Credit Easing, ETF Flows and Transfer Entropy

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1 Introduction

Quantitative easing (QE), basically the expansion of a central bank's balance sheet by means of the large scale purchase of government bonds or other assets with the aim of stimulating the economy,originated in Japan in 2001. QE focuses on bank reserves, or central bank liabilities. The term credit easing (CE) was coined in 2009 by Ben Bernanke, the then Chairman of the Federal Reserve,and focuses on the asset side of the balance sheet with the aim of stimulating credit markets.These markets were hit hard during the global financial crisis of 2007-2008 and central banks like the Federal Reserve and the ECB began introducing credit support measures in its aftermath in an effort to aid recovery and trigger growth. These are part of a suite of unconventional monetary policy measures implemented by central banks in recent years.

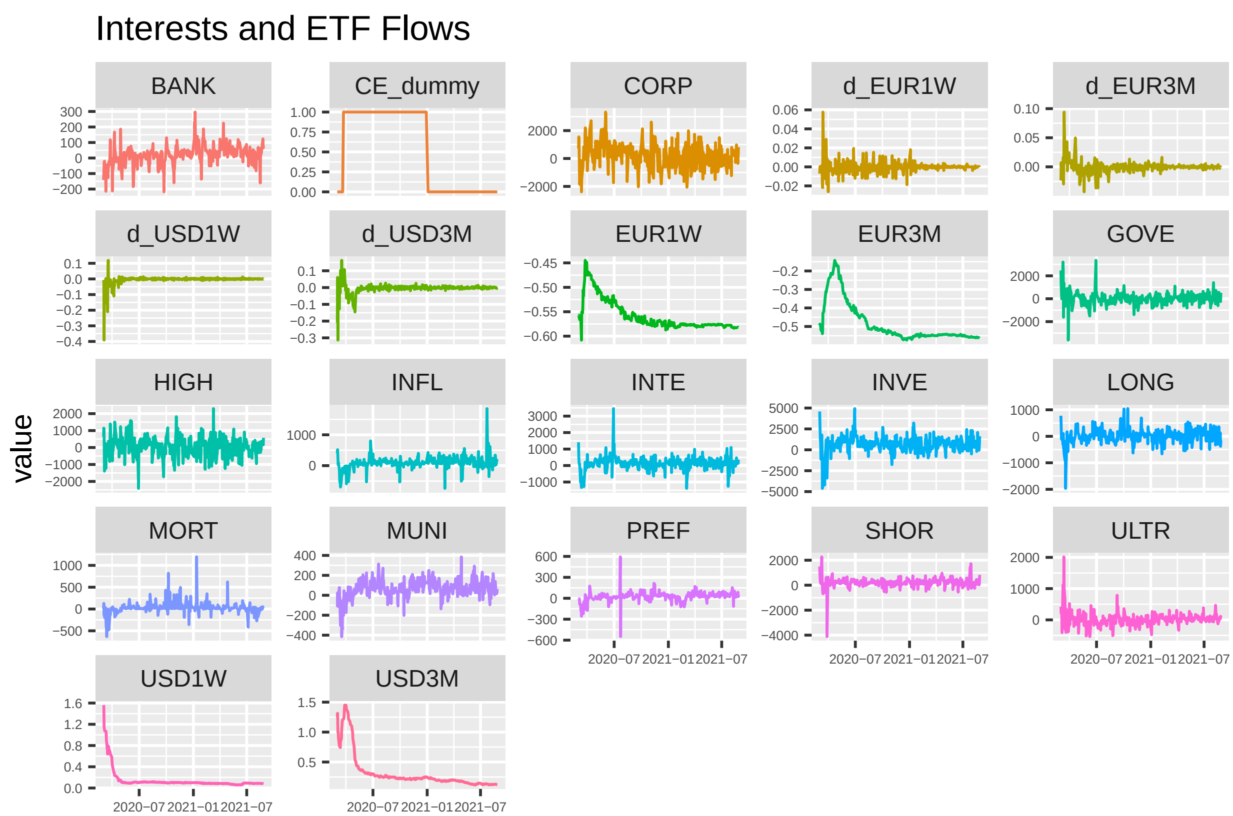
On 31st January 2020 the World Health Organisation (WHO) declared a global health emergency due to the COVID-19 pandemic, leading to lockdowns across the globe and, with this, a slowdown in the global economy and need for large scale assistance measures. On 23rd March 2020 the Federal Reserve announced the establishment of the Primary Market Corporate Credit Facility(PMCCF) and the Secondary Corporate Credit Facility (SMCCF), both aimed at supporting corporate bond markets. The SMCCF involves the purchase of corporate bonds in the secondary market, as well as U.S.-listed exchange-traded funds (ETFs).The European Central Bank had introduced a similar credit support program in June 2016 with the Corporate Sector Purchase Program (CSPP), which was then expanded on 18th March 2020 to include non-financial commercial paper, thus making all qualifying commercial papers eligible for purchase under the program.Although ETFs are not eligible for purchase under the CSPP following the initial announcement(and prior to the release of full details) of the program on 10th March 2016 corporate bond ETF trading boomed. The website ETFStrategy.com reported

> Data from European-listed ETF trading platform Tradeweb showed that trading in fixed income ETFs increased to 50.3% as a proportion of overall traded volume. The majority of this, 62.9%, was in corporate and high yield bonds, with 'buys' in corporate bond ETFs nearly double the amount of 'sells'.

We investigate the dynamic impact of fixed income ETF fund flows and central bank interest rates. Specifically, we assume that there is a substantive non-linear dynamic structure to bivariate relationships. We assess the bivariate information flow between fixed income ETFs and LIBOR interest rates using transfer entropy, a model-free measure of the asymmetric information flow between time series in a network. This is a popular approach to information diffusion and contagion in a complex systems such as global capital markets[@Bekiros2017,@Nam2019].

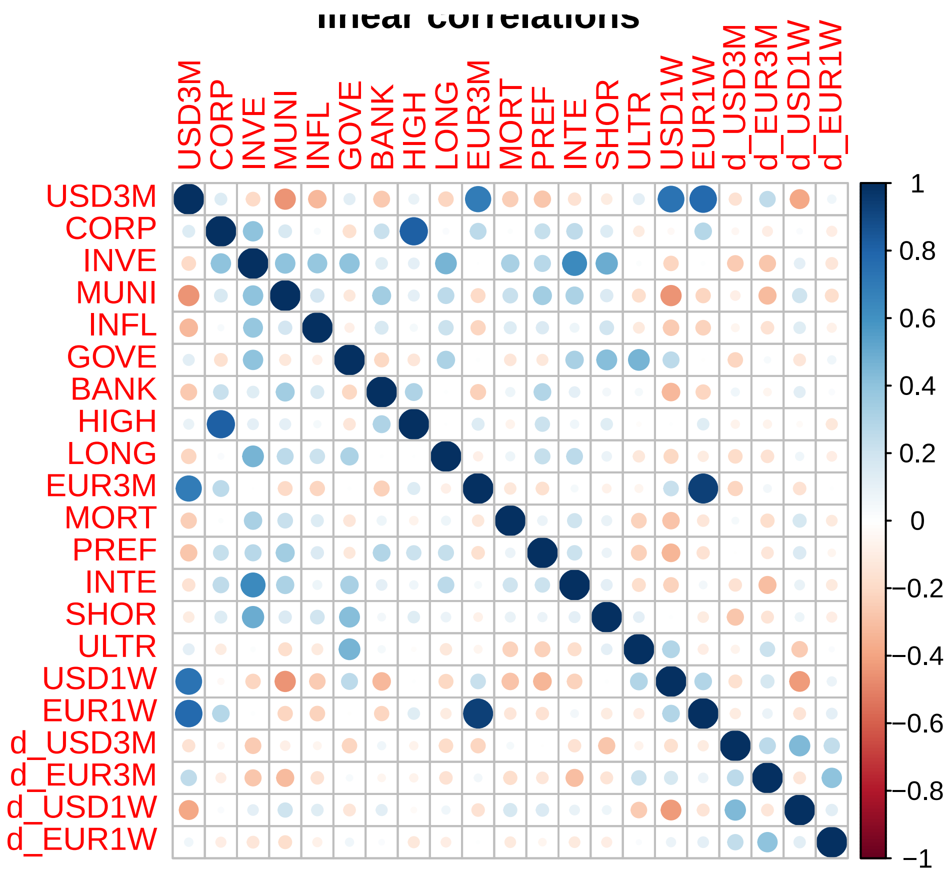
2 Data

The data is sourced from Bloomberg and consists of daily indices capturing net ETF Flows into different bond categories of ETF in the US market. The data is for the period 2020-03-02 - 2021-08-27. The sample also include three interest ratios, US 3-month LIBOR, EU 3-Month LIBOR and the SONIA interest rate benchmark.



Interests and ETF Flows
BANK
CE_dummy
CORP
d_EUR1W
d_EUR3M
d_USD1W
d_USD3M
EUR1W
EUR3M
GOVE
HIGH
INFL
INTE
INVE
LONG
MORT
MUNI
PREF
SHOR
ULTR
USD1W
USD3M
value
2020−07
2021−01
2021−07

2.1 Linear pairwise correlations



Some obvious correlation in the three interest rates. There are also some strong correlations among the ETF bond flows that will require careful consideration. Is this due to overlapping categorisation?

2.2 Information transfer measurement

The quantification of information transfer commonly relies on measures that have been derived from subject-specific assumptions and restrictions concerning the underlying stochastic processes or theoretical models. With the development of transfer entropy, information theory based measures have become a popular alternative to quantify information flows within various disciplines. Transfer entropy is a non-parametric measure of directed, asymmetric information transfer between two processes. We quantify the information flow between two stationary time series and test for its statistical significance using Shannon transfer entropy(TE)[1].

In the literature, the Granger causality has been addressed in many fields, including finance. Despite its success in the identification of couplings between the interacting variables, the use of structural models restricts its performance. Unlike Granger causality, TE is a quantity that is directly estimated from data and it does not suffer from such constraints. In the specific case of Gaussian distributed random variables, equivalence between TE and Granger causality has been proven.

2.3 Measuring information flows using transfer entropy

Let *log* denote the logarithm to the base 2, then informational gain is measured in bits. Shannon entropy (Shannon 1948) states that for a discrete random variable J with probability distribution $p(j)$, where j stands for the different outcomes the random variable J can take, the average number of bits required to optimally encode independent draws from the distribution of J can be calculated as

[1] We use the package `RTransferEntropy`

$$H_J = -\sum_j p(j) \cdot log\left(p(j)\right).$$

Formally, Shannon's formula is a measure for uncertainty, which increases with the number of bits needed to optimally encode a sequence of realizations of J. In order to measure the information flow between two processes, Shannon entropy is combined with the concept of the Kullback-Leibler distance [@KL51] and by assuming that the underlying processes evolve over time according to a Markov process (Schreiber 2000).

Let I and J denote two discrete random variables with marginal probability distributions $p(i)$ and $p(j)$ and joint probability distribution $p(i,j)$, whose dynamical structures correspond to stationary Markov processes of order k (process I) and l (process J). The Markov property implies that the probability to observe I at time $t+1$ in state i conditional on the k previous observations is $p(i_{t+1}|i_t, ..., i_{t-k+1}) = p(i_{t+1}|i_t, ..., i_{t-k})$. The average number of bits needed to encode the observation in $t+1$ if the previous k values are known is given by

$$h_I(k) = -\sum_i p\left(i_{t+1}, i_t^{(k)}\right) \cdot log\left(p\left(i_{t+1}|i_t^{(k)}\right)\right),$$

where $i_t^{(k)} = (i_t, ..., i_{t-k+1})$. $h_J(l)$ can be derived analogously for process J. In the bivariate case, information flow from process J to process I is measured by quantifying the deviation from the generalized Markov property $p(i_{t+1}|i_t^{(k)}) = p(i_{t+1}|i_t^{(k)}, j_t^{(l)})$ relying on the Kullback-Leibler distance (Schreiber 2000). Thus, (Shannon) transfer entropy is given by:

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

where $T_{J\rightarrow I}$ consequently measures the information flow from J to I ($T_{I\rightarrow J}$ as a measure for the information flow from I to J can be derived analogously).

The above transfer entropy estimates are commonly biased due to small sample effects. A remedy is provided by the effective transfer entropy [@MK02], which is computed in the following way:

$$ET_{J\rightarrow I}(k,l) = T_{J\rightarrow I}(k,l) - T_{J_{\text{shuffled}}\rightarrow I}(k,l),$$

where $T_{J_{\text{shuffled}}\rightarrow I}(k,l)$ indicates the transfer entropy using a shuffled version of the time series of J. Shuffling implies randomly drawing values from the time series of J and realigning them to generate a new time series. This procedure destroys the time series dependencies of J as well as the statistical dependencies between J and I. As a result $T_{J_{\text{shuffled}}\rightarrow I}(k,l)$ converges to zero with increasing sample size and any nonzero value of $T_{J_{\text{shuffled}}\rightarrow I}(k,l)$ is due to small sample effects. The transfer entropy estimates from shuffled data can therefore be used as an estimator for the bias induced by these small sample effects. To derive a consistent estimator, shuffling is repeated many times and the average of the resulting shuffled transfer entropy estimates across all replications is subtracted from the Shannon transfer entropy estimate to obtain a bias corrected effective transfer entropy estimate.

In order to assess the statistical significance of transfer entropy estimates, we rely on a Markov block bootstrap as proposed by (Dimpfl 2013). In contrast to shuffling, the Markov block bootstrap preserves the dependencies within each time series. Thereby, it generates the distribution of transfer entropy estimates under the null hypothesis of no information transfer, i.e. randomly drawn blocks of process J are realigned to form a simulated series, which retains the univariate dependencies of J but eliminates the statistical dependencies between J and I. Shannon transfer entropy is then estimated based on the simulated time series. Repeating this procedure yields the distribution of the transfer entropy estimate under the null of no information flow. The p-value associated with the null hypothesis of no information transfer is given by $1 - \hat{q}_{TE}$, where $\hat{q}_{TE}$ denotes the quantile of the simulated distribution that corresponds to the original transfer entropy estimate.

The calculation of Shannon transfer entropy is based on discrete data. If the data does not exhibit a discrete structure that allows for transfer entropy estimation, it has to be discretized. This can be achieved by symbolic recoding, i.e. by partitioning the data into a finite number of bins, which can either be based on defining upper and lower bounds for the bins a priori or by choosing specific quantiles of the empirical distribution of the data. Denote the bounds specified for the n bins by $q_1, q_2, ..., q_n$, where $q_1 < q_2 < ... < q_n$, and consider a time series denoted by y_t, the data is recoded as

$$S_t = \begin{cases} 1 & \text{for } \; y_t \leq q_1 \\ 2 & \text{for } \; q_1 < y_t \leq q_2 \\ \vdots & \qquad \vdots \\ n-1 & \text{for } \; q_{n-1} < y_t \leq q_n \\ n & \text{for } \; y_t \geq q_n \end{cases} .$$

Thereby, each value in the observed time series y_t is replaced by an integer (1,2,...,n), according to how S_t relates to the interval specified by the lower and upper bounds q_1 to q_n. The choice of the bins should be motivated by the distribution of the data.[2]

3 Results

Shannon's transfer entropy measure the information flow (reduction in uncertainty in probability) is a model-free way that captures the non-linear complexity of a financial network. As an exploratory exercise, we assess the information transfer from and to the changes of three interest rates.

Our analysis considers the full period of analysis and the period of the credit easing programme. For each period we assess the information gain, measured using the effective transfer entropy, between the fund flows and the three interest rate changes. We investigate the dynamic lead-lag information using up to $t-2$ period in each series.

[2] Behrendt et al. (2019) recommend that the number of bins is limited in order to avoid too many zero observations when calculating relative frequencies as estimators of the joint probabilities in the (effective) transfer entropy equations.

3.1 Results

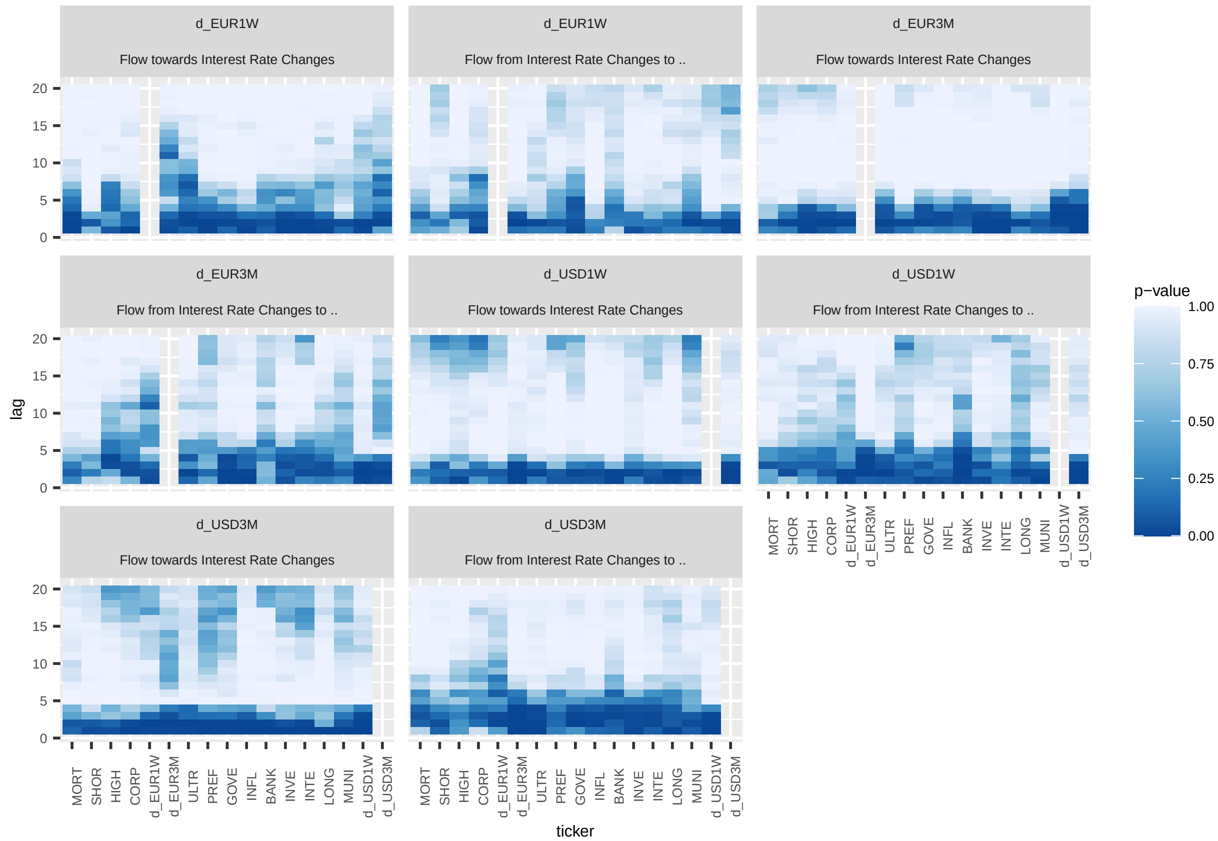


Figure 1: Full period grid search results

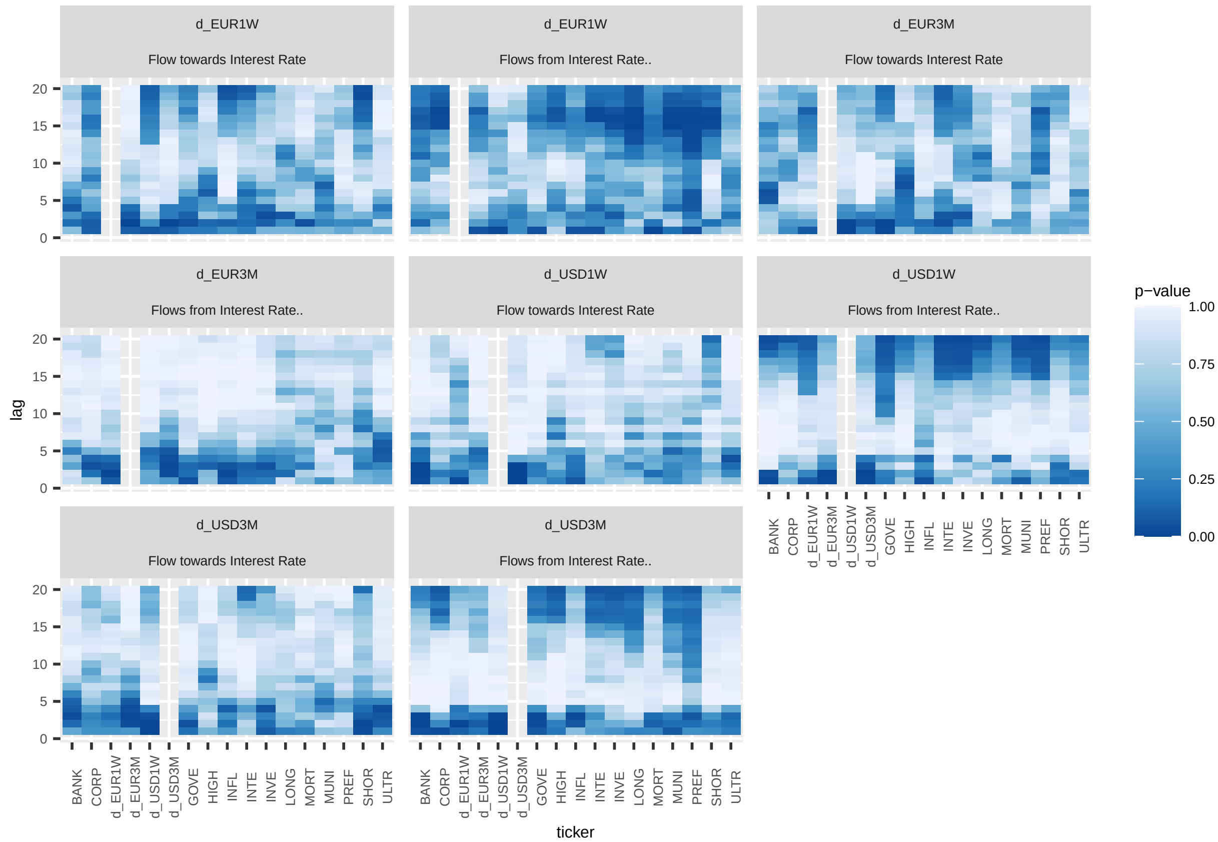


Figure 2: Credit Easing period grid search results

Figure 3: Full period grid search results (p value<5%)

Figure 4: Credit Easing period grid search results (p value < 5%)

3.2 False discovery correction

The previous procedure treats each effective transfer entropy estimates as independent when considering their level of significance. As we have over 2000 NHST p-values this is a unrealistic assumption.The replication crisis in finance has shown that researchers routinely explicitly or implicitly ignore multiple comparison bias and do not control for false discovery. This has lead many to assert that most research findings use the standard null hypothesis significance testing are likely false (Campbell ,2017). We correct for false discovery by applying the procedure first set in Benjamini and Hochberg (1995). Astonishingly, this correction is little used in finance, even though since its publication this paper has been cited over 50000 times.

When we adjust the previous results for false discovery we have more credible findings. Table 1 shows the effective transfer entropy values which remain after our Benjamini and Hochberg (1995) adjustment for the full sample period. Table 1 shows the effective transfer entropy estimates for the CE period. Some interesting insights emerge. . . .

Table 1: Full period grid search results adjusted for false discovery rate

Lag	ticker	te	ete	se	Direction
lag1	BANK	0.0485	0.0303	0.0058	Flow towards Interest Rate Changes:d_USD3M
lag1	d_EUR3M	0.0704	0.0534	0.0084	Flow from Interest Rate Changes to ..:d_EUR3M
lag1	d_USD1W	0.1189	0.1012	0.0077	Flow towards Interest Rate Changes:d_USD3M
lag1	d_USD1W	0.0590	0.0394	0.0083	Flow from Interest Rate Changes to ..:d_USD1W
lag1	INFL	0.0460	0.0278	0.0068	Flow towards Interest Rate Changes:d_USD3M
lag1	INVE	0.0504	0.0316	0.0064	Flow towards Interest Rate Changes:d_USD3M
lag1	LONG	0.0522	0.0335	0.0068	Flow towards Interest Rate Changes:d_USD3M
lag1	MUNI	0.0555	0.0369	0.0060	Flow towards Interest Rate Changes:d_USD3M
lag1	d_USD3M	0.0704	0.0544	0.0076	Flow towards Interest Rate Changes:d_EUR3M

Lag	ticker	te	ete	se	Direction
lag1	INFL	0.0628	0.0437	0.0068	Flow from Interest Rate Changes to ..:INFL
lag1	INTE	0.0595	0.0422	0.0064	Flow towards Interest Rate Changes:d_EUR3M
lag1	BANK	0.0423	0.0231	0.0057	Flow towards Interest Rate Changes:d_USD1W
lag1	d_USD3M	0.0590	0.0405	0.0084	Flow towards Interest Rate Changes:d_USD1W
lag1	d_USD3M	0.1189	0.1002	0.0079	Flow from Interest Rate Changes to ..:d_USD3M
lag1	MUNI	0.0543	0.0399	0.0081	Flow from Interest Rate Changes to ..:MUNI
lag1	INTE	0.0414	0.0220	0.0060	Flow towards Interest Rate Changes:d_EUR1W
lag1	INVE	0.0483	0.0292	0.0065	Flow towards Interest Rate Changes:d_EUR1W
lag2	d_EUR1W	0.1034	0.0636	0.0182	Flow towards Interest Rate Changes:d_USD3M
lag2	d_EUR3M	0.1261	0.0745	0.0156	Flow from Interest Rate Changes to ..:d_EUR3M

Lag	ticker	te	ete	se	Direction
lag2	d_USD1W	0.1381	0.0991	0.0175	Flow towards Interest Rate Changes:d_USD3M
lag2	d_USD1W	0.1762	0.1291	0.0167	Flow from Interest Rate Changes to ..:d_USD1W
lag2	GOVE	0.1058	0.0659	0.0166	Flow towards Interest Rate Changes:d_USD3M
lag2	GOVE	0.0999	0.0602	0.0159	Flow from Interest Rate Changes to ..:GOVE
lag2	ULTR	0.1085	0.0667	0.0171	Flow towards Interest Rate Changes:d_USD3M
lag2	ULTR	0.1140	0.0624	0.0167	Flow from Interest Rate Changes to ..:ULTR
lag2	CORP	0.1164	0.0652	0.0146	Flow towards Interest Rate Changes:d_EUR3M
lag2	d_EUR1W	0.1359	0.0837	0.0161	Flow towards Interest Rate Changes:d_EUR3M
lag2	d_USD1W	0.1341	0.0862	0.0171	Flow from Interest Rate Changes to ..:d_USD1W
lag2	d_USD3M	0.1261	0.0748	0.0161	Flow towards Interest Rate Changes:d_EUR3M

Lag	ticker	te	ete	se	Direction
lag2	GOVE	0.1092	0.0702	0.0171	Flow from Interest Rate Changes to ..:GOVE
lag2	ULTR	0.1024	0.0502	0.0176	Flow towards Interest Rate Changes:d_EUR3M
lag2	BANK	0.1030	0.0600	0.0160	Flow from Interest Rate Changes to ..:BANK
lag2	d_EUR3M	0.1341	0.0861	0.0178	Flow towards Interest Rate Changes:d_USD1W
lag2	d_EUR3M	0.1068	0.0552	0.0174	Flow from Interest Rate Changes to ..:d_EUR3M
lag2	d_USD3M	0.1762	0.1267	0.0158	Flow towards Interest Rate Changes:d_USD1W
lag2	d_USD3M	0.1381	0.0969	0.0180	Flow from Interest Rate Changes to ..:d_USD3M
lag2	LONG	0.1027	0.0523	0.0142	Flow towards Interest Rate Changes:d_USD1W
lag2	ULTR	0.1119	0.0632	0.0167	Flow from Interest Rate Changes to ..:ULTR
lag2	d_EUR3M	0.1359	0.0821	0.0172	Flow from Interest Rate Changes to ..:d_EUR3M

Lag	ticker	te	ete	se	Direction
lag2	INTE	0.1040	0.0562	0.0152	Flow towards Interest Rate Changes:d_EUR1W
lag2	PREF	0.1309	0.0818	0.0153	Flow towards Interest Rate Changes:d_EUR1W
lag3	d_EUR3M	0.1618	0.0796	0.0242	Flow from Interest Rate Changes to ..:d_EUR3M
lag3	d_USD1W	0.1562	0.0787	0.0233	Flow towards Interest Rate Changes:d_EUR3M
lag3	d_USD3M	0.1618	0.0803	0.0227	Flow towards Interest Rate Changes:d_EUR3M

Table 2: Credit easing period grid search results adjusted for false discovery rate

Lag	ticker	te	ete	se	Direction
lag1	d_USD1W	0.0961	0.0764	0.0141	Flow towards:d_USD3M
lag1	d_USD3M	0.0961	0.0749	0.0133	Flow towards:d_USD3M
lag2	d_USD1W	0.1758	0.1249	0.0248	Flow towards:d_USD3M
lag2	d_USD3M	0.1758	0.1235	0.0255	Flow towards:d_USD3M
lag3	d_USD3M	0.1885	0.1152	0.0330	Flow towards:d_USD3M
lag15	LONG	0.2390	0.0412	0.0387	Flow towards:d_EUR1W
lag15	MUNI	0.2390	0.0382	0.0376	Flow towards:d_EUR1W

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