Comparison of approaches to adjust for confounding

A simplified example with dichotomous treatment *A*, dichotomous confounder *L*, continuous outcome *Y*, and ignoring censoring.

Approach	**Estimand**	**Models we fit** *Note:* Product terms shown below are optional, based on whether you think there is effect modification.	**Interpretation: The mean weight gain would have been X kg higher had everyone quit smoking compared with had no one quit smoking …**	**To consistently estimate the average causal effect in the population, are you forced to make any assumption(s) about effect modification?**
Outcome regression on confounders, *L*	$E[Y^{a=1}\|L] - E[Y^{a=0}\|L]$ *Conditional*	Outcome model: $E[Y\|A,L] = \beta_0 + \beta_1 A + \beta_2 L + \beta_3 A*L$	conditional on the confounders *L*.	Yes
Outcome regression on propensity score, *PS*	$E[Y^{a=1}\|PS] - E[Y^{a=0}\|PS]$ *Conditional*	Propensity score model: logit $Pr[A=1\|L] = \beta_0 + \beta_1 L$ Outcome model: $E[Y\|A,PS] = \beta_0 + \beta_1 A + \beta_2 PS + \beta_3 A*PS$	conditional on the PS.	
Standardization	$E[Y^{a=1}] - E[Y^{a=0}]$ *Marginal* If interested: $E[Y^{a=1}\|L] - E[Y^{a=0}\|L]$ *Conditional*	Outcome model: $E[Y\|A,L] = \beta_0 + \beta_1 A + \beta_2 L + \beta_3 A*L$ or $E[Y\|A,PS] = \beta_0 + \beta_1 A + \beta_2 PS + \beta_3 A*PS$	. (marginal interpretation)	No
Inverse probability weighting	$E[Y^{a=1}] - E[Y^{a=0}]$ *Marginal* If interested: $E[Y^{a=1}\|V] - E[Y^{a=0}\|V]$ *Conditional*	Model for weights: logit $Pr[A=1\|L] = \beta_0 + \beta_1 L$ Outcome model (fit to pseudopopulation): $E[Y\|A] = \beta_0 + \beta_1 A$ or, if interested: Outcome model (fit to pseudopopulation): $E[Y\|A,V] = \beta_0 + \beta_1 A + \beta_2 V + \beta_3 A*V$		
G-estimation	$E[Y^{a=1}\|L] - E[Y^{a=0}\|L]$ *Conditional*	Model for $H(\psi)$ for the grid search method: logit $Pr[A=1\|H(\psi), L] = \beta_0 + \beta_1 H(\psi) + \beta_2 L$	conditional on the confounders *L*.	Yes

Instrumental variable estimation	$E[Y^{a=1}] - E[Y^{a=0}]$ *Marginal (under the homogeneity assumption)* $E[Y^{a=1} \mid A^{z=1}=1, A^{z=0}=0]$ - $E[Y^{a=0} \mid A^{z=1}=1, A^{z=0}=0]$ *Effect among the compliers (under the monotonicity assumption)* If interested: $E[Y^{a=1} \mid L] - E[Y^{a=0} \mid L]$ *Conditional* $E[Y^{a=1} \mid A^{z=1}=1, A^{z=0}=0, L]$ - $E[Y^{a=0} \mid A^{z=1}=1, A^{z=0}=0, L]$ *Conditional effect among the compliers*	<u>Using the ratio method:</u> Model for the numerator: $E[Y \mid Z] = \beta_0 + \beta_1 Z$ Model for the denominator: $E[A \mid Z] = \beta_0 + \beta_1 Z$ <u>Using two-stage-least-squares regression</u>**:** First-stage treatment model: $E[A \mid Z] = \beta_0 + \beta_1 Z$ Second-stage outcome model: $E[Y \mid Z] = \beta_0 + \beta_1 \hat{E}[A \mid Z]$	. (marginal interpretation) *or* among the compliers.	Yes