Supplemental Digital Appendix 1

Table A1.1
Items in the Dutch Residency Educational Climate Test (D-RECT) used to measure the learning climate in 16 non-tertiary obstetrics and gynecology departments in the Netherlands, From Study on Learning Climate and Adverse Obstetrical Outcomes, 2013.

<u>Educational atmosphere</u>

1. Continuity of care is not affected by differences of opinion between attendings.
2. Differences of opinion between attendings about patient management are discussed in such a manner that is instructive to others present.
3. Differences of opinion are not such that they have a negative impact on the work climate.
4. There is (are) NO attending physician(s) who have a negative impact on the educational climate.
5. My attendings treat me with respect.

<u>Teamwork</u>

6. Attendings, nursing staff, other allied health professionals and residents work together as a team.
7. Nursing staff and other allied health professionals make a positive contribution to my training.
8. Nursing staff and other allied health professionals are willing to reflect with me on the delivery of patient care.

<u>Role of specialty tutor</u>

9. The specialty tutor monitors the progress of my training.
10. The specialty tutor provides guidance to other attendings when needed.
11. The specialty tutor is actively involved in improving the quality of education and training.
12. In this rotation evaluations are useful discussions about my performance.
13. My plans for the future are part of the discussion.
14. During evaluations, input from several attendings is considered.

<u>Coaching and assessment</u>

15. My attendings take the initiative to evaluate my performance.
16. My attendings take the initiative to evaluate difficult situations I have been involved in.
17. My attendings evaluate whether my performance in patient care is commensurate with my level of training
18. My attendings occasionally observe me taking a history.
19. My attendings assess not only my medical expertise but also other skills such as teamwork, organization or professional behavior.
20. My attendings give regular feedback on my strengths and weaknesses

<u>Formal education</u>

21. Residents are generally able to attend scheduled educational activities.
22. Educational activities take place as scheduled.
23. Attendings contribute actively to the delivery of high-quality formal education.
24. Formal education and training activities are appropriate to my needs.

<u>Resident peer collaboration</u>

25. Residents work well together.
26. Residents, as a group, make sure the day's work gets done.
27. Within our group of residents it is easy to find someone to cover or exchange a call.

Work is adapted to residents' competence

28. The work I am doing is commensurate with my level of experience.
29. The work I am doing suits my learning objectives at this stage of my training.
30. It is possible to do follow up with patients.

Accessibility of supervisors

31. When I need an attending, I can always contact one.
32. When I need to consult an attending, they are readily available.
33. It is clear which attending supervises me.

Patient sign-out

34. Sign-out is used as a teaching opportunity.
35. Attendings encourage residents to join in the discussion during sign-out.

Table A1.2
Unadjusted odds ratios (and 95% confidence intervals) for the association between learning climate score category in quartiles and adverse perinatal and maternal outcome (n=23629 deliveries) in 16 non-tertiary obstetrics and gynecology departments in the Netherlands, From Study on Learning Climate and Adverse Obstetrical Outcomes, 2013

Learning climate score category (quartile)	Total number of deliveries, n (%)	Total deliveries with an adverse perinatal outcome, n (%)	Total deliveries with an adverse maternal outcome, n (%)	Crude Odds Ratio for adverse perinatal outcome	Crude Odds Ratio for adverse maternal outcome
Low Q1(<3.75)	6084 (25.8)	98 (1.6)	536 (8.8)	Reference	Reference
Q2 (3.75 – 3.96)	5741 (24.3)	108 (1.9)	516 (9.0)	1.17 (0.89 – 1.54)	1.02 (0.90 – 1.16)
Q3 (3.97-4.24)	6723 (28.5)	162 (2.4)	630 (9.4)	1.51 (1.17 – 1.94)*	1.07 (0.95 – 1.21)
High Q4 (>4.24)	5081 (21.5)	111 (2.2)	430 (8.5)	1.36 (1.04 – 1.79)*	0.96 (0.84 – 1.09)

*****p<0.05.

Table A1.3
Unadjusted odds ratios (and 95% confidence intervals) for the association between learning climate score category and adverse perinatal and maternal outcome for deliveries performed by residents only (n=10151 deliveries based on 14 hospitals using available information) in 16 non-tertiary obstetrics and gynecology departments in the Netherlands, From Study on Learning Climate and Adverse Obstetrical Outcomes, 2013

Learning climate score category (tertile)	Crude Odds Ratio for adverse perinatal outcome	Crude Odds Ratio for adverse maternal outcome
Lowest learning climate tertile	Reference	Reference
Middle learning climate tertile	1.49 (0.94 – 2.38)	1.07 (0.86 – 1.32)
Highest learning climate tertile	1.67 (1.05 – 2.64)*	1.13 (0.91 – 1.40)

*****p<0.05.

Table A1.4
Unadjusted odds ratios (and 95% confidence intervals) for the association between learning climate score category and adverse perinatal and maternal outcome for singletons only (n=22748 deliveries) in 16 non-tertiary obstetrics and gynecology departments in the Netherlands, From Study on Learning Climate and Adverse Obstetrical Outcomes, 2013

Learning climate score category (tertile)	Crude Odds Ratio for adverse perinatal outcome	Crude Odds Ratio for adverse maternal outcome
Lowest learning climate tertile	Reference	Reference
Middle learning climate tertile	1.37 (1.08 – 1.76)*	1.01 (0.90 – 1.13)
Highest learning climate tertile	1.43 (1.11 – 1.84)*	0.96 (0.86 – 1.09)

*****p<0.05.

Table A1.5
Unadjusted odds ratios (and 95% confidence intervals) for the association between learning climate score category and adverse perinatal and maternal outcome for subgroup excluding stillbirths (n=23592 deliveries) in 16 non-tertiary obstetrics and gynecology departments in the Netherlands, From Study on Learning Climate and Adverse Obstetrical Outcomes, 2013

Learning climate score category (tertile)	Crude Odds Ratio for adverse perinatal outcome	Crude Odds Ratio for adverse maternal outcome
Lowest learning climate tertile	Reference	Reference
Middle learning climate tertile	1.54 (1.20 – 2.00)*	1.04 (0.93 – 1.16)
Highest learning climate tertile	1.82 (1.40 – 2.36)*	0.98 (0.87 – 1.10)

*****$p<0.05$.

Supplemental Digital Appendix 2

Bias Analysis for Uncontrolled Confounding of the Relation Between Learning Climate and Adverse Obstetrical Outcomes

Like in all observational studies that investigate association or causation, this study can suffer from bias and uncertainty due to unmeasured confounder(s)[1-3] of the relation of between learning climate and adverse obstetrical outcomes, after controlling for measured confounders. To say our study is threatened by an unmeasured confounder *U* after controlling for measured confounders, we mean one of the following possible scenarios: (a) *U* is an unmeasured cause of adverse obstetric care outcome that is also a cause of learning climate; (b) *U* is an unmeasured cause of adverse obstetric care outcome but is only associated (i.e. shares another unmeasured common cause) with learning climate; (c) *U* is an unmeasured cause of learning climate but is only associated (i.e. shares another unmeasured common cause) with adverse obstetrical care outcome. The difference between scenario (a) and scenarios (b) and (c) is that U has a causal relationship with both variables. Although all of these situations could be possible in our study, we decided to focus our bias analysis on scenario (a) where *U* is the unmeasured cause of both adverse obstetrical care outcome as well as the learning climate because its results are applicable to all other scenarios.

Directed acyclic graphs (DAGs) have been widely used in other fields such as epidemiology, computer science, social sciences, and recently medical education research to illustrate causal relations between variables.[4,5] DAGs are used to explicate causal assumptions about relations between variables by drawing arrows in the direction of the causation.[4] The arrows can be augmented to indicate either a positive causation (+) or a negative causation (-). We constructed four DAGs for the following scenarios: (i) where the unmeasured confounder *U* has a positive effect on the learning climate and a negative effect on adverse obstetrical outcome (Figure A2.1); (ii) where the unmeasured confounder set *U* has a negative effect on learning climate and a positive effect on adverse obstetrical outcome (Figure A2.2); (iii) *U* has a positive effect on the learning climate and adverse obstetrical outcome (Figure A2.3); (iv) *U* has a negative effect on the learning climate and adverse obstetrical outcome (Figure A2.4).

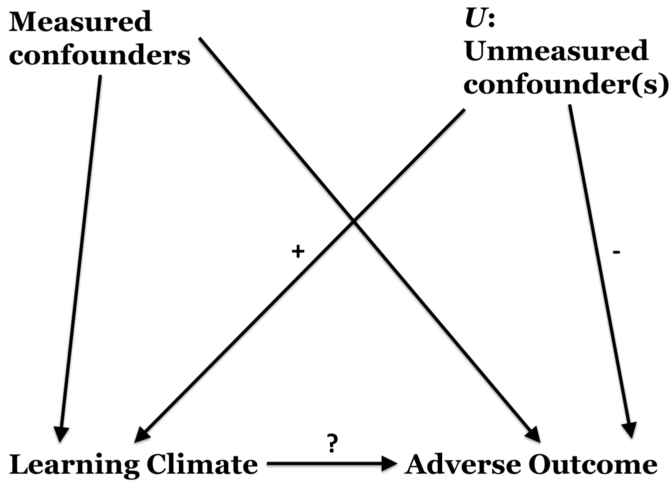

Figure A2.1: Directed acyclic graph (DAG) depicting uncontrolled confounding due to an unmeasured common cause U of both the learning climate and adverse outcome. In this diagram U positively affects the learning climate while decreasing the adverse outcome.

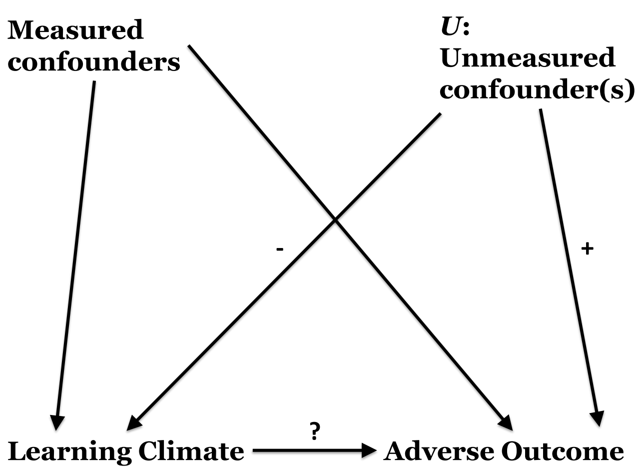

Figure A2.2: Directed acyclic graph (DAG) depicting uncontrolled confounding due to an unmeasured common cause *U* of both learning climate and adverse outcome. In this diagram *U* negatively affects learning climate but positively affects adverse outcome.

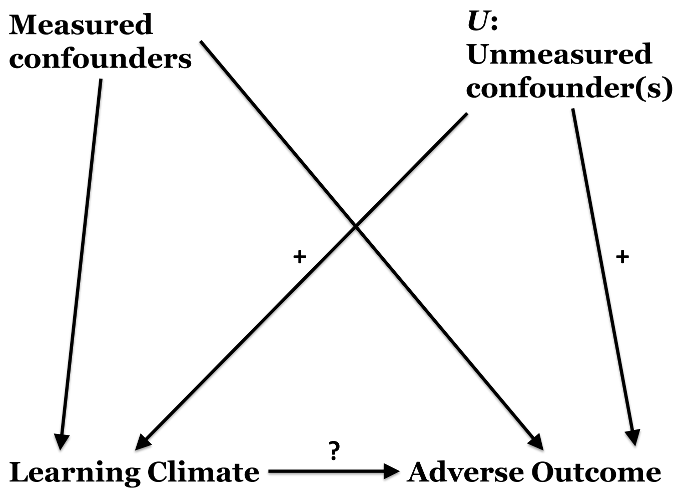

Figure A2.3: Directed acyclic graph (DAG) depicting uncontrolled confounding due to an unmeasured common cause *U* of learning climate and adverse outcome. Here, *U* increases both learning climate and adverse outcome.

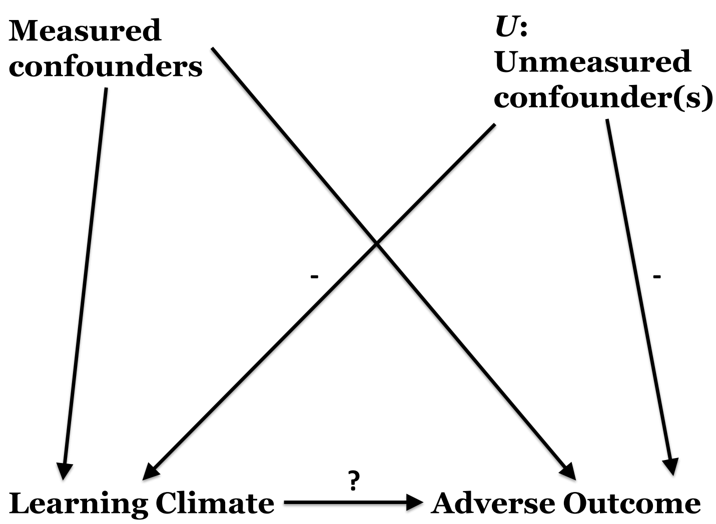

Figure A2.4: Directed acyclic graph (DAG) depicting uncontrolled confounding due to an unmeasured common cause *U* of both learning climate and adverse outcome. Here, *U* decreases both learning climate and adverse outcome.

In Figure A2.1, *U* positively affects the learning climate and negatively affects the adverse outcome, then accounting for this confounder would result in a net negative effect on the relation between learning climate and adverse outcomes. Therefore, controlling for this type of confounder would only strengthen the observed positive relationship between learning climate and adverse obstetrical outcomes. In Figure A2.2, *U* negatively affects the learning climate but positively affects the adverse obstetrical outcome; therefore, we would also expect a net negative uncontrolled confounding of the relation between learning climate and adverse outcomes due to unmeasured *U*. This implies that the potentially biased association between learning climate and adverse outcomes (not adjusted for *U*) could be attenuated by such negative confounding. Thus, adjusting for *U* in in Figures A2.1 and A2.2 would strengthen or increase the association. We believe the scenarios depicted in the Figures A2.1 and A2.2 are more plausible than those of A2.3 and A2.4 because it is more likely that an unmeasured factor that would increase (or decrease) learning climate would also be decrease (or increase) adverse outcomes.

In Figures A2.3 and A2.4, *U* affects both learning climate and adverse outcome in the same direction (either by increasing or decreasing both); therefore, we would expect a net positive uncontrolled confounding of the relation between learning climate and adverse obstetrical outcomes. Therefore, controlling for this type of confounding will attenuate the observed positive association between learning climate and adverse outcomes. We take this scenario to be less plausible because it is hard to imagine the type of factors or confounders that would simultaneously increase (or decrease) learning climate (a desirable result) and adverse outcomes (an undesirable result).

Using bias formulas to adjust the observed odds ratios for uncontrolled confounding due to unmeasured confounder *U* in each DAG, we estimated new odds ratios (and their corresponding 95% confidence intervals) after adjustment for the unmeasured confounder *U*.[6-10] Table A2.1 reports the bias adjusted odds ratios after bias analysis for uncontrolled confounding due to unmeasured confounder *U* in each of the four possible scenarios of uncontrolled confounding described above.

Table A2.1
Bias adjusted odds ratios (95% confidence intervals) for the relation between learning climate (*LC*) and adverse obstetric outcomes (*Y*) in 16 non-tertiary obstetrics and gynecology departments in the Netherlands, after bias analysis for uncontrolled confounding due to unmeasured confounder *U**, From Study on Learning Climate and Adverse Obstetrical Outcomes, 2013

	Odds ratio relating unmeasured confounder *U* to adverse outcome *Y*, conditional on measured confounders			
	Negative relation (-)		Positive relation (+)	
Regression coefficient relating *U* to *LC*	0.25	0.50	2	4
Positive (+)	DAG 1 (Figure A2.1)		DAG 3 (Figure A2.3)	
0.10	4.50 (1.57 – 12.91)	3.20 (1.17 – 8.76)	1.17 (0.50 – 2.76)	0.72 (0.33 – 1.57)
0.25	8.99 (3.46 – 23.36)	4.80 (1.93 – 11.97)	0.78 (0.35 – 1.72)	0.33 (0.16 – 0.68)
0.50	9.92 (4.37 – 22.57)	4.96 (2.28 – 10.83)	0.81 (0.40 – 1.62)	0.34 (0.17 – 0.66)
Negative (-)	DAG 4 (Figure A2.4)		DAG 2 (Figure A2.2)	
-0.10	0.84 (0.29 – 2.42)	1.20 (0.44 – 3.28)	3.41 (1.45 – 8.06)	5.75 (2.65 – 12.52)
-0.25	0.43 (0.17 – 1.13)	0.82 (0.33 – 2.04)	5.21 (2.37 – 11.49)	12.83 (6.20 – 26.60)
-0.50	0.41 (0.18 – 0.93)	0.82 (0.38 – 1.79)	5.15 (2.57 – 10.33)	12.45 (6.41 – 24.22)

*Prevalence of the U is set at P(U = 1) = 0.4 for the probabilistic bias analysis. Similar result patterns are obtained at different *U* prevalence values or distributions.

Results of the bias analysis indicate that adjusting for an unmeasured confounder in scenarios 1 and 2 (Fig. A2.1 and Fig. A2.2) would result in larger ORs and, as a result, strengthening of the observed association between learning climate and higher risk of adverse perinatal outcome. However, in situations where the unmeasured confounder has a positive or negative effect on both learning climate and adverse perinatal outcomes in scenarios 3 and 4 (Fig. A2.3 and Fig. A2.4), the association will be weaker and may even become reversed if the unmeasured confounder is strongly associated with both the learning climate and risk of adverse perinatal outcome.

In conclusion, unmeasured confounders may have substantial effects on the relationship between department's learning climate and risk of adverse perinatal outcome depending on the nature and strength of their relationship to both the learning climate and adverse perinatal outcome. Thus, controlling for variables that increase the learning climate of a department but decrease the risk of the perinatal outcome (or vice versa), the strength of the association between learning climate and risk of adverse perinatal outcomes would increase. On the other hand, after controlling for variables that either increase or decrease both the learning climate and the risk of adverse perinatal outcome, then a more positive learning climate would have a protective effect on adverse perinatal outcomes.

Selection Bias Analysis of the Relation Between Learning Climate and Adverse Obstetrical Outcomes

Our study results could have potentially been biased due to self-selection of respondents on the D-RECT questionnaire that was used to evaluate the departments' learning climate. To say that our results could potentially be affected by selection bias means that the learning climate (or cause of the learning climate) and the adverse outcome both directly or indirectly affect selection into or participation in the study.[11] In our case, it was possible that selection (S = 1) would be caused by the learning climate, an unmeasured confounder (U), measured confounders and the adverse outcomes. We investigated possible scenarios of multiple-bias due to selection and uncontrolled confounding by building on the DAGs in Figures A2.1 to A2.4. The new DAGs in Figures A2.5 to A2.8 respectively built on Figures A2.1 to A2.4 by allowing for selection bias to be dependent on learning climate, adverse outcomes, unmeasured confounder U, and measured confounders. If selection bias was caused only by the learning climate and the measured confounders, then our multivariable adjustment of those measured confounding variables will suffice to remove the selection bias in our primary analysis, the selection bias.[8,11] However, there would be residual selection bias if selective participation or response was additionally caused by an unmeasured confounder (or risk factor) and/or the adverse outcomes under study. The selection bias analysis reported here focuses on this more challenging residual selection bias, possibly in the presence of uncontrolled confounding.[1,3,6,8-11] Although we focused on the scenarios in which learning climate and U decreased response but adverse outcomes increased response directly, we explored other unreported scenarios. Those unreported scenarios yielded similar conclusions as the ones reported here.

We used inverse probability of selection weighting and investigator-specified obtained selection bias parameters to adjust the observed odds ratios for selection bias in each DAG.[11] Using published bias analytical methods described elsewhere,[6,8,10,11] we estimated new multiple-bias adjusted odds ratios and their corresponding multiple-bias adjusted 95% confidence intervals after adjustment for both uncontrolled confounding[10] and selection bias.[11] Table A2.2 reports the multiple-bias adjusted odds ratios for the DAGs in Figures A2.5 to A2.8.

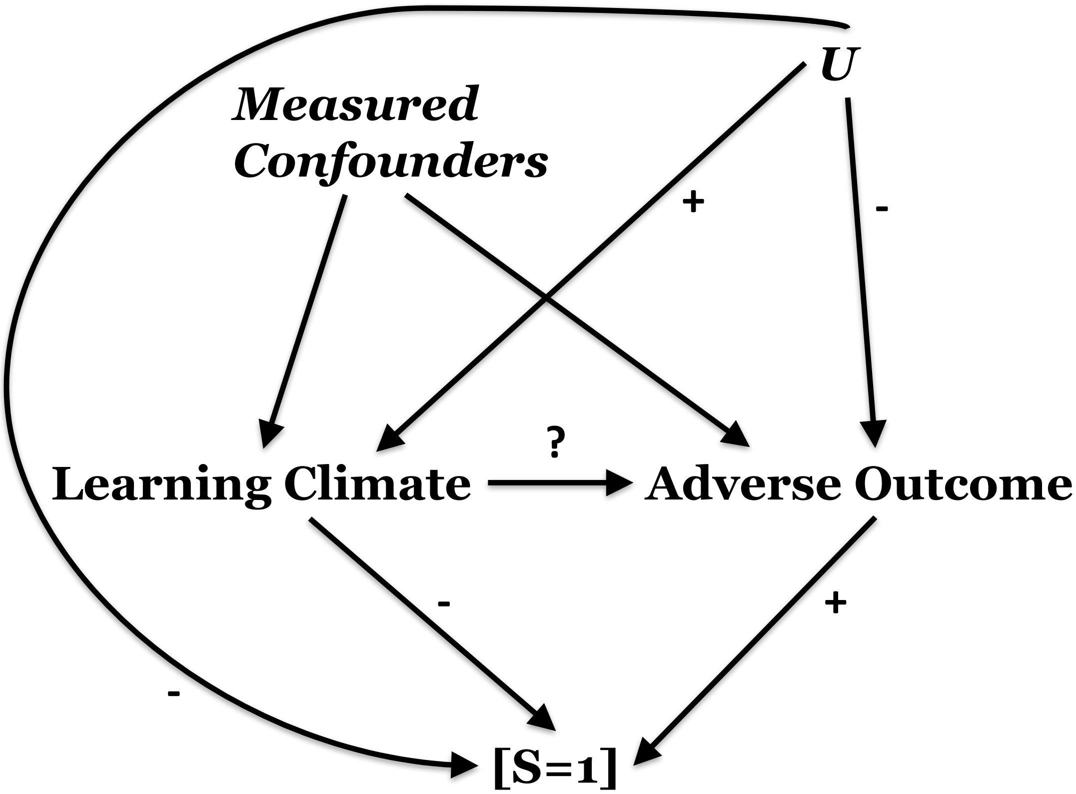

Figure A2.5. Directed acyclic graph (DAG) depicting selection or response (*S* = 1) bias caused by the adverse outcome (positively), the learning climate (negatively) and an unmeasured confounder *U* (negatively). Here, *U* decreases study response (*S* = 1) and adverse outcome but increases learning climate. [Arrow from measured confounders only omitted for visual reasons but can be assumed without loss of generality.]

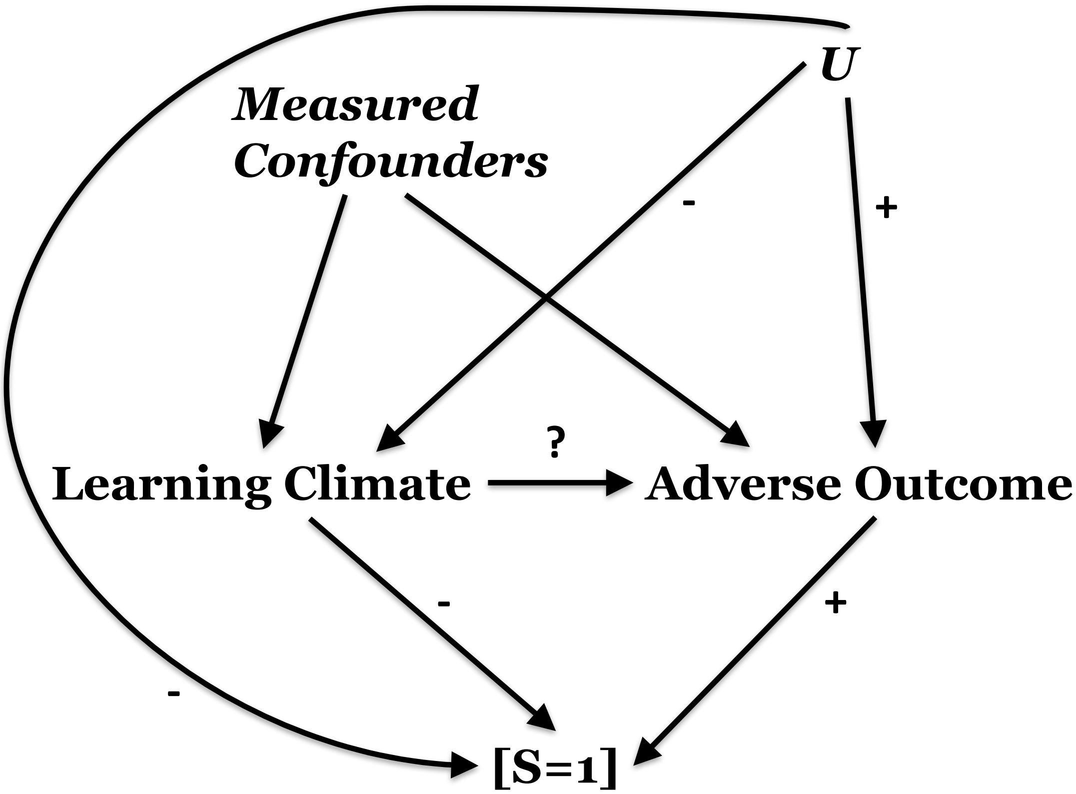

Figure A2.6. Directed acyclic graph (DAG) depicting selection or response (S = 1) bias caused by the adverse outcome (positively), the learning climate (negatively) and an unmeasured confounder U (negatively). Here, U decreases study response (S = 1) and learning climate but increases adverse outcome. [Arrow from measured confounders only omitted for visual reasons but can be assumed without loss of generality.]

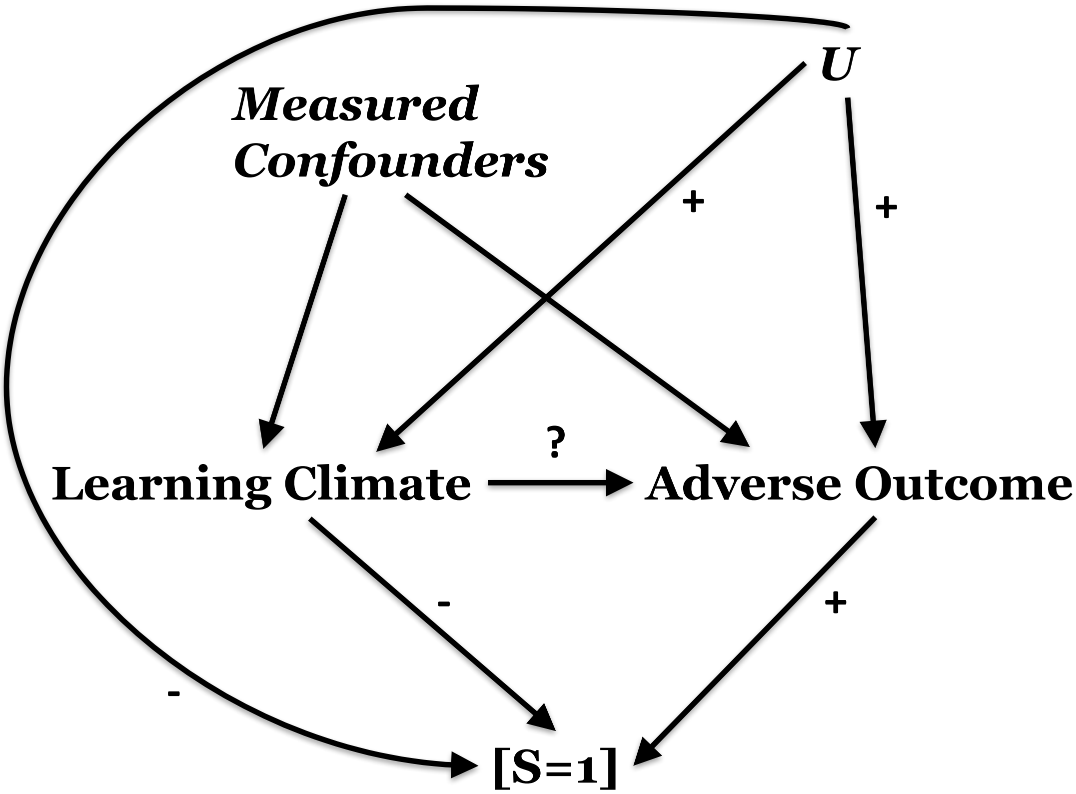

Figure A2.7. Directed acyclic graph (DAG) depicting selection or response (*S* = 1) bias caused by the adverse outcome (positively), the learning climate (negatively) and an unmeasured confounder *U* (negatively). Here, *U* decreases study response (*S* = 1) but increases learning climate and adverse outcome. [Arrow from measured confounders only omitted for visual reasons but can be assumed without loss of generality.]

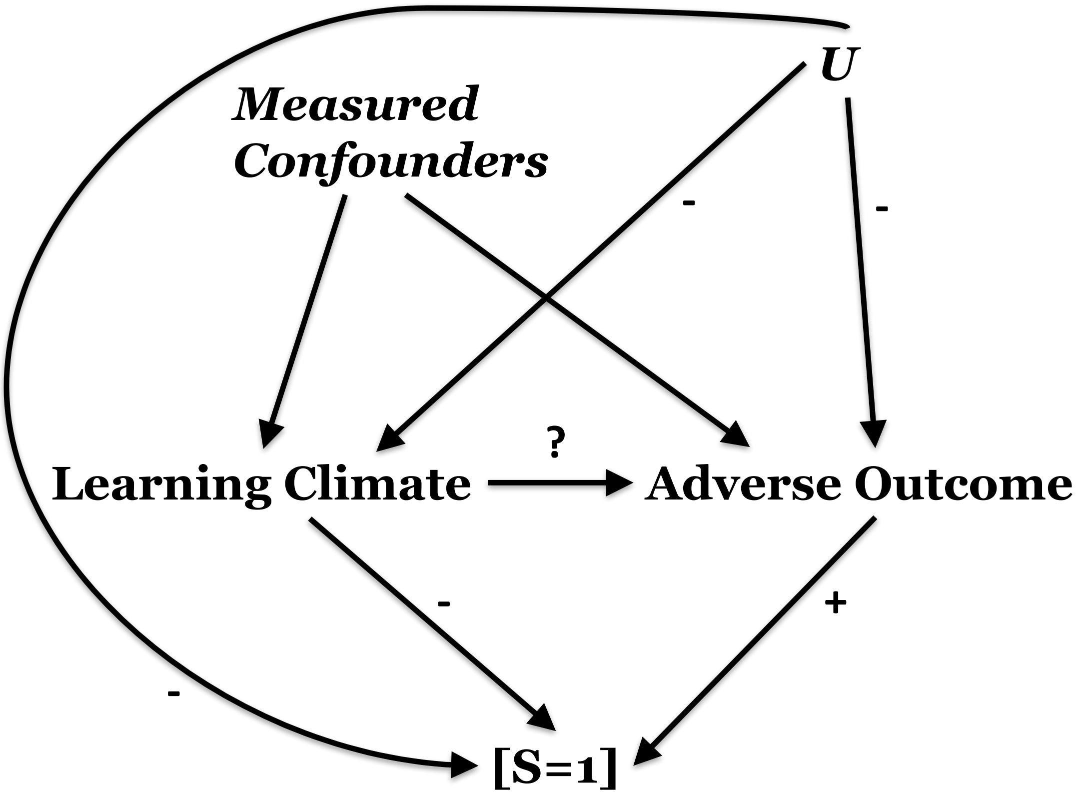

Figure A2.8. Directed acyclic graph (DAG) depicting selection or response (S = 1) bias caused by the adverse outcome (positively), the learning climate (negatively) and an unmeasured confounder U (negatively). Here, U decreases study response (S = 1), learning climate, and adverse outcome. [Arrow from measured confounders only omitted for visual reasons but can be assumed without loss of generality.]

Table A2.2
Multiple-bias adjusted odds ratios (95% confidence intervals) for the relation between learning climate (*LC*) and adverse obstetric outcome (*Y*), after bias adjustment for uncontrolled confounding due to unmeasured confounder *U* and for selection bias (selective response)*, From Study on Learning Climate and Adverse Obstetrical Outcomes, 2013

	Odds ratio relating unmeasured confounder *U* to adverse outcome *Y*, conditional on measured confounders			
	Negative relation (-)		Positive relation (+)	
Regression coefficient relating *U* to *LC*	0.25	0.50	2	4
Positive (+)	Figure A2.5		Figure A2.7	
0.10	5.06 (1.81 – 14.13)	3.58 (1.34 – 9.57)	1.30 (0.56 – 3.02)	0.81 (0.38 – 1.74)
0.25	10.49 (4.14 – 26.65)	5.57 (2.29 – 13.60)	0.90 (0.42 – 1.96)	0.38 (0.19 – 0.78)
0.50	11.51 (5.16 – 25.74)	5.75 (2.68 – 12.35)	0.94 (0.47 – 1.86)	0.40 (0.21 – 0.77)
Negative (-)	Figure A2.8		Figure A2.6	
-0.10	0.85 (0.31 – 2.37)	1.21 (0.45 – 3.24)	3.46 (1.49 – 8.01)	5.80 (2.71 – 12.46)
-0.25	0.42 (0.17 – 1.08)	0.80 (0.33 – 1.95)	5.08 (2.34 – 11.05)	12.45 (6.08 – 25.55)
-0.50	0.40 (0.18 – 0.90)	0.80 (0.37 – 1.73)	5.03 (2.53 – 10.03)	12.15 (6.70 – 23.51)

*Prevalence of *U* is set at P(*U* = 1) = 0.4 for the probabilistic bias analysis. Similar result patterns are obtained at different *U* prevalence values or distributions. The odds ratios relating learning climate, unmeasured confounder set *U*, and adverse outcome, adjusted for measured confounders, to study response or participation were respectively set to 0.75, 0.75 and 5.

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