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Neglected Heterogeneity, Simpson's Paradox, and the Anatomy of Least Squares

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Neglected heterogeneity, Simpson's paradox, and the anatomy of least squares*

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Abstract

When a sample combines data from two or more groups, multivariate regression yields a matrix-weighted average of the group-specific coefficient vectors. However, it is possible that the weighted average of a specific coefficient falls outside the range of the group-specific coefficients, and it may even have a different sign compared to both group-level coefficients, a manifestation of Simpson's paradox. The result of the combined regression is then prone to misinterpretation. The purpose of this paper is to raise awareness of this problem and to state conditions under which such non-convex weighting or sign reversal can arise, for a model with two regressors and two groups. Two illustrative examples, an investment equation estimated with panel data, and a cross-sectional earnings equation for men and women, highlight the relevance of these findings for applied work.

Keywords: Covariance-weighting, heterogeneity spillover, non-convex average, average treatment effect.

JEL classification: C21

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1 Introduction

It is well understood that adding a third variable to a bivariate regression can change the sign of the slope coefficient. Indeed this is a common definition of Simpson’s paradox (Pearl, 2014).¹ An alternative definition is broader: Simpson’s paradox refers then to a correlation that appears in several groups of data but disappears or reverses when the groups are combined (Simpson, 1951). The two definitions are closely related, since we can declare each specific value of the third variable a group and “control for confounding” by running a separate bivariate regression for each of them. The paradox emerges if the signs are opposite from that of a single bivariate regression on the entire sample.

The purpose of this paper is to extend the scope of the paradox and provide an additional explanation for sign reversal when comparing combined and group-level results, for the case where there is more than a single regressor of interest, as in most practical applications: here, the focus will be on group level heterogeneity, unimportant in the conventional argument above, but important in a multivariate context. Heterogeneity manifests itself by varying coefficients in separate group-level regressions. If, instead, a single regression is used for the pooled data, without allowing for group-level interactions, coefficients can display sign reversal, simply due to the way multivariate regression combines group-level coefficients. As it turns out, one of the surprising consequences is that adding a variable to a bivariate regression can lead to a sign reversal relative to the bivariate slope coefficient even if the additional regressor is unrelated to the outcome. This is impossible under standard omitted variable bias.

I provide general conditions under which neglected heterogeneity can give rise to sign reversal, or other less extreme forms of “heterogeneity bias”, such as pooled coefficients that are a non-convex combination of the group specific ones. When talking about “bias”, I treat the group specific coefficients as meaningful, perhaps also from a causal perspective, and similarly the benchmark of an average effect obtained by weighting the group-level effects by the respective group shares. This seems reasonable in many but not all applications. In the language of causal modeling, it requires the group variable to be exogenous, as would be the case if it is a pre-treatment variable (see Pearl, 2014, for further discussion). However, the results I derive are based on algebraic

¹As Pearl (2014) points out, the notion of paradox comes from the fact that people tend to interpret any correlation as a causal relationship, whereas a serious consideration of the two involved regressions would show that at most one of them can be causal.

properties of regression and as such remain valid independently of any notion of causality and “correct specification”.

To fix ideas, consider a stylized regression with two regressors, x and z and a group indicator w that, for simplicity of exposition, takes only two values, 0 and 1. Specifically, one can distinguish the following three regressions: The pooled, or aggregate, regression without heterogeneity is

$$y_i = b_0 + b_x x_i + b_z z_i + b_w w_i + e_i \tag{1}$$

where $w_i \in \{0, 1\}$ and x_i and z_i can be scaled arbitrarily. The two group-specific regressions are

$$y_i^0 = b_0^0 + b_x^0 x_i^0 + b_z^0 z_i^0 + e_i^0 \tag{2}$$

for $w_i = 0$, and

$$y_i^1 = b_0^1 + b_x^1 x_i^1 + b_z^1 z_i^1 + e_i^1 \tag{3}$$

for $w_i = 1$.² Below, I establish algebraic results for the relation between the coefficient of x in the pooled regression, b_x in (1), and the four group-specific coefficients b_x^0 , b_x^1 , b_z^0 , and b_z^1 .

Many applications in empirical economics can be condensed to this framework. For example, in a panel data context, assume that there are two years of data, and let a year corresponds to a group. Estimation is possible year-by-year, or by pooling the data over the two years.³ If a few individual units, say firms, are observed for many time periods, (2) and (3) can be seen as a set of seemingly unrelated regressions (e.g. Zellner, 1962) that are estimated separately for each unit. Coefficient heterogeneity simply means that there is variation in unit level coefficients, and one could be tempted to run a pooled regression with unit specific fixed effects in order to obtain average effects (see for example Campello et al., 2019, and Breitung and Salish, 2021). Another application is the estimation of treatment effects in a randomized controlled trial with several treatment arms, when treatment takes place at several sites and site-specific factors both confound and modify the treatment effects (e.g., Goldsmith-Pinkham et al., 2022).

The problem addressed in this paper is related to, but different from a sizeable literature on heterogeneous partial effects and the question what linear constant-coefficients regression estimates

²As is well known, an equivalent representation is obtained from a fully interacted regression. This is discussed in more detail in Section 3.1.

³Pooling is not limited to genuine panel data, it can also be applied to repeated cross-sections. The regression properties of aggregation, where repeated observations on the same unit are collapsed to individual means in order to run a between regression, or when going from monthly to annual data, are not considered in this paper.

in such a case. For example, if regressors are normally distributed, the regression slope coincides with the average partial effect for a general class of non-linear conditional expectation functions (Stoker, 1986). Angrist (1998) shows that in a model with a scalar binary treatment, a single discrete confounder and effect heterogeneity, OLS gives a variance-weighted average, thus precluding a Simpson’s reversal (see also Yitzhaki, 1996).

Apart from least squares regression, numerous covariate adjustments methods exist that actually recover the average treatment effect under the conditional independence assumption (see Wooldridge and Imbens, 2009, for a survey of such methods). For continuous, and potentially multiple, regressors of interest, methods for consistent estimation of average partial effects are discussed in Wooldridge (2004) and Graham and Pinto (2022), among others. Goldsmith-Pinkham et al. (2022) show how neglected heterogeneity in the effect of one regressor can “contaminate” the effect estimation of another one.

While most of this literature is model-based, the current paper solely exploits algebraic properties of ordinary least squares. Thus, results hold regardless of model assumptions, which may or may not be valid. Also, they hold for purely descriptive regressions, and for any sample size as they do not rely on asymptotic properties. On the other hand, this is not a framework to address questions of causality, population estimands and efficiency.

2 Linear regression with group-specific heterogeneity

2.1 Matrix-weighted averaging

Before considering the two-regressors two-groups case in detail, it is useful to recall a general result on pooled regressions, and its representation as a matrix-weighted average of subset regressions. Suppose that there are K regressors and two groups of size N_0 and N_1 , respectively. Let y_0 be the $(N_0 \times 1)$ vector of outcomes in group 0, and y_1 be the $(N_1 \times 1)$ vector of outcomes in group 1. The regression coefficient in group 0 is given by

$$b^0 = (X_0'X_0)^{-1}X_0y_0$$

where the group-specific constant has been partialled out, and therefore X_0 is an $(N_0 \times K)$ matrix with typical element $\{x_{ik} - \bar{x}_k^0\}$, $i = 1, \dots, N_0$, $k = 1, \dots, K$. Similarly, for group 1,

$$b^1 = (X_1'X_1)^{-1}X_1y_1$$

with typical X_1 element $\{x_{ik} - \bar{x}_k^1\}$. Heterogeneity means that $b^0 \neq b^1$. For the pooled regression, assume that data are sorted, such that the first N_0 observations pertain to group 0 and observations $N_0 + 1, \dots, N_0 + N_1$ to group 1. Correspondingly, we can define the vertically stacked outcome vector and the vertically stacked regressor matrix as

$$y = \begin{pmatrix} y_0 \\ y_1 \end{pmatrix} \text{ and } X = \begin{pmatrix} X_0 \\ X_1 \end{pmatrix},$$

where again, regressors are expressed as deviations from group specific means, which corresponds to a pooled regression that includes an indicator variable for group membership and thus allows for a group-specific constant.⁴ The pooled coefficient vector for the slopes of such a regression can then be written as

$$\begin{aligned} b &= (X'X)^{-1}X'y \\ &= (X_0'X_0 + X_1'X_1)^{-1}(X_0'y_0 + X_1'y_1) \\ &= (H^0 + H^1)^{-1}H^0b^0 + (H^0 + H^1)^{-1}H^1b^1 \end{aligned} \tag{4}$$

where $H^0 = X_0'X_0$, $H^1 = X_1'X_1$, $b^0 = (H^0)^{-1}X_0'y_0$ and $b^1 = (H^1)^{-1}X_1'y_1$. Hence, the overall vector of regression coefficients is a matrix-weighted average of subset specific regression coefficients. The weights are proportional to the group-specific variance-covariance matrices of the regressors.

This is a mechanical property of ordinary least squares. In the context of Bayesian updating for the normal linear model with homoskedastic errors, H^0 is referred to as the precision matrix of the prior location vector b^0 , while H^1 is the precision matrix of the likelihood location vector b^1 . Chamberlain and Leamer (1976) study the properties of this type of information pooling, with the goal of deriving bounds for the posterior location parameter when the prior precision matrix is unknown, and thus a kind of sensitivity analysis. Their key result is that without further restrictions on the prior precision matrix (such as being diagonal, or proportional to H_1), the posterior coefficient can lie essentially anywhere. The reason is that a matrix-weighted average of vectors does not mean that element-by-element, the pooled coefficients lie algebraically between b^0 and b^1 .

In the present context, H_0 is not arbitrary but rather an observed matrix, and therefore, it becomes possible to study the specific properties of the element-by-element weighting and thus the

⁴The full regression therefore has $2 + K$ coefficients, but the focus here is on the slopes, as obtained after partialing out the two constants. The constants satisfy the relations $a^0 = \bar{y}^0 - b\bar{x}^0$ and $a^1 = \bar{y}^1 - b\bar{x}^1$.

relationship between elements of b and the heterogeneous coefficients collected in b^0 and b^1 for a given dataset. Based on the results by Chamberlain and Leamer (1976), it is to be expected that depending on H_0 and H_1 , there can be situations where elements of b are arbitrarily far away from a simple convexly weighted average of the corresponding elements in b^0 and b^1 . The objective of this paper is to derive conditions for such non-convex weighting.

I proceed in two steps. First, I consider the case of a single regressor and thereby replicate results known from the literature (e.g. Angrist, 1998). In a second step, I extend the analysis to the case of two regressors, and I will show that counterintuitive results are possible, including Simpson’s reversals as defined above.

2.2 Special case: A single regressor

With a single x and a binary group variable w , the pooled model can be written as

$$y_i = b_0 + b_x x_i + b_w w_i + e_i \tag{5}$$

Directly applying (4) from the previous section, we obtain b_x as a scalar average

$$\begin{aligned} b_x &= \frac{(x_0 - \bar{x}_0)'(x_0 - \bar{x}_0) b_x^0 + (x_1 - \bar{x}_1)'(x_1 - \bar{x}_1) b_x^1}{(x_0 - \bar{x}_0)'(x_0 - \bar{x}_0) + (x_1 - \bar{x}_1)'(x_1 - \bar{x}_1)} \\ &= \frac{N_0 \hat{\sigma}_{x,w=0}^2}{N_0 \hat{\sigma}_{x,w=0}^2 + N_1 \hat{\sigma}_{x,w=1}^2} b_x^0 + \frac{N_1 \hat{\sigma}_{x,w=1}^2}{N_0 \hat{\sigma}_{x,w=0}^2 + N_1 \hat{\sigma}_{x,w=1}^2} b_x^1 \end{aligned}$$

where b_x^0 is the coefficient in a regression of y_i on x_i in group $w_i = 0$, b_x^1 is the corresponding coefficient for group $w_i = 1$, and

$$\hat{\sigma}_{x,w}^2 = \frac{1}{N_w} \sum_{i=1}^{N_w} (x_i - \bar{x}^w)^2 \quad w \in \{0, 1\}$$

are the within group variances of the regressor.

Hence, the pooled coefficient b_x is not the “average treatment effect”, defined as $N_0/(N_0+N_1)b_x^0 + N_1/(N_0 + N_1)b_x^1$. However, it is a convex average of b_x^0 and b_x^1 . The weights depend on relative group sizes, N_0 and N_1 , as well as on the within-group variances, $\hat{\sigma}_{x,w=0}^2$ and $\hat{\sigma}_{x,w=1}^2$. If the within-group variances are identical, the pooled model indeed estimates the group-size weighted average. A closely related population version of this result is given in Angrist (1998) who considers the reverse situation where the regression coefficient of interest is that of a binary treatment indicator and a multivalued, discrete or continuous, confounder is partialled out. Unfortunately, as the next subsection will show, this simple, and necessarily convex, weighting does not generalize when there are two or more regressors.

3 Results for two regressors and two groups

With two regressors of interest, labeled x and z , and the same group indicator w as before, the pooled regression is given by (1) and is restated here for convenience:

$$y_i = b_0 + b_x x_i + b_z z_i + b_w w_i + e_i \quad \text{for } i = 1, \dots, N$$

where e_i is a regression residual such that $Cov(e_i, x_i) = Cov(e_i, z_i) = Cov(e_i, w_i) = 0$. The regressors x and z can be binary, discrete, or continuous, and it is assumed that there are two groups only. The regression allows the constant to shift depending on w_i but imposes homogeneous slopes b_x and b_z . After partialing out the constant and w_i , we obtain the trivariate regression

$$y_i = b_x(x_i - \bar{x}^w) + b_z(z_i - \bar{z}^w) + u_i$$

where $\bar{x}^0, \bar{x}^1, \bar{z}^0$ and \bar{z}^1 are group-specific means. Define the following quantities:

$$\begin{aligned} S_{xx}^0 &= \sum_{i=1}^{N_0} (x_i - \bar{x}^0)^2 & S_{zz}^0 &= \sum_{i=1}^{N_0} (z_i - \bar{z}^0)^2 \\ S_{xy}^0 &= \sum_{i=1}^{N_0} (x_i - \bar{x}^0)y_i & S_{zy}^0 &= \sum_{i=1}^{N_0} (z_i - \bar{z}^0)y_i \\ S_{zx}^0 &= \sum_{i=1}^{N_0} (z_i - \bar{z}^0)(x_i - \bar{x}^0) \end{aligned}$$

and same for S_{xx}^1, S_{zz}^1 , etc. It follows that the weighting matrices are

$$H^0 = \begin{pmatrix} S_{xx}^0 & S_{xz}^0 \\ S_{zx}^0 & S_{zz}^0 \end{pmatrix} \quad \text{and} \quad H^1 = \begin{pmatrix} S_{xx}^1 & S_{xz}^1 \\ S_{zx}^1 & S_{zz}^1 \end{pmatrix}$$

With H^0 and H^1 defined as above, the pooled least squares coefficient $b = (b_x, b_z)'$ can be written using equation (4) as:

$$\begin{pmatrix} b_x \\ b_z \end{pmatrix} = \begin{pmatrix} S_{xx}^0 + S_{xx}^1 & S_{xz}^0 + S_{xz}^1 \\ S_{zx}^0 + S_{zx}^1 & S_{zz}^0 + S_{zz}^1 \end{pmatrix}^{-1} \left[\begin{pmatrix} S_{xx}^0 & S_{xz}^0 \\ S_{zx}^0 & S_{zz}^0 \end{pmatrix} \begin{pmatrix} b_x^0 \\ b_z^0 \end{pmatrix} + \begin{pmatrix} S_{xx}^1 & S_{xz}^1 \\ S_{zx}^1 & S_{zz}^1 \end{pmatrix} \begin{pmatrix} b_x^1 \\ b_z^1 \end{pmatrix} \right] \quad (6)$$

Solving (6) for b_x and b_z is straightforward. For example,

$$b_x = \frac{(S_{zz}^0 + S_{zz}^1)(S_{xx}^0 b_x^0 + S_{xz}^0 b_z^0 + S_{xz}^1 b_x^1 + S_{xz}^1 b_z^1) - (S_{xz}^0 + S_{xz}^1)(S_{zx}^0 b_x^0 + S_{zz}^0 b_z^0 + S_{zx}^1 b_x^1 + S_{zz}^1 b_z^1)}{(S_{xx}^0 + S_{xx}^1)(S_{zz}^0 + S_{zz}^1) - (S_{xz}^0 + S_{xz}^1)(S_{zx}^0 + S_{zx}^1)} \quad (7)$$

3.1 A re-interpretation using omitted variables

Formally, the same result can be obtained using the omitted variable bias formula for regression (e.g., Greene, 2003). First, extend (1) to include the two interactions between x_i and w_i and between z_i and w_i :

$$y_i = b_w^0 + b_w^1 w_i + b_x^0 x_i + b_z^0 z_i + b_w w_i + (b_x^1 - b_x^0) x_i w_i + (b_z^1 - b_z^0) z_i w_i + u_i \quad (8)$$

Omitted variable bias arises if the two interactions are dropped. The matrix of the level variables after partialing out the constant and w_i has the form

$$\mathcal{X}_1 = \begin{pmatrix} x - \bar{x}_0 & z - \bar{z}_0 \\ x - \bar{x}_1 & z - \bar{z}_1 \end{pmatrix}$$

whereas the residualized matrix for the interaction terms is given by

$$\mathcal{X}_2 = \begin{pmatrix} 0 & 0 \\ x - \bar{x}_1 & z - \bar{z}_1 \end{pmatrix}$$

Thus, the pooled regression coefficients without interactions are obtained as

$$\begin{aligned} \begin{pmatrix} b_x \\ b_z \end{pmatrix} &= \begin{pmatrix} b_x^0 \\ b_z^0 \end{pmatrix} + (\mathcal{X}'_1 \mathcal{X}_1)^{-1} (\mathcal{X}'_1 \mathcal{X}_2) \begin{pmatrix} b_x^1 - b_x^0 \\ b_z^1 - b_z^0 \end{pmatrix} \\ &= \begin{pmatrix} b_x^0 \\ b_z^0 \end{pmatrix} + \begin{pmatrix} S_{xx}^0 + S_{xx}^1 & S_{xz}^0 + S_{xz}^1 \\ S_{zx}^0 + S_{zx}^1 & S_{zz}^0 + S_{zz}^1 \end{pmatrix}^{-1} \begin{pmatrix} S_{xx}^1 & S_{xz}^1 \\ S_{zx}^1 & S_{zz}^1 \end{pmatrix} \begin{pmatrix} b_x^1 - b_x^0 \\ b_z^1 - b_z^0 \end{pmatrix} \end{aligned}$$

which is the same as (6).

3.2 Decomposing the regression coefficient b_x

We now come to the main result. Re-arranging and simplifying terms, (7) can be written as

$$b_x = \frac{\mathcal{A}b_x^0 + \mathcal{B}b_x^1 + \mathcal{C}(b_z^1 - b_z^0)}{\mathcal{A} + \mathcal{B}} \quad (9)$$

where

$$\mathcal{A} = S_{xx}^0 (S_{zz}^0 + S_{zz}^1) - S_{xz}^0 (S_{xz}^0 + S_{xz}^1)$$

$$\mathcal{B} = S_{xx}^1 (S_{zz}^0 + S_{zz}^1) - S_{xz}^1 (S_{xz}^0 + S_{xz}^1)$$

and

$$\mathcal{C} = S_{zz}^0 S_{xz}^1 - S_{xz}^0 S_{zz}^1 = S_{zz}^0 S_{zz}^1 (g_1 - g_0)$$

and where g_1 and g_0 are the slopes of a regression of x on z in group 1 and group 0, respectively.

The decomposition (9) makes it clear that b_x is in general not a simple convex average of b_x^0 and b_x^1 . The aggregation of heterogeneous group-specific coefficients depends on three weights, $\mathcal{A}/(\mathcal{A} + \mathcal{B})$ and $\mathcal{B}/(\mathcal{A} + \mathcal{B})$ for the own coefficients b_x^0 and b_x^1 , and $\mathcal{C}/(\mathcal{A} + \mathcal{B})$ for heterogeneity in the z -coefficients. The weights in turn are functions of products of variances and covariances of x and z in the two groups. Thus they do not depend on the outcome at all, and the weights can in principle be computed from the “design matrix” of regressors, before the data are collected. Of course, the heterogeneous coefficients themselves depend on the outcomes, and thus are not known before those data are available.

As I will show, each of the weights can be negative or greater than one. For reasons, that will become clear below, I refer to the first two weights as *covariance weights*. $\mathcal{C}/(\mathcal{A} + \mathcal{B})$ on the other hand is a *heterogeneity spillover weight*. As (9) shows, non-convex weighting can occur even if there is no heterogeneity in the z -coefficients, and, more surprisingly, even if the coefficient of z is zero in both groups.

3.3 Covariance weighting

To understand the interpretation of the terms \mathcal{A} and \mathcal{B} , consider the auxiliary regression of x on z and w for the pooled data. The slope after partialing out of w is equal to S_{xz}/S_{zz} , and the covariance between residuals $u_i = (x_i - \bar{x}^w) - S_{xz}/S_{zz}(z_i - \bar{z}^w)$ and x_i for group 0 can be written as

$$\begin{aligned} Cov_0(u_i, x_i) &= \frac{1}{N_0} \sum_{i=1}^{N_0} \left((x_i - \bar{x}^0) - \frac{S_{xz}}{S_{zz}}(z_i - \bar{z}^0) \right) X_i \\ &= \frac{S_{xx}(S_{zz}^0 + S_{zz}^1) - (S_{xz}^0 + S_{xz}^1)S_{xz}^0}{N_0(S_{zz}^0 + S_{zz}^1)} = \frac{\mathcal{A}}{N_0 S_{zz}} \end{aligned}$$

Thus, \mathcal{A} is proportional to a group-specific covariance. A covariance can be positive or negative. This is a fundamental difference to the single regressor case, discussed in Section 2.2, where \mathcal{A} was proportional to a conditional variance, and thus necessarily positive.

The weighting in the two-regressor case depends on covariances rather than variances, because $u_i = x_i - \hat{x}_i$ is not orthogonal to \hat{x}_i in the $w_i = 0$ subset, and hence $Cov(x_i - \hat{x}_i, x_i | w_i = 0) \neq Cov(x_i - \hat{x}_i, x_i - \hat{x}_i | w_i = 0)$. Subset-orthogonality of u_i and \hat{x}_i fails, because the auxiliary regression omits the interaction between z and w and is thus not “saturated” in w .⁵ This matters

⁵Angrist (1998) also noted that the variance-weighting result for the case of a single predictor requires a partialing

if the covariances between x and z differ in the two groups. Adding the interaction would be equivalent to separate group-wise regressions of x on z , which would restore orthogonality of u_i and \hat{x}_i in each group. But this does not correspond to the regression equation (1) under consideration.

We can now state conditions under which the covariance, and hence \mathcal{A} and the weight $\mathcal{A}/(\mathcal{A}+\mathcal{B})$, are negative. Since $\mathcal{A} = S_{xx}^0 S_{zz} - S_{xz}^0 S_{xz}$, we obtain

$$\mathcal{A} < 0 \quad \iff \quad 1 - \frac{S_{xz}^0 S_{xz}}{S_{xx}^0 S_{zz}} < 0 \quad \iff \quad \frac{S_{xz}}{S_{zz}} \frac{S_{xz}^0}{S_{xx}^0} > 1 \quad (10)$$

Similarly

$$\mathcal{B} < 0 \quad \iff \quad 1 - \frac{S_{xz}^1 S_{xz}}{S_{xx}^1 S_{zz}} < 0 \quad \iff \quad \frac{S_{xz}}{S_{zz}} \frac{S_{xz}^1}{S_{xx}^1} > 1 \quad (11)$$

For instance, \mathcal{A} is negative if the product of the full-sample x -on- z -and- w regression slope and the group 0 (inverse) z -on- x regression slope exceeds 1. This can be easily checked in the data. A negative \mathcal{A} implies that the weight $\mathcal{A}/(\mathcal{A}+\mathcal{B})$ is negative, since $\mathcal{A}+\mathcal{B} = S_{xx}S_{zz} - S_{xz}^2 > 0$ due to the Cauchy-Schwarz inequality. It also follows that either \mathcal{A} or \mathcal{B} can be negative, but not both, as their sum must be positive.

A necessary and sufficient conditions for convex weighting is that both \mathcal{A} and \mathcal{B} are positive. This is for example the case if the reverse regression slopes S_{xz}^w/S_{xx}^w are equal in the two groups. The argument is by contradiction: suppose S_{xz}^0/S_{xx}^0 is such that (10) holds. With equal slopes, (11) holds as well, but this is not possible because \mathcal{A} and \mathcal{B} cannot be both negative. Hence, with equal slopes, \mathcal{A} and \mathcal{B} must be both positive. If x and z are uncorrelated in both groups, $\mathcal{A}/(\mathcal{A}+\mathcal{B}) = S_{xx}^0/(S_{xx}^0 + S_{xx}^1)$ and the weighting is proportional to the within group variances and hence always convex.

An illustration using simulated data

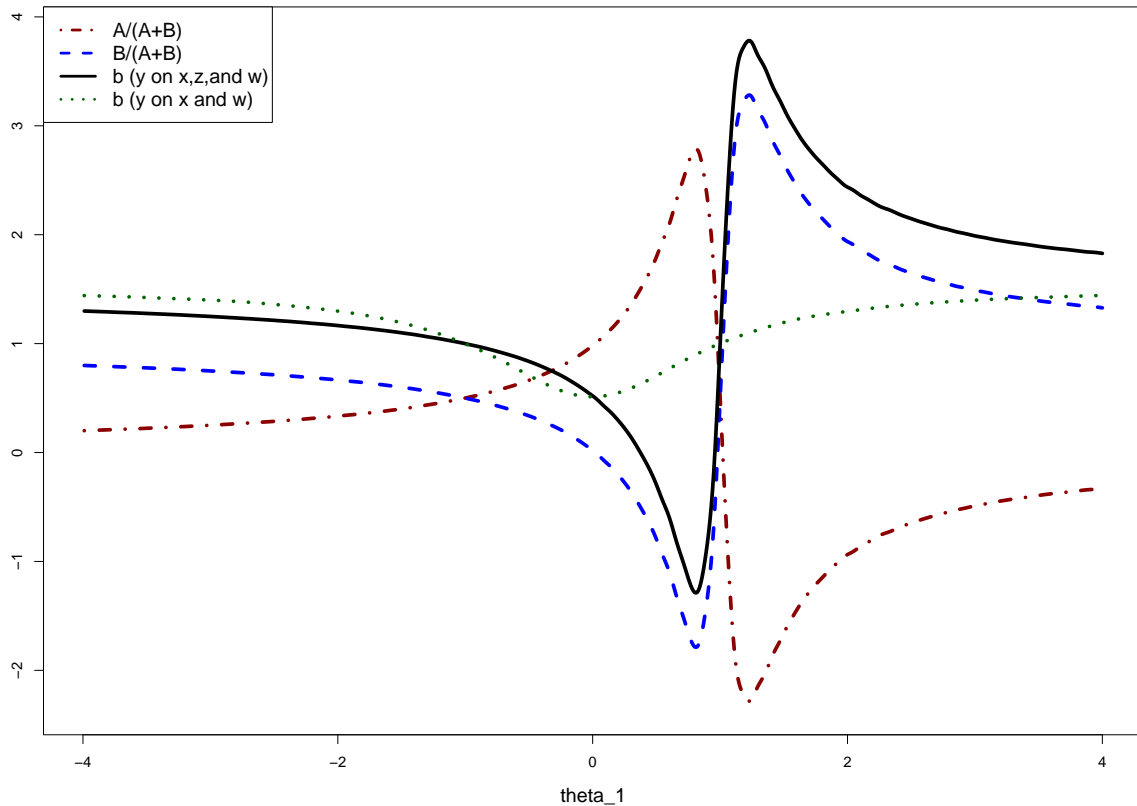
Consider the following generation of pseudo random numbers: There are two groups of equal size, $N_0 = N_1 = 1000$; z is drawn from a standard normal distribution in both groups. In group 0, $x_i^0 = z_i^0 + 0.1 \times \text{Normal}(0, 1)$; in group 1, $x_i^1 = \theta_1 z_i^1 + 0.1 \times \text{Normal}(0, 1)$, where θ_1 increases in steps of 0.01 from -4 to +4. Hence, $S_{xz}^0 = S_{xz}^1$ when $\theta_1 = 1$. For $\theta_1 > 1$ the covariance between x and z is greater in group 1 than in group 0; for $\theta_1 < 1$, it is smaller.

Figure 1 plots, for each value of θ_1 , the implied covariance weights $\mathcal{A}/(\mathcal{A}+\mathcal{B})$ and $\mathcal{B}/(\mathcal{A}+\mathcal{B})$. It also shows the pooled slope coefficient b_x (solid black line), assuming that outcome data are

out regression saturated in the confounder. By definition, a binary confounder as in (5) satisfies this requirement.

generated from the process $y = 0.5x + xw$, such that the true average partial effect is 1, and z does not affect y . If $\theta_r = 1$, the regression of y on x , z and w recovers the true average partial effect. However, a relatively small increase in θ_r from 1 to 1.1 leads to a much larger estimated pooled regression slope b_x . For $\theta_r = 1.1$, the full-sample x -on- z -and- w regression slope equals $S_{xz}/S_{zz} = 1.048$, and the group 0 (inverse) z -on- x regression slope equals $S_{xz}^0/S_{xx}^0 = 0.997$. Hence, their product exceeds 1, and \mathcal{A} is negative, giving rise to the implied weight $\mathcal{A}/(\mathcal{A} + \mathcal{B}) = -1.780$ and $\mathcal{B}/(\mathcal{A} + \mathcal{B}) = +2.780$, from where we get that $b_x = -1.780 \times 0.5 + 2.780 \times 1.5 = 3.28$.⁶

Figure 1: Covariance weighting of heterogeneous coefficients.



The data generating process (DGP) is quite simple. There is no effect of z on the outcome in either group, and all that is changing is the relative covariance between x and z in the two groups. Yet the relationship between θ_1 and b_x is non-monotonic, and asymmetrical around the value of 1. On the left of this point, $\mathcal{A}/(\mathcal{A} + \mathcal{B})$ is always positive, and $\mathcal{B}/(\mathcal{A} + \mathcal{B})$ always below 1; on the

⁶For $\theta_1 > 1$, \mathcal{A} decreases linearly in θ_1 whereas \mathcal{B} increases quadratically, leading to the non-monotonic weighting function $\mathcal{B}/(\mathcal{A} + \mathcal{B})$.

right, $\mathcal{A}/(\mathcal{A} + \mathcal{B})$ is always negative, and $\mathcal{B}/(\mathcal{A} + \mathcal{B})$ above 1. The pooled regression coefficients reflect the movements of the weights, and they vary between a minimum of -1.3 to a maximum of +3.8. Thus, the pooled regression of y on x , z and w produces highly misleading estimates of b_x that can be far away from the group size-weighted averages of the heterogenous x coefficients, here $1/2 \times 0.5 + 1/2 \times 1.5 = 1$. Moreover, in about 7% of simulated datasets, there is full Simpson’s reversal, i.e., a negative regression coefficient when the two groups are combined, although both separately estimated coefficients are positive.

In this DGP, z is not part of the outcome equation, so it would be better to just drop it from the regression. The result would be a variance weighted combination of the two group-specific coefficients, as described in Section 2.2. This average is depicted by the green, dotted line in Figure 1. Values are bounded between the estimated values of b_x^0 and b_x^1 , so approximately between 0.5 and 1.5, the two group-specific coefficients. The within-group-0 variance of x is always around 1 in this DGP, whereas the within-group-1 variance moves from $(-4)^2 + 0.1^2$ to a minimum of 0.1^2 and back to $4^2 + 0.1^2$. Hence, in the far left and right areas of the plot, almost all weight goes to the group-1 coefficient of 1.5 based on the much higher within-group variance, and the minimum is observed when $\theta_r = 0$, which corresponds to a residual slope value of $S_{xz}/S_{zz} = 0.5$.

The above example is admittedly somewhat unrealistic since x and z are highly collinear in both subgroups. This gives coefficients for the reverse regressions of z^w on x^w that are close to the inverse regression coefficients of x^w on z^w and the conditions for negative values of \mathcal{A} or \mathcal{B} in (10) and (11) are more likely satisfied.⁷ For example, if the errors were standard normal instead (with unit variance), all covariance weights are between zero and one for the specified data generating process. In applications with “normal” degrees of multicollinearity, the problem of non-convex weighting due to negative covariances may therefore turn out to be not such a serious issue.

3.4 Heterogeneity spillover

From (9), the heterogeneity spillover term is given by

$$\frac{\mathcal{C}(b_z^1 - b_z^0)}{\mathcal{A} + \mathcal{B}} = \frac{S_{zz}^0 S_{zz}^1 (g_1 - g_0) (b_z^1 - b_z^0)}{(S_{xx}^0 + S_{xx}^1)(S_{zz}^0 + S_{zz}^1) - (S_{xz}^0 + S_{xz}^1)^2}$$

⁷It does not matter whether the correlation between x^0 and z^0 is close to +1 or close to -1. For $x_i^0 = -z_i^0 + 0.1 \times Normal(0, 1)$, the graphs in Figure 1 are mirrored at 0, such that extreme values of b_x are observed for partialing-out regression slopes of around -1.

where g_1 and g_0 are the slopes of a regression of x on z in group 1 and group 0, respectively, and b_z^1 and b_z^0 are the coefficients of z in the group-wise trivariate regression of y^w on x^w and z^w .

Since $\mathcal{A} + \mathcal{B} > 0$, the sign of the spillover depends on the sign of the product $(g_1 - g_0)(b_z^1 - b_z^0)$. It is positive if the group with the greater x -on- z slope has also the greater slope of z in the group-specific outcome equation. Only the difference in slopes, i.e., the heterogeneity, matters for the spillover effect, not their absolute values. Clearly, there is no spillover effect if either $b_z^0 = b_z^1$ (no heterogeneity in the z -coefficient) or $g_1 = g_0$, or both.⁸

The two leading examples for $g_0 = g_1$ are as follows. First, x and z could be uncorrelated in both groups, such that $S_{xz}^0 = S_{xz}^1 = 0$. This assumption is unlikely to hold in applications. For example, in the case of two mutually exclusive treatment arms (when x and z are both dummy variables), $z = 0$ whenever $x = 1$ and vice versa, so x and z cannot be uncorrelated. Moreover, in many applications z is included exactly because it is a confounder, and thus necessarily correlated with x .

A second possibility is that the regressors are the same in both groups, for example $S_{zz}^0 = S_{zz}^1$ etc. A leading example is that of a stratified randomized controlled trial, where each group represents a stratum, there are multiple treatment arms, and the proportion treated is equal in each stratum. In this case, there is no heterogeneity spillover effect, and in fact, one can show that b_x in a regression of the outcome on the treatment indicators and strata fixed effects is equal to the average treatment effect, i.e., the weighted mean of b_x^0 and b_x^1 , where weights are proportional to the strata shares.

In general, however, the aggregate x -coefficient in the regression of y on x , z and w depends directly on the heterogeneous coefficients of the *other* regressor z . Thus, there can be a spillover of neglected heterogeneity, or a “contamination” as described recently by Goldsmith-Pinkham et al. (2022). Even if both sub-sample coefficients of x are zero, the estimated overall effect b_x can be non-zero, because the z -coefficients matter as well, another possible reason for a Simpson’s reversal.

An illustration using simulated data

The following numerical example illustrates the potential for contamination bias. As in the simulation results of the previous section, data are generated for two groups with $N = 1000$ observations each. In the context of heterogeneity spillovers, it is important that the association between x^w and z^w differs between the two groups. Therefore, I generate z^0 , z^1 , and x^0 as *i.i.d.* standard normal

⁸In the previous section, equality of the reverse regression slopes S_{xz}^w/S_{xx}^w was shown to be a sufficient condition for the absence of negative covariance weighting.

random variables, whereas in group 1, x^1 and z^1 are related by the equation

$$x^1 = g_1 z^1 + \text{Normal}(0, 1)$$

where g_1 increases stepwise from -2 to $+2$. Since x^0 and z^0 are uncorrelated, $g_1 = g_1 - g_0$ indicates the differential “response” of x to z in group 1 relative to group 0.⁹ Outcome data are generated using the equation

$$y = 1 + w + 0.05x + 2zw$$

This means that the true coefficient of x , equal to 0.05 , is the same in both groups, whereas there is heterogeneity in the z coefficient, since $b_z^1 - b_z^0 = 2$.

Figure 2: Heterogeneity spillover.

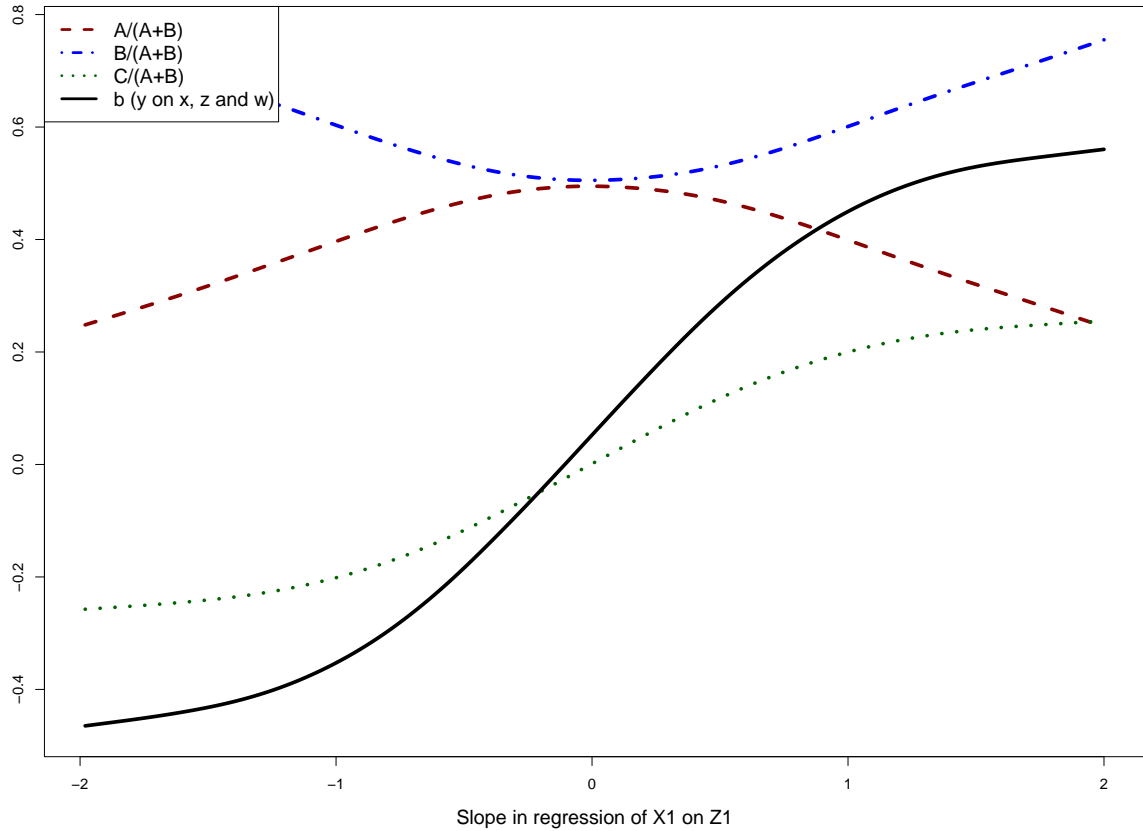


Figure 2 shows the three aggregation weights, together with the pooled regression coefficient b_x

⁹By construction, an increase in the absolute value of g_1 also affects the group-1 variance of x , since $\text{Var}(x^1) = g_1^2 + 1$. This explains the parabolic shape of the covariation weights $A/(A+B)$ and $B/(A+B)$ in Figure 2.

(solid, back line), as functions of $g_1 - g_0$. We know that there is no heterogeneity in the effect of x on y , so the covariance weights $\mathcal{A}/(\mathcal{A}+\mathcal{B})$ and $\mathcal{B}/(\mathcal{A}+\mathcal{B})$ do not contribute to departures of b_x from the true average coefficient of 0.05. Nevertheless, observed values of b_x take values between -0.45 and +0.55 which is entirely due to heterogeneity spillovers. The large group-1 specific effect of z (in combination with no effect in group 0) enters the estimation of b_x with positive or negative weight, depending on the sign of g_1 . In many instances, this leads to Simpson’s reversal: the coefficient of x in separate groupwise regressions is positive in both groups, but negative, when the two groups are combined.

4 Generalizations

In practice, one will rarely encounter an application with two regressors and two groups only, and the question arises whether any algebraic results can be derived for more complex regressions. In particular, what happens as the number of regressors or the number of groups is increased? Increasing the number of groups does not change the nature of the argument. For instance, with K groups, where $K \geq 2$, (4) generalizes to

$$b = \left(\sum_{k=1}^K H^k \right)^{-1} \sum_{k=1}^K H^k b^k$$

where the weight matrices H^k and the subset regression coefficients b^k , $k \in \{1, \dots, K\}$ are defined as before. It becomes, however, practically impossible to derive closed form results on the relation between single elements of b and the single elements of the subset coefficients b^k , as the number of terms in the numerator and denominator of the element-wise equation increases quadratically in the number of groups.

Similar issues arise if the number of groups is kept at two but the dimensionality of the regressor vector is increased. While the trivariate problem studied above was manageable, higher order regressions are less so. One exception is the case where the additional variables are group-wise orthogonal to the included ones. In this case, the H^k matrices are block-diagonal, and the above results still apply, as heterogeneity of the additional regressors cannot “spill over” to estimation of the other coefficients when groups are combined in a single pooled regression. This consideration can apply, for example, in a randomized controlled trial with multiple treatment arms, where additional regressors are included simply in order to soak up residual variation and increase precision.

5 Real data examples

While it is straightforward to produce numerical examples of Simpson’s reversal due to neglected heterogeneity in artificially generated data, it turns out that finding examples in actual applied work is more difficult. In the end, such an extreme form of heterogeneity bias is perhaps more of theoretical than of practical importance. However, non-convex weighting of heterogeneous coefficients occurs quite regularly when examining concrete dataset used in economics. In this section, I provide two examples, both based on publicly available textbook datasets.

The first one is the estimation of an investment equation, using times series data collected for two firms. This application fits exactly the theoretical decomposition results derived in this paper since there are two regressors, capital stock and market value, and two groups, in this case the two firms. Hence, it is possible to compute the covariance weights as well as the heterogeneity spillover weights in order to trace out, why, as will be the case, the pooled `value` coefficient is not a convex average of the firm-specific `value` coefficients.

The second example follows the spirit of the neglected heterogeneity problem, but applies it to a wage regression with many covariates, where either two subset regressions are run using male/female as the group variable, or alternatively a combined regression with a male dummy only, using data from the 1976 Current Population Survey. In order to document the combined effect of potentially negative covariance weightings and heterogeneity spillovers, I report the implicit overall own-coefficient weights, by comparing for each regressor the three coefficients b_k^{pooled} , b_k^{male} and b_k^{female} . It turns out that the implicit weights are outside the (0,1) interval for 6 out of 21 regression coefficients.

5.1 An investment equation (Grunfeld data)

This example considers time-series regressions of investment on market value and capital stock for two major U.S. corporations at the time, Union Oil and General Motors, using historical data for the years 1935-1954 obtained from the Grunfeld data distribution.¹⁰ The first two columns of Table 1 show the heterogenous coefficients obtained from separate, firm-level regressions. The coefficients of the combined regression that includes the two regressors as well as a firm dummy (General Motors yes/no), are shown in the third column of the Table.

¹⁰See Kleiber and Zeileis (2010) for further information, and <https://www.zeileis.org/grunfeld/> for a download link.

Table 1: Grunfeld investment equation

Dependent Variable: Investment	Union Oil b^0	General Motors b^1	Pooled b
Market value/100	8.75	11.93	12.27
Capital stock/100	12.38	37.14	35.98
General Motors (yes/no)			-73.07
Constant	-4.50	-149.78	-84.09
Number of observations	20	20	40

Generally speaking, Union Oil’s investment behavior seems to be less responsive to market value and capital stock than that of General Motors. Here, $b_x = 12.27$ correspond to the coefficient of market capitalization in the combined regression. We see that it is a non-convex combination of the firm level coefficients of $b_x^0 = 8.75$ for Union Oil and $b_x^1 = 11.93$ for General Motors.

We can now compute the two covariance weights as well as the heterogeneity spillover weight for this example. Specifically, $\mathcal{A}/(\mathcal{A} + \mathcal{B}) = 0.002$, $\mathcal{B}/(\mathcal{A} + \mathcal{B}) = 0.998$, and $\mathcal{C}/(\mathcal{A} + \mathcal{B}) = 0.014$. So the pooled coefficient puts almost all its weight on the General Motors coefficient for market capitalization. This in itself is an interesting result, since both firms contribute the same number of observations to the combined sample, but the regression weights are highly unequal. If it was not for heterogeneity spillover, the pooled coefficient would be a convex combination of the firm-level coefficients, since both covariance weights are positive. However, there is heterogeneity spillover, and it can be computed as $\mathcal{C}(b_z^1 - b_z^0)/(\mathcal{A} + \mathcal{B}) = 0.014(37.14 - 12.38) = 0.347$. Adding 0.347 to the otherwise convex combination of 11.923 yields the combined coefficient of 12.27 that is displayed in Table 1.

5.2 Wages of men and women (CPS)

In the second example, I use a textbook dataset on wages and worker’s characteristics from Wooldridge (2012), an extract from the 1976 Current Population Survey.¹¹ The dependent variable is the logarithm of average hourly earnings. Explanatory variables include years of education, years of potential experience and its square, years with current employer and its square, number of dependents, indicators for being nonwhite, married, living in a metropolitan area, as well as three regional and nine industry dummies. Thus, there is a total of 21 regressors and the dataset pro-

¹¹The data file "wage1" can be obtained from the R-repository, package name "wooldridge": <https://cran.r-project.org/web/packages/wooldridge/wooldridge.pdf>.

vides 526 observations. As group variable of interest, I consider here the gender of the worker. This choice is of course somewhat arbitrary, but wage related regression analyses that do not stratify by gender have been conducted in the literature (e.g. Oreopolous, 2006).

To estimate the group-specific, heterogeneous coefficients, the sample is split and two regressions are conducted, one using the subset of 274 men and one the using the subset of 252 women. Results are shown in Table 2. For 6 out of 21 coefficients, the aggregation weights are non-convex. This is seen in the last column of Table 2, where the equation $b_x = \alpha \times b_x^{men} + (1 - \alpha) \times b_x^{women}$ is solved for α . In three instances, this weight is negative (for tenure, for the number of dependents and for the wholesale dummy). In another three instances, it is greater than one (for tenure squared, services and professional occupations). This can lead to quite counterintuitive results. For instance, if one were to use these results to rank industries by their wage differentials, some reversals would occur. For example, for both genders, services pays higher wages than trade, ceteris paribus. Yet, in the aggregate, trade wages are estimated to lie above those of service workers.

Table 2: Wages of U.S. workers

Dependent variable: <i>logarithmic hourly wage</i>				
	b	b^{men}	b^{women}	weight
years of education	0.047	0.052	0.043	0.41
experience	0.025	0.032	0.020	0.44
experience squared	-0.001	-0.001	0.000	0.48
tenure	0.022	0.025	0.024	-4.82
tenure squared	0.000	0.000	-0.001	1.06
nonwhite	-0.004	0.051	-0.093	0.62
married	0.056	0.159	-0.054	0.52
number of dependents	-0.022	-0.032	-0.022	-0.09
lives in SMSA	0.139	0.142	0.101	0.91
lives in north central U.S	-0.058	-0.118	-0.023	0.37
lives in southern region	-0.044	-0.112	0.013	0.46
lives in western region	0.055	0.018	0.067	0.26
construc. indus.	-0.053	0.026	-0.081	0.26
nondur. manuf. indus.	-0.107	-0.060	-0.109	0.03
trans, commun, pub ut	-0.096	-0.073	-0.142	0.67
trade (wholesale or retail)	-0.303	-0.271	-0.271	-771.9
services indus.	-0.309	-0.255	-0.236	3.83
prof. serv. indus.	-0.095	-0.172	0.013	0.58
profess. occupation	0.225	0.215	0.193	1.44
clerical occupation	0.038	0.115	0.022	0.18
service occupation	-0.094	-0.087	-0.149	0.88
female	-0.268			

Note that this crude assessment of non-convex weighting cannot discriminate between the two

sources of non-convexity. So we do not know whether it is primarily due to heterogeneity spillover, or to covariance-weighting of own heterogeneous coefficient contrasts, or both. Since the formulae derived in this paper only dealt with the two-regressor-case, and not with a high-dimensional regressor vector as presently, such a decomposition is not feasible.

6 Discussion

The purpose of this paper was pointing out an algebraic relationship for heterogeneous effects, not to address inference. Estimated sub-group coefficients will never be identical in practice, which begs the question whether their difference is “statistically significant”. Such tests are widely available and straightforward to implement (e.g., Chow, 1960, Breitung and Salish, 2021). But in terms of point estimates, the presented results hold regardless of the outcomes of such a test: estimated coefficients in a regression with multiple regressors are not necessarily convex combinations of the group-level coefficients, and sign reversal is possible.

The non-convexity result follows directly from regression algebra: subgroup regression coefficients are aggregated using matrix level variance-covariance weighting, but this does not imply element by element convex aggregation. With several regressors of interest, non-convex weighting can arise due to two reasons. The first one is technical, since residuals in the partialing out equation cannot be mean independent, implying covariance-weighted averaging; the second reason is substantive, as coefficients in general suffer from spillovers, or contamination, from heterogeneous coefficients of *other* regressors. In theory, such non-convex weighting can easily lead to a Simpson’s reversal: a group-level association may switch its sign once the two groups are combined and a single regression is performed.

An application to estimating a wage regression illustrated that non-convex weights arise quite commonly in practice. When enforcing identical coefficients on 21 regressors, rather than letting them vary by gender, six out of these 21 estimates do not lie between the female and the male estimates.

As a remedy to these problems, one should better conduct group-wise (i.e. fully interacted) regressions, from where one can obtain average coefficients, for example by weighting the heterogeneous coefficients by their relative group sizes. In the context of panel data, this is straightforward as long as the number of years or the number of individual units is small. If the regression adjustment is made in order to satisfy a conditional independence assumption, the situation is more

complicated, as there are usually many confounders that may interact with the treatment effect in complicated ways. For example, regarding the model considered in this paper, the treatment effect of x could also vary with z , not only with w . In such cases, matching estimators can be preferable as they avoid the weighting issues inherent to regression (see, e.g. Imbens and Wooldridge, 2009).

7 References

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