SEDAR77-AW05 : Reconciling age-0 indices of relative abundance of the U.S. Atlantic and Gulf of Mexico scalloped hammerhead (Sphyrna lewini)

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Reconciling age-0 indices of relative abundance of the U.S. Atlantic and Gulf of Mexico scalloped hammerhead (*Sphyrna lewini*)

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Introduction

These analysis were adapted from (Latour and Peterson 2020), which previously evaluated the use of DFA for coastal shark species within SEDAR.

Latour and Peterson (2020) noted that trends in relative abundance generated from fisheries-independent and -dependent data are important inputs to stock assessments, as they are intended to represent an unbiased estimate of the underlying abundance pattern of a stock (Francis 2011). This representation is based on the assumption that relative abundance indices are proportional to total abundance. However, for species that are distributed over large spatial scales or that exhibit long range migrations, comprehensive population-wide relative abundance data are rarely available. As a result, it is sometimes necessary to rely on several independent data sources derived from spatially distinct sampling programs to estimate the patterns of abundance of widely distributed or highly migratory species. Operationally, multiple time-series of relative abundance are frequently included in a single stock assessment model, under the assumption that each provides representative information about the underlying abundance of the stock (Conn 2010, Cortés et al. 2015).

Latour and Peterson (2020) also noted that many of the coastal shark species that inhabit the southeast Atlantic are geographically widespread and display large-scale seasonal migrations.

Accordingly, collection of relative abundance data across spatial scales that match the home range of sharks is logistically challenging and not necessarily of high priority given their low economic impact when compared to species that support high value fisheries (Stevens et al. 2000). The development of relative abundance indices for sharks is therefore constrained to localized data collection programs that sample spatial ranges that are often much smaller than the actual distributions of target species. For the southeast Atlantic, there are several such data collection programs and it is not uncommon for the resulting indices of relative abundance to show conflicting trends over time.

Latour and Peterson (2020) also noted that in past stock assessments of coastal sharks in the southeast Atlantic, efforts have been directed at applying statistical techniques to reconcile contrasting patterns in relative abundance indices. In the previous sandbar shark assessment (SEDAR 2011), a hierarchical index compilation approach (Conn 2010) was used to develop a single time-series of relative abundance from the existing, disparate time-series derived from the localized sampling programs. The idea was to synthesize the information contained in the collection of relative abundance indices (11 total for sandbar shark, *Carcharhinus plumbeus*) into a single composite time-series that presumably reflected the trend in abundance at a broader spatial scale. Here, we build on that philosophy by introducing an alternative approach for the integration of multiple time-series, namely dynamic factor analysis (DFA). DFA is a multivariate dimension reduction technique designed to detect common, latent trends from a collection of time-series. This approach can accommodate short, non-stationary time-series like those commonly encountered in ecological data, input time-series with missing data, and covariation between time-series (Zuur et al. 2003a, 2003b, Holmes et al. 2020).

Recently, DFA was used to reconcile conflicting indices of relative abundance for seven coastal shark species along the east coast of the United States (Peterson et al. 2017). Subsequently, the performance of DFA for reconciling multiple indices of abundance that are in conflict was evaluated with an age-structured simulation model of two coastal shark species in the southeast United States (Peterson et al. 2021b). The reconciled trends obtained from the simulation study of DFA were also evaluated as relative abundance input into stock assessment models (Peterson et al. 2021a).

Consequently, we use the same DFA methods here for reconciling age-0 indices of relative abundance of the U.S. Atlantic and Gulf of Mexico scalloped hammerhead. Three DFA analyses were performed on time-series of relative abundance indices for age-0 individuals (Table 1): (a) combined Gulf of Mexico and Atlantic indices 1982-2019, (b) Gulf of Mexico indices 1982-2019, and (c) Atlantic indices 2001-2019.

Methods

Dynamic Factor Analysis

The general form of a DFA model can be written as follows (Zuur et al. 2003a):

$$\boldsymbol{y}_t = \boldsymbol{\Gamma}\boldsymbol{\alpha}_t + \boldsymbol{\varepsilon}_t, \text{ where } \boldsymbol{\varepsilon}_t \sim MVN(0, \boldsymbol{R})$$
$$\boldsymbol{\alpha}_t = \boldsymbol{\alpha}_{t-1} + \boldsymbol{\eta}_t, \text{ where } \boldsymbol{\eta}_t \sim MVN(0, \boldsymbol{Q})$$

where $\boldsymbol{y}_t$ is the vector (*n* x 1) of estimated z-scored index values from all time-series of relative abundance in year *t*, $\boldsymbol{\alpha}_t$ is the vector (*m* x 1) of common trends (*m* < *n*), $\boldsymbol{\Gamma}$ is the matrix (*n* x *m*) of loadings on the trends which indicates the strength of each time-series in determining the resulting trend, and $\boldsymbol{R}$ and $\boldsymbol{Q}$ denote the variance-covariance matrices associated with the observation error vector $\boldsymbol{\varepsilon}_t$ (*n* x1) and process error vector $\boldsymbol{\eta}_t$ (*m* x 1), respectively. Both observation and process error terms assume a multivariate normal distribution. To ensure that the model is identifiable, $\boldsymbol{Q}$ is set to equal to the identity matrix while $\boldsymbol{R}$ is free to take on various forms. All factor loadings, common trends, and fitted values are unitless.

Application of DFA to time-series of relative abundance requires some care to preserve the underlying error structure and the relative scale of the survey indices. Accordingly, the following analytical approach was adopted (Peterson et al. 2021b): (1) all time-series of relative abundance were log-transformed, thereby normalizing the time-series error, (2) each time-series was centered and demeaned by subtracting and dividing each by its mean, (3) the global standard deviation (*GSD*) was calculated for all relative abundance time-series after being log-transformed and demeaned, (4) each time-series was then divided by the *GSD*, (5) the DFA model was fitted, (6) the resulting DFA-predicted common trend was then multiplied by the *GSD* and back-transformed. Since the stock assessment model relies heavily on trend rather than magnitude of relative abundance indices, bias correcting will have little impact. However, standard errors estimated by the DFA model for the annual indices were multiplied by the *GSD* to preserve scale of uncertainty relative to the trend.

The above approach does not work well in situations where the log-transformed relative abundance mean was close to zero or negative, because the second step would essentially involve dividing by zero or a negative value, respectively. Simulation analyses have also shown that DFA model fitting is fairly robust when the standard deviation of each time-series resulting from step four are approximately one (Peterson et al. 2021b). Accordingly, the time-series of relative abundance were first multiplied by a survey-specific constant, *c*, to ensure that the resulting time-series approximately achieved these two general criteria. Multiplying indices by a constant is comparable to redefining effort such that the scale of the index changes. Best practices suggest that time-series be z-scored prior to DFA model fitting (Holmes et al. 2020), so in effect, the above analytical approach was developed in the spirit of maintaining consistency with that recommendation.

The underlying assumptions of a DFA model are equivalent to those of a linear regression, which include normality, independence, and homogeneity of residuals (Zuur et al. 2003b). Model validation was therefore based on standard diagnostic tools (QQ plots, analysis of residuals). Additionally, 'fit ratio' statistics were calculated as $\Sigma_t y_{it}^2 / \Sigma_t \varepsilon_{it}^2$, where *i* denotes an individual time-series. High fit ratios (i.e., $\gtrsim 0.6$) suggest that the DFA model poorly fits the time series, or a few years in the time series (Zuur et al. 2003b).

For application to scalloped hammerhead, within each analysis, a single common trend was estimated and each time-series was assumed to be independent with a unique value of uncertainty. Therefore, the $\boldsymbol{R}$ matrix of the DFA models each assumed a structure with the mean of the time-series-specific coefficients of variation (CVs) along the diagonal and zeros elsewhere. CVs were chosen over estimated variances so that the magnitude of uncertainty across time-series would be similar. Average CVs entered for TXPWD-Gillnet (Survey 1), GULFSPAN (Survey 2), COASTSPAN – LL (Survey 3), SCCOASTGN – LONG (Survey 4), and SCCOASTGN – SHORT (Survey 5) were CV1=0.665, CV2=0.255, CV3=0.618, CV4=0.663, and CV5=0.460, respectively. DFA models were fitted using the state-space multivariate autoregressive modelling package 'MARSS' in R (Holmes et al. 2020) and all uncertainty was reported as 95% confidence intervals.

Results/Discussion

The constants chosen for rescaling are provided in Table 2 and resulted in a GSD of 0.14, 0.14, and 0.15 for (a) the DFA model for the combined Gulf of Mexico and Atlantic indices (1982-2019), (b) the DFA model for the Gulf of Mexico indices (1982-2019), and (c) the DFA model for the Atlantic indices (2001-2019), respectively. Diagnostic plots are provided in Appendices. An outlier, which had a large influence on results, was removed from DFA trend (a) Gulf of Mexico and Atlantic indices and DFA trend (b) Gulf of Mexico indices to improve diagnostics.

The DFA model for (a) the combined Gulf of Mexico and Atlantic indices (1982-2019) successfully converged and yielded a common trend that decreased from 1982-1995 and then generally increased from 1995-2019 (Figures 1-4). Factor loadings on the common trend were positive and statistically significant for GULFSPAN (Survey 2, CI: 0.11, 0.39) and SCCOASTGN – LONG (Survey 4, CI: 0.10, 0.67). Factor loadings on the common trend were negative and statistically significant for COASTSPAN – LL (Survey 3, CI: -0.82, -0.14) and SCCOASTGN – SHORT (Survey 5, CI: -0.93, -0.17). The TXPWD-Gillnet (Survey 1, CI: 0.05, 0.28) showed a weakly positive and non-significant loading on the common trend. Fit ratios of the common trend to age-0 relative abundance from GULFSPAN (Survey 2, fit ratio = 0.41), COASTSPAN – LL (Survey 3, fit ratio = 0.42), and SCCOASTGN – SHORT (Survey 5, fit ratio = 0.43) were less than 0.6 suggesting a reasonable fit to these indices (Appendix A). However, fit ratios of the common trend to age-0 relative abundance from TXPWD-Gillnet (Survey 1) and SCCOASTGN – LONG (Survey 4) were greater than 0.6 suggesting a poor fit to these indices (Appendix A). A steep increase in the common trend from about 1995-2000 followed by a slight decrease in the common trend around 2004-2006 appears to be driven by GULFSPAN (Survey 2) likely due to the mean CV of that survey being the lowest amongst the time-series. However, the fluctuations also appear to be associated with significant autocorrelation in GULFSPAN (Survey 2) (Appendix A).

The DFA model for (b) the Gulf of Mexico indices (1982-2019) successfully converged and yielded a common trend that was very similar to that described above (Figures 5-8). Factor loadings on the common trend were positive and statistically significant for TXPWD-Gillnet

(Survey 1, CI: 0.06, 0.38) and GULFSPAN (Survey 2, CI: 0.10, 0.47). Fit ratios of the common trend to age-0 relative abundance from GULFSPAN (Survey 2, fit ratio = 0.30) was less than 0.6 suggesting a reasonable fit to this index (Appendix B). However, fit ratios of the common trend to age-0 relative abundance from TXPWD-Gillnet (Survey 1) were greater than 0.6 suggesting a poor fit to this index (Appendix B). A steep increase in the common trend from about 1995-2000 followed by a slight decrease in the common trend around 2004-2006 appears to be driven by GULFSPAN (Survey 2) likely due to the mean CV of that survey being the lowest amongst the time-series. The fluctuations also appear to be associated with significant autocorrelation in GULFSPAN (Survey 2) (Appendix B).

The DFA model for (c) the Atlantic indices (2001-2019) successfully converged and yielded a common trend that increased from 2001-2005 and then decreased from 2005-2019 (Figures 9-12). Factor loadings on the common trend were positive and statistically significant for COASTSPAN – LL (Survey 3, CI: 0.024, 0.579) and SCCOASTGN – SHORT (Survey 5, CI: 0.037, 0.687). The SCCOASTGN – LONG (Survey 4, CI: -0.356, 0.004) showed a weakly negative and non-significant loading on the common trend. Fit ratios of the common trend to age-0 relative abundance from COASTSPAN – LL (Survey 3, fit ratio 0.378) and SCCOASTGN – SHORT (Survey 5, fit ratio 0.307) were less than 0.6 suggesting a reasonable fit to these indices (Appendix C). However, fit ratios of the common trend to age-0 relative abundance from SCCOASTGN – LONG (Survey 4) were greater than 0.6 suggesting a poor fit to this index (Appendix C). Uncertainty in the back-transformed trend was greatest in the early years due to only one contributing relative abundance time-series but was reduced in more recent years.

Acknowledgements

The authors wish to acknowledge the efforts of individuals associated with collecting and analyzing the time-series of relative abundance: TXPWD-Gillnet (Survey 1), GULFSPAN (Survey 2), COASTSPAN – LL (Survey 3), SCCOASTGN – LONG (Survey 4), and SCCOASTGN – SHORT (Survey 5).

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Tables

Table 1. Raw time-series of scalloped hammerhead relative abundance indices for age-0 individuals 1982-2019 for (a) Gulf of Mexico, and (b) Atlantic[1].

	TXPWD-Gillnet SEDAR77 DW-16 Gulf of Mexico Sharks per net per hour		GULFSPAN SEDAR77 DW-17 Gulf of Mexico Sharks per net per hour		COASTSPAN - LL SEDAR77-DW-30 Atlantic Sharks per 100 hook hours		SCCOASTGN - LONG SEDAR77-DW-31 Atlantic Sharks per net hour		SCCOASTGN - SHORT SEDAR77 DW-32 Atlantic Sharks per net hour	
Year	**Index**	**CV**	**Index**	**CV**	**Index**	**CV**	**Index**	**CV**	**Index**	**CV**
1982	0.00033									
1983	0.00042	0.912								
1984	0.00000									
1985	0.00015									
1986	0.00035	0.732								
1987	0.00000									
1988	0.00050	0.618								
1989	0.00012									
1990	0.00090	0.603								
1991	0.00053	0.749								
1992	0.00000									
1993	0.00032	0.819								
1994	0.00027	0.848								
1995	0.00010	1.165								
1996	0.00093	0.536	0.009	0.294						
1997	0.00172	0.666	0.016	0.461						
1998	0.00031	0.842	0.002	0.548						
1999	0.00021	0.781	0.091	0.312						
2000	0.00048	0.589	0.156	0.253						
2001	0.00150	0.603	0.148	0.302			1.2498	0.4793		
2002	0.00033	0.822	0.15	0.166			0.7881	0.5178		
2003	0.00183	0.577	0.102	0.181			2.7417	0.4496		
2004	0.00075	0.689	0.07	0.227			0.5413	1.4316		
2005	0.00254	0.517	0.048	0.373	5.464	0.529	0.6254	0.5384		
2006	0.00069	0.630	0.079	0.22	8.119	0.416	0.9807	1.0179		
2007	0.00079	0.778	0.168	0.171	1.976	1.128	1.9521	0.5328	0.1709	0.4233
2008	0.00075	0.703	0.172	0.189	1.730	1.165	1.3839	0.7066	0.2857	0.5813
2009	0.00095	0.560	0.163	0.2	3.482	0.654	7.2980	1.3825	0.0000	
2010	0.00213	0.598	0.208	0.211	9.376	0.327	2.2974	0.8537	0.1135	0.5813
2011	0.00091	0.563	0.159	0.201	3.876	0.372	1.4874	0.5401	0.1129	0.3072
2012	0.00124	0.540	0.093	0.217	1.907	0.469	8.1799	0.5273	0.1155	0.3072
2013	0.00484	0.428	0.129	0.215	2.052	0.427	4.0580	0.4515	0.0897	0.4233
2014	0.00198	0.477	0.141	0.207	2.443	0.548	2.2039	0.6955	0.0000	
2015	0.00283	0.565	0.068	0.252	1.158	0.554	0.9686	0.6158	0.0199	0.5813
2016	0.00191	0.590	0.124	0.235	1.899	0.419	1.6754	0.5384	0.0978	0.3507
2017	0.00041	0.775	0.184	0.2	1.123	0.519	6.8082	0.3406	0.0000	
2018	0.00482	0.499	0.21	0.225	0.738	0.565	3.7252	0.5473	0.0000	
2019	0.00248	0.514	0.176	0.265	1.029	1.175	3.3050	0.4230	0.0208	0.5813

[1] Recommended base indices of abundance for the age-0 scalloped hammerhead including index name, the value of catch per unit effort, the area sampled and SEDAR 77 Data Workshop document number, adapted from SEDAR 77 HMS Hammerhead Sharks Data Workshop Final Report (draft April 2022, their Section 4 Table 9). See SEDAR 77 HMS Hammerhead Sharks Data Workshop Final Report (draft April 2022, their Section 4 Table 3) for the regions recommended for base model and sensitivity analysis with each index. CV is the coefficient of variation for the annual index value. Zero index values in a given year (representing both ns=not sampled and nc=the model did not converge) were excluded from these DFA analyses (TXPWD-Gillnet Gulf of Mexico 1984,1987,1993; SCCOASTGN – SHORT 2009, 2014, 2017, 2018).

Table 2. Vector of constants (c) obtained as described above.

	TXPWD-Gillnet SEDAR77 DW-16 Gulf of Mexico Sharks per net per hour Multiplier	GULFSPAN SEDAR77 DW-17 Gulf of Mexico Sharks per net per hour Multiplier	COASTSPAN – LL SEDAR77-DW-30 Atlantic Sharks per 100 hook hours Multiplier	SCCOASTGN - LONG SEDAR77-DW-31 Atlantic Sharks per net hour Multiplier	SCCOASTGN - SHORT SEDAR77 DW-32 Atlantic Sharks per net hour Multiplier
c	1042950.5	18596.211	60.942394	108.56484	4126.1178

Table 3. Back-transformed common trend (IndexBT on the nominal scale) and standard error (SEBT on the natural log scale) resulting from the DFA model fitted to the age-0 time-series of relative abundance for (a) combined Gulf of Mexico and Atlantic indices, (b) Gulf of Mexico indices, and (c) Atlantic indices (Table 1).

	DFA (a) Gulf of Mexico and Atlantic		DFA (b) Gulf of Mexico		DFA (c) Atlantic	
Year	**IndexBT**	**SEBT**	**IndexBT**	**SEBT**	**IndexBT**	**SEBT**
1982	0.677	0.2287	0.708	0.2002		
1983	0.641	0.2306	0.676	0.1993		
1984	0.609	0.2348	0.646	0.2030		
1985	0.577	0.2319	0.616	0.1975		
1986	0.567	0.2313	0.613	0.1963		
1987	0.559	0.2330	0.611	0.1992		
1988	0.551	0.2274	0.609	0.1923		
1989	0.538	0.2235	0.596	0.1884		
1990	0.546	0.2207	0.614	0.1868		
1991	0.537	0.2187	0.604	0.1868		
1992	0.520	0.2171	0.583	0.1887		
1993	0.504	0.2065	0.562	0.1789		
1994	0.488	0.1940	0.540	0.1686		
1995	0.477	0.1771	0.522	0.1544		
1996	0.485	0.1507	0.530	0.1299		
1997	0.546	0.1438	0.595	0.1252		
1998	0.636	0.1506	0.688	0.1347		
1999	0.748	0.1363	0.806	0.1215		
2000	0.861	0.1280	0.938	0.1174		
2001	0.911	0.1160	1.022	0.1162	1.415	0.2146
2002	0.895	0.1127	1.025	0.1158	1.479	0.2062
2003	0.901	0.1113	1.019	0.1157	1.501	0.1963
2004	0.802	0.1086	0.976	0.1157	1.583	0.1824
2005	0.768	0.0976	0.977	0.1157	1.592	0.1594
2006	0.794	0.0940	1.019	0.1157	1.523	0.1449
2007	0.907	0.0823	1.115	0.1157	1.348	0.1255
2008	0.933	0.0821	1.177	0.1157	1.291	0.1230
2009	1.016	0.0918	1.224	0.1157	1.210	0.1323
2010	0.965	0.0819	1.269	0.1157	1.212	0.1213
2011	0.980	0.0809	1.231	0.1157	1.125	0.1187
2012	1.065	0.0809	1.200	0.1157	0.996	0.1187
2013	1.113	0.0819	1.240	0.1157	0.928	0.1213
2014	1.133	0.0918	1.227	0.1157	0.868	0.1322
2015	1.183	0.0821	1.193	0.1159	0.783	0.1226
2016	1.152	0.0823	1.235	0.1164	0.784	0.1243
2017	1.328	0.0937	1.286	0.1183	0.683	0.1406
2018	1.452	0.0952	1.393	0.1245	0.628	0.1474
2019	1.462	0.0944	1.409	0.1436	0.606	0.1524

Figures

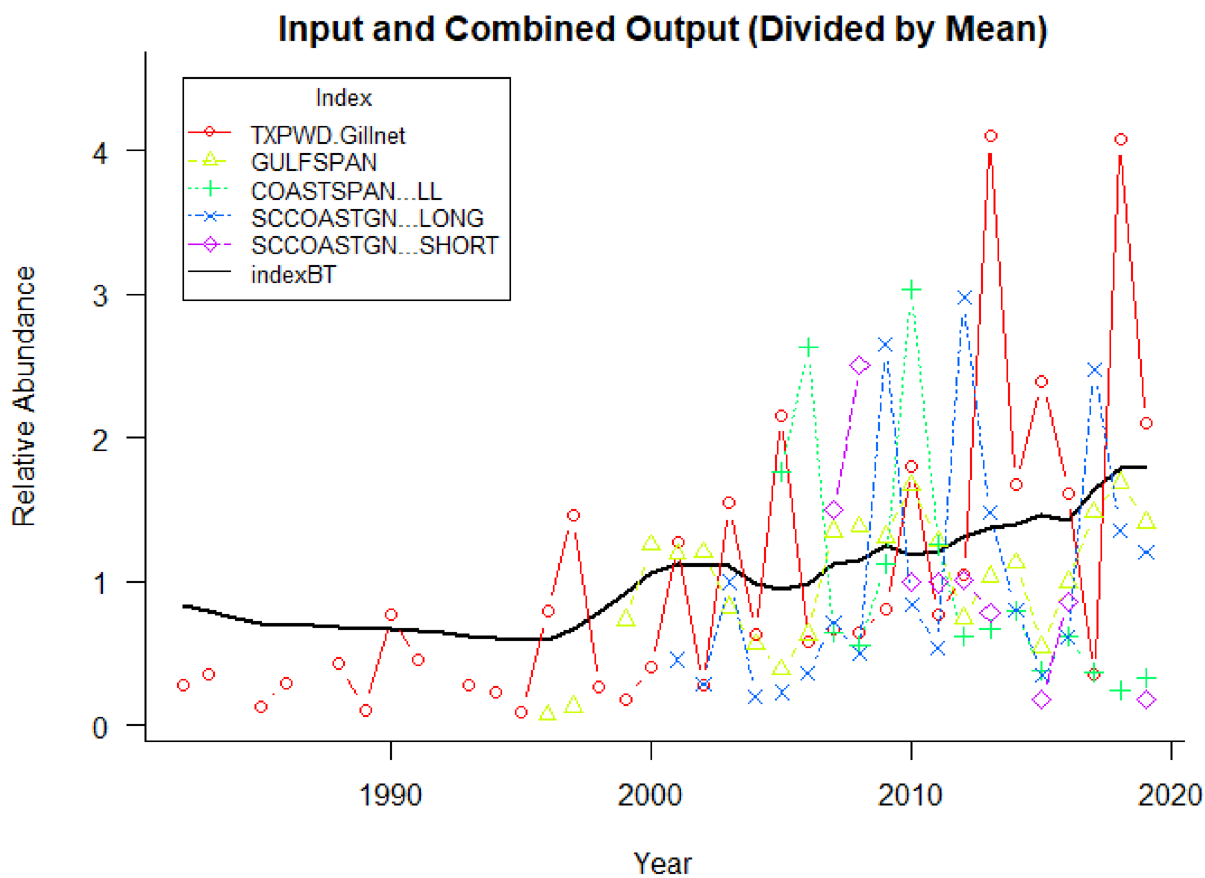


Figure 1. Raw time-series of relative abundance indices for age-0 individuals for combined Gulf of Mexico and Atlantic indices (Table 1) along with back-transformed common trend resulting from the DFA model fitted to the age-0 time-series of relative abundance (Table 3). All indices are divided by their mean for plotting.

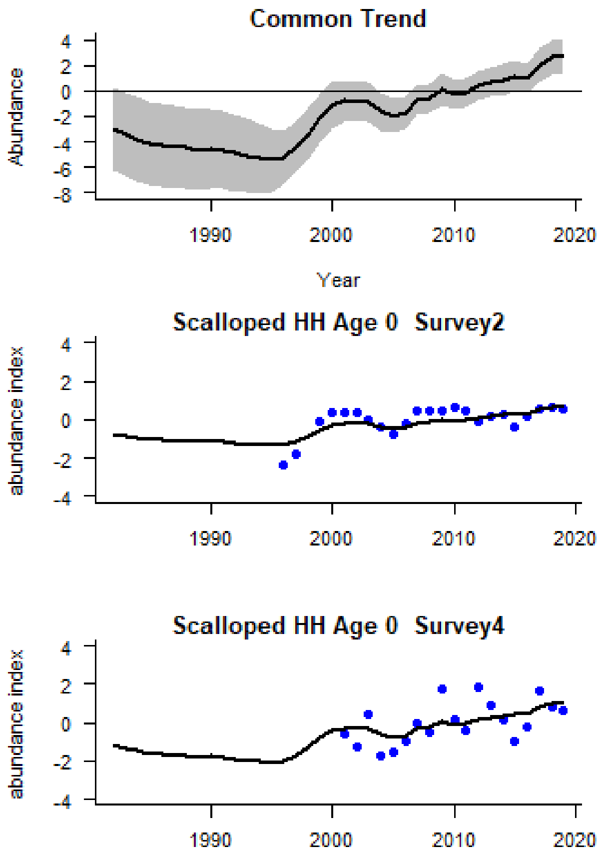


Figure 2. Results of the DFA model fitted to age-0 combined Gulf of Mexico and Atlantic indices of relative abundance (Table 1) showing (upper left panel) the common trend (solid line) and 95% CI (dashed lines) and fits to the time-series of relative abundance (remaining panels): TXPWD-Gillnet (Survey 1), GULFSPAN (Survey 2), COASTSPAN – LL (Survey 3), SCCOASTGN – LONG (Survey 4), and SCCOASTGN – SHORT (Survey 5).

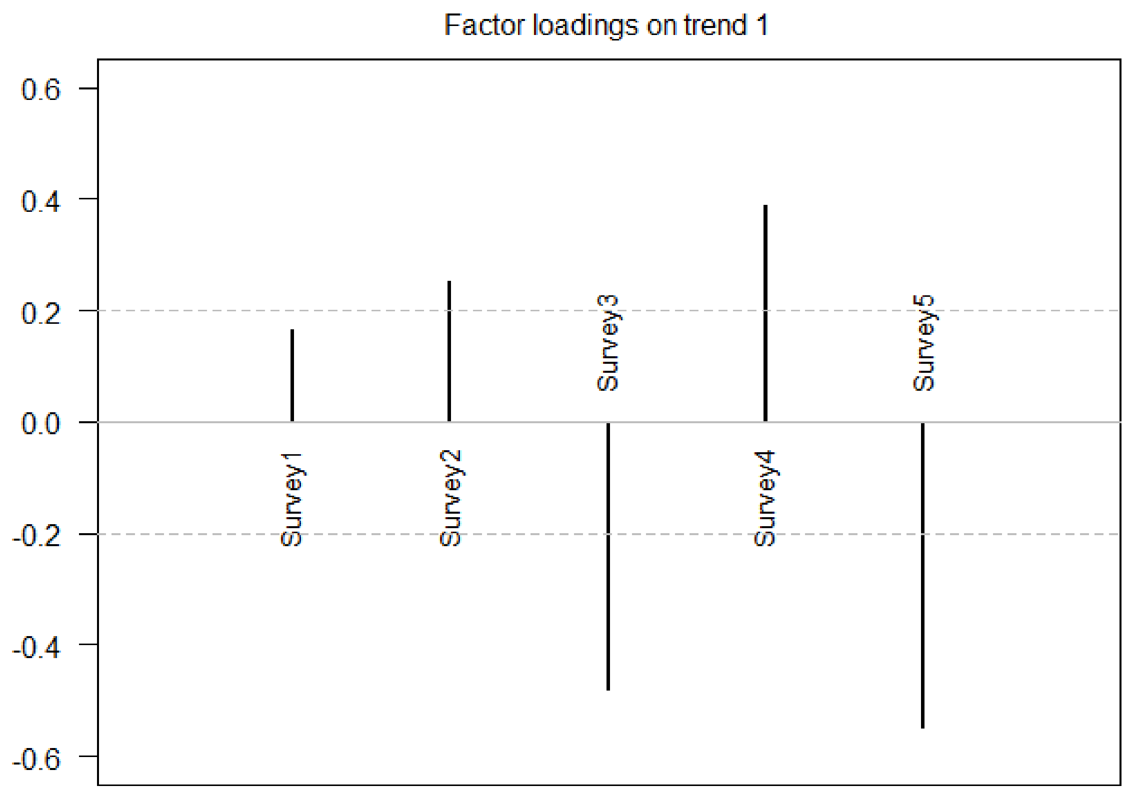


Figure 3. Results of the DFA model fitted to age-0 combined Gulf of Mexico and Atlantic indices of relative abundance (Table 1) showing factor loadings; values greater than 0.2 (horizontal dashed line) identify time-series that have a relatively strong influence on the common trend to the time-series of relative abundance: TXPWD-Gillnet (Survey 1), GULFSPAN (Survey 2), COASTSPAN – LL (Survey 3), SCCOASTGN – LONG (Survey 4), and SCCOASTGN – SHORT (Survey 5).

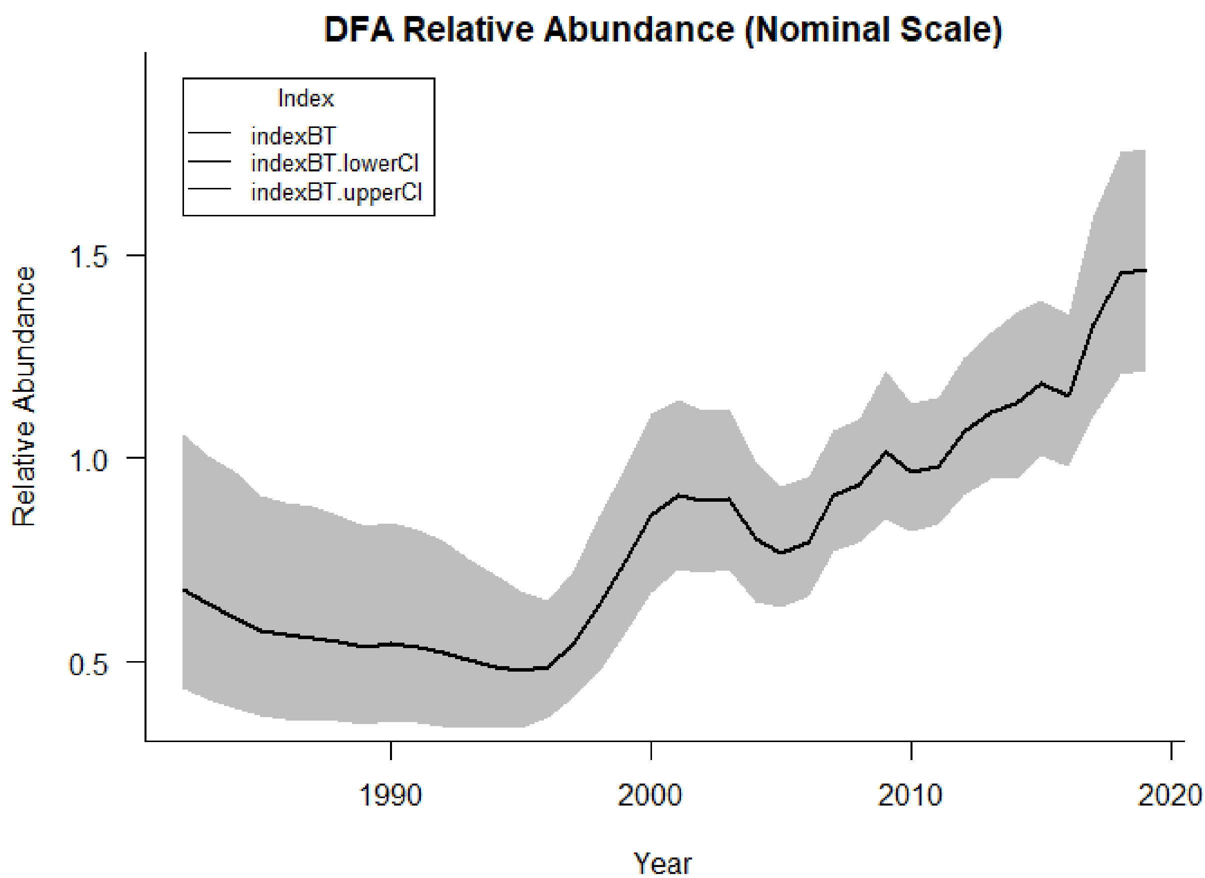


Figure 4. Back-transformed common trend resulting from the DFA model fitted to the age-0 time-series of relative abundance for combined Gulf of Mexico and Atlantic (Table 3). The shaded interval denotes the approximate 95% confidence interval.

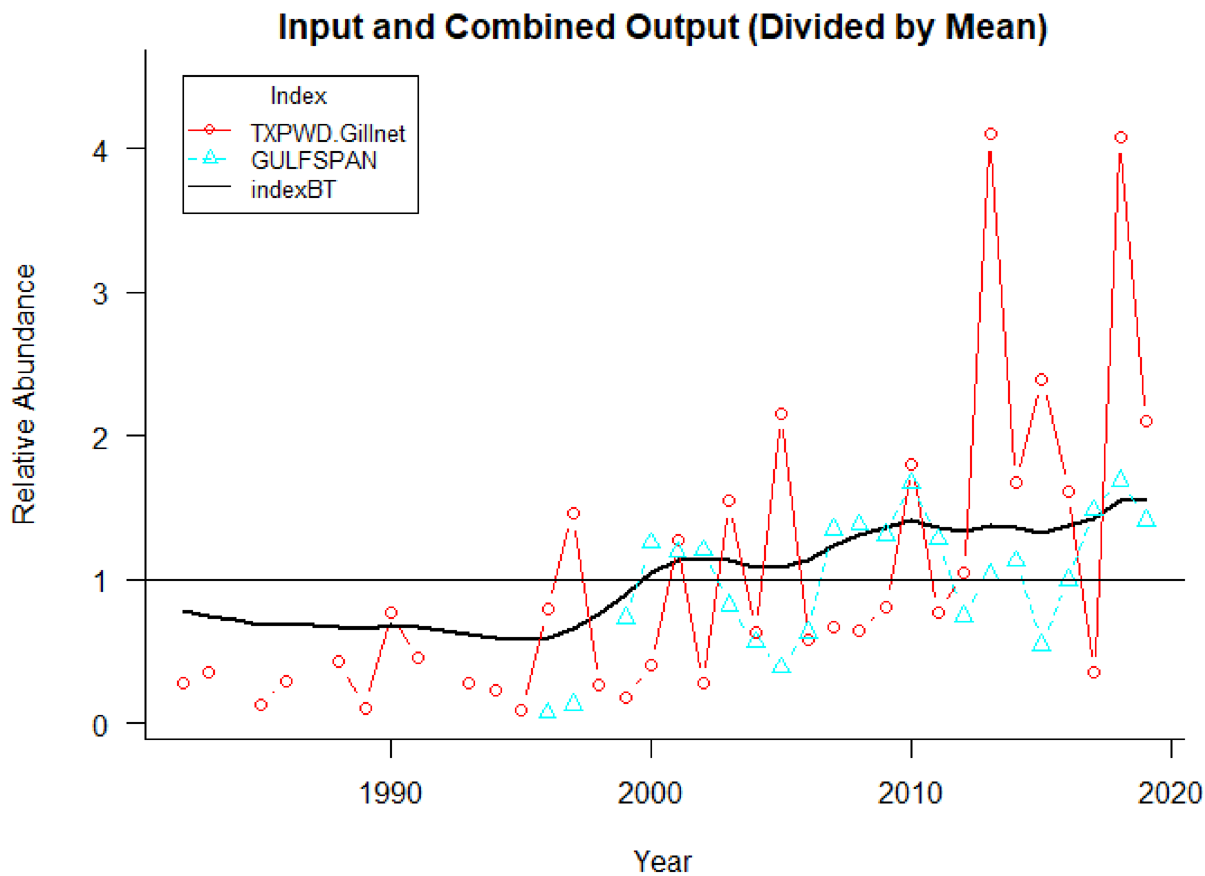


Figure 5. Raw time-series of relative abundance indices for age-0 individuals for Gulf of Mexico indices (Table 1) along with back-transformed common trend resulting from the DFA model fitted to the age-0 time-series of relative abundance (Table 3). All indices are divided by their mean for plotting.

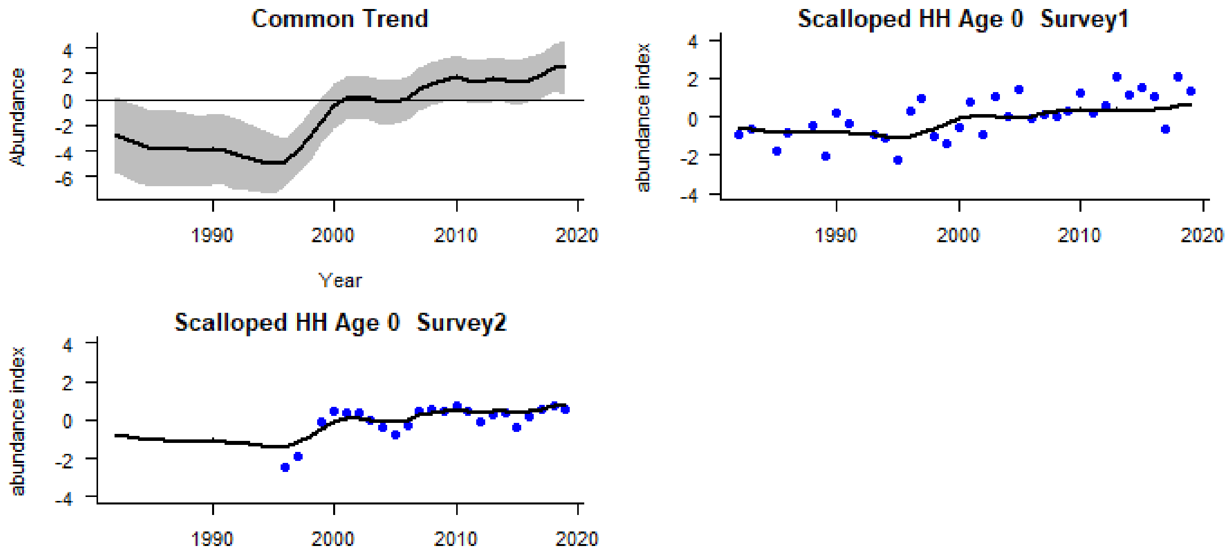


Figure 6. Results of the DFA model fitted to age-0 Gulf of Mexico indices of relative abundance (Table 1) showing (upper left panel) the common trend (solid line) and 95% CI (dashed lines) and fits to the time-series of relative abundance (remaining panels): TXPWD-Gillnet (Survey 1) and GULFSPAN (Survey 2).

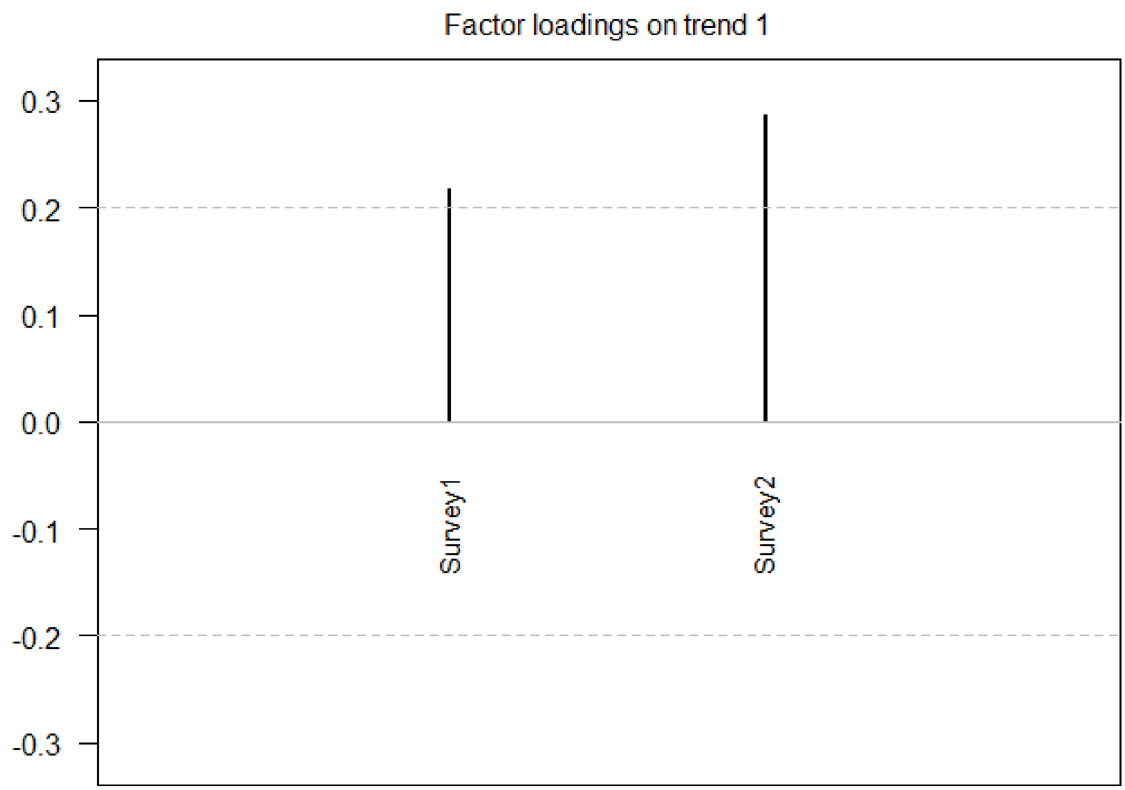


Figure 7. Results of the DFA model fitted to age-0 Gulf of Mexico indices of relative abundance (Table 1) showing factor loadings; values greater than 0.2 (horizontal dashed line) identify time-series that have a relatively strong influence on the common trend to the time-series of relative abundance: TXPWD-Gillnet (Survey 1) and GULFSPAN (Survey 2).

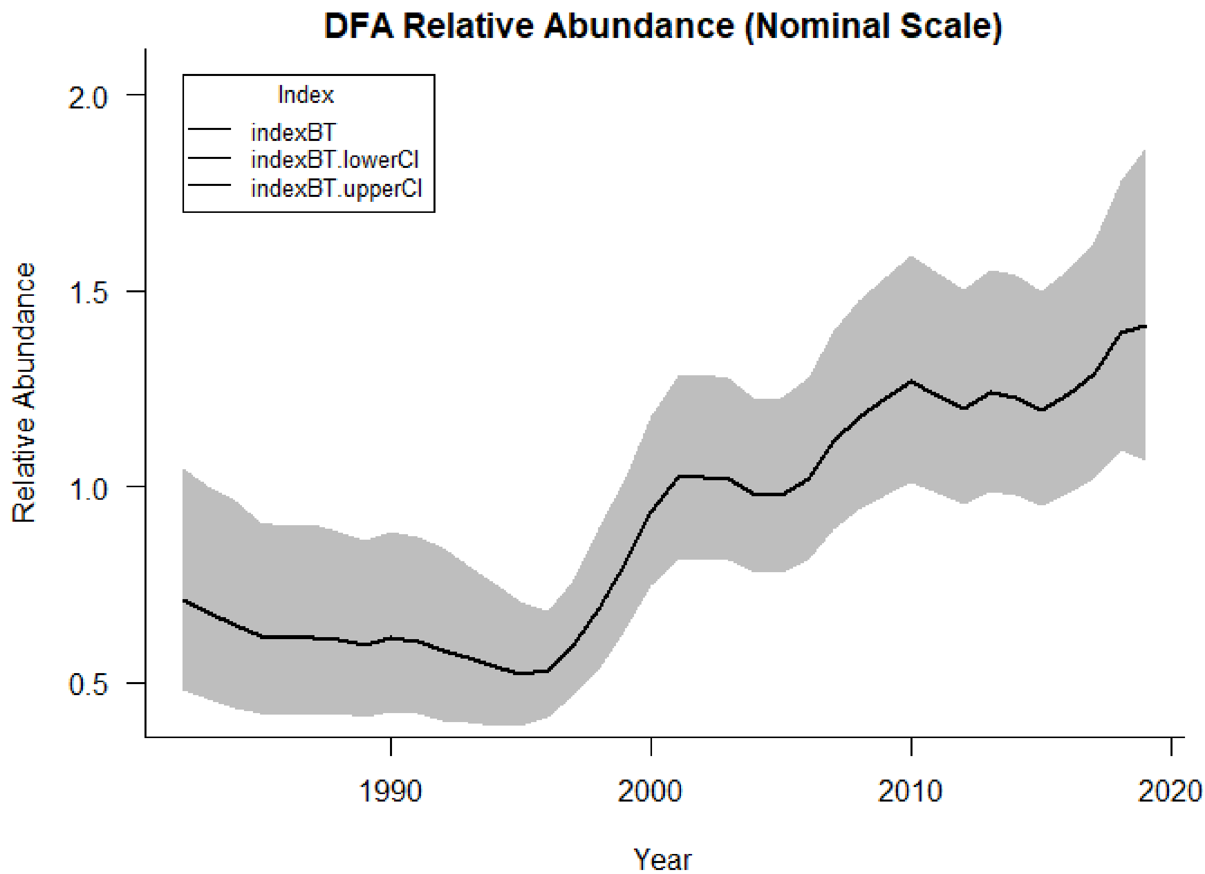


Figure 8. Back-transformed common trend resulting from the DFA model fitted to the age-0 time-series of relative abundance for Gulf of Mexico (Table 3). The shaded interval denotes the approximate 95% confidence interval.

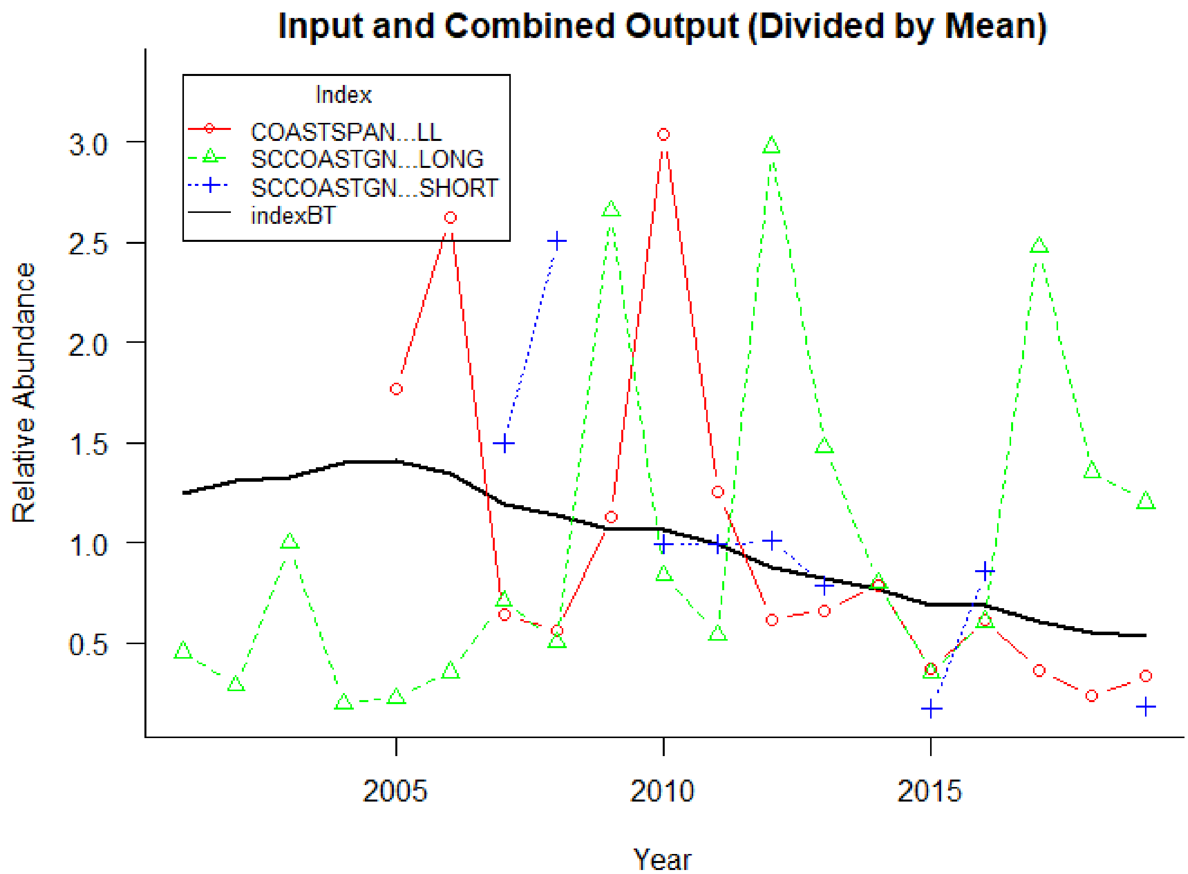


Figure 9. Raw time-series of relative abundance indices for age-0 individuals for Atlantic indices (Table 1) along with back-transformed common trend resulting from the DFA model fitted to the age-0 time-series of relative abundance (Table 3). All indices are divided by their mean for plotting.

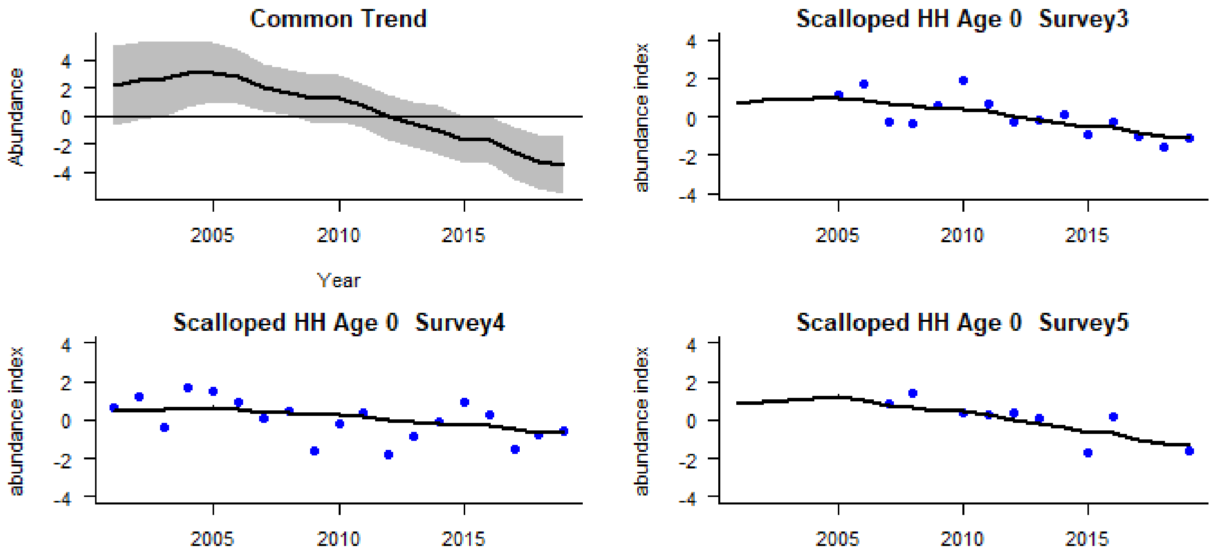


Figure 10. Results of the DFA model fitted to age-0 Atlantic indices of relative abundance (Table 1) showing (upper left panel) the common trend (solid line) and 95% CI (dashed lines) and fits to the time-series of relative abundance (remaining panels): COASTSPAN – LL (Survey 3), SCCOASTGN – LONG (Survey 4), and SCCOASTGN – SHORT (Survey 5).

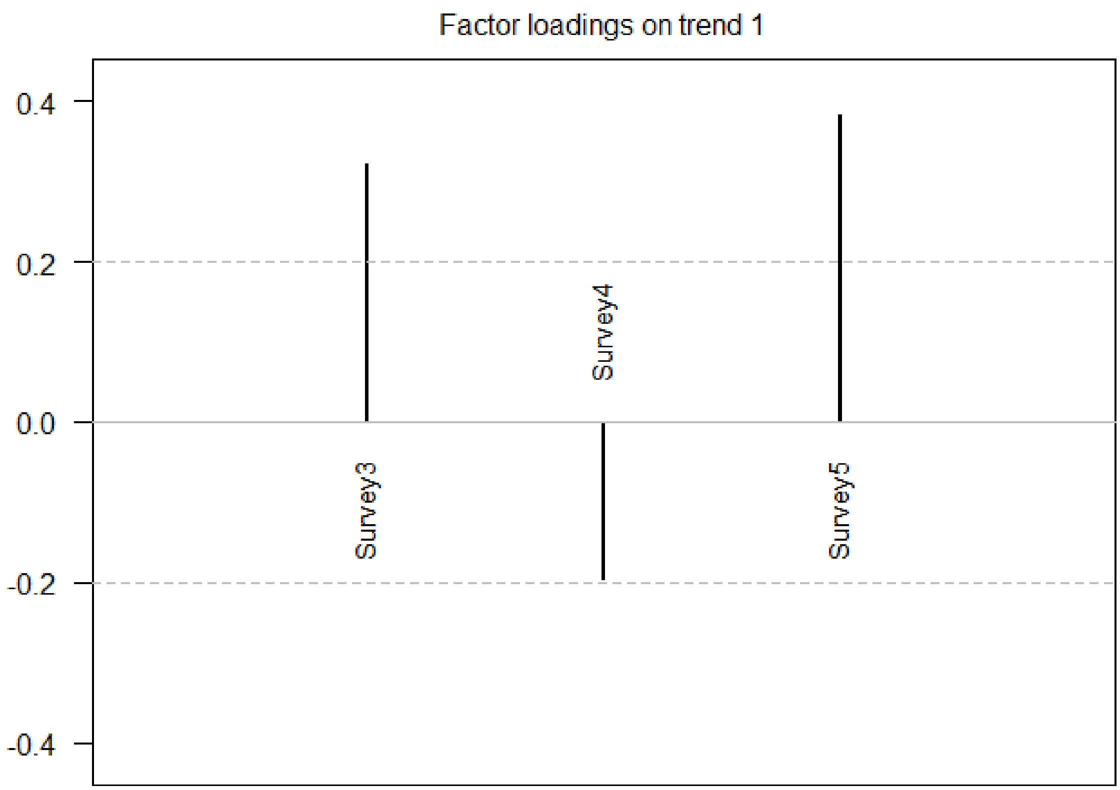


Figure 11. Results of the DFA model fitted to age-0 Atlantic indices of relative abundance (Table 1) showing factor loadings; values greater than 0.2 (horizontal dashed line) identify time-series that have a relatively strong influence on the common trend to the time-series of relative abundance: COASTSPAN – LL (Survey 3), SCCOASTGN – LONG (Survey 4), and SCCOASTGN – SHORT (Survey 5).

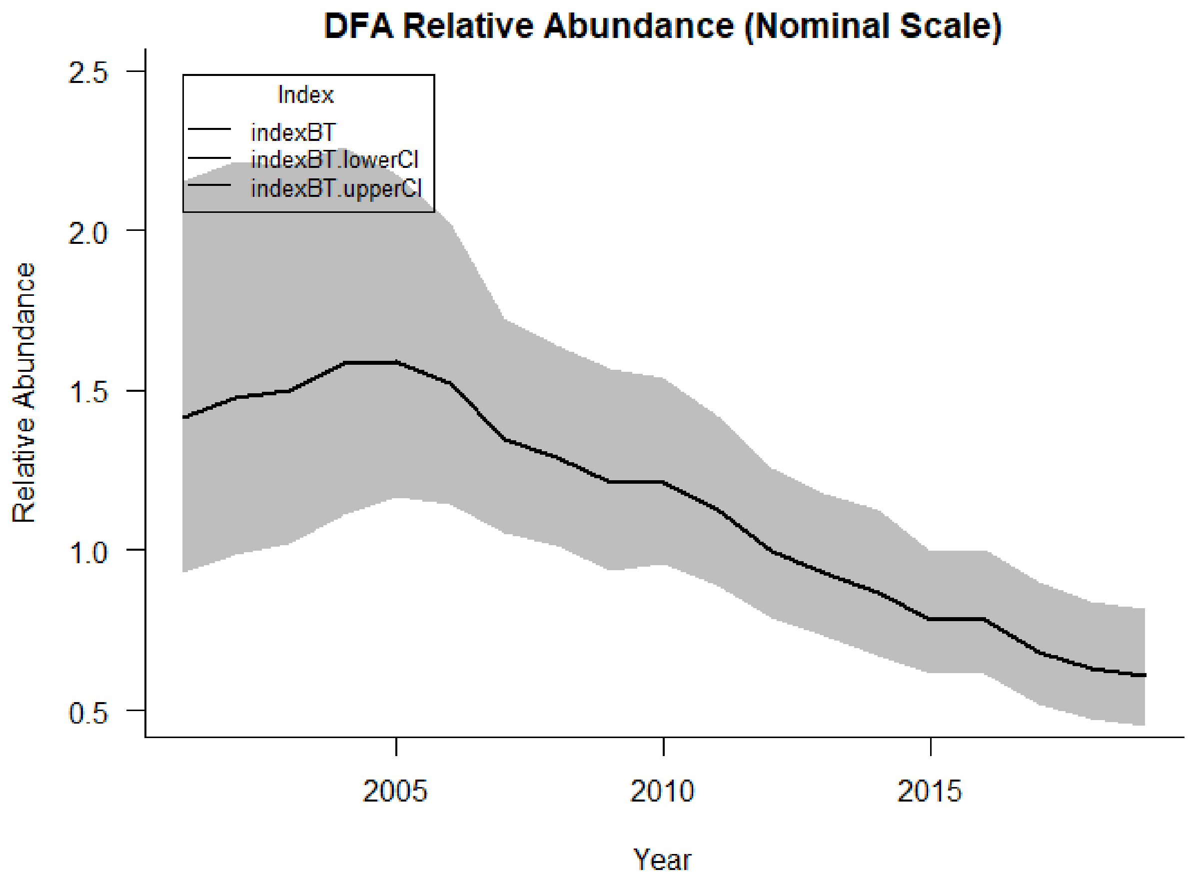


Figure 12. Back-transformed common trend resulting from the DFA model fitted to the age-0 time-series of relative abundance for Atlantic (Table 3). The shaded interval denotes the approximate 95% confidence interval.

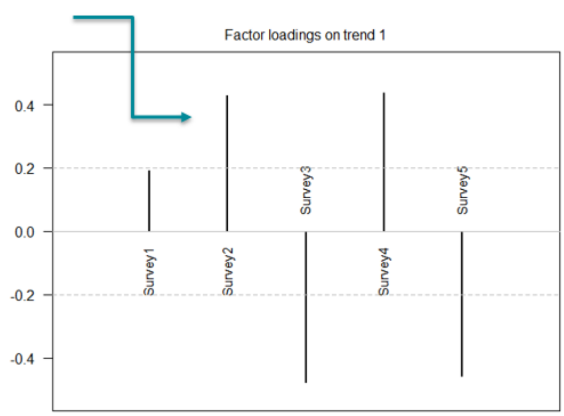
Appendix A – Diagnostics DFA (a) Gulf of Mexico and Atlantic Indices

- **Recommend for use in Sensitivity Analysis**

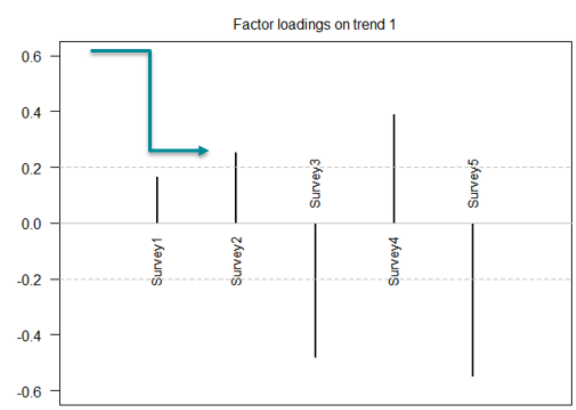
- **Recommend V2 for use in Sensitivity Analysis**
- Remove outlier survey 2 (1998)

TXPWD-Gillnet	GULFSPAN		COASTSPAN - LL	SCCOASTGN - LONG	SCCOASTGN - SHORT
SEDAR77 DW-16	SEDAR77 DW-17		SEDAR77-DW-30	SEDAR77-DW-31	SEDAR77 DW-32
Gulf of Mexico	Gulf of Mexico		Atlantic	Atlantic	Atlantic
sharks per net per hour	sharks per net per hour		sharks per 100 hook hours	sharks per net hour	sharks per net hour
	index	CV			
	0.009	0.294			
	0.016	0.461			
	0.002	0.548			

V1



V2



- Fit ratios (Fit ratio >=0.6 suggest poor fit)
- V1

```
> FitRatio
  Survey1   Survey2   Survey3   Survey4   Survey5
0.6907538 0.2845292 0.5466649 0.6591031 0.6637722
> mean(FitRatio)
[1] 0.5689646
```

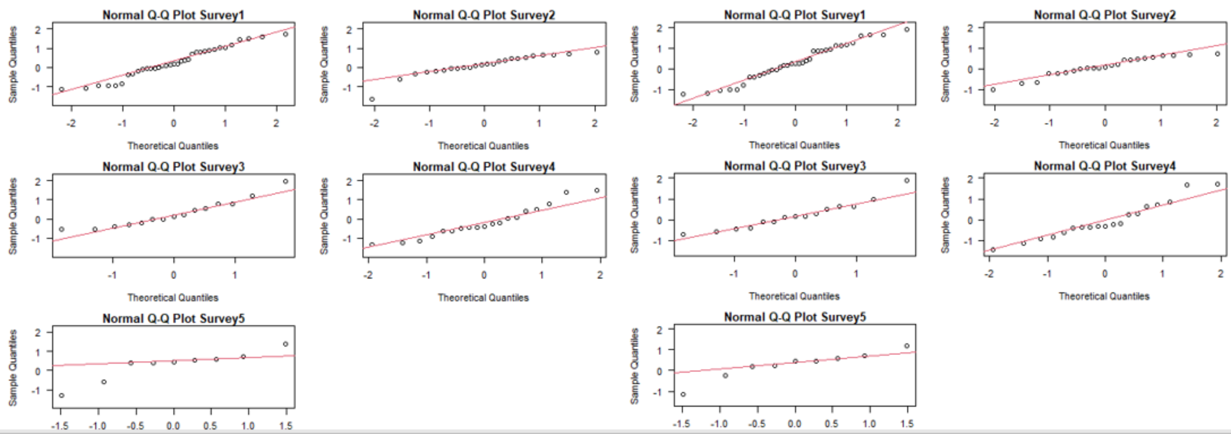
  - Survey 2, Good fit; but Survey 1, 4, 5 poor fit;
- V2

```
> FitRatio
  Survey1   Survey2   Survey3   Survey4   Survey5
0.7185246 0.4142706 0.4177663 0.6360371 0.4331884
> mean(FitRatio)
[1] 0.5239574
```

- Survey 1 and 4 similar poor fit as in V1
- Survey 2 reduced fit compared to V1
- Survey 3 and 4 improved fit compared to V1
  - Overall fit ratio improved

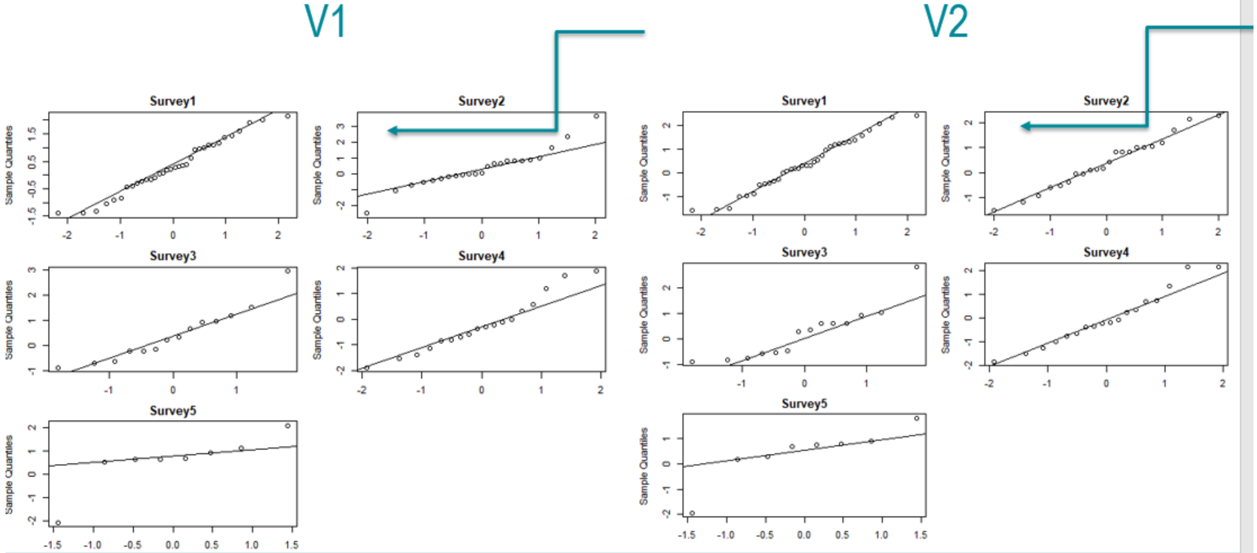
- Manual QQ plots “raw residuals” from fit (dat.z-fit.b)
- Survey 2 skewed in both V1 and V2
- Survey 5 has low sample size

V1 V2



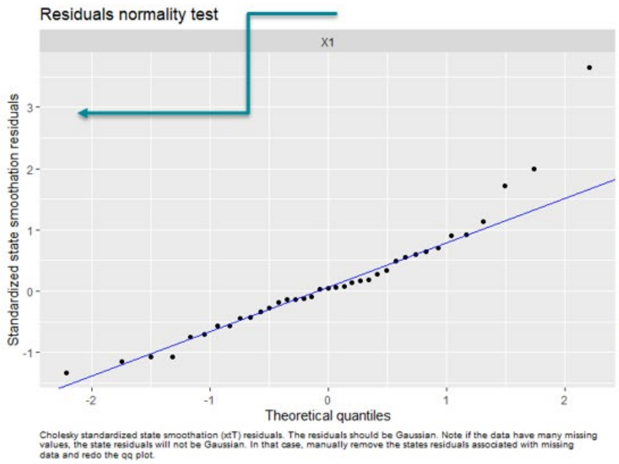
- QQ plots “standardized residuals”
- Survey 2 still has some skew in V1 but reduced in V2

V1 V2

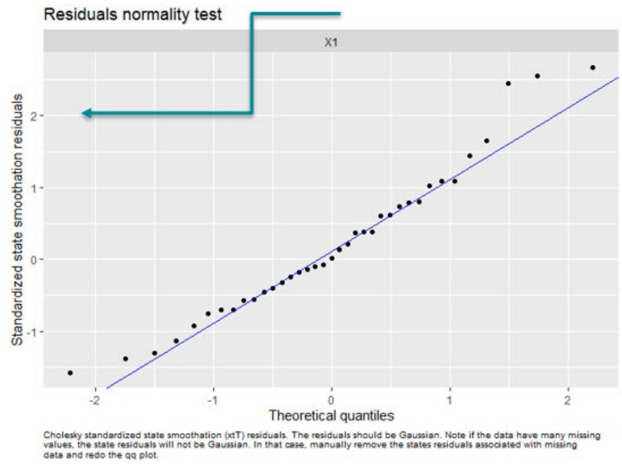


- QQ plots State Vector "standardized residuals"
- Some skew, but reduced in V2

V1

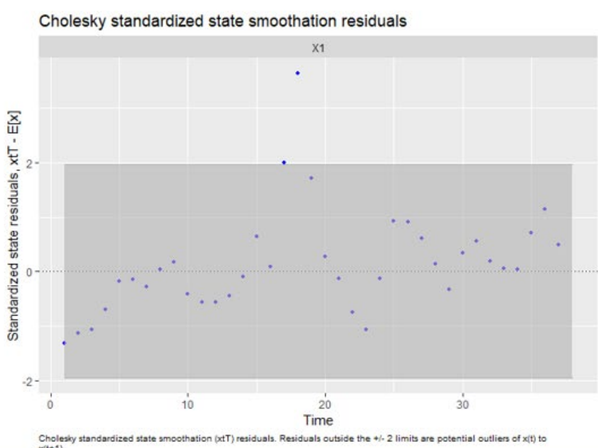


V2

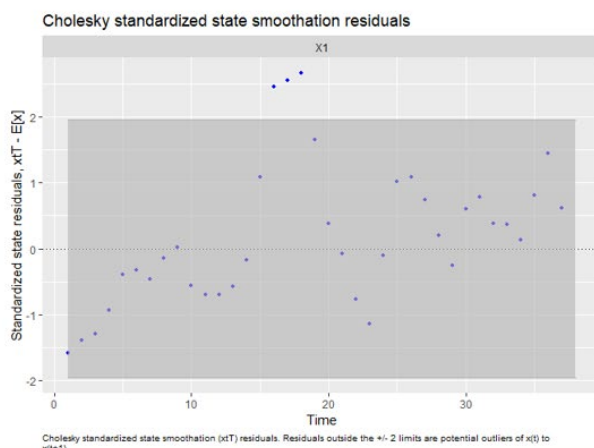


- Analysis of state vector standardized residuals
- Scale (influence) of outliers reduced but trend remains V2

V1

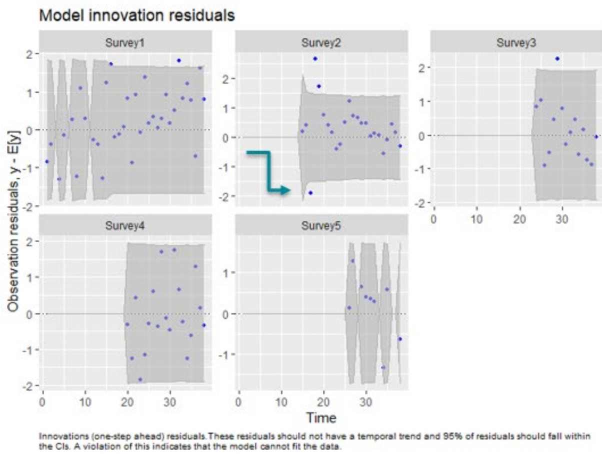


V2

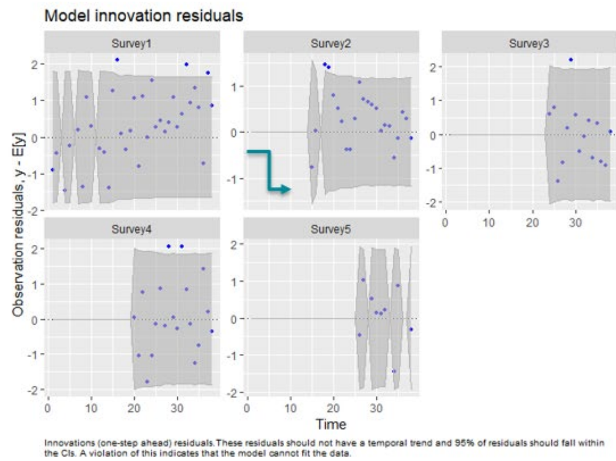


- Analysis of survey residuals to fit
- Survey 2 residual pattern reduced in V2

V1

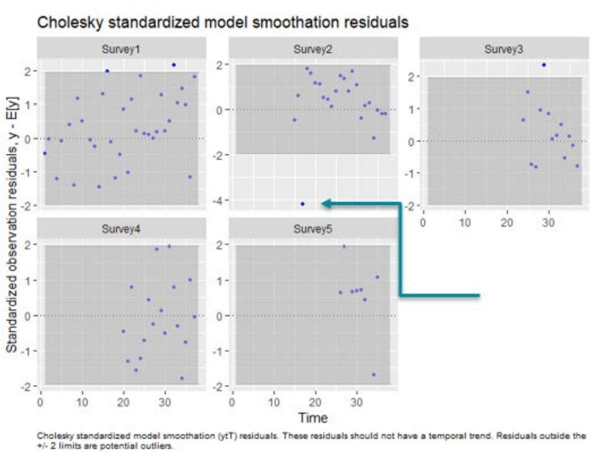


V2

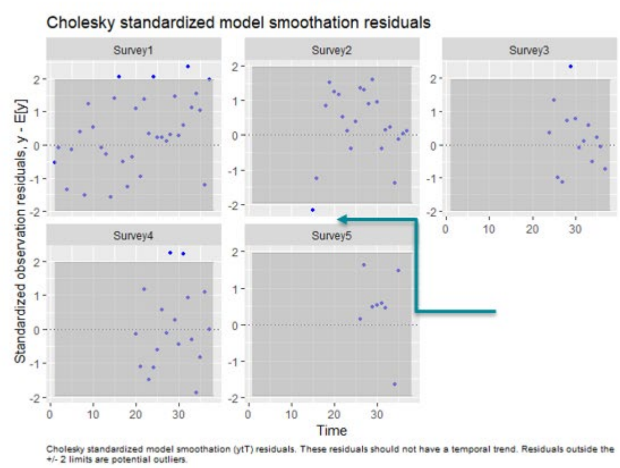


- Analysis of survey standardized residuals
- Scale (influence) of Survey 2 outliers reduced in V2

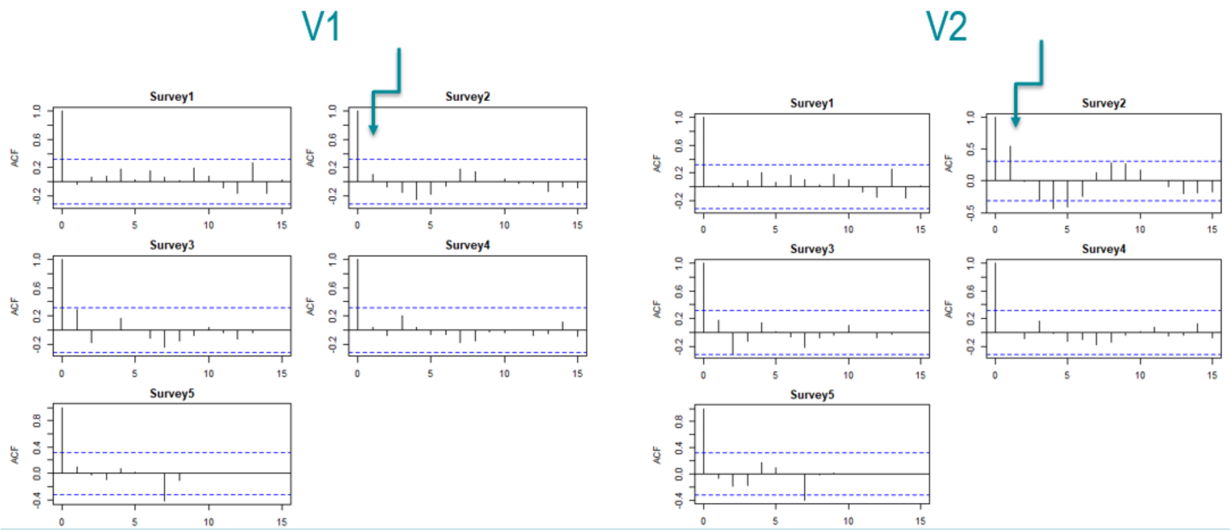
V1



V2



- Analysis of standardized residuals autocorrelation (acf)
- Survey 2 has autocorrelation (significant at lag 1 in V2)

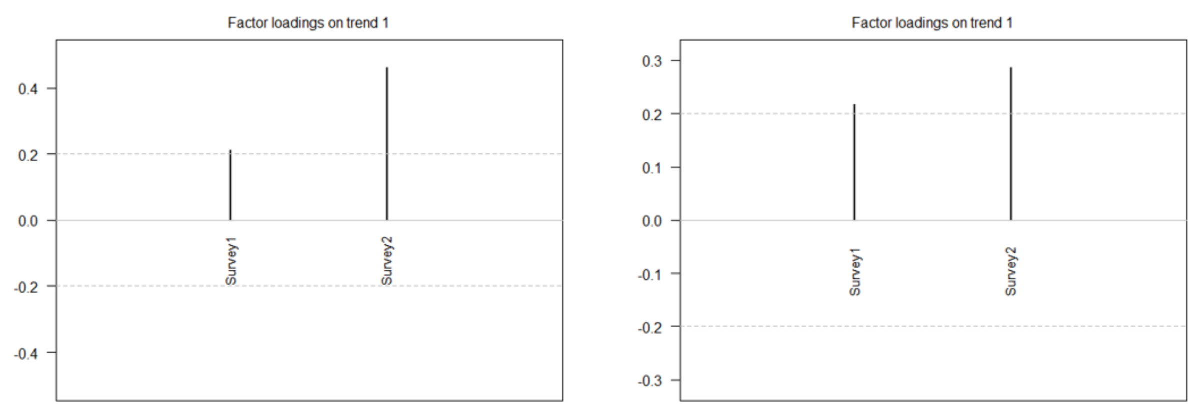


Appendix B – Diagnostics DFA (b) Gulf of Mexico Indices

- **Recommend for use in Sensitivity Analysis**

- **Recommend V2 for use in Sensitivity Analysis**
- Remove outlier survey 2 (1998)

TXPWD-Gillnet	GULFSPAN	
SEDAR77 DW-16	SEDAR77 DW-17	
Gulf of Mexico	Gulf of Mexico	
sharks per net per hour	sharks per net per hour	
	index	CV
	0.009	0.294
	0.016	0.461
	0.002	0.548



- Fit ratios (Fit ratio >=0.6 suggest poor fit)
- V1

```
> FitRatio
  Survey1   Survey2
0.6521836 0.1869621
> mean(FitRatio)
[1] 0.4195729
```

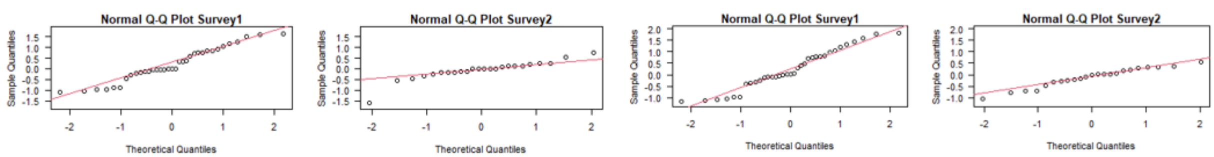
  - Survey 2, Good fit; but Survey 1 poor fit;
- V2

```
> FitRatio
  Survey1   Survey2
0.6227688 0.3028268
> mean(FitRatio)
[1] 0.4627978
```

- Survey 1 similar poor fit as in V1
- Survey 2 reduced fit compared to V1
  - Overall fit ratio slightly worse than V1

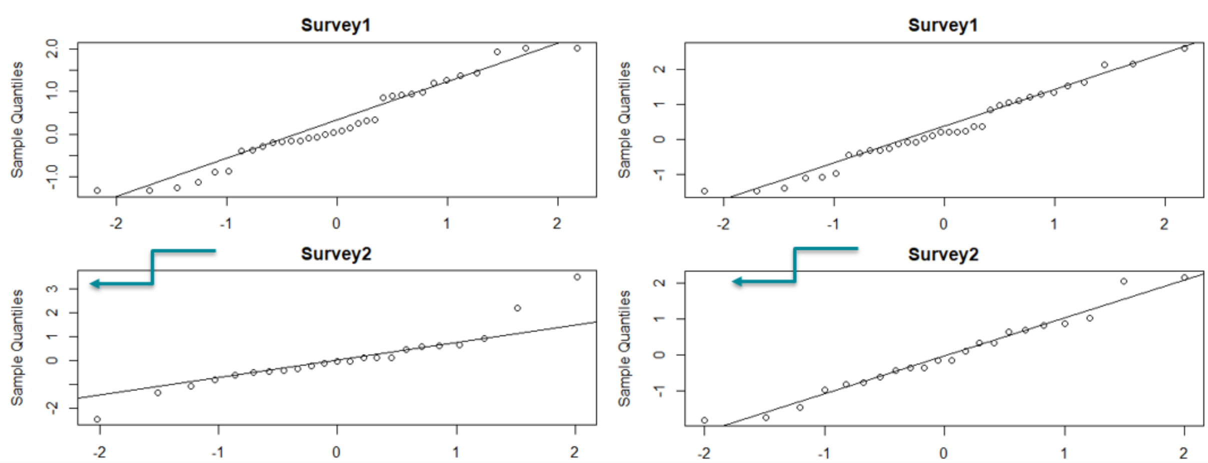
- Manual QQ plots "raw residuals" from fit (dat.z-fit.b)
- Survey 2 skewed in both V1 and V2

V1 V2



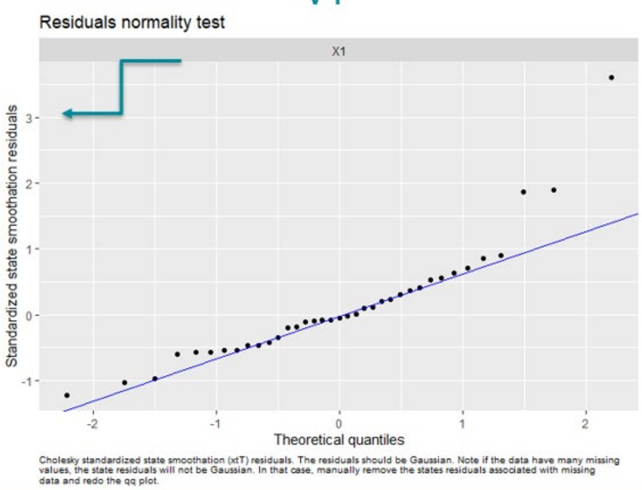
- QQ plots "standardized residuals"
- Survey 2 skew in V1 reduced in V2

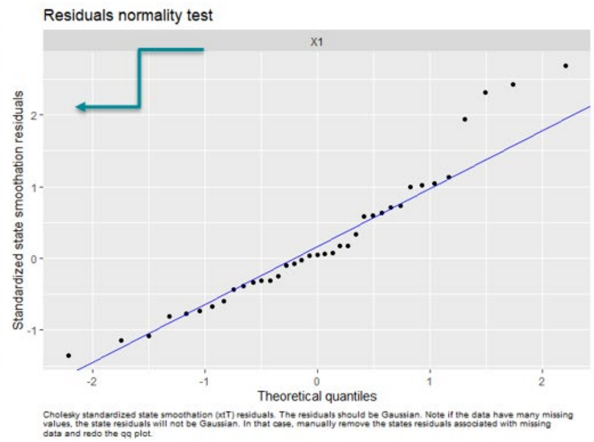
V1 V2



- QQ plots state vector “standardized residuals”
- Some skew, but reduced in V2

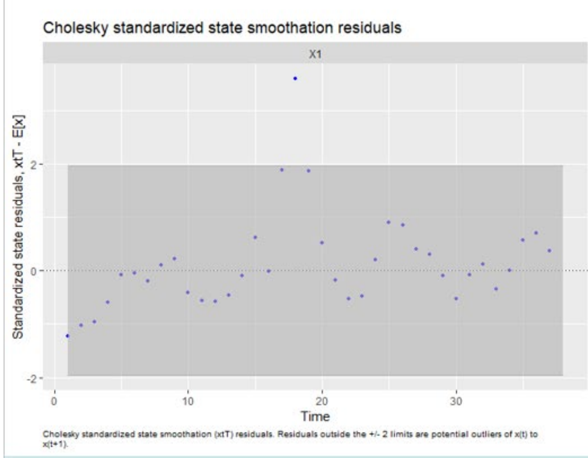
V1 V2

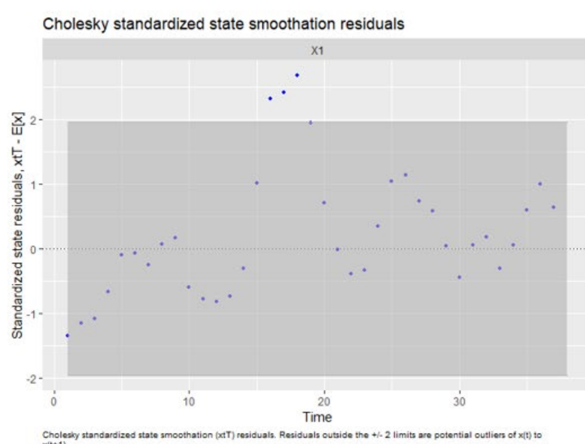




- Analysis of state vector standardized residuals
- Scale (influence) of outliers reduced but trend remains V2

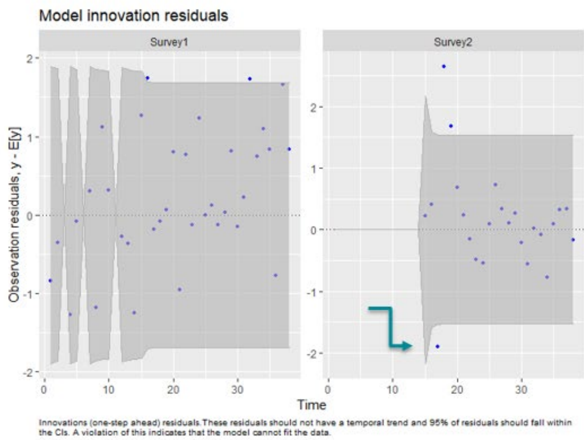
V1 V2



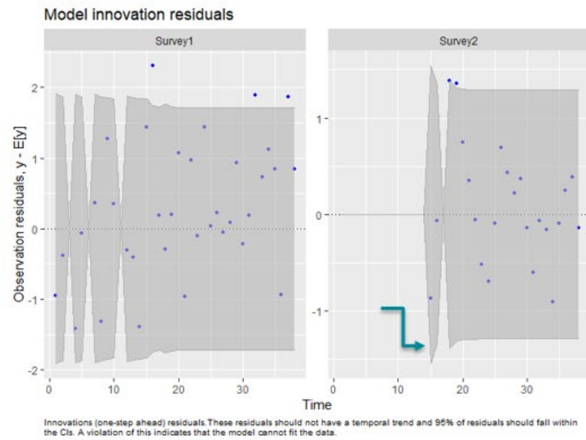


- Analysis of survey residuals to fit
- Survey 2 outlier pattern reduced in V2

V1

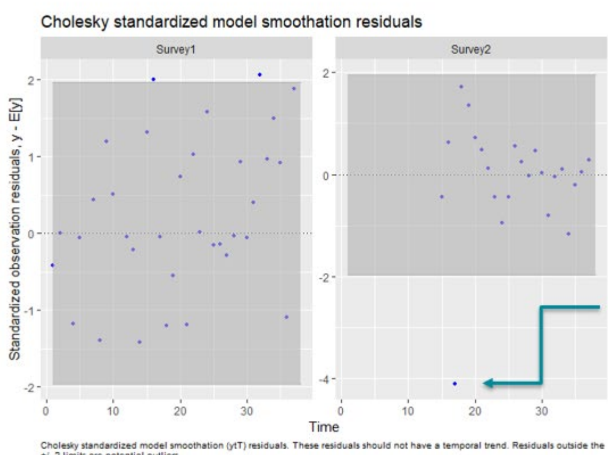


V2

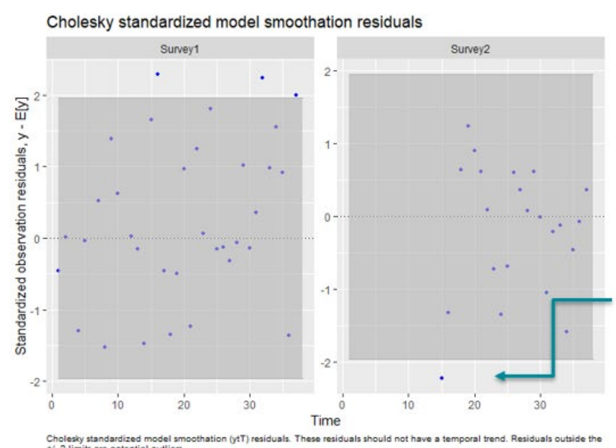


- Analysis of survey standardized residuals
- Scale (influence) of Survey 2 outliers reduced in V2

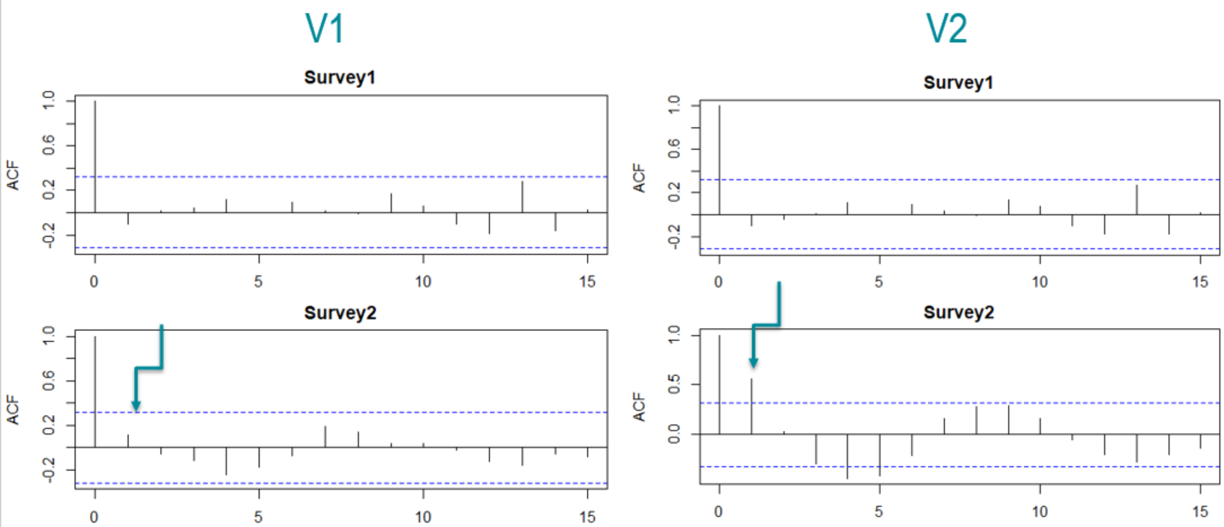
V1



V2

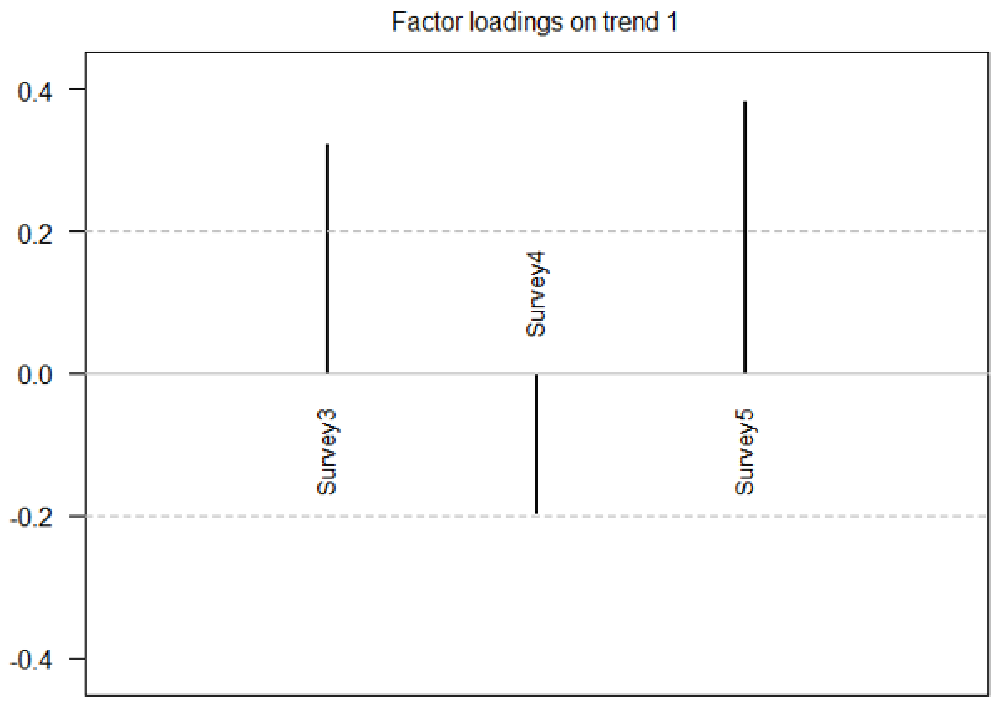


- Analysis of standardized residuals autocorrelation (acf)
- Survey 2 has autocorrelation (significant at lag 1 in V2)



Appendix C – Diagnostics DFA (c) Atlantic Indices

- **Recommend for use in Sensitivity Analysis**

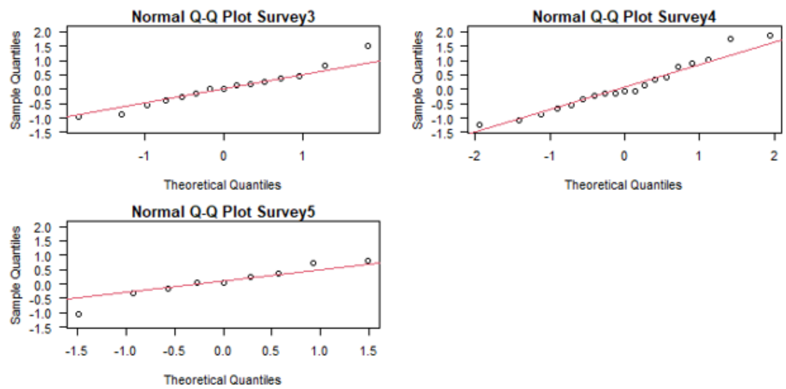


- Fit ratios (Fit ratio >=0.6 suggest poor fit)

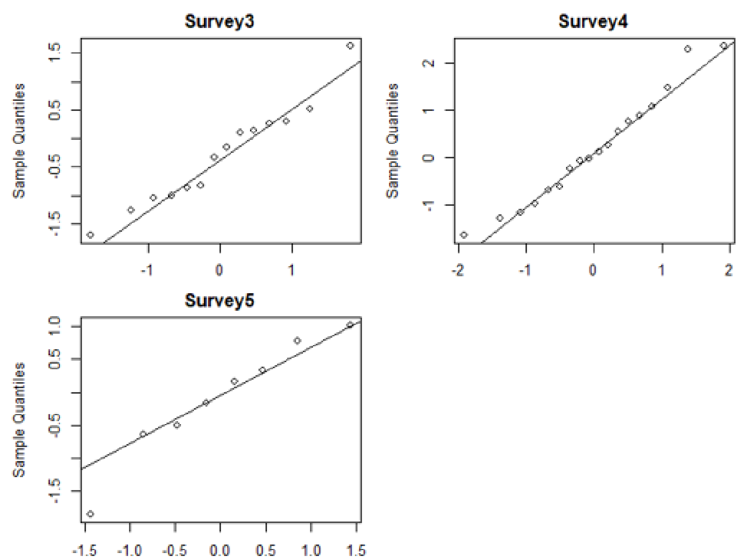
```
>   FitRatio
  Survey3   Survey4   Survey5
0.3782546 0.7334609 0.3071547
>   mean(FitRatio)
[1] 0.4729567
```

- Fit to Survey 4 is poor (Fit ratio >=0.6)

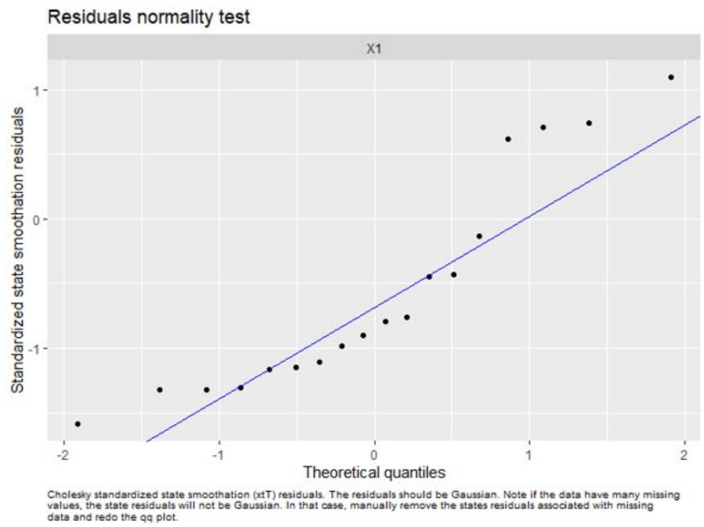
- Manual QQ plots “raw residuals” from fit (dat.z-fit.b)
- Survey 3 and 4 reasonable
- Survey 5 has low sample size



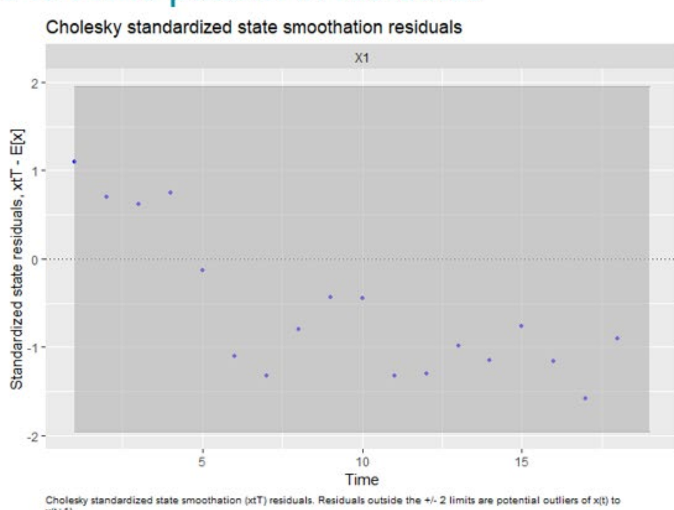
- QQ plots “standardized residuals”
- Survey 3 and 4 reasonable
- Survey 5 has low sample size



- QQ plots state vector “standardized residuals”
- Some skew but reasonable

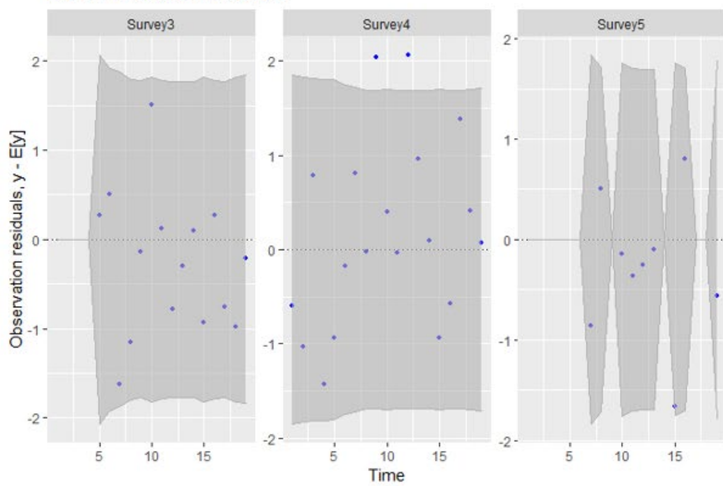


- Analysis of state vector standardized residuals
- Scale (influence) of outliers reduced relative to survey,
  - but there is some pattern in residuals



- Analysis of survey residuals to fit
- Some outlier pattern similar to DFA #1 and #2 V2 above

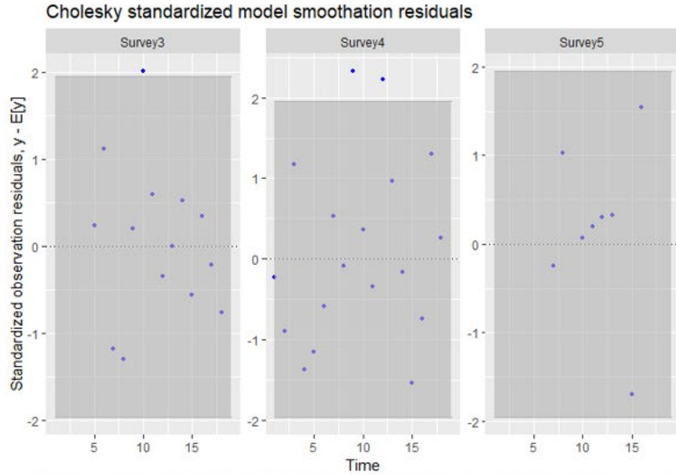
Model innovation residuals



Innovations (one-step ahead) residuals. These residuals should not have a temporal trend and 95% of residuals should fall within the CIs. A violation of this indicates that the model cannot fit the data.

- Analysis of survey standardized residuals
- Scale (influence) of outliers similar to DFA #1 and #2 V2

Cholesky standardized model smoothation residuals



Cholesky standardized model smoothation (ytT) residuals. These residuals should not have a temporal trend. Residuals outside the +/- 2 limits are potential outliers.

- Analysis of standardized residuals autocorrelation (acf)
- Survey 3 has some autocorrelation (significant at lag 2)