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The Usefulness of Directed Acyclic Graphs: What Can DAGs Contribute to a Residual Approach to Weight-Related Income Discrimination?*

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Abstract

This paper provides one of the first empirical applications of directed acyclic graphs (DAGs) on a research question typical for the social sciences: wage discrimination. Besides a substantial interest in the weight wage penalty we ask whether DAGs help to improve the widely applied residual approach to discrimination. Using the German Socio-economic Panel (GSOEP) we find that body composition is associated with wages and that the effects of fat mass and fat free mass are markedly stronger for females than for males. Further we show that DAGs help to identify covariates which should and should not be adjusted for and to reduce the statistical model without losing information with regard to the estimation of the effect of interest. However, DAGs do not necessarily ensure that the central assumption of the residual approach, selection on observables, holds.

JEL-Classification: C13, I10, J71, C51, C00

1. Introduction

A common strategy in social science research to isolate discrimination from differences in productivity is the so-called residual approach: All available variables that might be associated with the treatment or outcome of interest, especially differences in productivity, are adjusted for. The remaining effect of the ascriptive characteristic on the outcome variable is interpreted as discrimination. Other authors have heavily criticized this identification strategy calling it a "shot-gun" (Lieberson, 1985, 39) or "kitchen sink" approach. One main concern is that the presence of unobserved differences in productivity confounds

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estimates of the extent of discrimination. Another major concern is that controlling for everything which is potentially associated with treatment or outcome might induce new biases of estimates by overcontrol.

To avoid the general pitfalls of unobserved differences in productivity and overcontrol bias theoretical knowledge about the causal relationships between the variables and their structural positions in the causal network is essential for the adequate choice of the vector of covariates. In his influential book *Causality* (2009[2000]) Judea Pearl has proposed directed acyclic graphs (DAGs)[1] as a tool to depict theoretical assumptions about the causal relationship between variables and to formally identify possibilities to empirically isolate the (total, direct, or indirect) causal effect of a treatment variable.

This paper provides one of the first empirical applications of directed acyclic graphs (DAGs) on a research question typical for the social sciences: wage discrimination of the overweight and obese. Besides a substantial interest in the weight wage penalty we want to tackle the following methodological questions: Can DAGs help to improve the residual approach to discrimination? Which new pitfalls arise? And which problems remain unsolved?

2. Directed Acyclic Graphs

Graphs consist of nodes and edges. In the following nodes depict variables and edges indicate causal relationships between variables. DAGs are directed, because arrows indicate the direction of the causal effect. DAGs are acyclic, since circular associations, such as X → Y → Z → X, are excluded by definition, but can be mapped by simply adding a time subscript. The approach is equivalent to a simple, non-parametric form of model building: By drawing a directed edge between two nodes one assumes a relationship between the two variables (e.g., X → Y as $Y = f(X)$) without specifying whether this effect is positive or negative, and whether it is linear or non-linear. Thus, in contrast to parametric structural equations models (SEMs) DAGs are non-parametric SEMs. They do not impose parameter restrictions in order to estimate effects but only help to specify conditions under which identification of a causal effect can be achieved. Hence, although due to their close proximity it suggests itself to line up DAGs with parametric SEMs (see Bollen/Pearl 2013) and to estimate the complete causal model. However, the use of the former does not necessitate the application of the latter statistical method.

In order to understand the sources of bias in DAGs the concept of paths and their different types are essential. A path between two variables in a graph is

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1 For a compact summary see Pearl (2010). Elwert (2013), Glymour (2006), Greenland/Pearl (2007), and Morgan/Winship (2015) provide introductions, which are less technically demanding.

defined as any connection between two nodes regardless of the direction of the arrows. Only if at least one path between treatment and outcome variable exists, bias can potentially be present. Thereby, sources of bias vary with the different path types. Pearl distinguishes between front-door and back-door paths and between open and closed/blocked paths. Front-door paths are paths on which all arrows point from the treatment X to the outcome Y (e.g., X → Z → Y). Thus, X is exogenous, while Z and Y are endogenous. Open front-door paths transmit the causal effect from X to Y via Z and, hence, should not be blocked (e.g., by adjusting for Z) if the aim is to estimate the total causal effect of the treatment.

Paths between X and Y on which an arrow points into the treatment variable are back-door paths. In this scenario X is endogenous, whereby endogeneity is caused by the covariate Z. Hence, in contrast to front-door paths, bias flows through back-door paths, if they are open. To eliminate bias open back-door paths should, therefore, be closed by adjusting for covariates on the path. However, as shown in the next paragraph, caution is demanded as covariate adjustment can open new back-door paths. Thus, the task of identification of the total causal effects essentially boils down to blocking all open back-door paths, and avoiding opening new back-door paths and blocking front-door paths. Thereby, the fact that covariates sometimes lie on more than one path can severely complicate identification.

In Figure 1 three paths between X and Y exist. However, the three paths are quite different in their causal structure and in their consequences for the estimation of the causal effect of X on Y (see also Morgan/Winship, 2015, 81):

(a) X ← Z → Y: This type of path is well-known in the literature and has been discussed extensively in the context of confounding, endogeneity, and spurious correlation. For example, age might influence both weight and income. In this scenario weight is endogenous. Failing to adjust for Z leads to a biased estimate of the causal effect; in Pearl's terminology an open back-door between X and Y exists which causes biases. Adjusting for Z closes the open back-door path between X and Y.

(b) X → M → Y: This type of causal sequence is discussed in the literature on mediation, indirect causal effects, and causal mechanisms. For example, part of the effect of obesity on wages might be mediated by the jobs overweight and normal weight people get. If the researcher is interested in the total causal effect, which equals the sum of the direct causal effect and the indirect causal effect(s), she must not control for the mediator M. In Pearl's terminology the effect of X on Y is mediated by M if a front-door path between X and Y exists. Since X is exogenous, closing front-door paths by adjusting for the mediator is only adequate if the aim is to estimate the direct causal effect (for details see Knight/Winship, 2013).

(c) X → C ← Y: Sub-forms of this problem have been discussed independently in research on self-selection bias, truncation, censoring, non-responsebias, and contagion in social networks (Elwert/Winship, 2014). Pearl calls C a collider, since two arrows on the path collide at the node C. Hence, X is exogenous, while C is endogenous. For example, marital status might be an outcome of body composition and wages. In this scenario neither open front-door paths nor back-door paths between X and Y exist. However, in contrast to situation (a) controlling for C opens a new back-door path. Adjusting for the endogenous variable C induces (non-causal) conditional dependence between X and Y which is the reason why Elwert/Winship (2014) call the resulting distortions "endogenous selection bias". Thus, as well as failing to adjust for confounders controlling for colliders (or variables that are causally influenced by the latter) leads to biased estimates.

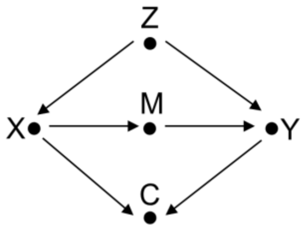


Figure 1: Three Basic Structural Positions of Covariates

Taken together, from a DAG perspective the central aim of causal inference is to close all open back-door paths while avoiding to open new back-door paths by adjusting for colliders and to wrongly block indirect causal effects by closing front-door paths. Pearl has developed algorithms to identify promising strategies for the identification of the total, direct, and indirect causal effect of interest for a given graph. We now apply this tool for the case of labor market discrimination of overweight and obese people.

3. A DAG for the Obesity Wage Penalty

As previously mentioned theoretical knowledge about causal relationships is essential for drawing a DAG and for the success of the chosen identification strategy. In addition, relying on available empirical evidence can be valuable in the development of a theoretical model. However, the process can become circular if model development is based on findings from (very likely) misspecified models. Thus, we mainly develop the DAG on the basis of theoretical considerations why overweight and obese people earn less. For the well-established finding of an obesity wage penalty (e.g., Atella et al., 2008; Bozoyan/Wolbring, 2011; Brunello/d´Hombres, 2007; Cawley, 2004; Han et al., 2009) different theoretical explanations have been brought forward in the literature.

First, some authors argue that this form of social inequality simply reflects differences in productivity. Variants of this argument point to the following mediators: On the one hand, body composition influences health which in turn might increase the number of days absent from work and reduces the workload one can cope with. On the other hand, overweight and obese people might have less work experience due to more and longer episodes of unemployment.

Moreover, theories of discrimination suggest that people either have tastes for/against certain groups (Becker, 1957) or ascribe group specific stereotypes to a person to reduce asymmetric information (Arrow, 1998; Phelps, 1972).[2] Thus, not only productivity but also stereotypes and preferences could mediate the effect of body composition. However, since both constructs, stereotypes and preferences, are usually unobserved, we subsume both effects under the label "direct causal effect" although the underlying mechanisms are quite different.

Third, jobs of overweight and normal weight employees might systematically differ. On the one hand, employers could give representative jobs more often to normal weight applicants. On the other hand, potential applicants might (rightly or wrongly) anticipate discrimination by employers, colleagues, or customers in certain occupations and, hence, aspire jobs which are less prone to discrimination.

Besides those mediating variables we identify two potential collider variables: First, body weight and wage level might influence self-esteem. Second, marital status is an outcome of body composition, self-doubts, and wages – slimmer and richer people are probably more successful on the marriage market. Controlling for these colliders might induce new biases.[3]

2 Research corroborates both explanations: On the one hand, adults and infants spend more time looking at good-looking faces which indicates a preference for/against certain bodily characteristics (Langlois et al., 1990; Maner et al., 2007). On the other hand, people perceive the overweight and obese as less dutiful, loyal, intelligent or emotional stable, and more weak-headed, lazy and insecure (see Polinko/Popovich, 2001; Sikorski et al., 2012) what leads to statistical discrimination.

3 From now on we will treat self-doubts and marital status as colliders, although theoretical arguments exist for treating these two variables as mediators or confounders. First, due to the deviation from the social norm or bad experiences in the past (e.g., bullying by peers) overweight and obese people might have less self-confidence and more self-doubts – factors which mediate the effect of weight on the chance of selling a product or establishing oneself in a company. Moreover, self-esteem could also influence weight and wage and, therefore, confound the estimate. Second, marriage could lead to weight gain since the partners do not have to invest in attractiveness any longer. Being married could also lead to higher incomes (marriage premium) especially for men. The breadwinner-model claims that married men have a higher motivation to perform well in their jobs since they have to take care of their family. To account for this we additionally drew a DAG which treats self-doubts and marital status as confounders. The consequences for our statistical model are that we need to include both variables in the regression, but this does not change our main results.

Furthermore, several covariates are regularly adjusted for in research on the effects of obesity on wages (Cawley et al., 2005; Han et al., 2009; Wada / Tekin, 2010). These include age, education, federal states, sex, nationality, panel wave, parental education, and the interviewer mode. Figure 2 entails all those covariates and all potential colliders and mediators mentioned above. At this point we cannot elaborate on the numerous arrows in the graph and (more importantly) on arrows assumed to be absent, but one can easily see that plenty of strong assumptions are made when adjusting for a vector of covariates.

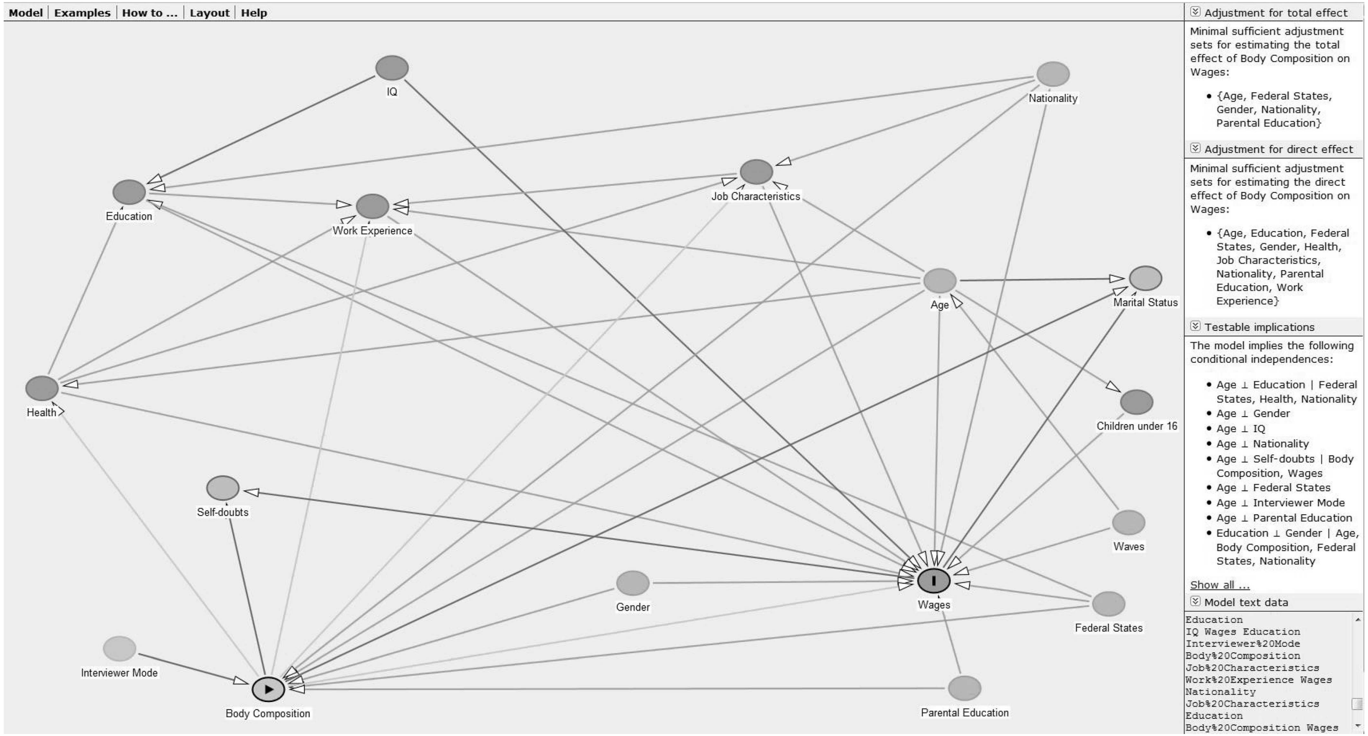
Since DAGs for more than a few covariates can become quite confusing and since it is not intuitively obvious which covariates one should include in the model, we rely on the software DAGitty (www.DAGitty.net) to automatically determine minimal sets of covariates which are sufficient to identify the causal effect of a treatment variable for a given graph (see Knüppel / Stang, 2010; Textor et al., 2011).

In the right panel of Figure 2 one can see the minimal sufficient adjustment sets (MSAS) to identify the total and the direct causal effect of body composition on wages (if the assumptions in the DAG are correct). For the analytical case under study it is sufficient to adjust for age, education, federal states, sex, health, job characteristics, parental education, nationality, and work experience to isolate the direct causal effect of body composition (statistical and / or taste-based discrimination) on wages. Hence, it is not necessary to include indicators for children living in the household, intelligence, interviewer mode, and panel waves into the model as is often done in research on obesity and wages. All the more, to control for self-doubts and marital status would even bias the estimates if these variables are actually colliders.

4. Data and Operationalization

Our empirical application of the DAG approach relies on six waves (2002, 2004, 2006, 2008, 2010, and 2012) of the German Socio-economic Panel (SOEP) (Wagner et al., 2007). We restrict our sample to German employees with a minimum hourly wage of 4 Euros aged from 18 to 66, whose body size is between 114 and 213 centimeters and whose body weight is between 31 and 180 kilograms. We also exclude self-employed persons, trainees, farmers, and pregnant women. The outcome variable is log-transformed gross hourly wage.

As the main explanatory variable we could use the body mass index (BMI). However, the BMI at most only moderately correlates with more reliable measures of body composition (e.g., Gallagher et al., 1996; Heyward / Wagner, 2004) and hence, has been heavily criticized for being a noisy measure of fatness and obesity (e.g., Burkhauser / Cawley, 2008; Samaras, 2006). This is especially true for males, since the BMI does not distinguish between two compartments of the body: fat free mass (mainly muscles and bones) and fat mass.



Note: Graph generated with the program DAGitty (www.DAGitty.net). ▶ indicates the treatment variable, I the outcome variable. The boxes in the right column contain the minimal sufficient adjustment sets (MSAS) for the total and the direct caul effect and further testable implications of the model in the form of conditional independencies. The assumption of two variables being not correlated is crucial in the DAG logic.

Figure 2: Directed Acyclic Graph for the Obesity Wage Penalty

Following Burkhauser/Cawley (2008) and Wada/Tekin (2010) we thus rely on indirect measurements of both constructs (for details see Bozoyan/Wolbring, 2011): First, we estimate body fat (BF) and fat-free mass (FFM) in an external data set, the BIA data base project,[4] on the basis of bioelectrical impedance analysis. Next, we re-estimate the generated values for BF and FFM using only the information, which is also available in the GSOEP: sex, age (age^2), weight ($weight^2$), and height ($height^2$). The optimal procedure here would be to use self-reported weight and height, because the GSOEP only collects subjective information. Since this is not possible with the BIAdata sample, we control for the presence of an interviewer in the GSOEP following the example of Cawley et al. (2005). Sex and age should be unbiased in both data sets. With R^2 between .75 and .91 the model fit is quite high indicating that the two components of the body can be approximated sufficiently close with this approach.

In order to allow for comparability of the SOEP and the external data set, we randomly drew a BIAdata subsample adjusted to match the BMI and sex distributions in the SOEP 2002 (for a detailed description of this procedure see Bozoyan/Wolbring, 2011). Finally, we transfer the estimation equations into the SOEP and account for the generated regressors by bootstrapping the standard errors in the final regressions (with a minimum of 199 replications)[5]. Since within-variation of FFM and BF over time is too low to estimate fixed effect models, we report results from random effects models.

According to the DAG the MSAS contains two mediator variables: First, we account for the mediator health measured with two indices for physical and mental condition ranging from 0 to 100 (Andersen et al., 2007). Additionally, we include the number of days absent from work, the number of doctor visits, and the perception of subjective health on a scale from 0 to 10. The second mediator is work experience, which is measured as the years of working full time, part time, and being unemployed. In addition to this mediating role of work experience it also has a well-known and important influence on wages on its own. But irrespective of whether work experience solely mediates the effect

4 For details see the homepage of the project: www.egofit.de/biadata_org/biadata_data.html.

5 Since the variables FFM and BF are generated and variability in the data is artificially reduced, we likely underestimate the true standard errors. To account for this bias we followed Wada/Tekin (2010) and bootstrapped the standard errors in the final regressions, which usually leads to more conservative p-values. Another account for model uncertainty and check for robustness of the results was to estimate the BF and the FFM in the external data set with over 40 different BIA-equations in a former version of this paper only with SOEP waves from 2002 to 2008 (Bozoyan/Wolbring, 2011). Results were remarkably robust to this variation in estimation equation. The equation we use in the current paper is based on Kyle at al. (2004) which was validated for the Swiss population and appears most adequate for the German SOEP.

of body composition on payments or has an additional independent influence on wages we need to control for work experience to isolate the direct effect of BF and FFM on incomes.

Besides the mediators all models contain several additional covariates. To operationalize educational level we rely on years of schooling and three dummy variables for completing a vocational training, masters of craftsmen, or university degree. Job specific characteristics are captured with job tenure measured as the years of employment in the same company. Job change (in the previous year) and upper white collar profession (based on the ISCO88 classification system) are included as dummy variables. Further we adjust for the parental education measured in years of schooling, individual's age, age^2, and dummies for German citizenship and for the federal states.

In the full model we additionally adjust for having children under 16 living in the household, panel wave dummies, and a dummy for the interviewer mode. Moreover, we include measures from a short version of the PIAT, the Symbol-Digit-Task and the Animal Naming Task (Lang et al., 2007), as a proxy for intelligence. In addition, we control in this model for the collider variables self-doubts ("If I encounter difficulties in my life, I often doubt my abilities")[6] and marital status.

5. Results

Before we present the empirical findings, we want to clarify our strategy to compare models with the full set of covariates (FM) and the minimal sufficient adjustment set of covariates (MSAS): We do not contrast the goodness of fit but compare coefficients of FFM and BF since the main aim of our endeavor is not to maximize explanatory power of the model but to estimate the direct causal effect of body composition correctly.

Table 1 presents the different models. At first glance, we see that the direction of all coefficients is in line with the predictions: Loosing ten kilogram of fat mass, increases the hourly wage of around 0.8 percent for females. Males do not suffer from a fat penalty. A gain in fat free mass by ten kilogram increases hourly wages of males by 0.3 – 0.4 percent and wages of females by 0.8 – 0.9 percent. Hence, effects are roughly twice as strong for females than for males. The strength of the effect of BF is nearly the same in the FM and MSAS models. The effects of FFM slightly differ and are more pronounced in

[6] The original scale runs from 1 to 7 and was dichotomized at the value 3. The main results stay the same if we do not dichotomize this variable. This information is only available for the years 2005 and 2010. For person years before 2010 we use the value for 2005, otherwise the value for 2010.

the MSAS models. One reason for this might be that we do not control for potential colliders in the latter models.

Table 1

Comparison of the full models (FM) and the MSAS models[7]

	Males		Females	
	MSAS	FM	MSAS	FM
Fat free mass	0.0039^{**}	0.0027^{+}	0.0090^{**}	0.0079^{*}
(in kg)	(0.0015)	(0.0015)	(0.0035)	(0.0035)
Body fat	–0.0012	–0.0011	$–0.0083^{**}$	$–0.0084^{***}$
(in kg)	(0.0015)	(0.0015)	(0.0025)	(0.0025)
$N_{Individuals}$	3717	3717	3439	3439
$N_{Observations}$	1057	1057	1066	1066
r^2_{within}	0.1055	0.1204	0.1077	0.1311
$r^2_{between}$	0.5648	0.5842	0.5183	0.5284
$r^2_{overall}$	0.4815	0.5007	0.4504	0.4609

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; dependent variable is the log. hourly wage FM = Full model; MSAS = Minimal sufficient adjustment set; SEs are bootstrapped and clustered around ID, the full model controls for all variables mentioned above, the MSAS model for all except marital status, self-doubts, children under 16 living in the HH, intelligence, interviewer mode, and panel waves.[8]

To test for significant differences between the coefficients we conducted Wald tests. Table 2 shows the four comparisons of the coefficients: None of the calculated *t*-values is above the critical value of 1.96. The null hypothesis, that the difference between the coefficients is null, cannot be rejected. In other words, we get rather similar, but more pronounced results with the more slender, more economical MSAS model as with the kitchen-sink approach. Thus, the DAG approach fosters parsimonious statistical modeling and, additionally, helps to communicate assumptions necessary for causal inference in a transparent and compact form.

7 We also ran the models with quadratic terms of fat free mass and fat mass. The models do not improve by this extension. We assume that a quadratic association between FFM, BF and wages is implicitly already implemented regarding the estimation of the indirect measurement of fat (free) mass with quadratic weight terms. Using the BMI Kropfhäußer / Sunder (2014) found a quadratic relationship between the BMI and wages for young workers.

8 The MSAS results for FFM and BF using the regression models that treated self-doubts and marital status as confounders instead of colliders are nearly the same as the MSAS results presented. For women we find a FFM coefficient of 0.0090 and a BF coefficient of -0.0083 and for men the estimates are 0.0038 for FFM and -0.0012 for BF.

Table 2

Wald test for coefficient comparisons

		t-value	p-value
Females	FFM	0.2222	0.2858
	BF	0.0283	0.5188
Males	FFM	0.5657	0.4121
	BF	–0.0471	0.4897

6. Conclusion

In this paper we provide one of the first applications of DAGs with a research question typical for the social sciences. A common empirical strategy to study discrimination is the so called residual approach – researchers typically control for a vector of covariates, which might somehow be associated with the treatment or outcome. However, adjusting for everything without thinking about the causal structure behind treatment, outcome, and covariates can lead to overcontrol bias.

One main value added by DAGs is to increase the likelihood to avoid confounding by overcontrol: The graphical depiction of causal relationships and their analysis (with DAGitty) helps to find these potential problematic variables, namely mediators and colliders, results in a parsimonious model, and, if the DAG is correct, leads to the reduction of biases. Certainly the theoretical assumptions on which the identification of the causal effect rests are open to discussion and will be criticized in many cases for being unrealistic. One reason for this is that social science theories do usually not explicate these necessary assumptions – DAGs cannot replace theory, they only graphically summarize the main propositions. The important point is that one has to make similarly strong assumptions in regression analysis or matching, which are, however, almost never explicitly highlighted in the standard kitchen-sink approach. In the DAG approach the theoretical propositions are fully transparent and a firmer link between the theoretical and statistical model can be established.

In general, if theory and state of research give no unanimous picture about the direction of effects, it appears wise to reflect this theoretical uncertainty about the causal structure in the statistical models. Thus, in such cases we recommend to investigate the causal effect under different model assumptions which correspond with a set of theoretically plausible scenarios. Obviously, the number of potential model specifications increases exponentially with the number of uncertain arrows. Hence, in such cases one could work through all potential combinations and, similar to Bayesian models, provide information on the variance or standard errors of the point estimates. Similarly, to sensitivity analyses such an uncertainty interval is informative about the robustness of the effect.

Finally, we want to emphasize that DAGs are no substitute for well-established methods of causal inference in the social sciences. With observational data violations of the selection on observables assumption can never fully be ruled out unless there is some source of exogenous variation. For example, one could criticize the application in this paper for the possibility of biases due to reverse causality and omitted variables, and might prefer an approach that does not rely on adjustment on observables. Certainly, fixed-effects models and instrumental variable regressions require weaker propositions and, therefore, are probably more promising ways to go. Nonetheless, identification still rests on rather bold theoretical assumptions. Hence, these statistical approaches can also profit from a *complementary* graphical clarification of the central theoretical argument and estimations of the MSAS model as a robustness check.

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