## Supplement materials of "Forecasting mortality rates with a coherent ensemble averaging approach"

## A. Proof of Theorem 1

For the *j*th model (j = 1, ..., J), Gao and Shi (2021) show that a sufficient and necessary condition to achieve age coherence is that  $|\hat{\mu}_{x,j} - \hat{\mu}_{x+k,j}| = O_p(1/h)^1$ , where x = 1, ..., N, k = 1, ..., N - 1, and  $\hat{\mu}_{x,j}$  is the estimated long-run mean of mortality improvements of age x ( $\Delta y_{x,t}$ ), using the model *j*. Hence, it can be inferred that

$$\hat{y}_{x,j,T+h} = O_p(1) + h\hat{\mu}_{x,j},$$

and age coherence is achieved as  $|\hat{y}_{x,j,T+h} - \hat{y}_{x+k,j,T+h}| = O_p(1).$ 

Using the MA approach, it is then easy to see

$$\hat{y}_{x,M,T+h} = O_p(1) + h \sum_{j=1}^{J_c} \hat{w}_{x,j} \hat{\mu}_{x,j} + h \sum_{j=1}^{J_n} \hat{w}_{x,j} \hat{\mu}_{x,j}.$$
(1)

Recall that  $\hat{w}_{x,j}$  of age-incoherent models are estimates of (13) and subject to the coherent penalty  $\lambda_1$ . Since  $\lambda_1$  is assumed to go large with  $T^2$ ,  $\hat{w}'C_1\hat{w}$  will need to be  $O_p(1/T^2)$ , or the loss function will be "overwhelmed" by  $\lambda_1$ . Essentially, this suggests that  $\hat{w}_{x,j} = O_p(1/T)$  for an age-incoherent model. Also, since  $\hat{\mu}_{x,j}$  is not increasing with h, it is equivalent to the fact that  $\hat{\mu}_{x,j}$  of all models have a lower or the same order of  $O_p(1)$ . Consequently, further with the assumption that h and T go to infinity at the same rate, we have that the highest order of the second summation in (1) is

$$h\sum_{j=1}^{J_n} \hat{w}_{x,j}\hat{\mu}_{x,j} = hO_p(1/h)O_p(1) = O_p(1).$$

Thus, (1) can be rewritten as

$$\hat{y}_{x,M,T+h} = O_p(1) + h \sum_{j=1}^{J_c} \hat{w}_{x,j} \hat{\mu}_{x,j}$$

<sup>&</sup>lt;sup>1</sup>Note that if  $\hat{\mu}_{x,j}$  is irrelevant to h (as in the STAR model), this condition is equivalent to  $\hat{\mu}_{x,j} = \hat{\mu}_{x+k,j}$ .

taking the difference between forecast logged mortality rates of two ages, we have that

$$\begin{aligned} &|\hat{y}_{x,M,T+h} - \hat{y}_{x+k,M,T+h}| \\ = &O_p(1) + h |\sum_{j=1}^{J_c} \hat{w}_{x,j} \hat{\mu}_{x,j} - \sum_{j=1}^{J_c} \hat{w}_{x+k,j} \hat{\mu}_{x+k,j}| \\ = &O_p(1) + h |\sum_{j=1}^{J_c} \hat{w}_{x,j} (\hat{\mu}_{x,j} - \hat{\mu}_{x+k,j}) + \sum_{j=1}^{J_c-1} (\hat{w}_{x,j} - \hat{w}_{x+k,j}) (\hat{\mu}_{x+k,j} - \hat{\mu}_{x+k,J_c})| \end{aligned}$$
(2)

Further, since  $\hat{w}_{x,j}$  is bounded in [0, 1], it is easy to see that

$$h[\sum_{j=1}^{J_c} \hat{w}_{x,j}(\hat{\mu}_{x,j} - \hat{\mu}_{x+k,j})] = hO_p(1)O_p(1/h) = O_p(1).$$

This verifies that the first summation in (2) is  $O_p(1)$ .

For the second summation in (2), since all  $\hat{\mu}_{x+k,j}$ 's are asymptotically consistent,

$$\hat{\mu}_{x+k,j} - \hat{\mu}_{x+k,J_c} = \hat{\mu}_{x+k,j} - \mu_{x+k} - (\hat{\mu}_{x+k,J_c} - \mu_{x+k}) = o_p(1),$$

where  $\mu_{x+k}$  is the true value of the mortality improvement at age x + k, it is then easy to see that

$$(\hat{w}_{x,j} - \hat{w}_{x+k,j})(\hat{\mu}_{x+k,j} - \hat{\mu}_{x+k,J}) = o_p(1)$$

for an age-coherent model.

Combine all the above results, we have that

$$|\hat{y}_{x,M,T+h} - \hat{y}_{x+k,M,T+h}| = O_p(1),$$

which completes the proof.

## **B.** Additional tables

Model	Parameter	Purpose	Selection procedure		
STAR	$\lambda_{lpha}$	A larger (smaller) value increases (reduces) the smoothness between $\alpha_x$ and $\alpha_{x+1}$	The selection takes place at the estimation stage. A grid search is performed to select the three smoothness penalties simultaneously. At each step, model		
	$\lambda_{eta_1}$	A larger (smaller) value increases (reduces) the smoothness between $\beta_{x,x-1}$ and $\beta_{x+1,x}$	coefficients are fitted after all tuning parameters are specified. Forecasts are then produced as in (6). An RMSFE is then produced following (12). The final		
	$\lambda_{eta_2}$	A larger (smaller) value increases (reduces) the smoothness between $\beta_{x,x-2}$ and $\beta_{x+1,x-1}$	selection of tuning parameters is that minimizes the RMSFE over all grids.		
LC-H	$d_1^l$	A larger (smaller) value indicates slower (faster) decay at the first age	The selection takes place at the forecasting stage. A grid search is performed to select both parameters simultaneously. Once a pair is specified, mortality rates		
	$b^w$	A larger (smaller) value indicates decline in $r_x^l$ starts from an older (younger) age	are forecast as in (9). RMSFE is then produced following (12). The final selection of tuning parameters is that minimizes the RMSFE over all grids.		
LC-G	$r_1^l\ b^w$	Same as in LC-H	Same as in LC-H		
SVAR-H	$\lambda_x$	A larger (smaller) value indicates fewer (more) none-zero AR coefficients	The selection takes place at the estimation stage. A grid search is performed. At each step, model coefficients are fitted after all tuning parameters are specified. Forecasts are then produced as in (10). An RMSFE is then produced following (12). The final selection of tuning parameters is that minimizes the RMSFE over all grids.		
	$egin{array}{c} d_1^s \ b^w \end{array}$	Same as in LC-H	Same as in LC-H		
SVAR-G	$egin{array}{c} \lambda_x \ r_1^s \ b^w \end{array}$	Same as in SVAR-H	Same as in SVAR-H		

 Table 1: Summary of the tuning parameter selection

	Mean	Std. Dev.	Median	$Q_1$	$Q_3$				
Panel A: Sixteen forecasting steps									
STAR	0.2172	0.0626	0.2283	0.1814	0.2649				
LC-H	0.2277	0.0656	0.2216	0.1748	0.2417				
LC-G	0.2319	0.0634	0.2284	0.1846	0.2446				
SVAR-H	0.2311	0.0686	0.2227	0.1890	0.2873				
SVAR-G	0.2314	0.0685	0.2226	0.1902	0.2876				
LC	0.2519	0.0611	0.2309	0.2177	0.2761				
SVAR	0.2297	0.0737	0.2160	0.1875	0.2820				
APC	0.3256	0.0630	0.3205	0.2741	0.3735				
HU	0.2427	0.0607	0.2219	0.2094	0.2770				
$\mathbf{RH}$	0.2675	0.0893	0.2760	0.2194	0.3192				
MA	0.2039	0.0611	0.2011	0.1571	0.2470				
Panel B. Starting year of 1960									
STAR	$\begin{array}{c} 0 1844 \end{array}$	0 0645	0.1794	0 1413	0.2451				
LC-H	0.1011 0.2041	0.0679	0 2041	0.1385	0.2101 0.2594				
LC-G	0.2041 0.2055	0.0676	0.2041	0.1430	0.2004 0.2612				
SVAR-H	0.2050 0.2054	0.0828	0.2000	0.1400 0.1377	0.2012 0.2805				
SVAR-G	0.2051 0.2058	0.0824	0.2010	0.1390	0.2800				
LC	0.2000 0.2305	0.0021 0.0672	0.2000 0.2289	0.1690	0.2001				
SVAR	0.2000	0.0842	0.1994	0.1351	0.2838				
APC	0.2638	0.0523	0.2820	0.2242	0.3010				
HU	0.2024	0.0680	0.2010	0.1512	0.2537				
RH	0.2021 0.2170	0.0649	0.2010 0.2205	0.1780	0.2607 0.2617				
MA	0.1837	0.0712	0.1938	0.1242	0.2413				
	012001	0.0112	0.10000	011212	0.2110				
Panel C: Ages 0–89									
STAR	0.1862	0.0688	0.1821	0.1380	0.2457				
LC-H	0.2059	0.0746	0.1859	0.1527	0.2500				
LC-G	0.2106	0.0719	0.1942	0.1562	0.2535				
SVAR-H	0.2067	0.0862	0.1876	0.1492	0.2835				
SVAR-G	0.2069	0.0863	0.1877	0.1495	0.2837				
LC	0.2469	0.0654	0.2452	0.1894	0.2989				
SVAR	0.2102	0.0929	0.1910	0.1351	0.2913				
APC	0.3274	0.0657	0.3114	0.2753	0.3805				
HU	0.2085	0.0768	0.1775	0.1573	0.2653				
$\mathbf{RH}$	0.2570	0.0838	0.2717	0.1957	0.3128				
MA	0.1834	0.0757	0.1695	0.1245	0.2471				

 Table 2: Summary of robustness checks

Note: bold numbers are the smallest quantity for each statistic across the eleven models.

## References

Gao, G., Shi, Y., 2021. Age-coherent extensions of the Lee–Carter model. Scandinavian Actuarial Journal , 1–19.