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CLUSTERING TECHNIQUES APPLIED TO OUTLIER DETECTION OF FINANCIAL MARKET SERIES USING A MOVING WINDOW FILTERING ALGORITHM

by Josep Maria Puigvert Gutiérrez
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In 2008 all ECB publications feature a motif taken from the €10 banknote.

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Abstract

In this study we combine clustering techniques with a moving window algorithm in order to filter financial market data outliers. We apply the algorithm to a set of financial market data which consists of 25 series selected from a larger dataset using a cluster analysis technique taking into account the daily behaviour of the market; each of these series is an element of a cluster that represents a different segment of the market. We set up a framework of possible algorithm parameter combinations that detect most of the outliers by market segment. In addition, the algorithm parameters that have been found can also be used to detect outliers in other series with similar economic behaviour in the same cluster. Moreover, the crosschecking of the behaviour of different series within each cluster reduces the possibility of observations being misclassified as outliers.

Keywords: Outliers; financial market; cluster analysis; moving filtering window algorithm

JEL Classification: C19; C49; G19

Non-technical summary

Financial markets time series are often affected by unknown external events which can have a large impact on individual observations. These suspicious observations or *outliers* might be difficult to detect using informal inspection and graphical displays, particularly when there are missing values or the data is of high frequency. In the past few years in the time series literature, different methodologies have already been described which also aim at detecting these wrong events.

In this paper, we study the combination of clustering techniques with a moving window algorithm, already described by Dacorogna et al. [2001] and Brownlees and Gallo [2006], in order to filter financial markets data outliers. This filtering algorithm depends on 3 parameters which might depend on the market type or the financial instrument. The novelty of our methodology is that by using the clustering technique, we manage to set up a framework for the 3 algorithm parameter combinations that detect most of the outliers depending on each of the market segments. The latter is done without the need of having to check all the series of the dataset but just a few series as representatives of each market segment. In addition, we show that the clustering technique reduces the possibility of detecting observations misclassified as outliers. This is obtained by comparing the suspicious observations with the other series within the same cluster.

We apply the algorithm to a set of financial markets data. The financial markets data set consists of 25 series selected using a cluster analysis technique taking into account the daily behaviour of the market; each of these series is an element of a cluster that represents a different segment of the market. A posteriori, some of the outliers are randomly introduced to each of these series in order to check whether the filtering algorithm is able to detect them. For each of the series we try to find the combination of algorithm parameters that maximises the ratio of detection. In order to find this combination we compute all possible parameter permutations and for each of them we calculate the ratio of detection and the number of outliers that are detected.

1. Introduction and motivation

Financial markets are an important channel in the transmission mechanism of monetary policy. Developments in financial markets reflect the expectations about future economic and financial developments which might have an influence on monetary policy decisions and vice versa. However, financial markets time series are often affected by either missing or erroneous observations, or unknown external events which can have a large impact on individual observations. These suspicious observations, or outliers, might be difficult to detect using informal inspection and graphical displays, particularly when the data are of high frequency. In this paper we present and test a method of outlier detection for daily data. This method would allow to detect outliers and would provide, after analysing the type of outliers, clean financial market data for daily use on monetary policy, financial stability or risk management analysis. Our method is based on a clustering technique combined with a moving window of values obtained up to the value to be tested, which is used to judge the validity of a single observation. We apply the algorithm to a set of financial market data which takes into account different financial market segments. To decide which variables should be tested, a hierarchical cluster analysis was previously performed on a total of 321 financial instruments. Each of the series of this set of data is a cluster representative of one of the clusters previously found. Some outliers are randomly introduced in each of the series to control whether the algorithm can detect them. The procedure, implemented using MATLAB, successfully detects most of the outliers which have been randomly introduced. The main caveat in our finding is that the algorithm depends on three parameters, the optimal values of which are not necessarily common to all the segments and series. In this paper, we set up a framework of possible algorithm parameters combinations that detect most of the outliers depending on each of the market segments. We observed that the parameters that have been found can also be used to detect outliers in other series with similar economical behaviour clustered in the same market type. This would allow, in general for larger datasets, that only a single series representative of a cluster of financial market series were initially needed to determine the common set of algorithm parameters for all the series contained within the same cluster. Moreover, it would be of relevance for practitioners that need to ensure the quality of large data sets. However, the latter does not work for all markets, specially when they are volatile, like for instance the equity market. In addition, we describe a new method that by using the initial cluster analysis can be used to cross-check the plausibility of observations marked as outliers. This method is independent of the moving window filtering algorithm and can be used with other algorithms or methodologies for outlier detection. It should be pointed out that the outlier detection is based on daily data and not high frequency and irregularly spaced data like tick or intra-day data, for which the results might differ when applying the same methodology, even if the methodology described in this paper is valid and can still be applied in these cases. The paper is structured as follows: *Section 2* describes in detail the moving window algorithm to identify outliers or wrong observations in financial markets statistics. *Section 3* describes the series that have been selected in the study and how some outliers have been included in the data. *Section 4* describes the cross-validation scheme used to test the goodness of detection of the algorithm. *Section 5* presents the results of the testing. *Section 6* applies the results of the filtering test to a particular cluster. It also proves, for a particular case, that the algorithm parameters used to filter one series are still valid for the other series belonging to the same cluster. By doing so, an additional method is provided to detect the remaining outliers. *Section 7* concludes. The *Appendix* presents the charts and tables describing our findings.

2. The algorithm in the literature and our contribution

Dacorogna, Gencay, Müller, Olsen and Pictet (2001) and Brownlees and Gallo (2005) outline two similar algorithms to detect outliers. The two algorithms consist of a neighbourhood of observations, called a filtering window, necessary to judge the reliability of a single observation. Such a data window can grow and shrink according to data quality and the volatility of the series. The idea behind the algorithm is to assess the validity of a new observation on the basis of its relative distance from a neighbourhood of the closest valid past observations. In both cases numerical methods with convergence problems are avoided. Hence, the algorithm chosen produces well-defined results in all situations. In both cases the algorithm can be described as follows:

Let T be the time span of the quoted series x *that needs to be filtered*

for i=1:k
$f_i = x_i$
end
until i≤T

compute $z_i = \left(f_i - \overline{f}_{[i-1:i-k]}\right) \Big/ \sqrt{s^2_{[i-1:i-k]} + \lambda}$

if $|z_i| < threshold$ *then* $f_i = x_i$ *and increment i*
else $f_i = x_{i-1}$ *and increment i*
end
end

For each observation in the sample a heuristic *z-score* is computed and then used to decide whether to accept the observation or not. In the z-score formulae, $\overline{f}_{[i-1:i-k]}$ and $S^2_{[i-1:i-k-1]}$ represent respectively the moving average and the moving variance of the previous k values. The *z-score* is obtained by subtracting the average value of the last k valid observations from the ith value level and dividing it by a factor which depends on the sample variance of the last k valid observations and a value λ which avoids the cases where the denominator is 0 or close to this value. In the next section, 25 series are selected, each of them representing a different segment of the financial market. For each of these series, the algorithm has to determine the optimal window width k, the parameter λ and the threshold that might be considered to identify an observation as an outlier. Depending on the statistical features of these previously observed series, these three parameters will differ.

The algorithm avoids starting *ab initio* for each new incoming observation. The chosen algorithm is sequential and iterative. It uses the existing filter information base for a new observation, and a minimum amount of updating is necessary. The result of the algorithm is a new filtered series f_i. The fact that the algorithm substitutes the possible outliers by a previous observation does not mean that eventually a suspect value would be substituted by a forward-filled value but that the algorithm for detecting the outliers, instead of eliminating the ith-observation, will replace it by the previous observation as part of the moving window calculations. Once the algorithm is finished, the ith-observation can take again its initial value and be flagged as an outlier. The observation that exceeds the threshold could alternatively be eliminated instead of being substituted by the previous values as suggested by Brownlees and Gallo. However, it has been observed that instead of deleting the data point, it is more robust for the purpose of detecting outliers if, internally, the algorithm forward fills the observation that exceeds the threshold, especially in those cases where the series already contains missing data or when the outliers in this series are close to each other. The algorithm has already been programmed and tested using MATLAB, producing in most cases satisfactory results, as presented in *Section 5* and the charts in the Annex. The time spent to estimate the parameters for each of the instruments is around 4 hours. The novelty of our method is that previous to the outlier detection of a series, by using a hierarchical cluster technique[4], we cluster in different groups all the series according to their market behaviour. The latter saves an enormous amount of time in deciding which is the best parameter combination to detect outliers since only a few series, as representative of each of

[4] See Dillon and Goldstein (1984), Everitt (1993) or Kok Sorensen and Puigvert (2006) for a theoretical hierarchical cluster description.

the clusters, need to be tested. It also sets up a framework of possible algorithm parameters combinations depending on each of the market segments. Moreover, as we will show in *Section 6* it reduces the possibility of observations being missclassified as outliers. The hierarchical clustering methodology is in fact independent of the moving window algorithm and could be used in combination with any other filtering technique.

3. Data and selection of variables

The variables used in this study have been selected taking into account that financial markets consist of different segments. To decide which variables should be tested, a hierarchical cluster analysis was previously performed on a total of 321 financial instruments corresponding to the following market types: bonds, equities, futures, implied volatilities, money market, swaps and zero coupons. Most of these variables are considered part of a set of financial market series and are used in different types of internal and external ECB publications. Around three years of daily data were used in our study covering the period from February 2005 to February 2008. Based on the 321 series already mentioned, different clusters or groups of financial market data series with similar daily behaviour were identified. A representative of each of the clusters was selected for the filtering exercise. In this way we expect to cover to some extent the whole range of financial market core series. A few series that could not be classified in any of the previous clusters were also included in the study. A total of 25 series were analysed and tested using the filtering algorithm. In order to be sure whether the method described in *Section 2* detects the outliers efficiently, some outliers following a t-Student distribution of 1 degree of freedom have been randomly introduced in all of the series. By including some outliers in the data we can control how efficient the filtering is. However, since the variables had different value ranges they were standardised before including the outliers. With the standardisation we expect that the outliers influence in the same way the different variables and we try to avoid that a particular outlier has almost no effect on one variable while it would have a bigger impact on others. After having introduced the outliers the data were unstandardised back to their original form together with the induced outliers.

In order to identify each of the series and the clusters to which they belong the series keep the same mnemonic as used in the cluster exercise. The table below contains the mnemonic of each of the series plus a short description. All the series that were used for the study are briefly described in the Annex.

Table 1. Description of the variables used in the testing exercise.

Mnemonic	**Type of instrument**	**Description**
A22	Bond	United States - Benchmark bond - 30-year nominal bond issued by US Treasury- Yield - US dollar.
A24	Bond	United States - Benchmark bond - 10-year inflation linked bond issued by US Treasury-TIPS (Treasury Inflation protected securities) - Yield - US dollar (US9128274Y5).
A41	Bond	Germany - Benchmark bond -10-year. Germany Government Benchmark bond yield - Yield – Euro.
A49	Bond	Spain - Benchmark bond -5-year. Spain Government Benchmark bond yield - Yield – Euro.
A73	Bond	Japan - Benchmark bond - Japan 10-year Government Benchmark bond yield - Yield - Japanese yen.
A87	Bond	Sweden - Benchmark bond - Sweden 2-year. Government Benchmark bond yield - Yield - Swedish krona.
A101	Bond	France - Government bond – Long term 30 years - Yield- (FR0000188799).
A119	Bond	United Kingdom - Benchmark bond - United Kingdom government bond inflation linked, gilt 4.125% with maturity 7/22/30 - Yield - UK pound sterling.
A120	Bond	United Kingdom - Government bond - Long term 30 years - Yield- (GBT628).
A123	Equity indices	OMX VGI Vilnius index - price index- Lithuanian litas.
A139	Equity indices	United States - Equity/index (put) - NASDAQ COMPOSITE - Price index - Historical close - US dollar,.
A158	Money market	Japan - Money Market - 3-month Libor interbank Japanese Yen deposit rate- Last trade price or value - Japanese yen.
A164	Money market	Denmark, Money Market, 3-month interbank Danish krone deposit rate.
A172	Money market	Euro area (changing composition), Money market rates, Money market,Euro, Euribor 360, 3 months.
A178	Money market	United Kingdom - Money Market - 3-month interbank Pound sterling deposit rate - Ask price or primary activity - UK pound sterling.
A181	Money market	Japan - Money Market - Real 3-month Libor interbank Japanese Yen deposit rate - Last trade price or value - Japanese yen.
A184	Money market	Sweden, Money Market, 1 year interbank Swedish krone deposit rate.
A189	Money market	United States - Money Market - 3-month Libor interbank USD deposit rate- Last trade price or value - US dollar.
A194	Swaps	Euro area (changing composition) - Interest rate swaps - 5-year euro swap rate with annual settlement and compounding vs 6-month Euribor (ACT/360) - Bid price or secondary activity – Euro.
A204	Swaps	Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 1 year- Ask price or primary activity – Euro.
A226	Swaps	Japan - Interest rate swaps - 10-year euro swap rate with semi-annual fixed rate vs, 6-month LIBOR (ACT/360)- Ask price or primary activity - Japanese yen.
A252	Zero coupons	Japan - 2-years and 3-months zero coupon yield. Historical close.
A258	Zero coupons	Japan - 3-years and 6-months zero coupon yield. Historical close.
A269	Zero coupons	Japan - 6-months zero coupon yield. Historical close.
A277	Zero coupons	Japan - 7 years zero coupon yield. Historical close.

Source: *Reuters*.

4. Cross-validation algorithm scheme

For each of the series we try to find the combination of the algorithm parameters that maximises the ratio of detection. In order to find this combination we have computed all possible parameter permutations and for each of them we have calculated the ratio of detection and the number of outliers that were detected. The best combination does not in general need to be unique for a series but should be robust in the sense that it should detect an outlier independently of its position or magnitude. To avoid this, we have also replicated the same study 15 times but with different outliers and in different positions each time. The suggested algorithm parameter combination presented in *Section 5* has globally detected most of the outliers introduced in the 15 replicas but is not necessarily the best for each of them.

Since the induced outliers follow a t-Student distribution, some of them will merely be oscillations around zero, which might not be detected by the algorithm, while others are supposed to be strong oscillations (positive or negative) that we expect the algorithm to be able to detect. In order to be able to assess the real effectiveness of the filtering algorithm we define a method based on a penalisation statistic.

Let f_i *be the filtered series that might still contain added outliers and* x_i *the original series.*

If $f_i > x_i + stdv(x_i)$ *then* $d_i = f_i - (x_i + stdv(x_i))$

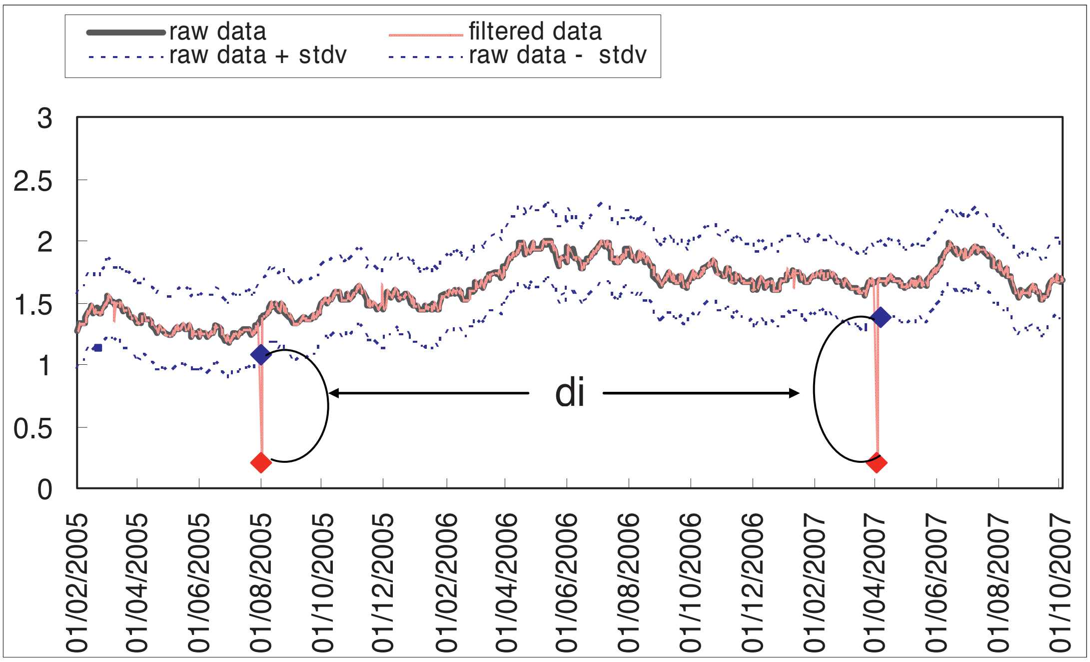
else if $f_i < x_i - stdv(x_i)$ $d_i = (x_i - stdv(x_i)) - f_i$

else $d_i = 0$

end if

Hence, each of the d_i values represents the distance from the one standard deviation interval to the filtered point, but only in the case where the filtered point exceeds the interval defined by one standard deviation from the original data.

Chart 1. Graphical description of the d_i distances.



We finally define $D_i = \frac{1}{T}\sum_{j=1}^{T}(d_j^i)^2$, where T is the total number of observations of the series x_i (i=1:25). The data-driven adjustment of the algorithm parameters is then based on the penalisation statistic D_i. For each of the x_i series we will try to find the algorithm parameters λ, k and the threshold as defined in *Section 2* that minimise D_i.

In addition, for each of the series we will count the number of values of the f_i series that are above or below the band defined by $x_i +/- stdv(x_i)$. Finally, we will also calculate the ratio of detection, which is defined as the total number of outliers detected by the algorithm divided by the total number of outliers randomly introduced. In the latter case we will take into account all outliers, even if the difference between the outlier and the value of the original x_i series is small.

To check the consistency of the algorithm parameters the following cross-validation scheme is applied. The complete sample, i.e. from February 2005 to February 2008, is split into two segments: a learning dataset, from February 2005 to October 2007, and a testing dataset, from October 2007 to February 2008. The same methodology is then applied to both periods. This is a way of cross-validating whether the parameters found during the first period, the learning phase, are consistent and still valid in a different period, the testing phase. The principle of cross-validation is a generic resource to validate statistical procedures and it has been applied in different contexts[5]. It is also crucial for applying this filtering algorithm in practice on a day-to-day basis. The period between October 2007 and February 2008 contains some turmoil data; it is interesting to see whether the algorithm detects these data as outliers. By using the algorithm with the parameters found in the first phase of the study, we expect to still be able to detect outliers for each of the 25 series for a different period range.

5. Results

The moving window algorithm has been tested in all the series described in *Section 3*. As presented in T*able 2* and in the Annex, it has yielded satisfactory results in most cases. The parameter combination presented in *Table 2* has shown to be very robust for all series and all replicas. On average, 95% of the added outliers were detected in the best of the 15 replicas. The optimal parameter combination is not always unique; for some replicas and series other combinations of different parameters are also valid and have, in some cases, even detected a larger number of outliers but cannot be generally used in the other replicas. The combination presented in T*able 2* is for each series the one common to all replicas and has detected most of the outliers for all cases but is not necessarily always the best for each of them. However, the parameters presented in *Table 2* for the equity series, i.e. A123 and A139, are an exception since they detected most of the outliers in some cases but are not generally common to all of the replicas. For these two series an algorithm parameter combination detecting most of the outliers can always be found but it is particular to the replica and depends on the position and magnitude of the outliers. Hence, the suggested method appears not to be the most appropriate for this type of instrument. It is also important to highlight that almost all of the outliers falling by one standard deviation above or below the original series are always detected. This means that almost all of the non-detected outliers are due to the fact that these outliers were very small (small oscillations close to zero). In some cases the raw series already contained true outliers or zeros, which have also been detected by the moving window algorithm. In the *Annex*, for each of the series we present two tables. The first shows how many outliers we have detected that were true outliers (i.e. those outliers inserted by us), how many outliers we have not detected that were true outliers (depending on the t-distribution some oscillations are minor), how many outliers we have detected that were not true outliers (also possible, as the raw data sometimes contain zeros or suspect observations) and how many outliers we have not detected that were not true outliers (i.e. the rest of the data). The second table shows the number of outliers falling by one standard

[5] See Hastie, Tibshirani and Friedman for a description of supervised and unsupervised learning in different fields.

deviation above or below the original series and the value of the statistic D_i as defined above. Also in the *Annex* we present two charts: the first compares the raw data series with the series containing outliers inserted by us, and the second compares the raw data with the filtered data. By looking at the tables, with the exception of one equity series, it can be observed that all of the non-detected outliers are small oscillations around zero and that, in principle, all of the economically relevant outliers are detected. From the charts it can be observed that there is almost no difference among the filtered and raw data with the exception of a few data points. By looking at the algorithm parameters presented in *Table 2* it could also be concluded that a relatively small window length, i.e. around five, and a lambda parameter of 0.1 would give the highest ratio of outlier detection. Once these parameters are fixed the detection depends only on the threshold parameter, which will be particular for each series.

Table 2. Parameters used for each of the series that have given the highest detection ratio.

Mnemonic	**Type of instrument**	**Window length**	**Lambda parameter**	**threshold**	**Remaining outliers above /below X_i+/-σ**	**D_i**	**Detection Ratio (%)**
A22	Bond	6	0.1	1.2	0	0	91.43
A24	Bond	5	0.1	1.8	0	0	90
A41	Bond	5	0.1	1.2	0	0	97.3
A49	Bond	8	0.1	2.1	0	0	92.86
A73	Bond	5	0.1	1	0	0	87.1
A87	Bond	5	0.1	2.2	0	0	89.47
A101	Bond	6	0.1	1.2	0	0	89.19
A119	Bond	5	0.1	1.1	0	0	92
A120	Bond	6	0.1	1.3	0	0	88.89
A123	Equity indices	34	1	3.2	0	0	85.19
A139	Equity indices	14	1	3	4	20.49	79.32
A158	Money market	5	0.1	1	0	0	92.86
A164	Money market	5	0.1	1.7	0	0	100
A172	Money market	5	0.1	1	0	0	97.37
A178	Money market	5	0.1	2.7	0	0	82.35
A181	Money market	8	0.1	1	0	0	91.18
A184	Money market	5	0.1	1.4	0	0	97.14
A189	Money market	5	0.1	1.7	0	0	96.43
A194	Swaps	5	0.1	1.1	0	0	96.67
A204	Swaps	5	0.1	1.4	0	0	89.47
A226	Swaps	6	0.1	1	0	0	93.33
A252	Zero coupons	5	0.1	1	0	0	93.94
A258	Zero coupons	5	0.1	1.2	0	0	100
A269	Zero coupons	5	0.1	1	0	0	93.75
A277	Zero coupons	5	0.1	1.2	0	0	90

A posteriori, the same algorithm parameters found for the test phase of the study were also used to find outliers using the same variables but for data obtained between October 2007 and February 2008. The results for this second set of data are shown in *Table 3*. In general, the algorithm, using the parameters estimated on the basis of the learning dataset, detects all of the inserted outliers. Only in a few cases does the algorithm not detect all the outliers contained in the dataset. Also in an only limited number of instances the algorithm detects as false outliers turmoil data as presented in the Annex. However, the false outliers could be still discarded with the method suggested in the next section. These would prevent that these observations would be wrongly discarded as suspicious data. This is very relevant in practice as users would like to monitor the market behaviour during times of high market volatility which would not be possible if they were discarded as outliers.

Table 3. Parameters used for each of the series that have given the highest detection ratio from October 2007 to February 2008.

Mnemonic	**Type of instrument**	**Window length**	**Lambda parameter**	**threshold**	**Remaining outliers above /below X_i+/-σ**	**D_i**	**Detection Ratio (%)**
A22	Bond	6	0.1	1.2	0	0	100
A24	Bond	5	0.1	1.8	0	0	100
A41	Bond	5	0.1	1.2	0	0	100
A49	Bond	8	0.1	2.1	0	0	100
A73	Bond	5	0.1	1	0	0	100
A87	Bond	5	0.1	2.2	0	0	100
A101	Bond	6	0.1	1.2	0	0	87.67
A119	Bond	5	0.1	1.1	0	0	100
A120	Bond	6	0.1	1.3	0	0	100
A123	Equity indices	34	1	3.2	6	9.12380	33
A139	Equity indices	14	1	3	0	0	100
A158	Money market	5	0.1	1	2	0.011	87
A164	Money market	5	0.1	1.7	0	0	100
A172	Money market	5	0.1	1	0	0	100
A178	Money market	5	0.1	2.7	0	0	100
A181	Money market	8	0.1	1	2	0.035	71.43
A184	Money market	5	0.1	1.4	0	0	100
A189	Money market	5	0.1	1.7	0	0	100
A194	Swaps	5	0.1	1.1	0	0	100
A204	Swaps	5	0.1	1.4	0	0	100
A226	Swaps	6	0.1	1	0	0	100
A252	Zero coupons	5	0.1	1	0	0	100
A258	Zero coupons	5	0.1	1.2	0	0	100
A269	Zero coupons	5	0.1	1	2	0.0026	72.73
A277	Zero coupons	5	0.1	1.2	0	0	100

6. Cross-checking within the clusters

The previous section shows that the three detection parameters on which the algorithm depends are somehow particular to each series. However, it cannot be ruled out that the same parameters may also be used for instruments belonging to the same cluster. In this section, we use the parameters that were found for the series A277 in the table above. They are used to filter all of the series belonging to the same cluster. The cluster contains seven series of zero coupon Japanese bonds of more than six years of maturity. The results in Table 4 show that for all of the series belonging to the same cluster as A277 the same filtering parameters can also be applied. In fact, the results for almost all of the series of the same cluster are even better than those for A277. For all of the series but one, all of the outliers falling above one sigma standard deviation from the original values have been detected and for all of the series but one their ratio of detection is larger than that obtained for A277.

Table 4. Results of the testing for the zero coupon Japanese bond series with algorithm parameters $k = 5$***,*** $\lambda = 0.1$ ***and*** $threshold = 1.2$***.***

Mnemonic	Outliers above /below X_i+/-σ	D_i	Detection Ratio (%)	Outliers that have been detected	Outliers that were not detected	Not outliers that were detected as outliers	Rest of the data
A272	0	0	88.63	39	5	0	661
A274	1	0.0006	67.56	25	12	0	668
A275	0	0	87.5	28	4	0	673
A276	0	0	96.15	25	1	0	679
A277	0	0	82.05	32	7	0	666
A278	0	0	94.7	36	2	1	666
A279	0	0	91.42	32	3	0	670

In addition, the outliers that have not been detected by the algorithm can be detected by comparing them with the values of the other series in the same cluster. This is graphically shown in the comparison of *Chart 2* with *Chart 3*. *Chart 2* shows the original data from the cluster of seven series of zero coupon Japanese bonds. It can be observed that the seven series belonging to this cluster follow the same pattern.

Chart 2. Original data from the zero-coupon Japanese bond cluster.

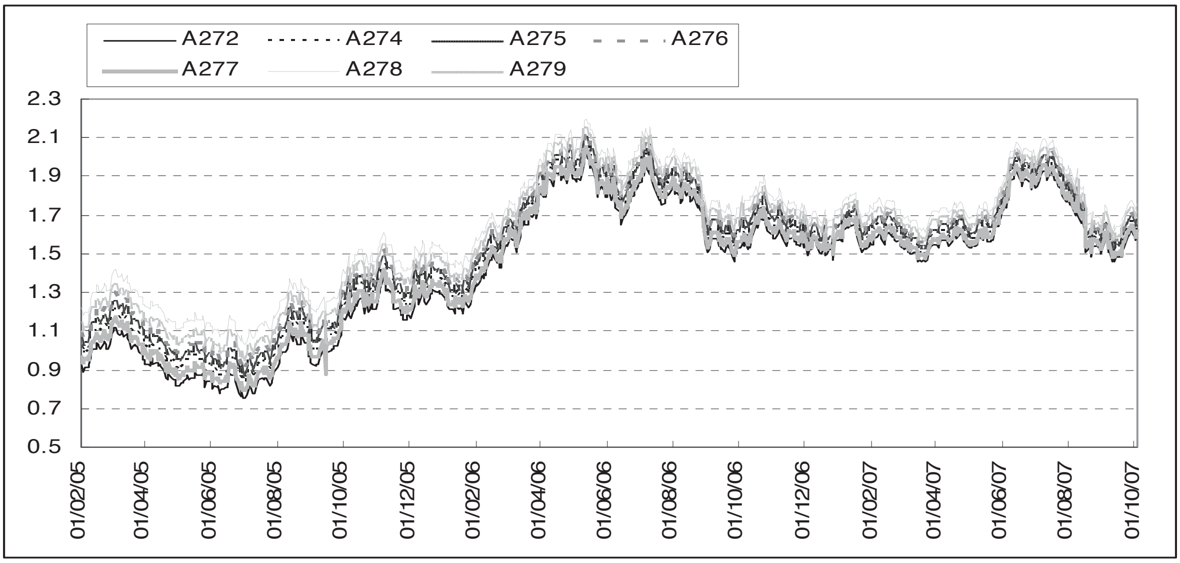
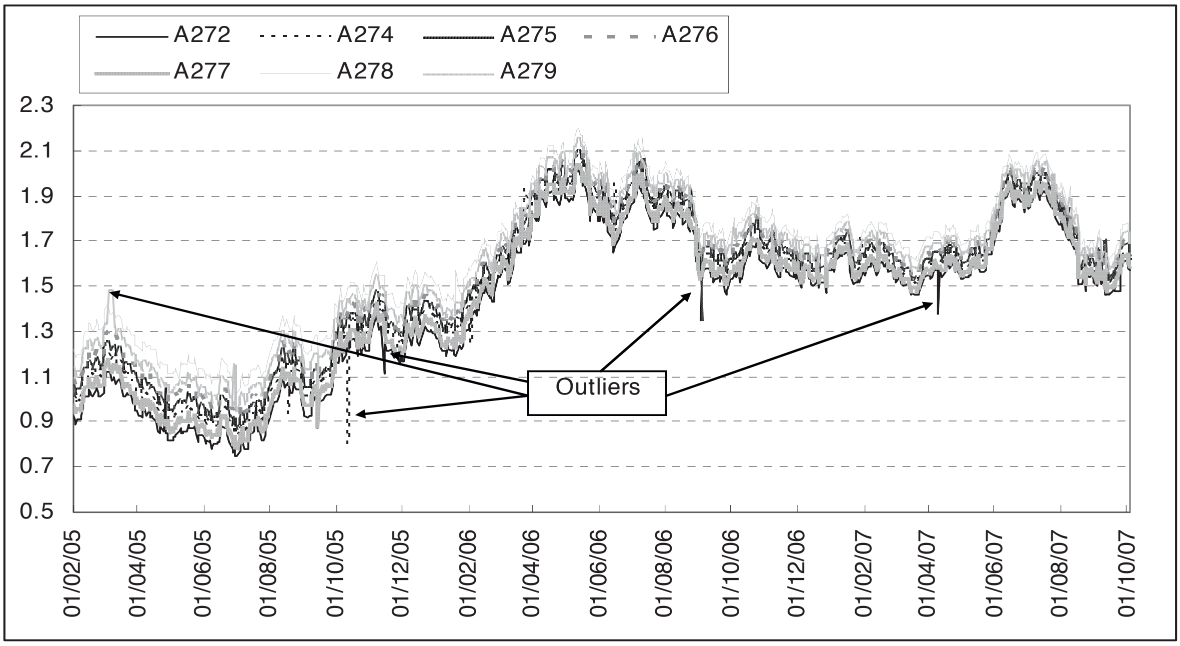


Chart 3 shows the filtered data with the remaining outliers that were not detected even though they are easily visible in the chart by plotting several series of the same cluster next to each other. This suggests developing a method whereby it is possible to detect the outliers by comparing them with the behaviour of other series in the cluster. It also can decide by cross-checking with the other series in the same cluster on the plausibility of the series flagged as an outlier or whether those are merely turmoil fluctuations. Such a method could also be used to prevent the erroneous exclusion of suspicious observations during periods of higher volatility as for instance a turmoil. In essence, the logic would be that in case that several series of one cluster show co-movements this would appear for a true shock that is rightly reflected in the data. In case only one series was affected, it would instead be likely that only this observation had been previously recorded.

Chart 3. Filtered data from the zero-coupon Japanese bond cluster still containing a few outliers.



The same clustering exercise has been applied to the October 2007 – February 2008 period. In this case we were interested to see whether the parameters obtained in the learning phase, February 2005 – October 2008, were also consistent within the series of a particular cluster and during a different period than the learning phase. In the October 2007 – February 2008 period there are also a few cases where the turmoil affected financial markets. One example took place on the 23 January 2008, when some of the Eonia swaps fell by 5%. It was also interesting to observe whether the filtering algorithm was detecting the turmoil observation erroneously as an outlier. Also, if this was the case, whether this could be rectified by cross-checking with the behaviour of other series within the same cluster.

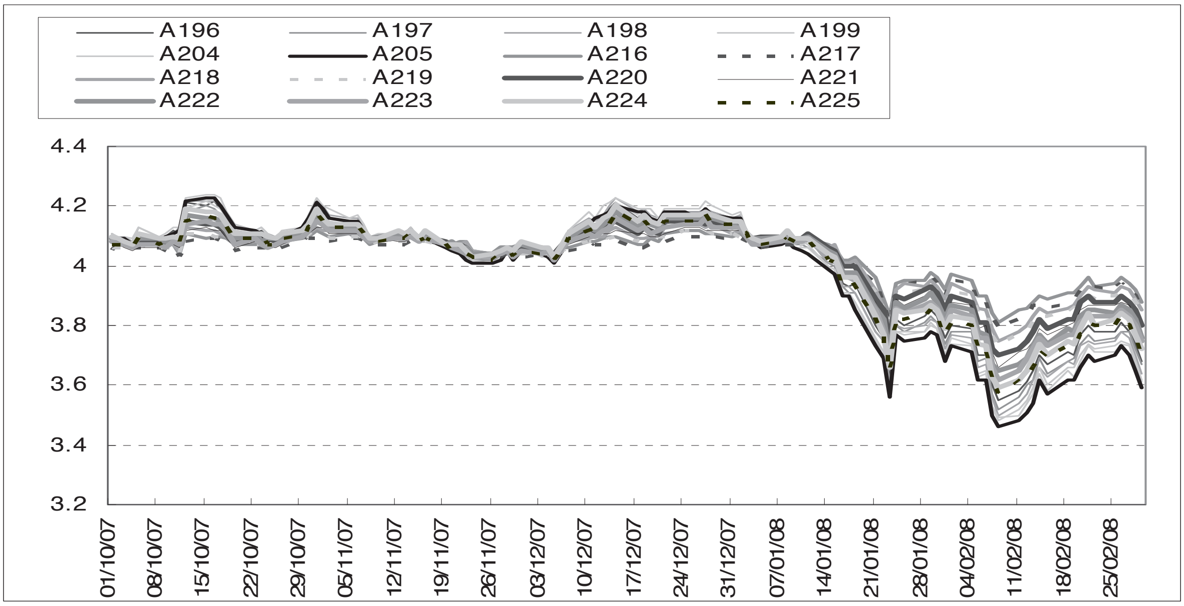
Table 5 shows again that for all of the series belonging to the same cluster as A204, Eonia swap 1 year, the same filtering parameters can also be applied. In this case, for all series but two, all of the outliers falling above one sigma standard deviation from the original values have been detected. Only for one series, A199, Eonia swap 11 months, a value has been detected as a false outlier. This observation is precisely the one corresponding to the 23 of January 2008 during the turmoil period.

Table 5. Results of the testing for the Eonia swap series with algorithm parameters $k = 5$***,*** $\lambda = 0.1$ ***and*** $threshold = 1.4$***.***

Mnemonic	Outliers above /below X_i+/-σ	D_i	Detection Ratio (%)	Outliers that have been detected	Outliers that were not detected	Not outliers that were detected as outliers	Rest of the data
A196	0	0	100	12	0	0	98
A197	1	0.013	90.9	10	1	0	99
A198	0	0	100	10	0	0	100
A199	0	0	100	6	0	1	103
A204	0	0	91.9	11	1	0	98
A205	0	0	100	13	0	0	97
A216	0	0	100	6	0	0	104
A217	0	0	88.8	8	1	0	101
A218	0	0	100	10	0	0	100
A219	1	0.00094	88.8	8	1	0	101
A220	0	0	100	9	0	0	101
A221	0	0	100	13	0	0	97
A222	0	0	87.5	7	1	0	102
A223	0	0	100	12	0	0	98
A224	0	0	88.8	8	1	0	101
A225	0	0	100	7	0	0	103

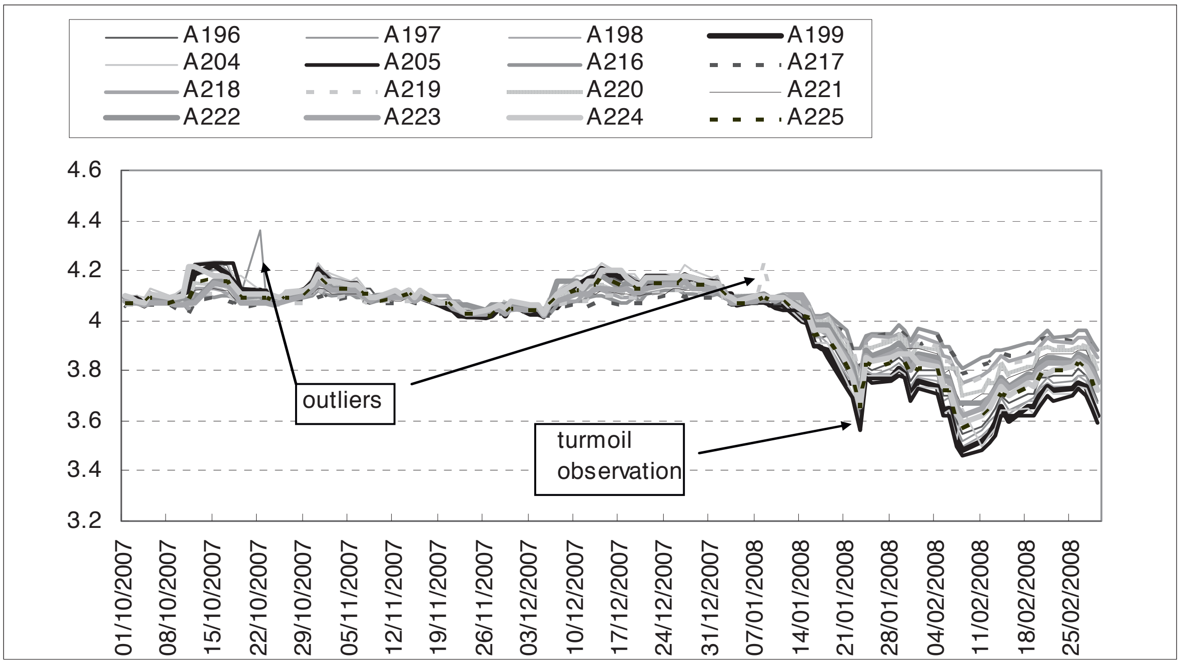
Also in this example, the outliers that have not been detected by the algorithm can be detected by comparing them with the values of the other series in the same cluster. This is graphically shown in the comparison of *Chart 4* with *Chart 5*.

Chart 4. Original data of the Eonia swaps cluster.



As presented in Chart 3, Chart 5 shows the filtered data with the non-detected outliers and the turmoil observation. By comparing these observations with the rest of the data, this chart makes evident which values are still outliers which have not been detected by the filtering algorithm. It is also graphically clear that the turmoil observation of the 23 January, i.e. A199, is not an outlier since it follows the same pattern than the other series within the cluster for this particular day.

Chart 5. Filtered data from the Eonia swaps containing a few outliers and a turmoil observation.



It should be pointed out that the clustering methodology is independent of the underlying moving window filtering algorithm and can be complemented with other algorithms or methodologies for outlier detection as for instance GARCH models for outlier detection or wavelet analysis[6].

7. Conclusions and final discussion

This paper has introduced and tested a method of outlier detection for daily continuous data. It depends on three parameters and has generally produced fairly satisfactory results. In the first part of the study, i.e. in the learning phase, we replicated 15 times each of the 25 series with outliers in different positions and of different magnitudes. Nearly all of the outliers randomly introduced were detected by the algorithm. Those outliers that were not detected seem to be small oscillations of very limited economic significance. All the outliers falling

[6] See for instance Doornik and Ooms (2005) or Greenblatt Seth A. (1994).

above one sigma standard deviation from the original values have been detected with the exception of only a few observations. For day-to-day filtering, this finding is therefore of limited relevance. The sigma standard deviation represents a deviation of at least 20 to 30 basis points from the mean for bond series and for money market series respectively. Hence, the observations falling above the one sigma standard deviation which have been detected can be considered true and economically significant outliers. Furthermore, they represent observations which are very significant and are not very likely to happen. Almost all other significant outliers below one sigma standard deviation from the original value are also detected and only in very few cases, less than 5%, the algorithm has not succeeded in flagging them as possible outliers. In this first part of the study, for each individual series, a common set of parameters detecting almost all of the outliers for all the replicas of this series has been found. In general, it has been observed that the best parameter combination is that which uses a relative small window length, i.e. around five days, and a lambda parameter of 0.1. The sigma value depends on the series and could always be changed to a larger or smaller value depending on the required detection sensitivity. Since we have replicated 15 times each of the 25 series with outliers in different positions and of different magnitudes, it has been proven that the algorithm with the parameters is robust within that period and that it does not depend on the position or the magnitudes of the outliers. Nevertheless, these positive findings cannot be extended to the equity series analysed in this study. Although for these two series there is always a combination that detects most of the outliers, this combination is not common among all replicas.

The optimal parameter combinations found during the testing phase, i.e. the period between February 2005 and October 2007, have shown to be equally robust between October 2007 and February 2008. The number of outliers detected during the second phase of the study almost did not change. In addition, some true turmoil data comprised in the latter period have not been detected as outliers. Since the results are positive this method could then be used and extended to filter all of the 321 series contained in the study.

While it appears that the three detection combination parameters on which the algorithm depends are particular to each series, in some instruments, such as bond series or zero coupon bonds, it seems that similar parameters could be used for instruments exhibiting different features and belonging, in principle, to different clusters. However for other instruments, such as equity indices, it has already been observed in the testing exercise that a small oscillation in one of the parameters substantially changes the filtering results. Hence, we can conclude that although there always exists an optimal combination whereby the whole set of outliers can actually be detected for all the series within the cluster; we are not sure whether this combination will always apply to all of the series in the same cluster. In *Section 6*, it has been shown that the same parameters found for the cluster representative can also be used to detect the outliers in the other series. Moreover, this section graphically suggests a method for detecting the possible remaining outliers that can decide by cross-checking with the other series in the same cluster on the plausibility of the series flagged as outliers.

The present paper not only tests the robustness of the moving window filtering methodology but also sets up a framework of possible algorithm parameters combinations depending on the financial market instrument and sets the scope for defining a novel outlier detection method based on the clustering of data. The latter method is in fact independent of the moving window filtering algorithm and can be complemented with other algorithms or outlier detection methodologies.

The moving window algorithm parameters that have been found in the study can also be used to detect outliers in other series with a similar economical behaviour. Since this method has produced satisfactory results for the series representing each of the clusters, it could be extended to the rest of the 321 series of the study on a daily basis. This method would allow outliers of a relative magnitude to be detected and would provide clean financial market data for daily use.

References

Bollerslev, T. (2001), "Financial econometrics: Past developments and future challenges", Journal of econometrics 100, 45-51

Brownlees C.T., Gallo G. M. (2006), "Financial Econometric Analysis at Ultra-High Frequency: Data Handling Concerns", Computational Statistics and Data analysis, Elsevier, vol. 51(4), pages 2232-2245, December.

Dacorogna, M. M., Gencay, R. Muller, U. A., Olsen, R. and Pictet, O.V. (2001), "An introduction to high frequency finance", Academic Press, London

Cuadras, C.M (1989), "Distance Analysis in discrimination and classification using both continuous and categorical variables", in: Y. Dodge (ed.), Statistical Data Analysis and Inference, Amsterdam: North Holland Publishing Co., pp. 459–473.

Dillon, W., Goldstein M. (1984), "Multivariate Analysis", John Wiley and Sons.

Doornik Jurgen A., Ooms Marius 2005. "Outlier Detection in GARCH Models," Tinbergen Institute Discussion Papers 05-092/4, Tinbergen Institute.

Van Dijk D., Franses P.H. (1999), "Outlier detection in the GARCH(1,1) model", Econometric Institute Research Report.

Everitt, Brian (1993), "Cluster analysis", John Wiley & Sons Inc, April 1993.

Falkenberry, T.N. (2002), "High frequency data filtering. Technical report, Tick data.

Greenblatt Seth A. (1994), "Wavelets in Econometrics: An Application to Outlier Testing", Working Paper, University of Reading.

Hair, J., Anderson R. , Tatham, R., Black W. (1998), "Multivariate Data Analysis", Fifth Edition, Prentice Hall.

Hastie T., Tibshirani R., Friedman J. (2001), "The Elements of Statistical Learning", First Edition, Springer-Verlag.

Christoffer Kok Sørensen, Josep Maria Puigvert Gutiérrez (2006) "Euro area banking sector integration: using hierarchical cluster analysis techniques", European Central Bank, Working Paper Series No. 627.

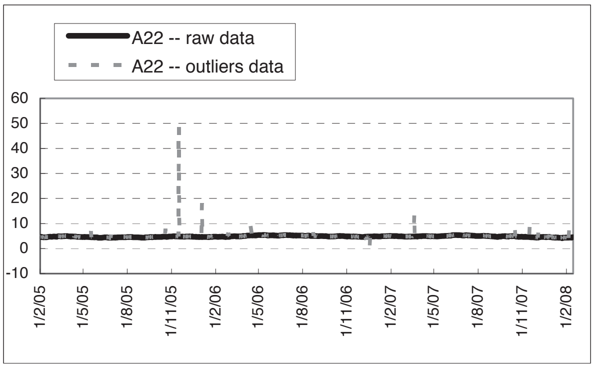
Korobow, L. and Stuhr D.P. (1991), "Using cluster analysis as a tool for economic and financial analysis", Federal Reserve Bank of New York, Research Paper No. 9132.

Rousseeuw P. J., Leroy A.M. (2003) "Robust Regression and Outlier detection", Wiley Series in Probability and Statistics.

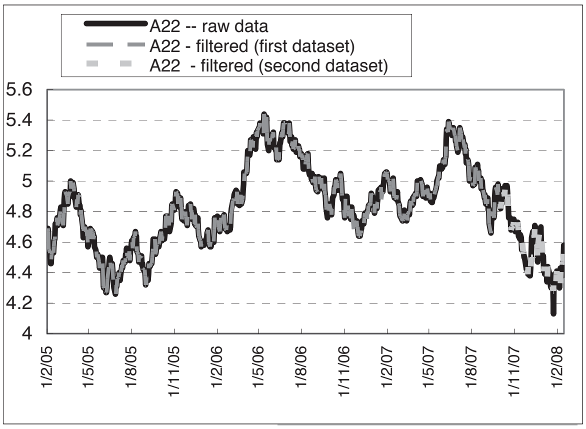
Zivot E., Wang J. (2003), "Modelling Financial Time Series in S-Plus", Springer.

Annex

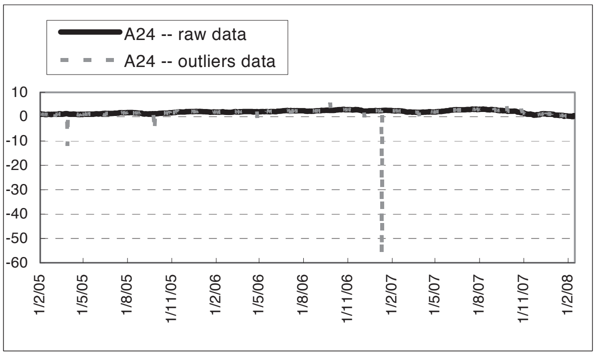
Charts and tables



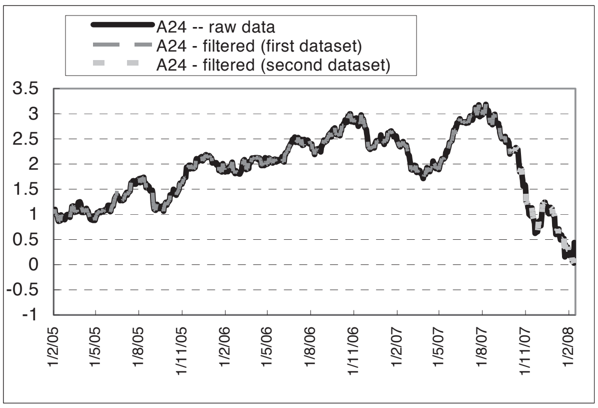
A22 optimal solution (first dataset)		
window length	6	
lambda parameter	0.1	
threshold	1.2	
	outlier	not outlier
detected	32	0
not detected	3	662
Ratio detection	91.43	
Di	0	
Number of outliers above or below Xi+/-σ	0	



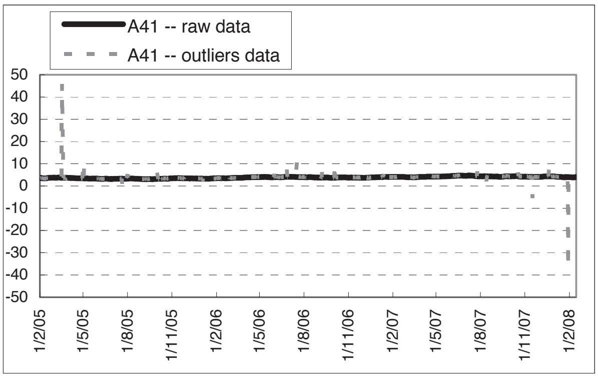
A22 optimal solution (second dataset)		
window length	6	
lambda parameter	0.1	
threshold	1.2	
	outlier	not outlier
detected	8	3
not detected	0	86
Ratio detection	100.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



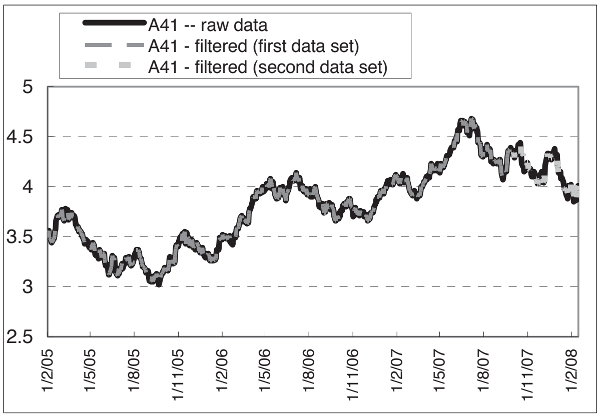
A24 optimal solution (first dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.8	
	outlier	not outlier
detected	27	0
not detected	3	667
Ratio detection	90.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



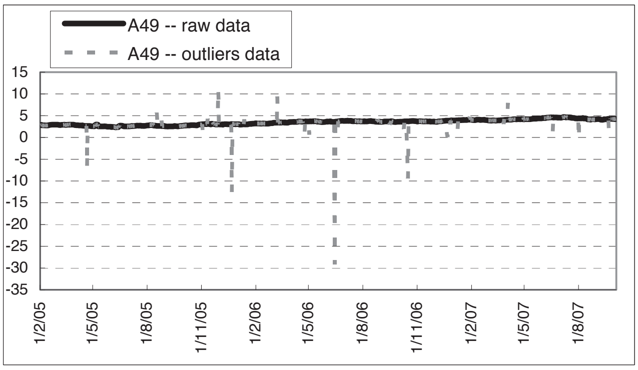
A24 optimal solution (second dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.8	
	outlier	not outlier
detected	5	0
not detected	0	92
Ratio detection	100.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



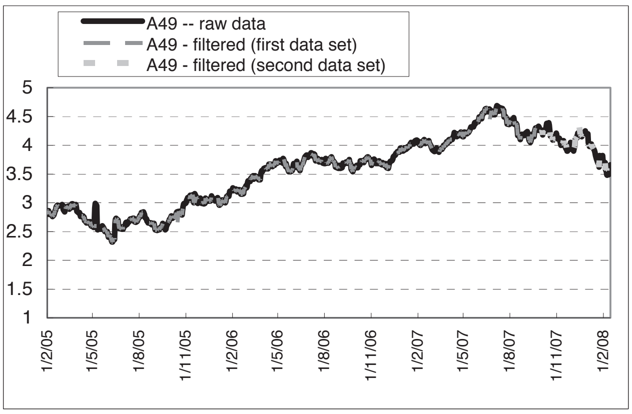
A41 optimal solution (first dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.2	
	outlier	not outlier
detected	36	0
not detected	1	660
Ratio detection	97.30	
Di	0	
Number of outliers above or below Xi+/-σ	0	



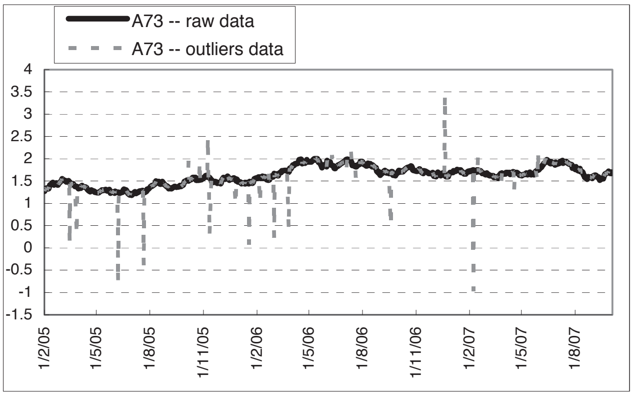
A41 optimal solution (second dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.2	
	outlier	not outlier
detected	9	2
not detected	1	85
Ratio detection	90.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



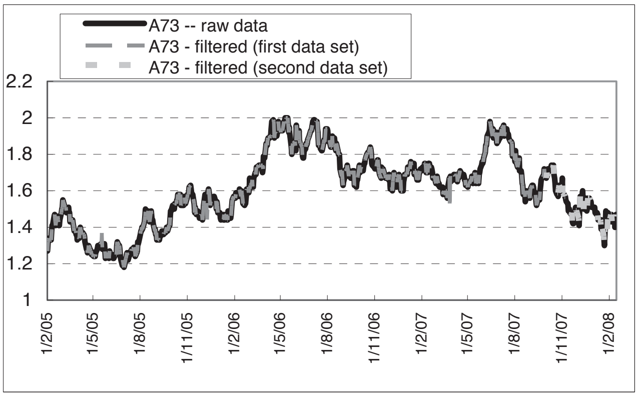
A49 optimal solution (first dataset)		
window length	8	
lambda parameter	0.1	
threshold	2.1	
	outlier	not outlier
detected	39	3
not detected	3	652
Ratio detection	92.86	
Di	0	
Number of outliers above or below Xi+/-σ	0	



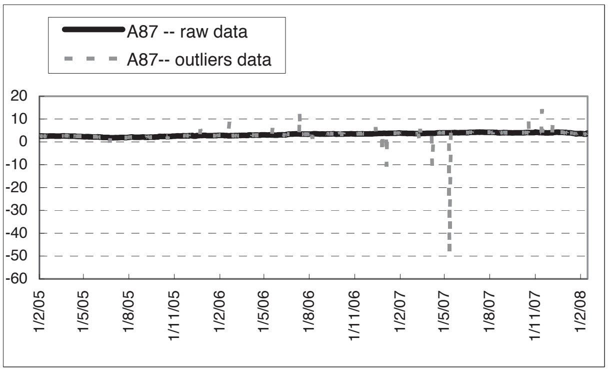
A49 optimal solution (second dataset)		
window length	8	
lambda parameter	0.1	
threshold	2.1	
	outlier	not outlier
detected	9	0
not detected	1	87
Ratio detection	90.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



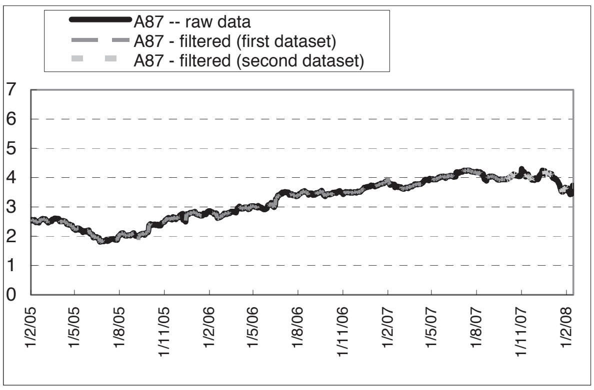
A73 optimal solution (first dataset)		
window length	5	
lambda parameter	0.1	
threshold	2.1	
	outlier	not outlier
detected	27	0
not detected	4	666
Ratio detection	87.10	
Di	0	
Number of outliers above or below Xi+/-σ	0	



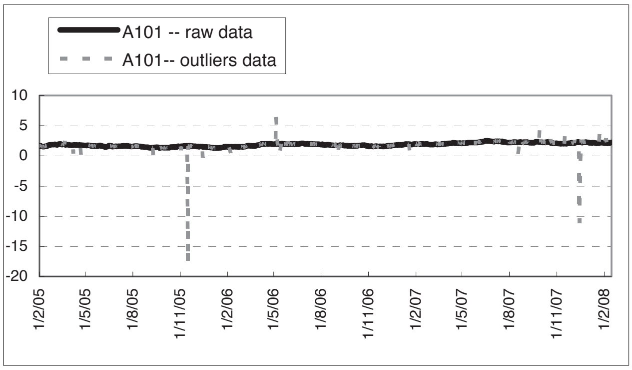
A73 optimal solution (second dataset)		
window length	5	
lambda parameter	0.1	
threshold	2.1	
	outlier	not outlier
detected	4	0
not detected	0	93
Ratio detection	100.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



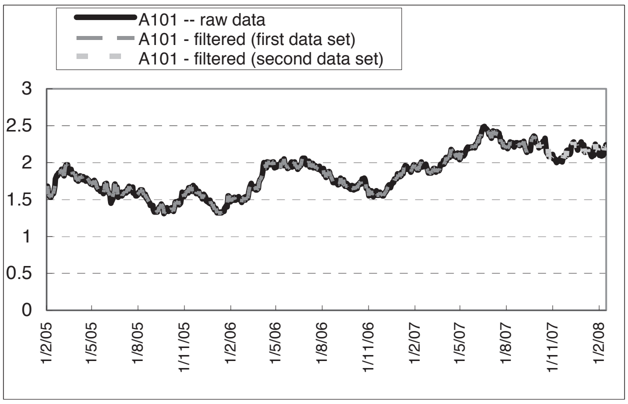
A87 optimal solution (first dataset)		
window length	5	
lambda parameter	0.1	
threshold	2.2	
	outlier	not outlier
detected	34	0
not detected	4	659
Ratio detection	89.47	
Di	0	
Number of outliers above or below Xi+/-σ	0	



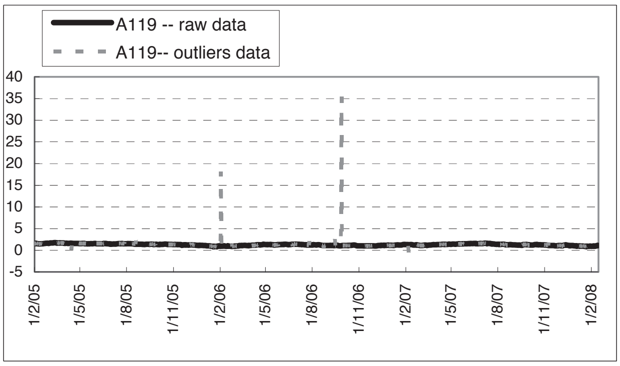
A87 optimal solution (second dataset)		
window length	5	
lambda parameter	0.1	
threshold	2.2	
	outlier	not outlier
detected	6	0
not detected	0	91
Ratio detection	100.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



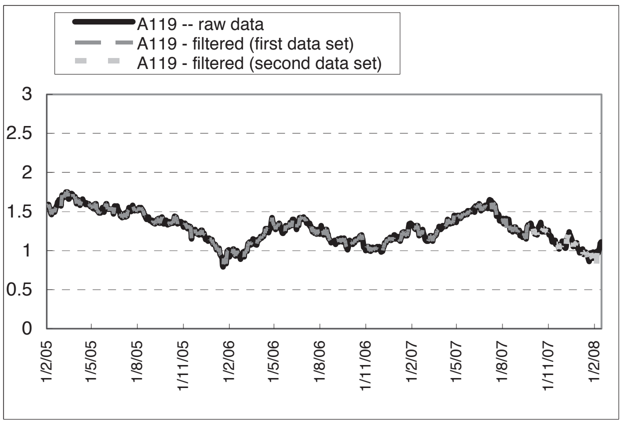
A101 optimal solution		
window length	6	
lambda parameter	0.1	
threshold	1.2	
	outlier	not outlier
detected	33	0
not detected	4	660
Ratio detection	89.19	
Di	0	
Number of outliers above or below Xi+/-σ	0	



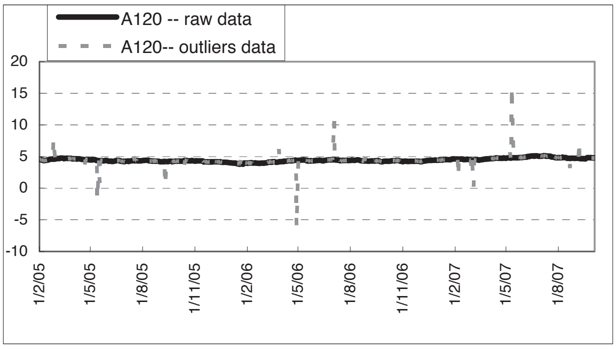
A101 optimal solution (second dataset)		
window length	6	
lambda parameter	0.1	
threshold	1.2	
	outlier	not outlier
detected	10	1
not detected	0	86
Ratio detection	100.00	
Di	3	
Number of outliers above or below Xi+/-σ	0.0017	



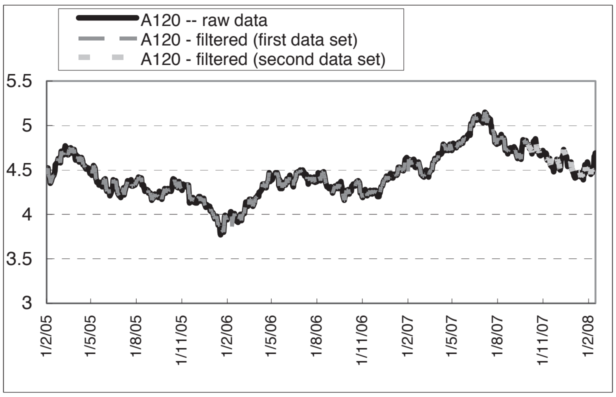
A119 optimal solution		
window length	5	
lambda parameter	0.1	
threshold	1.1	
	outlier	not outlier
detected	23	0
not detected	2	672
Ratio detection	92.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



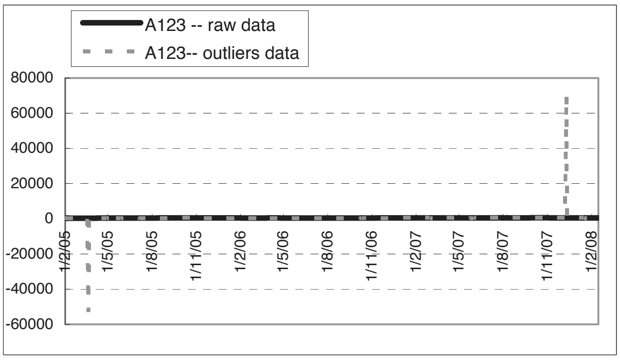
A119 optimal solution (second dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.1	
	outlier	not outlier
detected	1	0
not detected	1	95
Ratio detection	50.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



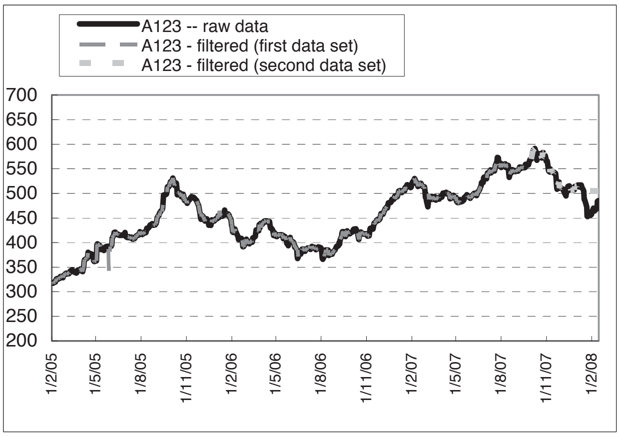
A120 optimal solution		
window length	6	
lambda parameter	0.1	
threshold	1.3	
	outlier	not outlier
detected	24	0
not detected	3	670
Ratio detection	88.89	
Di	0	
Number of outliers above or below Xi+/-σ	0	



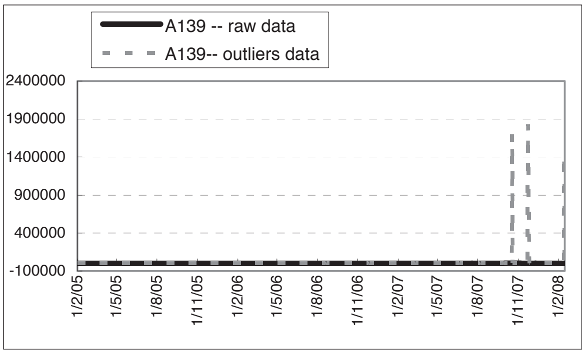
A120 optimal solution (second dataset)		
window length	6	
lambda parameter	0.1	
threshold	1.3	
	outlier	not outlier
detected	4	0
not detected	0	93
Ratio detection	100.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



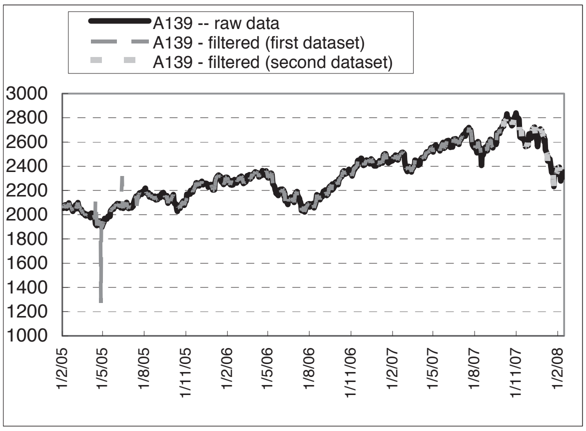
A123 optimal solution		
window length	34	
lambda parameter	1	
threshold	3.2	
	outlier	not outlier
detected	23	11
not detected	4	659
Ratio detection	85.19	
Di	0	
Number of outliers above or below Xi+/-σ	0	



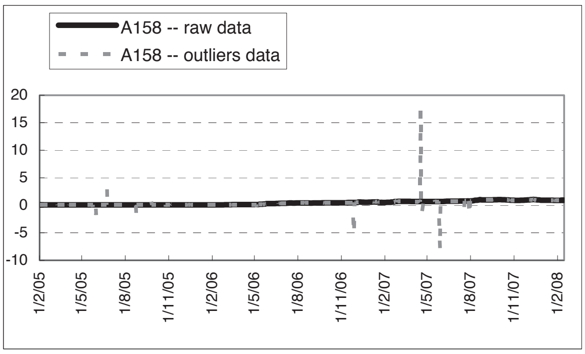
A123 optimal solution (second dataset)		
window length	34	
lambda parameter	1	
threshold	3.2	
	outlier	not outlier
detected	1	22
not detected	0	74
Ratio detection	100.00	
Di	16	
Number of outliers above or below Xi+/-σ	4.0559	



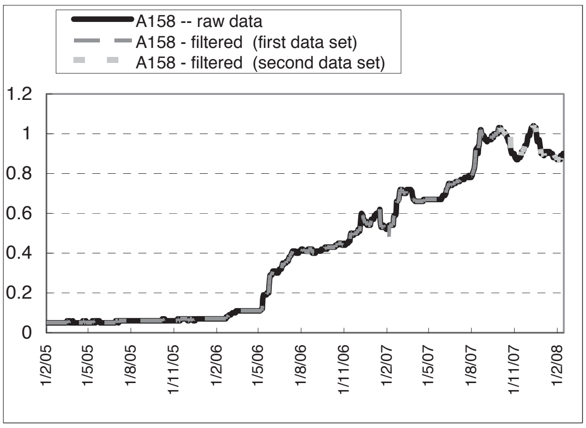
A139 optimal solution (first dataset)		
window length	44	
lambda parameter	1	
threshold	3	
	outlier	not outlier
detected	23	14
not detected	6	652
Ratio detection	79.31	
Di	4	
Number of outliers above or below Xi+/-σ	20.49	



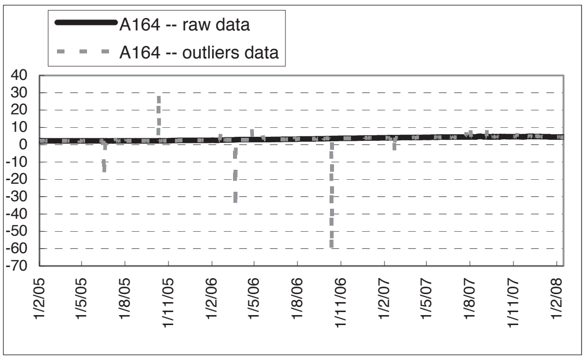
A139 optimal solution (second dataset)		
window length	44	
lambda parameter	1	
threshold	3	
	outlier	not outlier
detected	2	3
not detected	1	91
Ratio detection	66.67	
Di	4	
Number of outliers above or below Xi+/-σ	20.49	



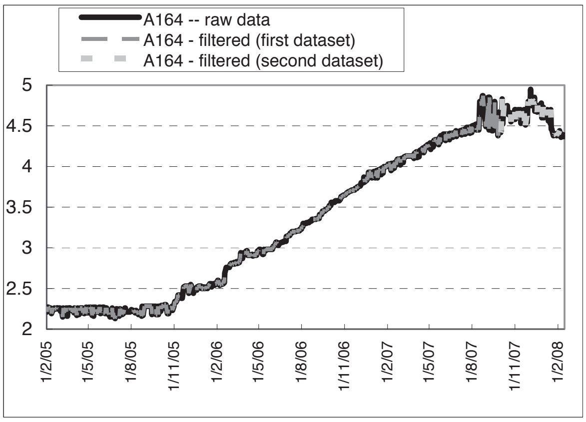
A158 optimal solution		
window length	5	
lambda parameter	0.1	
threshold	1	
	outlier	not outlier
detected	26	0
not detected	2	669
Ratio detection	92.86	
Di	0	
Number of outliers above or below Xi+/-σ	0	



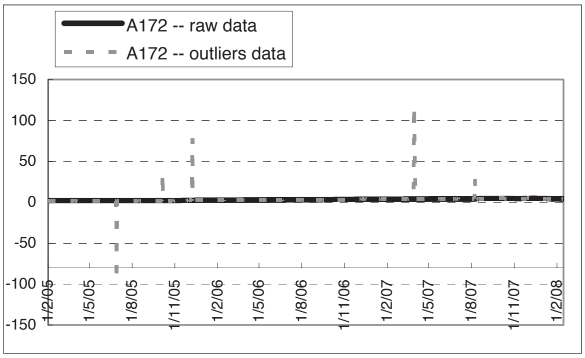
A158 optimal solution (second dataset)		
window length	5	
lambda parameter	0.1	
threshold	1	
	outlier	not outlier
detected	0	0
not detected	2	95
Ratio detection	0.00	
Di	6.99E-05	
Number of outliers above or below Xi+/-σ	1	



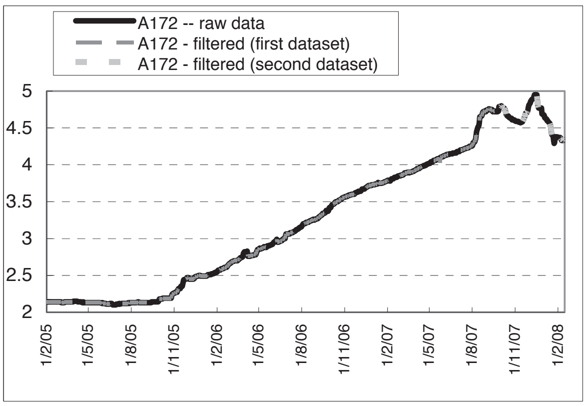
A164 optimal solution		
window length	5	
lambda parameter	0.1	
threshold	1.7	
	outlier	not outlier
detected	24	0
not detected	0	673
Ratio detection	100.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



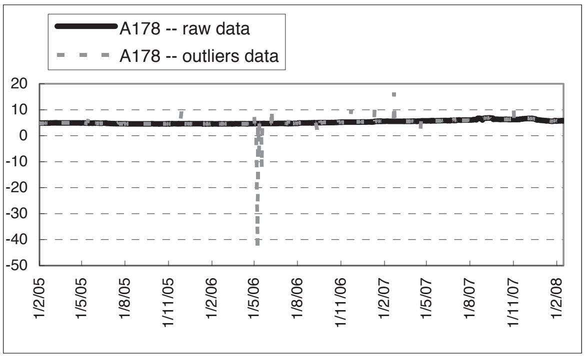
A164 optimal solution (second dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.7	
	outlier	not outlier
detected	3	0
not detected	0	94
Ratio detection	100.00	
Di	1	
Number of outliers above or below Xi+/-σ	0.000555	



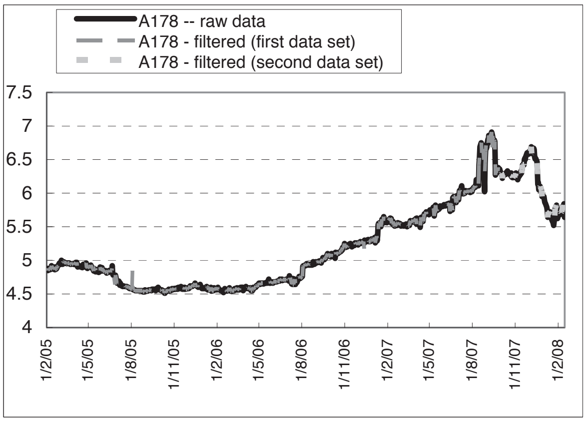
A172 optimal solution		
window length	5	
lambda parameter	0.1	
threshold	1	
	outlier	not outlier
detected	37	0
not detected	1	659
Ratio detection	97.37	
Di	0	
Number of outliers above or below Xi+/-σ	0	



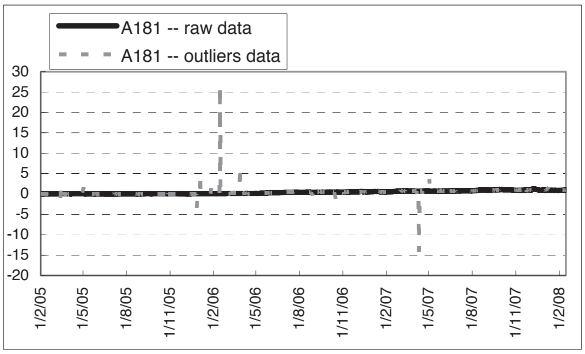
A172 optimal solution (second dataset)		
window length	5	
lambda parameter	0.1	
threshold	1	
	outlier	not outlier
detected	1	0
not detected	0	96
Ratio detection	100.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



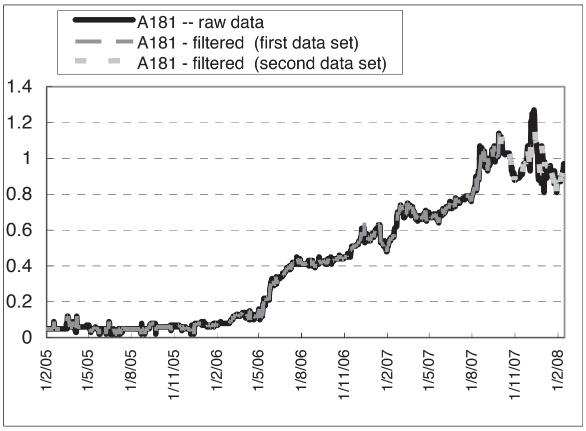
A178 optimal solution		
window length	5	
lambda parameter	0.1	
threshold	2.7	
	outlier	not outlier
detected	28	0
not detected	6	663
Ratio detection	82.35	
Di	0	
Number of outliers above or below Xi+/-σ	0	



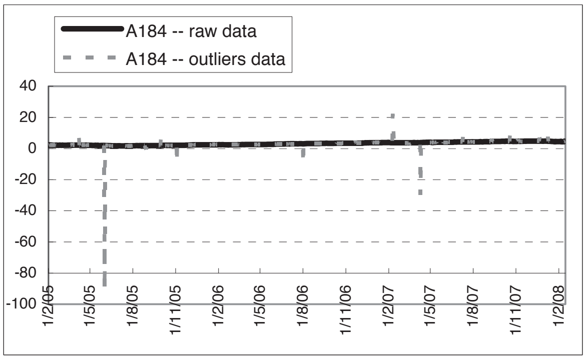
A178 optimal solution (second dataset)		
window length	5	
lambda parameter	0.1	
threshold	2.7	
	outlier	not outlier
detected	1	0
not detected	0	96
Ratio detection	100.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



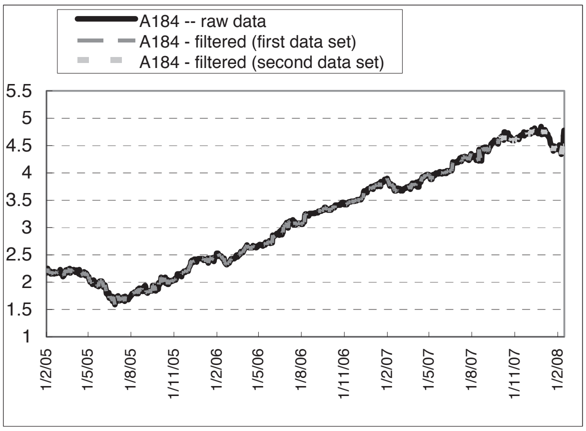
A181 optimal solution (first dataset)		
window length	8	
lambda parameter	0.1	
threshold	1	
	outlier	not outlier
detected	31	1
not detected	3	659
Ratio detection	91.18	
Di	0	
Number of outliers above or below Xi+/-σ	0	



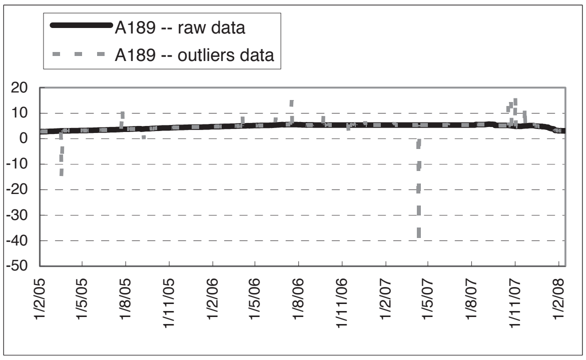
A181 optimal solution (second dataset)		
window length	8	
lambda parameter	0.1	
threshold	1	
	outlier	not outlier
detected	4	9
not detected	0	84
Ratio detection	100.00	
Di	8	
Number of outliers above or below Xi+/-σ	0.011	



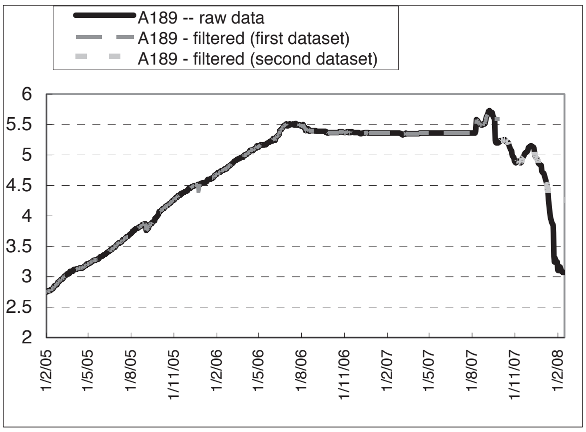
A184 optimal solution (first dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.4	
	outlier	not outlier
detected	34	0
not detected	1	657
Ratio detection	97.14	
Di	0	
Number of outliers above or below Xi+/-σ	0	



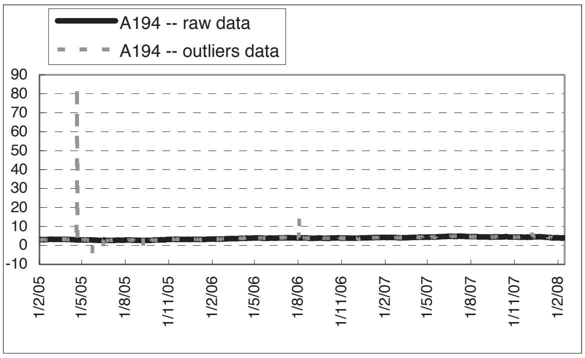
A184 optimal solution (second dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.4	
	outlier	not outlier
detected	6	2
not detected	0	89
Ratio detection	100.00	
Di	2	
Number of outliers above or below Xi+/-σ	0.0052	



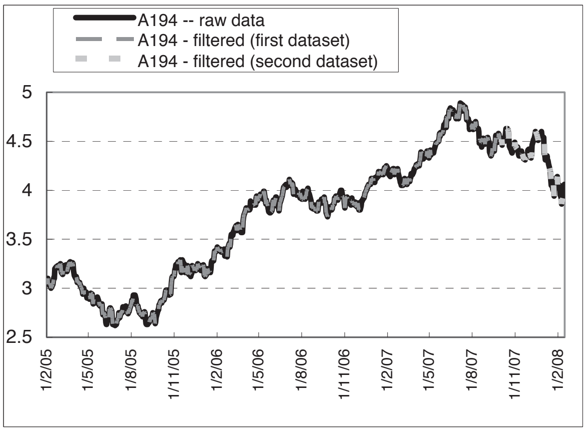
A189 optimal solution (first dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.7	
	outlier	not outlier
detected	27	11
not detected	1	658
Ratio detection	96.43	
Di	0	
Number of outliers above or below Xi+/-σ	0	



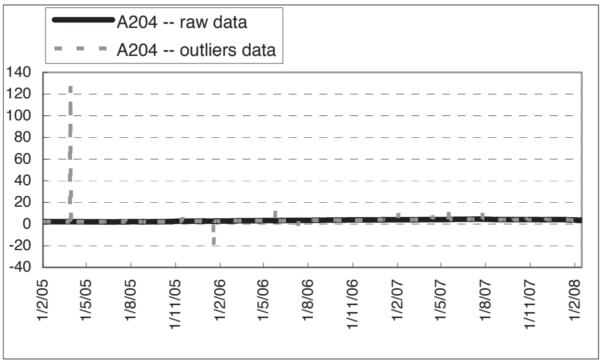
A189 optimal solution (second dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.7	
	outlier	not outlier
detected	5	24
not detected	0	68
Ratio detection	100.00	
Di	20	
Number of outliers above or below Xi+/-σ	0.2628	



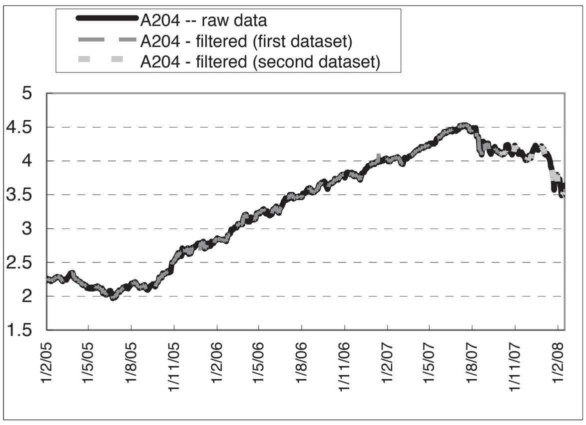
A194 optimal solution (first dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.1	
	outlier	not outlier
detected	29	1
not detected	1	666
Ratio detection	96.67	
Di	0	
Number of outliers above or below Xi+/-σ	0	



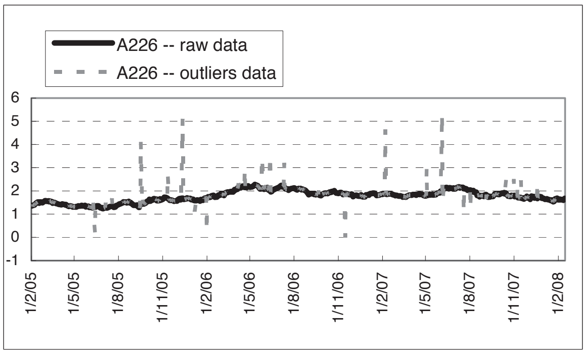
A194 optimal solution (second dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.1	
	outlier	not outlier
detected	29	1
not detected	1	666
Ratio detection	96.67	
Di	0	
Number of outliers above or below Xi+/-σ	0	



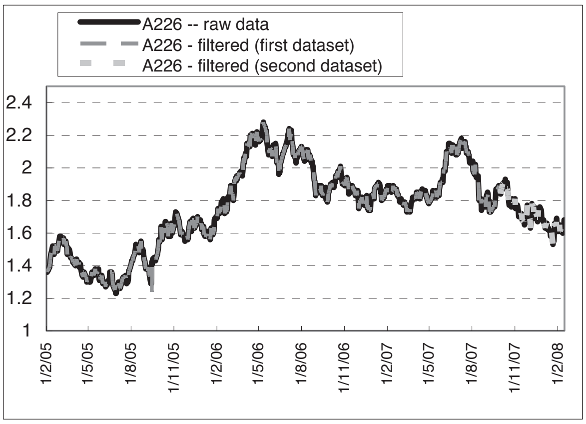
A204 optimal solution (first dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.4	
	outlier	not outlier
detected	34	0
not detected	4	0
Ratio detection	89.47	
Di	0	
Number of outliers above or below Xi+/-σ	0	



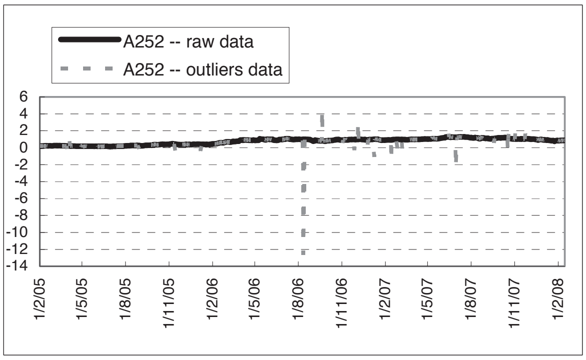
A204 optimal solution (second dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.4	
	outlier	not outlier
detected	3	1
not detected	0	93
Ratio detection	100.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



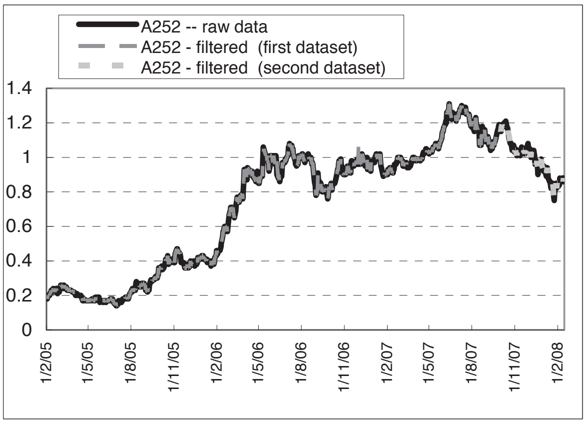
A226 optimal solution (first dataset)		
window length	6	
lambda parameter	0.1	
threshold	1	
	outlier	not outlier
detected	28	0
not detected	2	667
Ratio detection	93.33	
Di	0	
Number of outliers above or below Xi+/-σ	0	



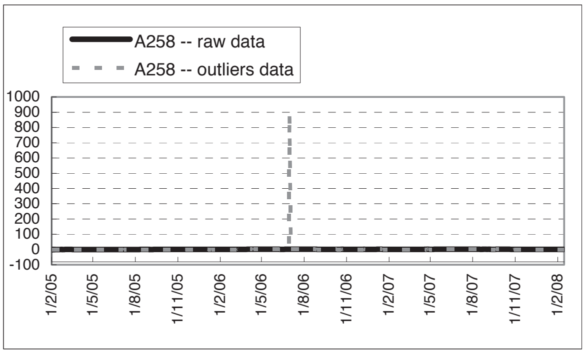
A226 optimal solution (second dataset)		
window length	6	
lambda parameter	0.1	
threshold	1	
	outlier	not outlier
detected	6	0
not detected	0	91
Ratio detection	100.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



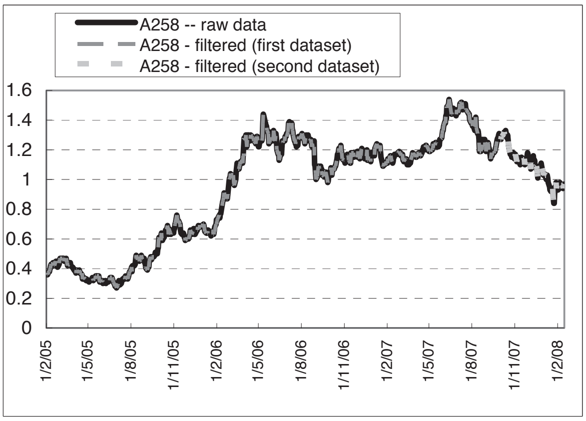
A252 optimal solution (first dataset)		
window length	5	
lambda parameter	0.1	
threshold	1	
	outlier	not outlier
detected	31	1
not detected	2	663
Ratio detection	93.94	
Di	0	
Number of outliers above or below Xi+/-σ	0	



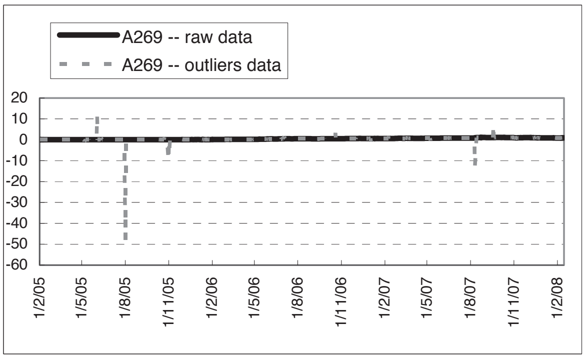
A252 optimal solution (second dataset)		
window length	5	
lambda parameter	0.1	
threshold	1	
	outlier	not outlier
detected	5	0
not detected	0	92
Ratio detection	100.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



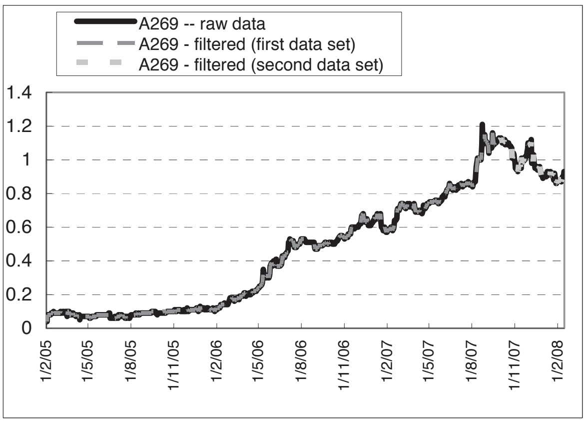
A258 optimal solution (first dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.2	
	outlier	not outlier
detected	21	0
not detected	0	676
Ratio detection	100.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



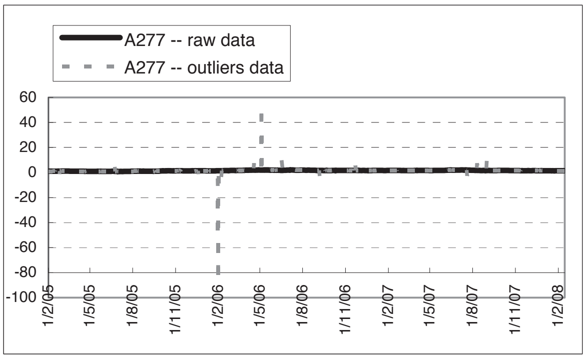
A258 optimal solution (second dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.2	
	outlier	not outlier
detected	4	0
not detected	0	93
Ratio detection	100.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



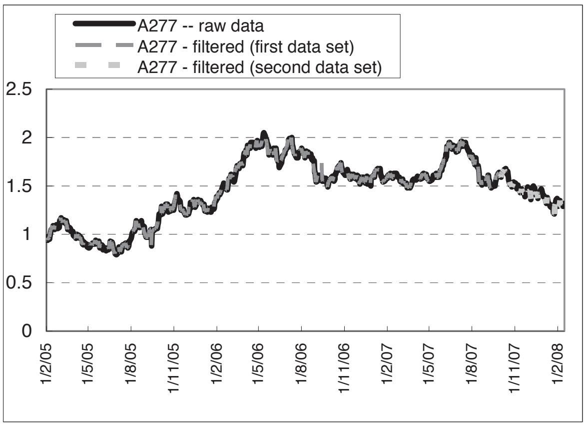
A269 optimal solution (first dataset)		
window length	5	
lambda parameter	0.1	
threshold	1	
	outlier	not outlier
detected	30	1
not detected	2	664
Ratio detection	93.75	
Di	0	
Number of outliers above or below Xi+/-σ	0	



A269 optimal solution (second dataset)		
window length	5	
lambda parameter	0.1	
threshold	1	
	outlier	not outlier
detected	2	1
not detected	2	92
Ratio detection	50.00	
Di	2	
Number of outliers above or below Xi+/-σ	0.0014	



A277 optimal solution (first dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.2	
	outlier	not outlier
detected	27	0
not detected	3	667
Ratio detection	90.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	



A277 optimal solution (second dataset)		
window length	5	
lambda parameter	0.1	
threshold	1.2	
	outlier	not outlier
detected	2	0
not detected	0	95
Ratio detection	100.00	
Di	0	
Number of outliers above or below Xi+/-σ	0	

Table. Description of the variables used in the clustering exercise.

	Type of instrument	*Description*
A1	*Bonds*	*Interest Rate Benchmark Bond- 10-year Government Bond Index- Redemption Yield.*
A2	*Bonds*	*Merryll Lynch US Corporate A bond. 7 to 10 years (E) - Redemption yield.*
A3	*Bonds*	*Merryll Lynch US Corporate AA bond. 7 to 10 years (E) - Redemption yield.*
A4	*Bonds*	*Merryll Lynch US Corporate AAA bond. 7 to 10 years (E) - Redemption yield.*
A5	*Bonds*	*Merryl Lynch EMU Direct Government. 7 to 10 years (E) - Redemption yield.*
A6	*Bonds*	*Merryll Lynch EMU Corporate A bond. 7 to 10 years (E) - Redemption yield.*
A7	*Bonds*	*Merryll Lynch EMU Corporate AA bond. 7 to 10 years (E) - Redemption yield.*
A8	*Bonds*	*Merryll Lynch EMU Corporate AAA bond. 7 to 10 years (E) - Redemption yield.*
A9	*Bonds*	*Merryll Lynch EMU Corporate BBB bond. 7 to 10 years (E) - Redemption yield.*
A10	*Bonds*	*Merryll Lynch US Corporate BBB bond. 7 to 10 years (E) - Redemption yield.*
A11	*Bonds*	*Merryll Lynch US Treasury 7 to 10 Years ($) - Redemption Yield.*
A12	*Bonds*	*France - Government bond - Long term 10 years - Yield.*
A13	*Bonds*	*France - Government bond - Long term 11 years indexed-linked bonds- Yield.*
A14	*Bonds*	*France - Government bond - Long term 10 years- Yield.*
A15	*Bonds*	*Japan - Benchmark bond - Real Japan 10-year Government Benchmark bond yield - Yield - Japanese yen.*
A16	*Bonds*	*Euro area (changing composition) 10-year Government Benchmark bond yield - Yield - Euro.*
A17	*Bonds*	*Euro area (changing composition) 2-year Government Benchmark bond yield - Yield - Euro.*
A18	*Bonds*	*Euro area (changing composition) 3-year Government Benchmark bond yield - Yield - Euro.*
A19	*Bonds*	*Euro area (changing composition) 5-year Government Benchmark bond yield - Yield - Euro.*
A20	*Bonds*	*Euro area (changing composition) 7-year Government Benchmark bond yield - Yield - Euro.*
A21	*Bonds*	*United States USA 10-year Government Benchmark bond yield - Yield - US dollar.*
A22	*Bonds*	*United States 30-year nominal bond issued by US Treasury - Yield - US dollar.*
A23	*Bonds*	*United States - Benchmark bond - 10-year inflation linked bond issued by US Treasury- TIPS (Treasury Inflation protected securities) - Yield - US dollar.*
A24	*Bonds*	*United States - Benchmark bond - 10-year inflation linked bond issued by US Treasury- TIPS (Treasury Inflation protected securities) - Yield - US dollar.*
A25	*Bonds*	*United States - Benchmark bond - 10-year inflation linked bond issued by US Treasury- TIPS (Treasury Inflation protected securities) - Yield - US dollar.*
A26	*Bonds*	*United States - Benchmark bond - 10-year inflation linked bond issued by US Treasury- TIPS (Treasury Inflation protected securities) - Yield - US dollar.*
A27	*Bonds*	*United States - Benchmark bond - 5-year nominal bond issued by US Treasury- Yield - US dollar.*
A28	*Bonds*	*United States - Government bond - Long term 10 years- Yield- US dollar.*
A29	*Bonds*	*United States - Government bond - Long term 10 years indexed linked- Yield- US dollar.*
A30	*Bonds*	*United States - Government bond series - 10 year - redemption yield .*
A31	*Bonds*	*Austria - Benchmark bond - 10-year Austria Government Benchmark bond yield - Yield – Euro.*
A32	*Bonds*	*Austria - Benchmark bond - 2-year Austria Government Benchmark bond yield - Yield – Euro.*
A33	*Bonds*	*Austria - Benchmark bond - 3-year Austria Government Benchmark bond yield - Yield – Euro.*
A34	*Bonds*	*Austria - Benchmark bond - 5-year Austria Government Benchmark bond yield - Yield – Euro.*
A35	*Bonds*	*Austria - Benchmark bond - 7-year Austria Government Benchmark bond yield - Yield – Euro.*
A36	*Bonds*	*Belgium - Benchmark bond - 10-year Belgium Government Benchmark bond yield - Yield – Euro.*
A37	*Bonds*	*Belgium - Benchmark bond - 2-year Belgium Government Benchmark bond yield - Yield – Euro.*
A38	*Bonds*	*Belgium - Benchmark bond - 3-year Belgium Government Benchmark bond yield - Yield – Euro.*
A39	*Bonds*	*Belgium - Benchmark bond -5-year Belgium Government Benchmark bond yield - Yield – Euro.*
A40	*Bonds*	*Belgium - Benchmark bond -7-year Belgium Government Benchmark bond yield - Yield – Euro.*
A41	*Bonds*	*Germany - Benchmark bond -10-year Germany Government Benchmark bond yield - Yield - Euro, .*
A42	*Bonds*	*Germany - Benchmark bond -2-year Germany Government Benchmark bond yield - Yield - Euro, .*
A43	*Bonds*	*Germany - Benchmark bond -3-year Germany Government Benchmark bond yield - Yield – Euro.*
A44	*Bonds*	*Germany - Benchmark bond -5-year Germany Government Benchmark bond yield - Yield – Euro.*
A45	*Bonds*	*Germany - Benchmark bond -7-yearGermany Government Benchmark bond yield – Euro.*
A46	*Bonds*	*Spain - Benchmark bond -10-year Spain Government Benchmark bond yield - Yield – Euro.*
A47	*Bonds*	*Spain - Benchmark bond -2-year Spain Government Benchmark bond yield - Yield – Euro.*
A48	*Bonds*	*Spain - Benchmark bond -3-year Spain Government Benchmark bond yield - Yield – Euro.*
A49	*Bonds*	*Spain - Benchmark bond -5-year Spain Government Benchmark bond yield - Yield – Euro.*
A50	*Bonds*	*Spain - Benchmark bond -7-year Spain Government Benchmark bond yield - Yield – Euro.*
A51	*Bonds*	*Euro area 30-year Euro area Government Benchmark bond yield - Yield - Euro.*
A52	*Bonds*	*Finland - Benchmark bond -10-year Finland Government Benchmark bond yield - Yield – Euro.*
A53	*Bonds*	*Finland - Benchmark bond -2-yearFinland Government Benchmark bond yield - Yield – Euro.*
A54	*Bonds*	*Finland - Benchmark bond -3-yearFinland Government Benchmark bond yield - Yield – Euro.*
A55	*Bonds*	*Finland - Benchmark bond -5-year Finland Government Benchmark bond yield - Yield – Euro.*
A56	*Bonds*	*France - Benchmark bond -10-year France Government Benchmark bond yield – Euro.*
A57	*Bonds*	*France - Benchmark bond -2-yearFrance Government Benchmark bond yield – Euro.*
A58	*Bonds*	*France - Benchmark bond -3-year France Government Benchmark bond yield - Yield – Euro.*
A59	*Bonds*	*France - Benchmark bond -5-year France Government Benchmark bond yield - Yield – Euro.*
A60	*Bonds*	*France - Benchmark bond -7-yearFrance Government Benchmark bond yield - Yield – Euro.*
A61	*Bonds*	*France - Benchmark bond.30-year long term Treasury bond.*
A62	*Bonds*	*Great Britain - Benchmark bond- 30-year government bond .*
A63	*Bonds*	*Greece - Benchmark bond -10-year Greece Government Benchmark bond yield - Yield – Euro.*
A64	*Bonds*	*Greece - Benchmark bond -2-year Greece Government Benchmark bond yield - Yield – Euro.*
A65	*Bonds*	*Greece - Benchmark bond -3-year Greece Government Benchmark bond yield - Yield – Euro.*
A66	*Bonds*	*Greece - Benchmark bond -5-year Greece Government Benchmark bond yield - Yield – Euro.*
A67	*Bonds*	*Greece - Benchmark bond -7-yearGreece Government Benchmark bond yield - Yield – Euro .*

A68	Bonds	Ireland - Benchmark bond -3-yearIreland Government Benchmark bond yield - Yield – Euro.
A69	Bonds	Italy - Benchmark bond -10-yearItaly Government Benchmark bond yield - Yield – Euro.
A70	Bonds	Italy - Benchmark bond -2-yearItaly Government Benchmark bond yield - Yield – Euro.
A71	Bonds	Italy - Benchmark bond -3-yearItaly Government Benchmark bond yield - Yield – Euro.
A72	Bonds	Italy - Benchmark bond -5-yearItaly Government Benchmark bond yield - Yield – Euro.
A73	Bonds	Japan - Benchmark bond - Japan 10-year Government Benchmark bond yield - Yield - Japanese yen.
A74	Bonds	Japan - Benchmark bond - Japan 10-year Government Benchmark bond yield - Yield - Japanese yen.
A75	Bonds	Japan - Benchmark bond - Japan 5-year Government Benchmark bond yield - Yield – Japanese yen.
A76	Bonds	Netherlands - Benchmark bond -10-year Netherlands Government Benchmark bond yield - Yield – Euro.
A77	Bonds	Netherlands - Benchmark bond -2-year Netherlands Government Benchmark bond yield - Yield – Euro.
A78	Bonds	Netherlands - Benchmark bond -3-year Netherlands Government Benchmark bond yield - Yield – Euro.
A79	Bonds	Netherlands - Benchmark bond -5-year Netherlands Government Benchmark bond yield - Yield – Euro.
A80	Bonds	Netherlands - Benchmark bond -7-year Netherlands Government Benchmark bond yield - Yield – Euro.
A81	Bonds	Portugal - Benchmark bond -10-year Portugal Government Benchmark bond yield - Yield – Euro.
A82	Bonds	Portugal - Benchmark bond -2-yearPortugal Government Benchmark bond yield - Yield – Euro.
A83	Bonds	Portugal - Benchmark bond -3-yearPortugal Government Benchmark bond yield - Yield – Euro.
A84	Bonds	Portugal - Benchmark bond -5-yearPortugal Government Benchmark bond yield - Yield – Euro.
A85	Bonds	Portugal - Benchmark bond -7-yearPortugal Government Benchmark bond yield - Yield – Euro.
A86	Bonds	Sweden - Benchmark bond - Sweden 10-years Government Benchmark bond yield- Yield - Swedish krona .
A87	Bonds	Sweden - Benchmark bond - Sweden 2-years Government Benchmark bond yield- Yield - Swedish krona .
A88	Bonds	Sweden - Benchmark bond - Sweden 5-years Government Benchmark bond yield- Yield - Swedish krona .
A89	Bonds	United States - Benchmark bond - USA 2-year Government Benchmark bond yield - Yield - US dollar .
A90	Bonds	United States - Benchmark bond - USA 30-year Government Benchmark bond yield- Yield - US dollar .
A91	Bonds	United States - Benchmark bond - USA 5-year Government Benchmark bond yield- Yield - US dollar .
A92	Bonds	United States - Benchmark bond - 10-year inflation linked bond issued by US Treasury- TIPS (Treasury Inflation protected securities) - Yield - US dollar .
A93	Bonds	United States - Benchmark bond - 30-year inflation linked bond issued by US Treasury- TIPS (Treasury Inflation protected securities) - Ask price or primary activity - US dollar .
A94	Bonds	United States - Benchmark bond - 30-year inflation linked bond issued by US Treasury- TIPS (Treasury Inflation protected securities) - Bid price or secondary activity - US dollar.
A95	Bonds	United States - Benchmark bond - 30-year inflation linked bond issued by US Treasury- TIPS (Treasury Inflation protected securities) - Yield - US dollar .
A96	Bonds	United States - Benchmark bond - 30-year inflation linked bond issued by US Treasury- TIPS (Treasury Inflation protected securities) - Secondary yield - US dollar .
A97	Bonds	France - Government bond - Long term 30 years – Yield. (FR0000186413)
A98	Bonds	France - Government bond - Long term 30 years – Yield. (FR0000187635)
A99	Bonds	France - Government bond - Long term 30 years - Yield. (FR0000188013)
A100	Bonds	France - Government bond - Long term 10 years – Yield. (FR0000188328)
A101	Bonds	France - Government bond - Long term 30 years – Yield . (FR0000188799)
A102	Bonds	France - Government bond - Long term 10 years – Yield . (FR0000188955)
A103	Bonds	France - Government bond - Long term 10 years – Yield. (FR0000188989)
A104	Bonds	France - Government bond - Long term 15 years – Yield . (FR0000189151)
A105	Bonds	France - Government bond - Long term 15 years – Yield . (FR0000570780)
A106	Bonds	France - Government bond - Long term 30 years – Yield . (FR0000188013)
A107	Bonds	France - Government bond - Long term 10 years – Yield . (FR0000571424)
A108	Bonds	France - Government bond - Long term 10 years – Yield . (FR0000571432)
A109	Bonds	France - Government bond - Long term 15 years – Yield . (FR0010050559)
A110	Bonds	Greece - Government bond - Long term 10 years – Yield . (GR22102220G)
A111	Bonds	Greece - Government bond - Long term 20 years – Yield . (GR25072522G)
A112	Bonds	Italy - Government bond - Long term 10 years – Yield. (IT361838)
A113	Bonds	Italy - Government bond - Long term 10 years – Yield . (IT362590)
A114	Bonds	Italy - Government bond - Long term 5 years – Yield . (IT353209)
A115	Bonds	Italy - Government bond - Long term 5 years – Yield.. (IT353291)
A116	Bonds	United Kingdom - Benchmark bond - United Kingdom government bond inflation linked, gilt 2.5% with maturity 5/20/09- Yield - UK pound sterling, .
A117	Bonds	United Kingdom - Government bond - Long term 20 years - Yield . (GBIL2H13)
A118	Bonds	United Kingdom - Government bond - Long term 20 years – Yield . (GBIL4E30)
A119	Bonds	United Kingdom - Benchmark bond - United Kingdom government bond inflation linked, gilt 4.125% with maturity 7/22/30 - Yield - UK pound sterling .
A120	Bonds	United Kingdom - Government bond - Long term 30 years – Yield. (GBT628)
A121	Bonds	United Kingdom - Government bond - Long term 20 years - Yield. (GBT813)
A122	Equity indices	NIKKEI 225 stock average - price index.
A123	Equity indices	OMX VGI Vilnius index - price index- Lithuanian litas .
A124	Equity indices	Dow Jones EURO STOXX 50 - price index - Euro.
A125	Equity indices	Dow Jones EURO STOXX - price index - Euro.
A126	Equity indices	Dow Jones EURO STOXX basic materials - price index - Euro.
A127	Equity indices	Dow Jones EURO STOXX consumer goods - price index - Euro.
A128	Equity indices	Dow Jones EURO STOXX consumer services - price index - Euro.
A129	Equity indices	Dow Jones EURO STOXX financials - price index - Euro.
A130	Equity indices	Dow Jones EURO STOXX technology - price index - Euro.
A131	Equity indices	Dow Jones EURO STOXX healthcare - price index - Euro.
A132	Equity indices	Dow Jones EURO STOXX industrials - price index - Euro.
A133	Equity indices	Dow Jones EURO STOXX oil & gas - price index - Euro.

A134	Equity indices	Dow Jones EURO STOXX telecom - price index - Euro.
A135	Equity indices	Dow Jones EURO STOXX utilities - price index - Euro.
A136	Equity indices	Standard & Poor's 500 composite - price index - Euro.
A137	Equity indices	Dow Jones EURO STOXX 50 - price index - Euro .
A138	Equity indices	Euro area (changing composition) - Equity/index - Dow Jones Euro STOXX 50 - Price index - Historical close, average of observations through period – Euro.
A139	Equity indices	United States - Equity/index (put) - NASDAQ COMPOSITE- Price index - Historical close - US dollar .
A140	Equity indices	United States - Equity/index - Nasdaq Equity Index - Last trade price or value - US dollar .
A141	Futures	Euro area (changing composition) - Futures - LIFFE- 3 months EURIBOR - Expiry March 2007 - Implied interest rate - Euro.
A142	Futures	Euro area (changing composition) - Futures - LIFFE- 3 months EURIBOR - Expiry September 2006 - Implied interest rate - Euro.
A143	Futures	Euro area (changing composition) - Futures - LIFFE- 3 months EURIBOR - Expiry December 2006 - Implied interest rate - Euro.
A144	Implied Volatilities	Japan - Implied volatility on call options for the 10 year Japanese bond. Tokio Stock Exchange .
A145	Implied Volatilities	Japan - Implied volatility on put options for the 10 year Japanese bond. Tokio Stock Exchange .
A146	Implied Volatilities	Europe - Implied volatility on call options for the Euro-bund. Eurex Deutschland - Frankfurt.
A147	Implied Volatilities	Europe - Implied volatility on put options for the Euro-bund. Eurex Deutschland - Frankfurt .
A148	Implied Volatilities	United States - Implied volatility on call options for the US 10 year note. Chicago board of Trade .
A149	Implied Volatilities	United States - Implied volatility on put options for the US 10 year note. Chicago board of Trade .
A150	Implied Volatilities	Japan - Implied volatility on call options for the NKY-Nikkei 225 index. Tokio Stock Exchange .
A151	Implied Volatilities	Japan - Implied volatility on put options for the NKY-Nikkei 225 index. Tokio Stock Exchange .
A152	Implied Volatilities	United States - Implied volatility on call options for the SPX - S&P 500 index. American Stock Exchange .
A153	Implied Volatilities	United States - Implied volatility on put options for the SPX - S&P 500 index. American Stock Exchange .
A154	Implied Volatilities	Europe - Implied volatility on call options for the SX5E-Dow Jones Euro Stoxx 50. Frankfurt Stock Exchange .
A155	Implied Volatilities	Europe - Implied volatility on put options for the SX5E-Dow Jones Euro Stoxx 50. Frankfurt Stock Exchange .
A156	Money market	Denmark - Money Market - Denmark interbank 3 month - offered rate - Ask price or primary activity, average of observations through period - Danish krone.
A157	Money market	United Kingdom - Money Market - Money market, Pound sterling, Libor, 3 months - Last trade price or value - UK pound sterling, .
A158	Money market	Japan - Money Market - 3-month Libor interbank Japanese Yen deposit rate - Last trade price or value - Japanese yen .
A159	Money market	Euro area (changing composition) - Money Market - Eonia rate - Last trade price or value - Euro.
A160	Money market	Euro area (changing composition) - Money Market - Eonia rate - Last trade price or value - Euro.
A161	Money market	Reuters.Money market.US Dollar.Libor.3 months.Last
A162	Money market	Denmark, Money Market, 1-month interbank Danish krone deposit rate .
A163	Money market	Denmark, Money Market, 1 year interbank Danish krone deposit rate .
A164	Money market	Denmark, Money Market, 3-month interbank Danish krone deposit rate .
A165	Money market	Denmark, Money Market, 6-month interbank Danish krone deposit rate .
A166	Money market	Denmark, Money Market, overnight interbank Danish krone deposit rate .
A167	Money market	Euro area (changing composition) - Money Market - 3-month interbank EUR deposit rate - Ask price or primary activity - Euro .
A168	Money market	Euro area (changing composition) - Money Market - 3-month interbank EUR deposit rate - Bid price or secondary activity - Euro .
A169	Money market	Euro area (changing composition), Money market rates, Money market, Euro, Euribor 360, 1 month .
A170	Money market	Euro area (changing composition), Money market rates, Money market, Euro, Euribor 360, 1 year .
A171	Money market	Euro area (changing composition), Money market rates, Money market, Euro, Euribor 360, 2 months .
A172	Money market	Euro area (changing composition), Money market rates, Money market, Euro, Euribor 360, 3 months.
A173	Money market	Euro area (changing composition), Money market rates, Money market, Euro, Euribor 360, 4 months .
A174	Money market	Euro area (changing composition), Money market rates, Money market, Euro, Euribor 360, 3 months .
A175	Money market	Euro area (changing composition), Money market rates, Money market, Euro, Euribor 360, 6 months .
A176	Money market	United Kingdom - Money Market - 1-month interbank Pound sterling deposit rate - Ask price or primary activity - UK pound sterling, .
A177	Money market	United Kingdom - Money Market - 1-year interbank Pound sterling deposit rate - Ask price or primary activity - UK pound sterling .
A178	Money market	United Kingdom - Money Market - 3-month interbank Pound sterling deposit rate - Ask price or primary activity - UK pound sterling .
A179	Money market	United Kingdom - Money Market - 6-month interbank Pound sterling deposit rate - Ask price or primary activity - UK pound sterling,.
A180	Money market	United Kingdom - Money Market - overnight interbank Pound sterling deposit rate - Ask price or primary activity - UK pound sterling .
A181	Money market	Japan - Money Market - Real 3-month Libor interbank Japanese Yen deposit rate - Last trade price or value - Japanese yen .
A182	Money market	Japan - Money Market - 3-month Libor interbank Japanese Yen deposit rate - Last trade price or value - Japanese yen .
A183	Money market	Sweden, Money Market, 1-month interbank Swedish krone deposit rate .
A184	Money market	Sweden, Money Market, 1 year interbank Swedish krone deposit rate .
A185	Money market	Sweden, Money Market, 3-month interbank Swedish krone deposit rate .
A186	Money market	Sweden, Money Market, 6-month interbank Swedish krone deposit rate .
A187	Money market	Sweden, Money Market, overnight interbank Swedish krone deposit rate .
A188	Money market	United States, Money market rates, Money market, US Dollar, Deposit, 1 month .
A189	Money market	United States Money Market - 3-month Libor interbank USD deposit rate - Last trade price or value - US dollar.
A190	Swaps	Euro area (changing composition) - Interest rate swaps - 10-year euro swap rate with annual settlement and compounding vs 6-month Euribor (ACT/360) - Ask price or primary activity - Euro .

A191	*Swaps*	*Euro area (changing composition) - Interest rate swaps -10-year euro swap rate with annual settlement and compounding vs 6-month Euribor (ACT/360)- Bid price or secondary activity - Euro .*
A192	*Swaps*	*Euro area (changing composition) - Interest rate swaps - 2-year euro swap rate with annual settlement and compounding vs 6-month Euribor (ACT/360)- Bid price or secondary activity - Euro .*
A193	*Swaps*	*Euro area (changing composition) - Interest rate swaps -3-year euro swap rate with annual settlement and compounding vs 6-month Euribor (ACT/360) - Bid price or secondary activity - Euro .*
A194	*Swaps*	*Euro area (changing composition) - Interest rate swaps -5-year euro swap rate with annual settlement and compounding vs 6-month Euribor (ACT/360)- Bid price or secondary activity - Euro .*
A195	*Swaps*	*Euro area (changing composition) - Interest rate swaps - 7-year euro swap rate with annual settlement and compounding vs 6-month Euribor (ACT/360)- Bid price or secondary activity - Euro .*
A196	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 10 months- Ask price or primary activity - Euro .*
A197	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 10 months- Bid price or secondary activity - Euro .*
A198	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 11 months- Ask price or primary activity – Euro .*
A199	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 11 months- Bid price or secondary activity – Euro.*
A200	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 1 month- Ask price or primary activity - Euro .*
A201	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 1 month- Bid price or secondary activity - Euro.*
A202	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 1 week- Ask price or primary activity – Euro.*
A203	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 1 week - Bid price or secondary activity – Euro.*
A204	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 1 year - Ask price or primary activity – Euro.*
A205	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 1 year- Bid price or secondary activity – Euro.*
A206	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 2 months- Ask price or primary activity – Euro.*
A207	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 2 months- Bid price or secondary activity – Euro.*
A208	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 2 weeks- Ask price or primary activity – Euro.*
A209	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 2 weeks- Bid price or secondary activity - Euro.*
A210	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 3 months- Ask price or primary activity – Euro.*
A211	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 3 months- Bid price or secondary activity – Euro.*
A212	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 3 weeks- Ask price or primary activity – Euro.*
A213	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 3 weeks- Bid price or secondary activity - Euro.*
A214	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 4 months- Ask price or primary activity – Euro.*
A215	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 4 months- Bid price or secondary activity – Euro.*
A216	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 5 months- Ask price or primary activity – Euro.*
A217	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 5 months- Bid price or secondary activity – Euro.*
A218	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 6 months- Ask price or primary activity – Euro.*
A219	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 6 months- Bid price or secondary activity - Euro.*
A220	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 7 months- Ask price or primary activity - Euro.*
A221	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 7 months- Bid price or secondary activity - Euro.*
A222	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 8 months- Ask price or primary activity – Euro.*
A223	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 8 months- Bid price or secondary activity - Euro.*
A224	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 9 months- Ask price or primary activity - Euro.*
A225	*Swaps*	*Interest rate swaps (put) - Swap, Euro, Money market, Eonia, 9 months- Bid price or secondary activity - Euro .*
A226	*Swaps*	*Japan - Interest rate swaps - 10-year euro swap rate with semi-annual fixed rate vs, 6-month LIBOR (ACT/360)- Ask price or primary activity - Japanese yen, .*
A227	*Swaps*	*Japan - Interest rate swaps - 10-year euro swap rate with semi-annual fixed rate vs, 6-month LIBOR (ACT/360)- Bid price or secondary activity - Japanese yen.*
A228	*Swaps*	*United States - Interest rate swaps (put) - Swap, US Dollar, Annual Money, 3-month Libor, 10 years - Ask price or primary activity - US dollar .*
A229	*Swaps*	*United States - Interest rate swaps (put) - Swap, US Dollar, Annual Money, 3-month Libor, 10 years - Bid price or secondary activity - US dollar .*
A230	*Swaps*	*Euro area (changing composition) - Interest rate swaps - Fixed rate, European inflation swaps, Harmonised Index of Consumer Price Index - all items excluding tobacco for the Eurozone, Zero coupon, 10 years - Last trade price or value - Euro.*
A231	*Swaps*	*Euro area (changing composition) - Interest rate swaps - Fixed rate, European inflation swaps, Harmonised Index of Consumer Price Index - all items excluding tobacco for the Eurozone, Zero coupon, 12 years - Last trade price or value - Euro .*
A232	*Swaps*	*Euro area (changing composition) - Interest rate swaps - Fixed rate, European inflation swaps, Harmonised Index of Consumer Price Index - all items excluding tobacco for the Eurozone, Zero coupon, 15 years - Last trade price or value - Euro .*
A233	*Swaps*	*Euro area (changing composition) - Interest rate swaps - Fixed rate, European inflation swaps, Harmonised Index of Consumer Price Index - all items excluding tobacco for the Eurozone, Zero coupon, 2 years - Last trade price or value - Euro .*
A234	*Swaps*	*Euro area (changing composition) - Interest rate swaps - Fixed rate, European inflation swaps, Harmonised Index of Consumer Price Index - all items excluding tobacco for the Eurozone, Zero coupon, 20 years - Last trade price or value - Euro .*
A235	*Swaps*	*Euro area (changing composition) - Interest rate swaps - Fixed rate, European inflation swaps, Harmonised Index of Consumer Price Index - all items excluding tobacco for the Eurozone, Zero coupon, 25 years - Last trade price or value - Euro .*
A236	*Swaps*	*Euro area (changing composition) - Interest rate swaps - Fixed rate, European inflation swaps, Harmonised Index of Consumer Price Index - all items excluding tobacco for the Eurozone, Zero coupon, 3 years - Last trade price or value - Euro .*
A237	*Swaps*	*Euro area (changing composition) - Interest rate swaps - Fixed rate, European inflation swaps, Harmonised Index of Consumer Price Index - all items excluding tobacco for the Eurozone, Zero coupon, 30 years - Last trade price or value – Euro .*
A238	*Swaps*	*Euro area (changing composition) - Interest rate swaps - Fixed rate, European inflation swaps, Harmonised Index of Consumer Price Index - all items excluding tobacco for the Eurozone, Zero coupon, 4 years - Last trade price or value – Euro .*

A239	Swaps	Euro area (changing composition) - Interest rate swaps - Fixed rate, European inflation swaps, Harmonised Index of Consumer Price Index - all items excluding tobacco for the Eurozone, Zero coupon, 5 years - Last trade price or value - Euro .
A240	Swaps	Euro area (changing composition) - Interest rate swaps - Fixed rate, European inflation swaps, Harmonised Index of Consumer Price Index - all items excluding tobacco for the Eurozone, Zero coupon, 6 years - Last trade price or value - Euro .
A241	Swaps	Euro area (changing composition) - Interest rate swaps - Fixed rate, European inflation swaps, Harmonised Index of Consumer Price Index - all items excluding tobacco for the Eurozone, Zero coupon, 7 years - Last trade price or value - Euro .
A242	Swaps	Euro area (changing composition) - Interest rate swaps - Fixed rate, European inflation swaps, Harmonised Index of Consumer Price Index - all items excluding tobacco for the Eurozone, Zero coupon, 8 years - Last trade price or value – Euro .
A243	Swaps	Euro area (changing composition) - Interest rate swaps - Fixed rate, European inflation swaps, Harmonised Index of Consumer Price Index - all items excluding tobacco for the Eurozone, Zero coupon, 9 years - Last trade price or value - Euro .
A244	Zero coupons	Japan - 10-years zero coupon yield. Historical close.
A245	Zero coupons	Japan - 1-month zero coupon yield. Historical close.
A246	Zero coupons	Japan - 1-week zero coupon yield. Historical close.
A247	Zero coupons	Japan - 1 year and 3-months zero coupon yield. Historical close.
A248	Zero coupons	Japan - 1 year and 6-months zero coupon yield. Historical close.
A249	Zero coupons	Japan - 1 year and 9-months zero coupon yield. Historical close.
A250	Zero coupons	Japan - 1 year zero coupon yield. Historical close.
A251	Zero coupons	Japan - 2-months zero coupon yield. Historical close.
A252	Zero coupons	Japan - 2-years and 3-months zero coupon yield. Historical close.
A253	Zero coupons	Japan - 2-years and 6-months zero coupon yield. Historical close.
A254	Zero coupons	Japan - 2-years and 9-months zero coupon yield. Historical close.
A255	Zero coupons	Japan - 2 years zero coupon yield. Historical close.
A256	Zero coupons	Japan - 3-months zero coupon yield. Historical close.
A257	Zero coupons	Japan - 3-years and 3-months zero coupon yield. Historical close.
A258	Zero coupons	Japan - 3-years and 6-months zero coupon yield. Historical close.
A259	Zero coupons	Japan - 3-years and 9-months zero coupon yield. Historical close.
A260	Zero coupons	Japan - 3-years zero coupon yield. Historical close.
A261	Zero coupons	Japan - 4-years and 3-months zero coupon yield. Historical close.
A262	Zero coupons	Japan - 4-years and 6-months zero coupon yield. Historical close.
A263	Zero coupons	Japan - 4-years and 9-months zero coupon yield. Historical close.
A264	Zero coupons	Japan - 4 years zero coupon yield. Historical close.
A265	Zero coupons	Japan - 5-years and 3-months zero coupon yield. Historical close.
A266	Zero coupons	Japan - 5-years and 6-months zero coupon yield. Historical close.
A267	Zero coupons	Japan - 5-years and 9-months zero coupon yield. Historical close.
A268	Zero coupons	Japan - 5 years zero coupon yield. Historical close.
A269	Zero coupons	Japan - 6-months zero coupon yield. Historical close.
A270	Zero coupons	Japan - 6-years and 3-months zero coupon yield. Historical close.
A271	Zero coupons	Japan - 6-years and 6-months zero coupon yield. Historical close.
A272	Zero coupons	Japan - 6-years and 9-months zero coupon yield. Historical close.
A273	Zero coupons	Japan - 6 years zero coupon yield. Historical close.
A274	Zero coupons	Japan - 7-years and 3-months zero coupon yield. Historical close.
A275	Zero coupons	Japan - 7-years and 6-months zero coupon yield. Historical close.
A276	Zero coupons	Japan - 7-years and 9-months zero coupon yield. Historical close.
A277	Zero coupons	Japan - 7 years zero coupon yield. Historical close.
A278	Zero coupons	Japan - 8-years and 6-months zero coupon yield. Historical close.
A279	Zero coupons	Japan - 8 years zero coupon yield. Historical close.
A280	Zero coupons	Japan - 9-months zero coupon yield. Historical close.
A281	Zero coupons	Japan - 9-years and 6-months zero coupon yield. Historical close.
A282	Zero coupons	Japan - 9 years zero coupon yield. Historical close.
A283	Zero coupons	United States - 10-years zero coupon yield. Historical close.
A284	Zero coupons	United States - 1-month zero coupon yield. Historical close.
A285	Zero coupons	United States - 1-week zero coupon yield. Historical close.
A286	Zero coupons	United States - 1 year and 3-months zero coupon yield. Historical close.
A287	Zero coupons	United States - 1 year and 6-months zero coupon yield. Historical close.
A288	Zero coupons	United States - 1 year and 9-months zero coupon yield. Historical close.
A289	Zero coupons	United States - 1 year zero coupon yield. Historical close.
A290	Zero coupons	United States - 2-months zero coupon yield. Historical close.
A291	Zero coupons	United States - 2-years and 3-months zero coupon yield. Historical close.
A292	Zero coupons	United States - 2-years and 6-months zero coupon yield. Historical close.
A293	Zero coupons	United States - 2-years and 9-months zero coupon yield. Historical close.
A294	Zero coupons	United States - 2 years zero coupon yield. Historical close.
A295	Zero coupons	United States - 3-months zero coupon yield. Historical close.
A296	Zero coupons	United States - 3-years and 3-months zero coupon yield. Historical close.
A297	Zero coupons	United States - 3-years and 6-months zero coupon yield. Historical close.
A298	Zero coupons	United States - 3-years and 9-months zero coupon yield. Historical close.
A299	Zero coupons	United States - 3-years zero coupon yield. Historical close.
A300	Zero coupons	United States - 4-years and 3-months zero coupon yield. Historical close.
A301	Zero coupons	United States - 4-years and 6-months zero coupon yield. Historical close.
A302	Zero coupons	United States - 4-years and 9-months zero coupon yield. Historical close.

A303	*Zero coupons*	*United States - 4 years zero coupon yield. Historical close.*
A304	*Zero coupons*	*United States - 5-years and 3-months zero coupon yield. Historical close.*
A305	*Zero coupons*	*United States - 5-years and 6-months zero coupon yield. Historical close.*
A306	*Zero coupons*	*United States - 5-years and 9-months zero coupon yield. Historical close.*
A307	*Zero coupons*	*United States - 5 years zero coupon yield. Historical close.*
A308	*Zero coupons*	*United States - 6-months zero coupon yield. Historical close.*
A309	*Zero coupons*	*United States - 6-years and 3-months zero coupon yield. Historical close.*
A310	*Zero coupons*	*United States - 6-years and 6-months zero coupon yield. Historical close.*
A311	*Zero coupons*	*United States - 6-years and 9-months zero coupon yield. Historical close.*
A312	*Zero coupons*	*United States - 6 years zero coupon yield. Historical close.*
A313	*Zero coupons*	*United States - 7-years and 3-months zero coupon yield. Historical close.*
A314	*Zero coupons*	*United States - 7-years and 6-months zero coupon yield. Historical close.*
A315	*Zero coupons*	*United States - 7-years and 9-months zero coupon yield. Historical close.*
A316	*Zero coupons*	*United States - 7 years zero coupon yield. Historical close.*
A317	*Zero coupons*	*United States - 8-years and 6-months zero coupon yield. Historical close.*
A318	*Zero coupons*	*United States - 8 years zero coupon yield. Historical close.*
A319	*Zero coupons*	*United States - 9-months zero coupon yield. Historical close.*
A320	*Zero coupons*	*United States - 9-years and 6-months zero coupon yield. Historical close.*
A321	*Zero coupons*	*United States - 9 years zero coupon yield. Historical close.*

Source: Reuters, Bloomberg, Datastream and ECB.

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