**Supplemental Appendix for Survival , Attrition and Biased Decision-Making**

i) Note that ${\partial B_n}/{\partial n}$ is clearly positive since:

$\frac{\partial B_n}{\partial n} = \frac{\sigma_\varepsilon\ \sigma_\mu^2(\bar{s}-g(\bar{s}))}{(\sigma_\varepsilon^2+n\sigma_\mu^2)\int_{(\beta-\hat{p})/\sigma_\varepsilon}^{\infty} e^{-1/2 t^2}dt}$ with all parameters larger than zero and $E(\bar{s}-g(\bar{s}))$ free of n as well.

ii) In the case of ${\partial B_n}/{\partial \sigma_\varepsilon}$ ,there are no clear-cut signs of the derivative; parameters produce both positive and negative results. Nonetheless, some bounds could be established, for example in order for ${\partial B_n}/{\partial \sigma_\varepsilon} > 0$ there is a necessary and sufficient condition

*Proof:*

*Note that after taking expectations:*

$$ {\partial B_n}/{\partial \sigma_\varepsilon} = \frac{2e^{-\frac{(\beta-\mu)^2}{2\sigma_\varepsilon^2}-\frac{(\mu-\beta)^2}{2\sigma_\varepsilon^2}}\, n(\beta-\mu)\sigma_\mu^2}{\pi\sigma_\varepsilon^2(n\sigma_\mu^2+\sigma_\varepsilon^2)(1+Erf\left[\frac{\mu-\beta}{\sqrt{2}\sigma_\varepsilon}\right])^2} - \frac{2ne^{-\frac{(\mu-\beta)^2}{2\sigma_\varepsilon^2}}\sqrt{\frac{2}{\pi}}\sigma_\mu^2\sigma_\varepsilon^2}{(n\sigma_\mu^2+\sigma_\varepsilon^2)^2(1+Erf\left[\frac{\mu-\beta}{\sqrt{2}\sigma_\varepsilon}\right])} + \frac{e^{-\frac{(\mu-\beta)^2}{2\sigma_\varepsilon^2}}\sqrt{\frac{2}{\pi}}n\sigma_\mu^2}{(n\sigma_\mu^2+\sigma_\varepsilon^2)(1+Erf\left[\frac{\mu-\beta}{\sqrt{2}\sigma_\varepsilon}\right])} + \frac{e^{-\frac{(\mu-\beta)^2}{2\sigma_\varepsilon^2}}\sqrt{\frac{2}{\pi}}(\mu-\beta)^2 n\sigma_\mu^2}{\sigma_\varepsilon^2(n\sigma_\mu^2+\sigma_\varepsilon^2)(1+Erf\left[\frac{\mu-\beta}{\sqrt{2}\sigma_\varepsilon}\right])} \quad (A) $$

*Now to see how can* ${\partial B_n}/{\partial \sigma_\varepsilon} > 0$ I re-arrange and simplify (A) equation to compare first two terms to the second two, the resulting necessary and sufficient condition is then given by:

$$ {\partial B_n}/{\partial \sigma_\varepsilon} > 0 \quad \boldsymbol{iff} \quad \frac{2e^{-\frac{(\beta-\hat{p})^2}{2\sigma_\varepsilon^2}}(\hat{p}-\beta)}{\sqrt{2\pi}(1-Erf(\frac{\beta-\hat{p}}{\sqrt{2}\sigma_\varepsilon}))} + \frac{2\sigma_\varepsilon^4}{n\sigma_\mu^2+\sigma_\varepsilon^2} < \sigma_\varepsilon^2 + (\hat{p}-\beta)^2 $$

*From which it clearly follows that assuming* $\sigma_\varepsilon^2 > \frac{2\sigma_\varepsilon^4}{n\sigma_\mu^2+\sigma_\varepsilon^2}$ , $(\hat{p}-\beta)^2 > \frac{2e^{-\frac{(\beta-\hat{p})^2}{2\sigma_\varepsilon^2}}(\hat{p}-\beta)}{\sqrt{2\pi}(1-Erf(\frac{\widehat{\beta-p)}}{\sqrt{2}\sigma_\varepsilon})}$ *are a sufficient and necessary condition for above inequality to hold* ■

There is also a range of parameters for which $\partial B_n / \partial\sigma_\varepsilon < 0$ . It is clear that reversing the inequality signs produces the two necessary and sufficient conditions for that range of parameters.

iii) $\partial B_n / \partial\sigma_\mu > 0$ for all values of parameters, this follows from the fact that differentiating Bias with respect to prior variance yields:

$$\partial B_n / \partial\sigma_\mu = \frac{2\,e^{-\frac{(\mu-\beta)^2}{2\sigma_\varepsilon^2}} n^2 \sqrt{\frac{2}{\pi}}\sigma_\mu\,\sigma_\varepsilon}{\left(n\sigma_\mu^2+\sigma_\varepsilon^2\right)(1+Erf\left[\frac{\mu-\beta}{\sqrt{2}\sigma_\varepsilon}\right])} - \frac{2\,e^{-\frac{(\mu-\beta)^2}{2\sigma_\varepsilon^2}} n \sqrt{\frac{2}{\pi}}\sigma_\mu^3\sigma_\varepsilon}{\left(n\sigma_\mu^2+\sigma_\varepsilon^2\right)^2(1+Erf\left[\frac{\mu-\beta}{\sqrt{2}\sigma_\varepsilon}\right])}$$

which can be easily simplified to:

$$\partial B_n / \partial\sigma_\mu = \frac{2\,e^{-\frac{(\mu-\beta)^2}{2\sigma_\varepsilon^2}} \sqrt{\frac{2}{\pi}}\sigma_\varepsilon^3 n\sigma_\mu}{\left(n\sigma_\mu^2+\sigma_\varepsilon^2\right)^2(1+Erf\left[\frac{\mu-\beta}{\sqrt{2}\sigma_\varepsilon}\right])}$$

It is immediately clear that $\partial B_n / \partial\sigma_\mu > 0$.

iv) $\partial B_n / \partial\beta$ could also take on both positive and negative values depending on parameters since differentiating with respect to the truncation point yields:

$$\partial B_n/_{\partial\beta} = \frac{2e^{-\frac{(\beta-\mu)^2}{2\sigma_\varepsilon^2}-\frac{(\mu-\beta)^2}{2\sigma_\varepsilon^2}} n\sigma_\mu^2}{\pi\left(n\sigma_\mu^2+\sigma_\varepsilon^2\right)\ \ (1+Erf\left[\frac{\mu-\beta}{\sqrt{2}\sigma_\varepsilon}\right])^2} - \frac{e^{-\frac{(\mu-\beta)^2}{2\sigma_\varepsilon^2}}\sqrt{\frac{2}{\pi}}(\mu-\beta)\ \ n\sigma_\mu^2}{\sigma_\varepsilon\left(n\sigma_\mu^2+\sigma_\varepsilon^2\right)\left(1+Erf\left[\frac{\mu-\beta}{\sqrt{2}\sigma_\varepsilon}\right]\right)} \quad \text{(B)}$$

where in case of severe truncation ($\beta > \mu$) it is clear that $\partial B_n/_{\partial\beta} > 0$. In the case of milder truncation ($\beta < \mu$) this result is more difficult to obtain. More specifically an additional condition needs to be imposed.

Rearranging (B), while assuming $\beta < \mu$, it becomes clear that

$$\partial B_n/_{\partial\beta} > 0 \qquad \textbf{\textit{iff}} \qquad 2\sigma_\varepsilon\ \ e^{-\frac{(\mu-\beta)^2}{2\sigma_\varepsilon^2}} > \sqrt{2\pi}\,(\hat{p}-\beta)\ \ \left(1+Erf\left[\frac{\mu-\beta}{\sqrt{2}\sigma_\varepsilon}\right]\right)$$

**Dynamics**

*Note that while Equation 13 has no impact on bias we need to make sure solution exists and that is finite.*

$$solution\ to\ \sigma_{t+1} = \frac{\sigma_\varepsilon^2\sigma_{\mu(t)}^2}{\sigma_{\mu(t)}^2 + n\sigma_\varepsilon^2} \quad is \quad \sigma_{\mu(t)} = \frac{(n-1)n\sigma_\varepsilon^2}{n^{t+1} - n^t\sigma_\varepsilon^2 + n^{t+1}\sigma_\varepsilon^2 - n}$$

*Assuming that initial condition constant is equal to 1. Clearly above solution converges to 0.*