In this eAppendix, we show that for the causal DAG given in Figure 4, it is possible to identify the joint effects, $\mathbb{E}[D_{eq}]$, of $E$ and $Q$ on $D$ and thus to assess interaction but that it is not possible to identify conditional causal effects of the form $\mathbb{E}[D_e|Q = q]$ and thus not in general possible to assess effect modification in Figure 4.

We first use Result 2 in Appendix 2 to show that the joint effects, $\mathbb{E}[D_{eq}]$, of $E$ and $Q$ on $D$ are identified in the example represented by Figure 4. If, in Result 2, we choose $A_1 = E$, $A_2 = Q$ and $W = \emptyset$, we can see that all backdoor paths from $E$ to $D$ are blocked in the graph with the arrows into $Q$ removed. Furthermore, if we select $V = X$ then we can easily verify that all backdoor paths from $Q$ to $D$ on the original graph are blocked by $(E, X)$; the backdoor paths $Q - U_2 - E - D$ and $Q - U_2 - E - X - D$ are both blocked by $E$; the backdoor path $Q - U_1 - X - D$ is blocked by $X$; and the backdoor path $Q - U_1 - X - E - D$ is not blocked by $X$ (since $X$ is a collider on this path) but it is nevertheless blocked by $E$. Thus we can apply Result 2 to Figure 4 to identify the joint effects, $\mathbb{E}[D_{eq}]$, of $E$ and $Q$ on $D$ and thus to assess interaction between the effects of $E$ and $Q$ on $D$.

We now show that quantities of the form $\mathbb{E}[D_e|Q = q]$ are not identified in causal DAG given in Figure 4. The argument is subtle and uses a number of technical results concerning causal DAGs. First we note that there is a backdoor path from $Q$ to $D$ in the graph corresponding to Figure 4 with the node $E$ removed, namely $Q - U_1 - X - D$; from Theorem 6 of Shpitser and Pearl we have that $P(D_e|Q = q)$ is identified if and only if $P(D_e, Q_e)$ is identified. Since $E$ has no effect on $Q$ in Figure 4, it follows that $P(D_e|Q = q)$ is identified if and only if $P(D_e)$ is identified. Now, in Figure 4, there is path from $E$ to $X$ which consists entirely of consecutive confounding
arcs, namely $E - U_2 - Q$ and $Q - U_1 - X$; $X$ is a child of $E$ and from Theorem 3 of Tian and Pearl\textsuperscript{31} it follows that $P(D_e)$ and thus that $P(D_e|Q = q)$ is not identified.

Intuitively, one might reason that if we are interested in estimating the effect of $E$ on $D$ conditional on $Q$ we must use data on $E$, $Q$ and $D$. However, if one controls for $X$, then control is being made for an effect of $E$ and this will bias the estimate. If control is not made for $X$ then there is an unblocked backdoor path from $E$ to $D,$ namely, $E - U_2 - Q - U_1 - X - D$ (note that this path is unblocked because $Q$ is a collider on this path and one is conditioning on $Q$). The situation may seem analogous to the classical time-dependent confounding issue (that marginal structural models handle) in which a confounder of a subsequent exposure is on the causal pathway between prior exposure and the outcome. However, in Figure 4, unlike in the time-dependent confounding case, marginal structural models cannot help in the identification of the effect of interest, $E[D_e|Q = q]$. The argument given above using the results of Shpitser and Pearl\textsuperscript{28} and Tian and Pearl\textsuperscript{31} demonstrates that the $P(D_e|Q = q)$ is not identified; no method of adjustment can be used to identify $E[D_e|Q = q]$. The distinction is that in the time-dependent confounding case, data is available to identify the causal effects of interest but simple adjustment approaches like regression and stratification do not suffice; inverse-probability-of-treatment weighting techniques are needed. In Figure 4 the issue does not concern the method of adjustment but rather the fact that the data available are insufficient to identify the conditional causal effect of interest.