**Supporting Information.** Freshwater, Cameron, Sean C. Anderson, Kendra R. Holt, Ann-Marie Huang, and Carrie A. Holt. 2019. Weakened portfolio effects constrain management effectiveness for population aggregates. *Ecological Applications.*

**Appendix S2: Supplementary Results and Sensitivity Analyses**

**S1: Retrospective Analysis Sensitivity Analysis**

We re-ran retrospective analyses estimating aggregate variability using a larger sample of 16 Fraser River sockeye salmon CUs with time series starting in 1975. We excluded the Shuswap-ES time series due to its short length and the Cultus time series due to large hatchery and captive brood stock influences. Similar to our results for 10 CUs with time-series beginning in 1951, both component variability and synchrony increased in recent years using the larger CU sample size and shorter time-series (Fig. S1). These patterns appear more extreme using the shorter time-series because the period during the 1950s and 60s when component variability and synchrony were previously elevated is absent (Fig. 2 main text).
Figure S1. Observed trends in generational mean (a) CU-specific productivity \(\log_e(\text{recruits per spawner})\), (b) aggregate returner abundance, and (c) aggregate catch (millions of fish), as well as estimates of the mean component coefficient of variation, synchrony, and aggregate coefficient of variation (d–f) of 16 CUs recruit abundance with time series extending back to 1975. Note that all values are lagged by four years (one generation; a–c) or 12 years (three generations; d–f) such that the first point in the time-series of each panel represents the value for the preceding four or 12 years. In panel (a) grey lines represent productivity trends for the 16 individual CUs from which the mean (black line) was calculated. In panels (d–f) black lines represent estimates and grey bands represent 95% confidence intervals.
S2: Low Productivity, Heavy-Tailed Scenario

To increase the frequency of “black-swan” events (Anderson et al. 2017), we paired $\alpha$ estimates from the low productivity scenario described in the main text with a heavy-tailed distribution that increases the probability of sampling extreme values. Recruitment deviations $\eta$ (Eq. 6b main text) were fit with a multivariate Student $t$ distribution, which includes a third parameter $\eta$ representing degrees of freedom and controlling the extent to which recruitment deviations have heavy tails. Lower values of $\eta$ correspond to heavier tails and as $\eta$ approaches infinity, the $t$ distribution approaches the normal. Accurately estimating the parameters of heavy-tailed distributions is difficult given the short length of ecological time series. Following Anderson et al. (2017), therefore, we set $\eta = 2$, representing a scenario that allows for an event three SDs above or below the mean to occur approximately once every 21 years, rather than once every 741 years using a normal distribution.

The low productivity, heavy-tailed scenario resulted in more frequent extreme recruitment events, which increased variation in conservation-based performance metrics among trials (Fig. S2c, f, i, l) and increased the strength of the positive relationship between component variability and return abundance when synchrony was low (Fig. S2c). Declines in median status for conservation-based metrics, however, were broadly similar to those in the low productivity scenario (Fig. S2).

The impacts of more frequent extreme recruitment events were more variable among catch-based performance metrics. For example, relative to the low productivity scenario, median aggregate catch abundance increased in the low productivity, heavy-tailed scenario when component variability was low (purple symbols Fig. S3c) and variation in catch abundance increased (Fig. S3c). Conversely, the proportion of years the aggregate catch threshold was met was similar as for the low productivity scenario (Fig. S3f). Finally, catch stability was reduced in the low productivity, heavy-tailed scenario relative to the low productivity scenario (e.g., ~37% decline with moderate synchrony and reference component variability). While high synchrony in the low productivity, heavy-tailed scenario still resulted in reduced stability, the additional effect of greater component variability was small relative to the reference or low productivity scenarios (Fig. S3i vs. S3g or S3h).
Figure S2. Effects of component variability and synchrony on conservation-based performance metrics for three productivity scenarios (reference (a,d,g,j); low productivity (b,e,h,k); low productivity, heavy-tailed recruitment deviations (c,f,i,l)) and for four performance metrics (aggregate return abundance (a-c); CU-specific standardized return abundance (d-f); proportion of MUs above their escapement goal (g-i); and proportion of CUs above their biological benchmark (j-l)). Points represent medians and whiskers 90% probability intervals among 1500 Monte Carlo trials.
Figure S3. Effects of component variability and synchrony on catch-based performance metrics for three productivity scenarios (reference (a,d,g); low productivity (b,e,h); very low productivity (c,f,i)) and for three performance metrics (catch (a-c); proportion of years above catch threshold (d-f); and catch stability (g-i)). Points represent medians and whiskers 90% probability intervals among 1500 Monte Carlo trials.
To test the robustness of our simulation results to model parameterization (Table S1), we conducted local sensitivity analyses by varying several stochastic parameters to higher or lower values, which bounded plausible ranges, while holding all other parameters constant. Note that we did not conduct sensitivity analyses on CU-specific standardized recruitment because this performance metric is only interpretable across multiple component variability and synchrony scenarios.

For temporal autocorrelation $\tau$ we set the minimum value at zero (i.e. no autocorrelation in recruitment deviations) and the maximum at the largest estimated value from a study of Alaskan sockeye salmon, which used a Ricker model with lag-1 temporal autocorrelation (Peterman et al. 2003; Table S1). To produce alternative parameter values for $\omega$ and $\sigma_{mort}$ we applied scalars that produced values that reflected CU-specific variation (i.e. were within approximately one SD of the mean of observed values; Table S1). A similar approach could not be used for outcome uncertainty because there were insufficient data to fit MU-specific beta distributions. Therefore we set the minimum value at zero (i.e. target exploitation rates were perfectly applied) and the maximum value at 0.15. The latter value is arbitrary but results in approximately 20% of harvest rate deviations (the difference between target and realized harvest rate), exceeding the maximum harvest rate deviation observed in the Fraser River (2006-2017). In contrast the reference value (0.07) results in ~0.2% of harvest rate deviations exceeding the maximum observed deviation.
Table S1. Parameter values for components of operating model and management procedure that were adjusted in local sensitivity analyses. Relevant equations are in the main text or Appendix S1.

| Parameter | Definition | Reference Values | Minimum | Maximum |
|-----------|------------|------------------|---------|---------|
| $\tau$ (Eq. 6) | Temporal autocorrelation coefficient of residuals | 0.2 | 0 | 0.72 |
| $\omega$ (Eq. S3) | Interannual variability in maturation proportion | CU-specific (range 0.68-1.48) | $0.5 \times \text{ref } \omega$ | $1.25 \times \text{ref } \omega$ |
| $\sigma_{\text{mort}}$ (Eq. S4) | SD of CU-specific en-route mortality | CU-specific (range 0.17-0.48) | $0.75 \times \text{ref } \sigma_{\text{mort}}$ | $1.25 \times \text{ref } \sigma_{\text{mort}}$ |
| $\sigma_{\text{out}}$ (Eq. S6) | SD of location parameter in beta distribution for outcome uncertainty | 0.07 | 0 | 0.15 |
The relative impact of increasing or decreasing stochasticity varied across parameters with the strength of temporal autocorrelation in recruitment residuals (τ) having the strongest effect. Increasing τ from its reference value of 0.2 to 0.72 resulted in declines in median return abundance and the proportion of CUs above their biological benchmark (Fig. S4), as well as median catch (Fig. S5). However, the impacts of increasing τ on the remaining performance metrics were minor. Similarly, reducing τ to zero resulted in only modest improvements in all performance metrics (Fig. S4-S5). These patterns suggest that populations with evidence of strong temporal autocorrelation in productivity or survival may exhibit a stronger response to increases in component variability or synchrony. As noted above, however, the upper value of τ was chosen because it was the maximum value estimated in a previous sockeye salmon study (Peterman et al. 2003). Given that published values for τ in sockeye salmon populations typically range between 0.1 and 0.4, the reference value is likely more appropriate (Korman et al. 1995, Holt and Peterman 2008).

Conversely, the impacts of changing interannual variability in age-at-maturity, en-route mortality, and outcome uncertainty were minor. Generally increasing variability lead to only modest declines in performance and 90% quantile intervals for each of the sensitivity analysis operating models largely overlapped the reference operating model (Fig. S4-S5).
Figure S4. Conservation-based performance metrics across various sensitivity operating models. Points represent medians of 1500 Monte Carlo trials and whiskers the 90% quantile interval. Horizontal black lines represent median (solid) and 90% quantile interval (dashed) of reference operating model with moderate component variability and moderate synchrony.
Figure S5. Catch-based performance metrics across various sensitivity operating models. Points represent medians of 1500 Monte Carlo trials and whiskers the 90% quantile interval. Horizontal black lines represent median (solid) and 90% quantile interval (dashed) of reference operating model with moderate component variability and moderate synchrony.
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