011).

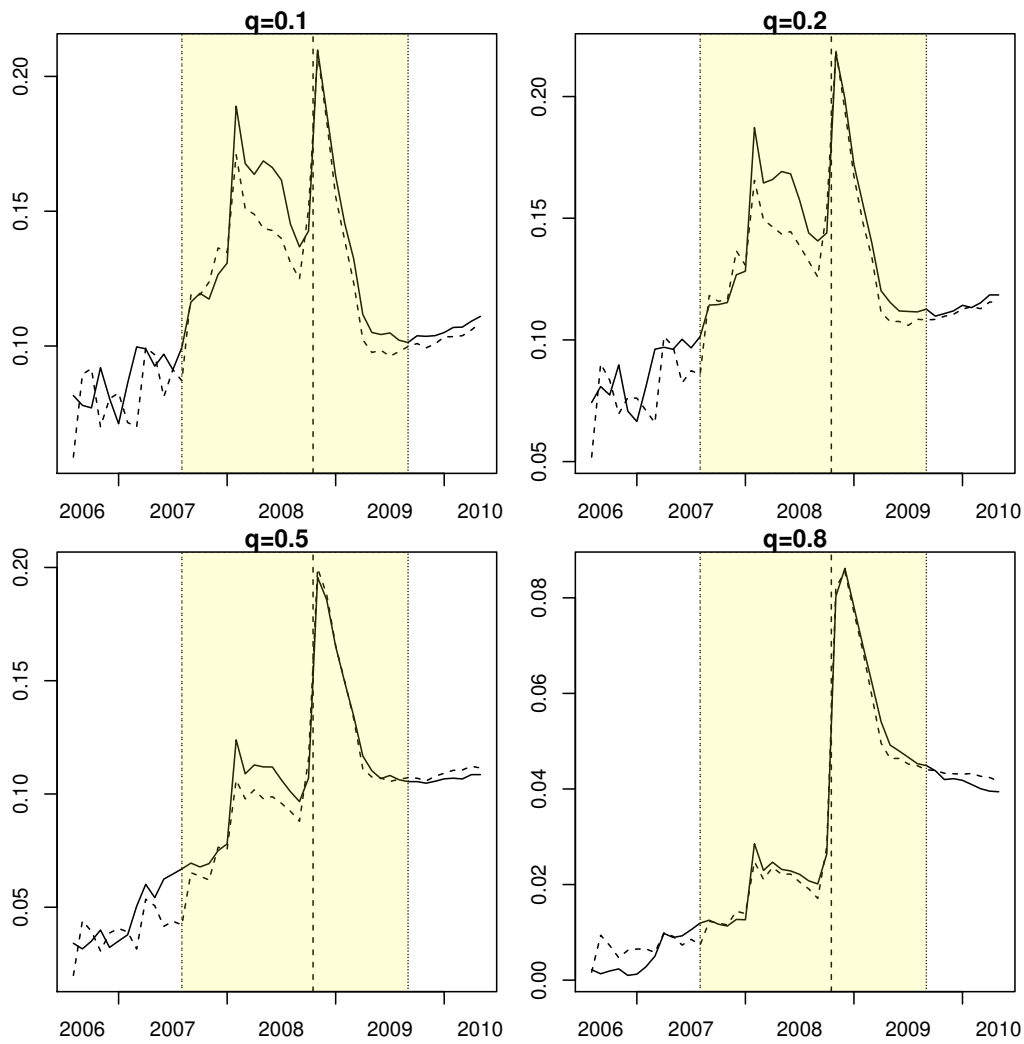


Figure 4: Monthly RTE of FTSE and S&P 500. The figure displays monthly Rényi transfer entropy estimates for FTSE and S&P 500 for four different weighting values  $q$ . The solid line presents the information flow from the S&P 500 to the FTSE, the dashed line presents the information flow from the FTSE to the S&P 500. The dashed vertical line depicts September 2008, the yellow shaded area highlights the crisis period as defined by Bai and Collin-Dufresne (2011).