

# An Omitted Variable Bias Framework for Sensitivity Analysis of Instrumental Variables

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We develop an omitted variable bias framework for sensitivity analysis of instrumental variable estimates that naturally handles multiple side-effects (violations of the exclusion restriction assumption) and confounders (violations of the ignorability of the instrument assumption) of the instrument, exploits expert knowledge to bound sensitivity parameters, and can be easily implemented with standard software. Specifically, we introduce sensitivity statistics for routine reporting, such as (extreme) *robustness values* for instrumental variables, describing the minimum strength that omitted variables need to have to change the conclusions of a study. Next we provide visual displays that fully characterize the sensitivity of point estimates and confidence intervals to violations of the standard instrumental variable assumptions. Finally, we offer formal bounds on the worst possible bias under the assumption that the maximum explanatory power of omitted variables is no stronger than a multiple of the explanatory power of observed variables. Conveniently, many pivotal conclusions regarding the sensitivity of the instrumental variable estimate (e.g. tests against the null hypothesis of zero causal effect) can be reached simply through separate sensitivity analyses of the effect of the instrument on the treatment (the *first stage*) and the effect of the instrument on the outcome (the *reduced form*). We apply our methods in a running example that uses proximity to college as an instrumental variable to estimate the returns to schooling.

*Some key words:* Instrumental Variables; Omitted Variable Bias; Sensitivity Analysis; Robustness Values.

## 1. INTRODUCTION

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Unobserved confounding often complicates efforts to make causal claims from observational data (e.g. Pearl, 2009; Imbens and Rubin, 2015). Instrumental variable (IV) regression offers a powerful and widely used tool to address unobserved confounding, by exploiting exogenous sources of variation of the treatment (e.g. Angrist et al., 1996; Angrist and Pischke, 2009). IV methods are “a central part of the econometrics canon since the first half of the twentieth century” (Imbens, 2014, p.324), and, beyond economics, are now prominent tools in the arsenal of

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investigators seeking to make causal claims across the social sciences, epidemiology, medicine, genetics, and other fields (see e.g. Hernán and Robins, 2006; Burgess and Thompson, 2015).

Yet, instrumental variable methods carry their own set of demanding assumptions. Principally, conditionally on certain observed covariates, an instrumental variable must not be confounded with the outcome, and it should influence the outcome only by affecting uptake of the treatment. In recent literature, the first assumption is usually called *exogeneity*, *ignorability*, or *unconfoundedness* of the instrument, whereas the second assumption is called the *exclusion* restriction (Angrist and Pischke, 2009; Imbens and Rubin, 2015). These assumptions can be violated by omitted confounders of the instrument-outcome association, and by omitted side-effects of the instrument that influence the outcome via paths other than through the treatment. Although in certain cases such assumptions may entail testable implications (Pearl, 1995; Gunsilius, 2020; Kédagni and Mourifié, 2020), they are often unverifiable and must be defended by appealing to domain knowledge. Whether a given IV study identifies the causal effect of interest, then, turns on debates as to whether these assumptions hold.

Particularly in recent years, economists and other scholars have adopted a more skeptical posture towards instrumental variable methods, emphasizing the importance of both defending the credibility of these assumptions as well as assessing the consequences of their failures (e.g., Deaton, 2009; Heckman and Urzua, 2010). Extensive reviews of many widely-used instrumental variables have catalogued several plausible violations of the exclusion restriction for such instruments (e.g. Gallen, 2020; Mellon, 2020). More worrisome, if traditional assumptions fail to hold, it is well known that the bias of the IV estimate may be *worse* than the original confounding bias of the simple regression estimate (Bound et al., 1995). Therefore, researchers are also advised to perform *sensitivity analyses* to assess the degree of violation of the IV assumptions that would be required to alter the conclusions of a study.

While a number of sensitivity analyses for instrumental variables have been proposed (e.g., Small, 2007; Small and Rosenbaum, 2008; Conley et al., 2012; Wang et al., 2018; Cinelli et al., 2019; Masten and Poirier, 2021), they have rarely been employed in practice. For example, in economics, only 1 out of 27 papers using instrumental variables, published in the *American Economic Review* in 2020, performed formal sensitivity analysis to unobserved variables. In political science, this number was 1 out of 12 papers across the top three general interest journals in 2019 (Cinelli and Hazlett, 2020). In Sociology, none of the 34 papers published between 2004 and 2022 in the *American Journal of Sociology* and the *American Sociology Review* did so (Felton and Stewart, 2022). Note that sensitivity to *unobserved* variables is distinct from (though related to) sensitivity to analytical choices of the investigator, which is more commonly found in the applied literature; these include, for example, sensitivity to different estimators, the presence of outliers, effect heterogeneity, or covariate selection (see, Blundell et al., 2001; Belzil and Hansen, 2002; Jaeger and Parys, 2009 for examples applied to returns to education).

We suggest several reasons for this slow uptake. First, the traditional approach for sensitivity analysis of instrumental variable estimates has focused on parameterizing violations of the IV assumptions with a single parameter summarizing the overall bias in the association of the instrument with the outcome. While this parameterization may be well-suited when the bias is only due to the direct effect of the instrument on the outcome (not through the treatment), it is not as straightforward to use when reasoning about multiple side-effects or confounders of the instrument, in which case that sensitivity parameter is a complicated composite of many sources of bias (see Supplementary Material for a comparison of our proposal with traditional approaches). Second, while users of IV methods are instructed to routinely report quantities to diagnose certain inferential problems such as “weak instruments” (e.g. the F-statistic, Stock and Yogo, 2002), we lack sensitivity statistics that can quickly communicate how robust a study is to violations in

the form of omitted confounders or side-effects of the instrument. Additionally, it is often difficult to connect the formal results of a sensitivity analysis to a cogent argument about what types of biases can be ruled out by expert knowledge.

In this paper, we develop an omitted variable bias (OVB) framework for assessing the sensitivity of IV estimates that aims to address these challenges. Building on the Anderson-Rubin approach (Anderson and Rubin, 1949) and on recent developments of OVB for ordinary least squares (OLS) (Cinelli and Hazlett, 2020), we develop a simple suite of sensitivity analysis tools for IV that: (i) naturally handles violations due to multiple side-effects and confounders, possibly acting non-linearly; (ii) is well suited for routine reporting; and (iii) exploits expert knowledge to bound sensitivity parameters. (Here we focus on the just-identified case of one treatment and one instrument for two reasons. First, examining violations of identification assumptions is already challenging enough with a single instrument (Angrist and Pischke, 2009). Second, most applied work falls into this category: for instance, Young (2022) finds that 80% of instrumental variable regressions in the *American Economic Review* and 15 other journals of the *American Economic Association* used a single instrument. Even in multiple-instrument studies, it is not uncommon for researchers to report and give special focus to their best single instrument.)

Specifically, we introduce two main sensitivity statistics for instrumental variable estimates: (i) the *robustness value* describes the minimum strength of association (in terms of partial  $R^2$ ) that omitted variables (side-effects or confounders) need to have, both with the instrument and with the outcome, in order to change the conclusions of the study; and (ii) the *extreme robustness value*, which describes the minimal strength of association that omitted variables need to have with the *instrument alone* in order to be problematic. Routine reporting of these quantities provides a quick and simple way to improve the transparency and facilitate the assessment of the credibility of IV studies. Next, we offer intuitive graphical tools for investigators to assess how postulated confounding of any degree would alter hypothesis tests, as well as lower or upper limits of confidence intervals. These tools can be supplemented with formal bounds on the worst possible bias that side-effects or confounders could cause, under the assumption that the maximum explanatory power of these omitted variables is no stronger than a chosen multiple of the explanatory power of observed variables.

A final contribution of this paper is the proposal of a novel *bias-adjusted critical value* that accounts for a postulated degree of omitted variable bias. Notably, this correction on the critical value does not depend on the observed data, and can be computed by simply postulating a hypothetical partial  $R^2$  of the omitted variables with the dependent and independent variables of the regression. Applied researchers can thus quickly and easily perform sensitivity analysis by simply substituting traditional thresholds with bias-adjusted thresholds, when testing a particular null hypothesis, or when constructing confidence intervals. All proofs and details can be found in the Supplementary Material. Open-source software for R implements the methods discussed in this paper: <https://github.com/carloscinelli/iv.sensemakr>.

## 2. BACKGROUND AND RUNNING EXAMPLE

### 2.1. Ordinary least squares and the omitted variable bias problem

Many observational studies have established a positive and large association between educational achievement and earnings using regression analysis. Here we consider the work of Card (1993), which employed a sample of  $n = 3,010$  individuals from the National Longitudinal Survey of Young Men.

Considering the following multiple linear regression  $Y = \hat{\tau}_{OLS,res} D + \mathbf{X} \hat{\beta}_{OLS,res} + \hat{\varepsilon}_{OLS,res}$ , where  $Y$  denotes *Earnings* and measures the log transformed hourly wages of the individual,  $D$

denotes *Education* and consists of an integer-valued variable indicating the completed years of education of the individual, and the matrix  $\mathbf{X}$  comprises race, experience, and a set of regional factors, Card concluded that each additional year of schooling was associated with approximately 7.5% higher wages.

135 Educational achievement, however, is not randomly assigned; perhaps individuals who obtain more education have higher wages for other reasons, such as family background, or higher levels of some other unobserved characteristic such as *Ability* or *Motivation*. If data on these variables were available, then further adjustment for such variables would capture the causal effect of educational attainment on schooling, as in  $Y = \hat{\tau}_{OLS}D + \mathbf{X}\hat{\beta}_{OLS} + \mathbf{U}\hat{\gamma}_{OLS} + \hat{\varepsilon}_{OLS}$ , where  $\mathbf{U}$  is a  
 140 set of variables that, along with  $\mathbf{X}$ , eliminates confounding concerns (if the treatment effect is heterogeneous, this may affect the causal interpretation of  $\tau_{OLS}$ , see, e.g. [Angrist and Pischke, 2009](#)). Unfortunately, such detailed information on individuals is not available, and researchers  
 145 may not agree on which variables  $\mathbf{U}$  are needed. Regression estimates that adjust for only a partial list of characteristics (such as  $\mathbf{X}$ ) may suffer from omitted variable bias, likely overestimating the true returns to schooling.

## 2.2. Instrumental variables as a solution to the omitted variable bias problem

Instrumental variable methods offer an alternative route to estimate the causal effect of schooling on earnings without having data on the unobserved variables  $\mathbf{U}$ . The key for such methods to work is to find a new variable (the *instrument*) that changes the incentives to educational achievement, but is associated with earnings only through its effect on education. To that end, Card (1993) proposed exploiting the role of geographic differences in college accessibility. In particular, consider the variable *Proximity*, encoding an indicator of whether the individual grew up in an area with a nearby accredited 4-year college, which we denote by  $Z$ . Students who grow up far from the nearest college may face higher educational costs, discouraging them from pursuing higher level studies. Next, and most importantly, Card (1993) argues that, conditional on the set of observed variables  $\mathbf{X}$ , whether one lives near a college is not itself confounded with earnings, nor does proximity to college affect earnings apart from its effect on years of education. If we believe such assumptions hold it is possible to recover a valid estimate of the (weighted average of local) average treatment effect(s) of *Education* on *Earnings* by simply taking the ratio of two OLS coefficients, one measuring the effect of *Proximity* on *Earnings*, and another measuring the effect of *Proximity* on *Education*, as in the two regression models

$$\text{First Stage: } D = \hat{\theta}_{\text{res}}Z + \mathbf{X}\hat{\psi}_{\text{res}} + \hat{\varepsilon}_{d,\text{res}}, \quad (1)$$

$$\text{Reduced Form: } Y = \hat{\lambda}_{\text{res}}Z + \mathbf{X}\hat{\beta}_{\text{res}} + \hat{\varepsilon}_{y,\text{res}}. \quad (2)$$

Throughout the paper we refer to these equations as the *first stage* (1) and the *reduced form* (2), as these are now common usage ([Angrist and Pischke, 2009](#); [Imbens and Rubin, 2015](#); [Andrews et al., 2019](#)). The coefficient for *Proximity* ( $Z$ ) on the first-stage regression reveals that those who grew up near a college indeed have higher educational attainment, having completed an additional 0.32 years of education, on average. Likewise, the coefficient for *Proximity* ( $Z$ ) on the reduced-form regression suggests that those who grew up near a college have 4.2% higher earnings. The IV estimate is then given by the ratio,  $\hat{\tau}_{\text{res}} := \hat{\lambda}_{\text{res}}/\hat{\theta}_{\text{res}} \approx 0.042/0.319 \approx 0.132$ . The value of  $\hat{\tau}_{\text{res}} \approx 0.132$  suggests that, contrary to the OLS estimate of 7.5%, and perhaps surprisingly, each additional year of schooling instead raises wages by much more—13.2%. (Conditions that allow a causal interpretation of the traditional IV estimand are extensively discussed elsewhere and will not be reviewed here, see [Angrist et al. \(1996\)](#); [Angrist and Pischke \(2009\)](#); [Swanson et al. \(2018\)](#); [Słoczyński \(2020\)](#) and [Blandhol et al. \(2022\)](#). See also Section 6.)

The ratio  $\hat{\lambda}_{\text{res}}/\hat{\theta}_{\text{res}}$  is sometimes called the *indirect least squares* estimator. Inference in this framework is usually performed using the delta-method. A closely related approach is denoted by *two-stage least squares*, in which one saves the predictions of the first-stage regression, and then regress the outcome on these fitted values. By the Frisch-Waugh-Lovell (FWL) theorem (Frisch and Waugh, 1933; Lovell, 1963) one can readily show that two-stage least squares and indirect least squares yield numerically identical estimates and standard errors. 180

### 2.3. Anderson-Rubin regression, Fieller's theorem and weak instruments

Inference using the previous methods may prove unreliable when the first-stage coefficient is too close to zero relative to the sampling variability of its estimator. This is known as the “weak instrument” problem. The Anderson-Rubin regression (Anderson and Rubin, 1949) provides one approach to constructing confidence intervals with correct coverage, regardless of the strength of the first stage. Additionally, it also yields the uniformly most powerful unbiased test under this setup (Moreira, 2009). 185

The approach starts by creating the random variable  $Y_{\tau_0} := Y - \tau_0 D$  in which we subtract from  $Y$  a putative causal effect of  $D$ , namely,  $\tau_0$ . If  $Z$  is a valid instrument, under the null hypothesis  $H_0 : \tau = \tau_0$ , we should not see an association between  $Y_{\tau_0}$  and  $Z$ , conditional on  $X$ . In other words, if we run the regression 190

$$\text{Anderson-Rubin: } Y_{\tau_0} = \hat{\phi}_{\tau_0, \text{res}} Z + \mathbf{X} \hat{\beta}_{\tau_0, \text{res}} + \hat{\varepsilon}_{\tau_0, \text{res}}, \quad (3)$$

we should find that  $\hat{\phi}_{\tau_0, \text{res}}$  is equal to zero, but for sampling variation. To test the null hypothesis  $H_0 : \phi_{\tau_0, \text{res}} = 0$  in the Anderson-Rubin regression is thus equivalent to test the null hypothesis  $H_0 : \tau = \tau_0$ . The  $1 - \alpha$  confidence interval is constructed by collecting all values  $\tau_0$  such that the null hypothesis  $H_0 : \phi_{\tau_0, \text{res}} = 0$  is not rejected at the chosen significance level  $\alpha$ . This approach is numerically identical to Fieller's theorem (Fieller, 1954). It is convenient to define the point estimate  $\hat{\tau}_{\text{AR}, \text{res}}$  as the value  $\tau_0$  which makes  $\hat{\phi}_{\tau_0, \text{res}}$  exactly equal to zero. By the FWL theorem, we can easily show that  $\hat{\tau}_{\text{AR}, \text{res}}$  is also numerically identical to the indirect least squares and two-stage least squares estimates. 195 200

The literature on weak instruments is extensive (see, e.g., Nelson and Startz, 1990; Staiger and Stock, 1994; Kleibergen, 2002; Moreira, 2003, 2009; Andrews et al., 2019), and users are routinely advised to report diagnostic measures (e.g. the F-statistic of the first stage). It is important to note, however, that sensitivity to unobserved confounders or side-effects is distinct from issues posed by weak instruments. In particular, the latter depends on sample size, whereas the former does not. Thus, instruments deemed “strong” by conventional statistics may still be fragile in the face of unobserved variables—see Remark 4. 205

### 2.4. The instrumental variable estimate may still suffer from omitted variable bias

The previous instrumental variable estimate relies on the assumption that, conditional on  $X$ , *Proximity* and *Earnings* are unconfounded, and the effect of *Proximity* on *Earnings* must go entirely through *Education*. As is often the case, neither assumption is easy to defend. First, the same factors that might confound the relationship between *Education* and *Earnings* could similarly confound the relationship of *Proximity* and *Earnings* (e.g. family wealth or connections). Second, as argued in Card (1993), the presence of a college nearby may be associated with high school quality, which in turn also affects earnings. Finally, other geographic confounders can make some localities likely to both have colleges nearby and lead to higher earnings. These are only coarsely conditioned on by the observed regional indicators, and residual biases may still remain. 210 215

220 Therefore, instead of adjusting for  $\mathbf{X}$  only, as in the previous regressions, we should have adjusted for both the observed covariates  $\mathbf{X}$  and unobserved covariates  $\mathbf{W}$  as in

$$\text{First Stage: } D = \hat{\theta}Z + \mathbf{X}\hat{\psi} + \mathbf{W}\hat{\delta} + \hat{\varepsilon}_d, \quad (4)$$

$$\text{Reduced Form: } Y = \hat{\lambda}Z + \mathbf{X}\hat{\beta} + \mathbf{W}\hat{\gamma} + \hat{\varepsilon}_y, \quad (5)$$

$$\text{Anderson-Rubin: } Y_{\tau_0} = \hat{\phi}_{\tau_0}Z + \mathbf{X}\hat{\beta}_{\tau_0} + \mathbf{W}\hat{\gamma}_{\tau_0} + \hat{\varepsilon}_{\tau_0}, \quad (6)$$

225 where  $\mathbf{W}$  stands for all unobserved factors necessary to make *Proximity* a valid instrument for the effect of *Education* on *Earnings*. See Supplementary Material for canonical causal diagrams illustrating settings in which  $\{\mathbf{X}, \mathbf{W}\}$  renders  $Z$  a valid instrument for the effect of  $D$  and  $Y$ ; equivalent assumptions can be articulated in the potential outcomes framework (Angrist et al., 1996; Pearl, 2009; Swanson et al., 2018).

### 230 2.5. Problem statement

Our task is to characterize how instrumental variable estimates, as given by the OLS regressions in (4)-(6), would have changed due to the inclusion of omitted variables  $\mathbf{W}$ . As such, we should be able to leverage sensitivity analysis tools for OLS to examine the sensitivity of IV. The next section thus extends and refines several results for the sensitivity analysis of arbitrary OLS 235 estimates. These results are not only useful on their own right, but, importantly, they will later be applied to the development of a suite sensitivity analysis tools for instrumental variables in Section 4. Finally, throughout the paper, we impose the following regularity condition.

*Assumption 1 (Full Rank).* The matrices of independent variables in (4)-(6) have full rank.

This ensures all relevant quantities discussed below are finite.

## 240 3. EXTENSIONS TO THE OMITTED VARIABLE BIAS FRAMEWORK FOR OLS

### 3.1. Preliminaries

We start by briefly establishing key ideas, formulae, and notation from prior work (Cinelli and Hazlett, 2020). For concreteness, in this section we discuss the omitted variable bias framework in the context of the reduced-form regression. Readers should keep in mind, however, that all 245 results presented here hold for *arbitrary OLS estimates*—including, but not limited to, the first stage and the Anderson-Rubin regression. The logical implications of the sensitivity of these auxiliary regressions for the sensitivity of IV itself are deferred to Section 4.

Consider the regression coefficient estimate  $\hat{\lambda}$  and the classical (i.e, homoskedastic) standard error estimate  $\hat{s}_e(\hat{\lambda})$  of Equation (5), namely, the regression of the outcome  $Y$  on the instrument  $Z$ , adjusting for a set of observed covariates  $\mathbf{X}$  and (for now) a single *unobserved* covariate  $W$  (we generalize to multivariate  $W$  below). Here  $Y$ ,  $Z$  and  $W$  are  $(n \times 1)$  vectors,  $\mathbf{X}$  is an  $(n \times p)$  matrix (including a constant), with  $n$  observations;  $\hat{\lambda}$ ,  $\hat{\beta}$  and  $\hat{\gamma}$  are the regression coefficient estimates and  $\hat{\varepsilon}_y$  the corresponding residuals. As  $W$  is unobserved, the investigator instead estimates the *restricted* model of Equation (2) where  $\hat{\lambda}_{\text{res}}$  and  $\hat{\beta}_{\text{res}}$  are the coefficients adjusting for  $Z$  and  $\mathbf{X}$  alone, and  $\hat{\varepsilon}_{y,\text{res}}$  the corresponding residuals. The omitted variable bias framework seeks to 255 answer the following question: how do the estimates from the restricted model compare with the estimates from the full model?

Let  $R^2_{Y \sim W|Z, \mathbf{X}}$  denote the (sample) partial  $R^2$  of  $W$  with  $Y$ , after controlling for  $Z$  and  $\mathbf{X}$ , and let  $R^2_{Z \sim W|\mathbf{X}}$  denote the partial  $R^2$  of  $W$  with  $Z$  after adjusting for  $\mathbf{X}$ . It is also useful to

define Cohen's partial  $f^2$ , e.g,  $f_{Z \sim W | \mathbf{X}}^2 := \frac{R_{Z \sim W | \mathbf{X}}^2}{1 - R_{Z \sim W | \mathbf{X}}^2}$  which will appear frequently throughout derivations. Given the point estimate and (estimated) standard error of the restricted model actually run,  $\hat{\lambda}_{\text{res}}$  and  $\hat{\text{se}}(\hat{\lambda}_{\text{res}})$ , these two  $R^2$  values are sufficient to recover  $\hat{\lambda}$  and  $\hat{\text{se}}(\hat{\lambda})$ . 260

**THEOREM 1 (OVB IN THE PARTIAL  $R^2$  PARAMETERIZATION).** *Under Assumption 1, the absolute difference between the restricted and full OLS estimates is given by,*

$$|\hat{\lambda}_{\text{res}} - \hat{\lambda}| = \underbrace{\sqrt{R_{Y \sim W | Z, \mathbf{X}}^2 f_{Z \sim W | \mathbf{X}}^2}}_{\text{BF}} \times \frac{\text{sd}(Y^{\perp \mathbf{X}, Z})}{\text{sd}(Z^{\perp \mathbf{X}})}; \quad (7) \quad 265$$

moreover, the (classical) standard error of the full OLS estimate is given by

$$\hat{\text{se}}(\hat{\lambda}) = \underbrace{\sqrt{\frac{1 - R_{Y \sim W | Z, \mathbf{X}}^2}{1 - R_{Z \sim W | \mathbf{X}}^2} \times \frac{\text{sd}(Y^{\perp \mathbf{X}, Z})}{\text{sd}(Z^{\perp \mathbf{X}})}}}_{\text{SEF}} \times \sqrt{\frac{1}{\text{df} - 1}}, \quad (8)$$

where  $\text{sd}(Y^{\perp \mathbf{X}, Z})$  is the (sample) residual standard deviation of  $Y$  after removing the part linearly explained by  $\{\mathbf{X}, Z\}$ ,  $\text{sd}(Z^{\perp \mathbf{X}})$  is the (sample) residual standard deviation of  $Z$  after removing the part linearly explained by  $\mathbf{X}$ , and  $\text{df} = n - p - 1$  is the residual degrees of freedom from the restricted model (2). To aid interpretation, we call the term  $\text{BF}$  in (7) the "bias factor" of  $W$ , and the term  $\text{SEF}$  in (8) the "standard error factor" of  $W$ . 270

For simplicity of exposition, throughout the text we usually refer to a single omitted variable  $W$ . These results, however, can be used for performing sensitivity analyses considering multiple omitted variables  $\mathbf{W} = [W_1, W_2, \dots, W_l]$ , and thus also non-linearities and functional form misspecification of observed variables. In such cases, barring an adjustment in the degrees of freedom, the equations are conservative, and reveal the maximum bias a multivariate  $\mathbf{W}$  with such pair of partial  $R^2$  values could cause (Cinelli and Hazlett, 2020, Sec. 4.5). 275

Note Theorem 1 is stated in terms of sample estimates. All results presented in this paper are of this type: they are exact algebraic results of how traditional OLS coefficients and standard error estimates change due to the inclusion of omitted variables. Conditions under which traditional estimates yield valid inferences are well-known and thus omitted. 280

### 3.2. Bias-adjusted critical values

We now introduce a novel correction to traditional critical values that researchers can use to account for omitted variable bias. Let  $t_{\alpha, \text{df} - 1}^* > 0$  denote the (absolute value of) the critical value for a standard t-test with significance level  $\alpha$  and  $\text{df} - 1$  degrees of freedom. Now let  $\text{LL}_{1-\alpha}(\lambda)$  be the lower limit and  $\text{UL}_{1-\alpha}(\lambda)$  be the upper limit of a  $1 - \alpha$  confidence interval for  $\lambda$  in the full model, i.e., 285

$$\text{LL}_{1-\alpha}(\lambda) := \hat{\lambda} - t_{\alpha, \text{df} - 1}^* \times \hat{\text{se}}(\hat{\lambda}), \quad \text{UL}_{1-\alpha}(\lambda) := \hat{\lambda} + t_{\alpha, \text{df} - 1}^* \times \hat{\text{se}}(\hat{\lambda}). \quad (9)$$

Considering the worst-case direction of the bias that further reduces the lower limit (or increases the upper limit) in (9), Equations (7) and (8) of Theorem 1 imply that both quantities can be written as a function of the restricted estimates and a new multiplier. 290

THEOREM 2 (BIAS ADJUSTED CRITICAL VALUE). *Under Assumption 1, for given  $\mathbf{R}^2 = \{R_{Y \sim W|Z, \mathbf{X}}^2, R_{Z \sim W|Z, \mathbf{X}}^2\}$ , and  $\alpha$ , consider the direction of the bias that reduces  $LL_{1-\alpha}(\lambda)$ . Then*

$$295 \quad LL_{1-\alpha}(\lambda) = \hat{\lambda}_{res} - t_{\alpha, df-1, \mathbf{R}^2}^\dagger \times \widehat{se}(\hat{\lambda}_{res}). \quad (10)$$

*Conversely, considering the direction of the bias that increases  $UL_{1-\alpha}(\lambda)$ , we have*

$$UL_{1-\alpha}(\lambda) = \hat{\lambda}_{res} + t_{\alpha, df-1, \mathbf{R}^2}^\dagger \times \widehat{se}(\hat{\lambda}_{res}). \quad (11)$$

Here  $t_{\alpha, df-1, \mathbf{R}^2}^\dagger$  denotes the bias-adjusted critical value

$$t_{\alpha, df-1, \mathbf{R}^2}^\dagger := SEF \sqrt{df/(df-1)} \times t_{\alpha, df-1}^* + BF \sqrt{df}, \quad (12)$$

300 where  $BF$  and  $SEF$  are the bias and standard error factors of Theorem 1.

As the subscript  $\mathbf{R}^2 = \{R_{Y \sim W|Z, \mathbf{X}}^2, R_{Z \sim W|Z, \mathbf{X}}^2\}$  conveys,  $t_{\alpha, df-1, \mathbf{R}^2}^\dagger$  depends on both sensitivity parameters. Notably, this correction does not depend on the observed data, but for the degrees of freedom. In other words, the bias correction is a function of the strength of unobserved confounding and the sample size alone. This allows one to quickly assess the robustness of reported 305 findings to omitted variables of any postulated strength  $\mathbf{R}^2$ , by simply comparing the reported t-statistic with the desired adjusted critical value, even without access to the original data.

*Example 1.* It is instructive to consider the case in which the omitted variable  $W$  has equal strength of association with  $Y$  and  $Z$ , i.e.,  $R_{Y \sim W|Z, \mathbf{X}}^2 = R_{Z \sim W|Z, \mathbf{X}}^2 = R^2$ . We then have that  $SEF = 1$  and  $BF = R^2/\sqrt{1-R^2}$  resulting in a very simple correction formula,

$$310 \quad t_{\alpha, df-1, R^2}^\dagger \approx t_{\alpha, df-1}^* + \frac{R^2}{\sqrt{1-R^2}} \sqrt{df}, \quad (13)$$

where we employ the approximation  $\sqrt{df/(df-1)} \approx 1$ . Table 1 shows the adjusted critical values for this case, considering different strengths of the omitted variable and various sample sizes.

$R^2$	Degrees of Freedom (sample size)				
	100	1,000	10,000	100,000	1,000,000
0.00	1.98	1.96	1.96	1.96	1.96
0.01	2.08	2.28	2.97	5.14	12.01
0.02	2.19	2.60	3.98	8.35	22.16
0.03	2.29	2.92	5.01	11.59	32.42
0.04	2.39	3.25	6.04	14.87	42.78
0.05	2.50	3.58	7.09	18.18	53.26

Table 1: Bias-adjusted critical values,  $t_{\alpha, df-1, R^2, R^2}^\dagger$ , for different strengths of the omitted variable  $W$  (with  $R_{Y \sim W|Z, \mathbf{X}}^2 = R_{Z \sim W|Z, \mathbf{X}}^2 = R^2$ ) and various sample sizes;  $\alpha = 5\%$ .

Tests using these new critical values account both for sampling uncertainty and residual biases with the postulated strength. Note  $t_{\alpha, df-1, \mathbf{R}^2}^\dagger$  increases the larger the sample size. This behaviour 315 is simply a consequence of the well-known, but often overlooked fact that in large samples any signal will eventually be detected, even if it is spurious. Thus, as the sample size grows, a higher threshold is needed in order to protect inferences against systematic biases.

We note Table 1 picks  $R_{Y \sim W|Z, \mathbf{X}}^2 = R_{Z \sim W|\mathbf{X}}^2 = R^2$  for illustrative purposes only. Researchers can construct bias-adjusted critical values for any arbitrary pair of  $R^2$  values—see, e.g, Supplementary Material for  $2 \times 2$  tables of  $t_{\alpha, df-1, \mathbf{R}^2}^\dagger$  where both  $R_{Y \sim W|Z, \mathbf{X}}^2$  and  $R_{Z \sim W|\mathbf{X}}^2$  are varied simultaneously. 320

*Remark 1.* Sensitivity analysis cannot reveal the strength of confounding present, only the strength of confounding required to alter a research conclusion. For instance, Table 1 reveals that in a study with 1 million observations, one needs a t-value of at least 12 in order to guarantee that the results are robust to latent variables that explain 1% of the residual variation both of the dependent and independent variables. The table also tells us that any study with a t-value less than 12 is vulnerable to such biases. The table *does not* tell us whether latent variables with such strength do exist in any particular study—this needs to be adjudicated using expert knowledge. Note, however, that knowing what one needs to know is useful, and represents an improvement over conventional analysis, which assumes  $R^2 = 0$ . See Section 6 for additional discussion. 330

### 3.3. Compatible inferences given bounds on partial $R^2$

Given hypothetical values for  $R_{Y \sim W|Z, \mathbf{X}}^2$  and  $R_{Z \sim W|\mathbf{X}}^2$ , the previous results allow us to determine exactly how the inclusion of  $W$  with such strength would change inference regarding the parameter of interest. Often, however, the analyst does not know the exact strength of omitted variables, and wishes to investigate the *worst* possible inferences that could be induced by a  $W$  with bounded strength, for instance,  $R_{Y \sim W|Z, \mathbf{X}}^2 \leq R_{Y \sim W|Z, \mathbf{X}}^{2 \max}$  and  $R_{Z \sim W|\mathbf{X}}^2 \leq R_{Z \sim W|\mathbf{X}}^{2 \max}$ . Writing  $t_{\alpha, df-1, \mathbf{R}^2}^\dagger$  as a function of the sensitivity parameters  $R_{Y \sim W|Z, \mathbf{X}}^2$  and  $R_{Z \sim W|\mathbf{X}}^2$ , we then solve the maximization problem, 335

$$\max_{R_{Y \sim W|Z, \mathbf{X}}^2, R_{Z \sim W|\mathbf{X}}^2} t_{\alpha, df-1, \mathbf{R}^2}^\dagger \quad \text{s.t.} \quad R_{Y \sim W|Z, \mathbf{X}}^2 \leq R_{Y \sim W|Z, \mathbf{X}}^{2 \max}, \quad R_{Z \sim W|\mathbf{X}}^2 \leq R_{Z \sim W|\mathbf{X}}^{2 \max}. \quad (14)$$

Denoting the solution to the optimization problem in expression (14) as  $t_{\alpha, df-1, \mathbf{R}^2}^{\dagger \max}$ , we obtain the maximum bias-adjusted critical value. 340

**THEOREM 3 (MAXIMUM BIAS-ADJUSTED CRITICAL VALUE).** Fix  $\alpha$ ,  $R_{Y \sim W|Z, \mathbf{X}}^{2 \max}$  and  $R_{Z \sim W|\mathbf{X}}^{2 \max} < 1$  in the optimization problem (14). Then,

$$t_{\alpha, df-1, \mathbf{R}^2}^{\dagger \max} = t_{\alpha, df-1, \mathbf{R}^{2*}}^\dagger,$$

with  $\mathbf{R}^{2*} = \{R_{Y \sim W|Z, \mathbf{X}}^{2 \max}, R_{Z \sim W|\mathbf{X}}^{2 \max}\}$  if  $R_{Z \sim W|\mathbf{X}}^{2 \max} \geq f_{\alpha, df-1}^{*2} f_{Y \sim W|Z, \mathbf{X}}^{2 \max}$ , and 345  
 $\mathbf{R}^{2*} = \{R_{Z \sim W|\mathbf{X}}^{2 \max} / (f_{\alpha, df-1}^{*2} + R_{Z \sim W|\mathbf{X}}^{2 \max}), R_{Z \sim W|\mathbf{X}}^{2 \max}\}$  otherwise, where here we define  $f_{\alpha, df-1}^* := t_{\alpha, df-1}^* / \sqrt{df-1}$ .

Once in possession of  $t_{\alpha, df-1, \mathbf{R}^2}^{\dagger \max}$ , the most extreme possible lower and upper limits of confidence intervals after adjusting for  $W$  are then given by

$$\text{LL}_{1-\alpha, \mathbf{R}^2}^{\max}(\lambda) = \hat{\lambda}_{\text{res}} - t_{\alpha, df-1, \mathbf{R}^2}^{\dagger \max} \times \hat{\text{se}}(\hat{\lambda}_{\text{res}}), \quad \text{UL}_{1-\alpha, \mathbf{R}^2}^{\max} = \hat{\lambda}_{\text{res}} + t_{\alpha, df-1, \mathbf{R}^2}^{\dagger \max} \times \hat{\text{se}}(\hat{\lambda}_{\text{res}}). \quad (350)$$

The interval composed of such limits,

$$\text{CI}_{1-\alpha, \mathbf{R}^2}^{\max}(\lambda) := \left[ \text{LL}_{1-\alpha, \mathbf{R}^2}^{\max}(\lambda), \quad \text{UL}_{1-\alpha, \mathbf{R}^2}^{\max}(\lambda) \right], \quad (15)$$

retrieves the union of all confidence intervals for  $\lambda$  that are compatible with an omitted variable with such strengths.

355 Widespread adoption of sensitivity analysis benefits from simple and interpretable statistics that quickly convey the overall robustness of an estimate. To that end, [Cinelli and Hazlett \(2020\)](#) proposed two sensitivity statistics for routine reporting: (i) the partial  $R^2$  of  $Z$  with  $Y$ ,  $R^2_{Y \sim Z | \mathbf{X}}$ ; and, (ii) the *robustness value* (RV). In what follows, we generalize the notion of a partial  $R^2$  as a measure of robustness to extreme scenarios, by introducing the *extreme robustness value* (XRV),  
 360 for which the partial  $R^2$  is a special case. We also recast these sensitivity statistics as a solution to an “inverse” question regarding the interval  $\text{CI}_{1-\alpha, R^2}^{\max}(\lambda)$ . This framework facilitates extending these metrics to other contexts, in particular to the IV setting in Section 4.

### 3.4. The extreme robustness value

365 Our first inverse question is: what is the *bare minimum* strength of association of the omitted variable  $W$  with  $Z$  that could bring its estimated coefficient to a region where it is no longer statistically different than zero (or another threshold of interest)? To answer this question, we can see  $\text{CI}_{1-\alpha, R^2}^{\max}(\lambda)$  as a function of the bound  $R^2_{Z \sim W | \mathbf{X}}$  alone, obtained from maximizing the adjusted critical value in expression (14) where: (i) the parameter  $R^2_{Y \sim W | Z, \mathbf{X}}$  is left completely unconstrained (i.e.,  $R^2_{Y \sim W | Z, \mathbf{X}} \leq 1$ ); and, (ii) the parameter  $R^2_{Z \sim W | \mathbf{X}}$  is bounded by XRV (i.e.,  
 370  $R^2_{Z \sim W | \mathbf{X}} \leq \text{XRV}$ ). The *Extreme Robustness Value*  $\text{XRV}_{q^*, \alpha}(\lambda)$  is defined as the greatest lower bound XRV such that the null hypothesis that a change of  $(100 \times q^*)\%$  of the original estimate,  $H_0 : \lambda = (1 - q^*)\hat{\lambda}_{\text{res}}$ , is not rejected at the  $\alpha$  level,

$$\text{XRV}_{q^*, \alpha}(\lambda) := \inf \left\{ \text{XRV}; (1 - q^*)\hat{\lambda}_{\text{res}} \in \text{CI}_{1-\alpha, 1, \text{XRV}}^{\max}(\lambda) \right\}. \quad (16)$$

The solution to this problem gives the following result.

375 **THEOREM 4 (EXTREME ROBUSTNESS VALUE—OLS).** *Under Assumption 1, for given  $q^*$  and  $\alpha$ , the extreme robustness value equals*

$$\text{XRV}_{q^*, \alpha}(\lambda) = \begin{cases} 0, & \text{if } f_{q^*}(\lambda) \leq f_{\alpha, df-1}^*, \\ \frac{f_{q^*}^2(\lambda) - f_{\alpha, df-1}^{*2}}{1 + f_{q^*}^2(\lambda)}, & \text{otherwise,} \end{cases}$$

where  $f_{q^*}(\lambda) := q^* |f_{Y \sim Z | \mathbf{X}}|$ , and  $f_{\alpha, df-1}^* := t_{\alpha, df-1}^* / \sqrt{df-1}$ .

380 **Remark 2.** Beyond its procedural interpretation,  $\text{XRV}_{q^*, \alpha}(\lambda)$  can also be interpreted as an “adjusted partial  $R^2$ ” of  $Z$  with  $Y$ . To see why, consider the case of the minimal strength to bring the point estimate ( $\alpha = 1$ ) to exactly zero ( $q^* = 1$ ). We then have that  $f_{\alpha=1, df-1}^* = 0$  and  $f_{q^*=1}^2(\lambda) = f_{Y \sim Z | \mathbf{X}}^2$ , resulting in  $\text{XRV}_{q^*=1, \alpha=1}(\lambda) = \frac{f_{Y \sim Z | \mathbf{X}}^2}{1 + f_{Y \sim Z | \mathbf{X}}^2} = R^2_{Y \sim Z | \mathbf{X}}$ . For the general case, we simply perform two adjustments that dampens the “raw” partial  $R^2$  of  $Z$  with  $Y$ . First we adjust it by the proportion of reduction deemed to be problematic  $q^*$  through  
 385  $f_{q^*} = q^* |f_{Y \sim Z | \mathbf{X}}|$ ; next, we subtract the threshold for which statistical significance is lost.

### 3.5. The robustness value

390 An alternative measure of robustness of the OLS estimate is to consider the minimal strength of association that the omitted variable needs to have, *both* with  $Z$  and  $Y$ , so that a  $1 - \alpha$  confidence interval for  $\lambda$  will include a change of  $(100 \times q^*)\%$  of the current restricted estimate. Write  $\text{CI}_{1-\alpha, R^2}^{\max}(\lambda)$  as a function of both bounds varying simultaneously,  $\text{CI}_{1-\alpha, \text{RV}, \text{RV}}^{\max}(\lambda)$ , by maximizing the adjusted critical value with bounds given by  $R^2_{Y \sim W | Z, \mathbf{X}} \leq \text{RV}$  and  $R^2_{Z \sim W | \mathbf{X}} \leq \text{RV}$ .

The *Robustness Value*  $\text{RV}_{q^*,\alpha}(\lambda)$  for not rejecting the null hypothesis that  $H_0 : \lambda = (1 - q^*)\hat{\lambda}_{\text{res}}$ , at the significance level  $\alpha$ , is defined as

$$\text{RV}_{q^*,\alpha}(\lambda) := \inf \left\{ \text{RV}; (1 - q^*)\hat{\lambda}_{\text{res}} \in \text{CI}_{1-\alpha,\text{RV},\text{RV}}^{\max}(\lambda) \right\}. \quad (17)$$

The RV of OLS estimates has then the following characterization.

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**THEOREM 5 (ROBUSTNESS VALUE—OLS).** *Under Assumption 1, for given  $q^*$  and  $\alpha$ , the robustness value equals*

$$\text{RV}_{q^*,\alpha}(\lambda) = \begin{cases} 0, & \text{if } f_{q^*}(\lambda) \leq f_{\alpha,df-1}^*, \\ \frac{1}{2} \left( \sqrt{f_{q^*,\alpha}^4(\lambda) + 4f_{q^*,\alpha}^2(\lambda)} - f_{q^*,\alpha}^2(\lambda) \right), & \text{if } f_{\alpha,df-1}^* < f_{q^*}(\lambda) < f_{\alpha,df-1}^{*-1}, \\ \text{XRV}_{q^*,\alpha}(\lambda), & \text{otherwise,} \end{cases}$$

where  $f_{q^*,\alpha}(\lambda) := q^*|f_{Y \sim Z|\mathbf{X}}| - f_{\alpha,df-1}^*$ , and  $f_{\alpha,df-1}^* := t_{\alpha,df-1}^*/\sqrt{df-1}$ .

The first case occurs when the confidence interval already includes  $(1 - q^*)\hat{\lambda}_{\text{res}}$  or the mere change of one degree of freedom achieves this. In the second case, both associations of  $W$  reach the bound (here, when the  $f$  statistic is very large, it may be numerically convenient to use the equivalent expression  $2/\left(1 + \sqrt{1 + 4/f_{q^*,\alpha}^2(\lambda)}\right)$  which avoids catastrophic cancellations). The last case is an interior point solution—when the constraint on the partial  $R^2$  with the outcome is not binding, the RV reduces to the XRV.

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### 3.6. Bounding the plausible strength of omitted variables

One final result is required before turning to the sensitivity of instrumental variables. Let  $X_j$  be a specific covariate of the set  $\mathbf{X}$ , and define

$$k_Z := \frac{R_{Z \sim W|\mathbf{X}_{-j}}^2}{R_{Z \sim X_j|\mathbf{X}_{-j}}^2}, \quad k_Y := \frac{R_{Y \sim W|Z,\mathbf{X}_{-j}}^2}{R_{Y \sim X_j|Z,\mathbf{X}_{-j}}^2}, \quad (18)$$

where  $\mathbf{X}_{-j}$  represents the vector of covariates  $\mathbf{X}$  excluding  $X_j$ . These new parameters,  $k_Z$  and  $k_Y$ , stand for how much “stronger”  $W$  is relatively to the observed covariate  $X_j$  in terms of residual variation explained of  $Z$  and  $Y$ . Our goal in this section is to re-express (or bound) the sensitivity parameters  $R_{Z \sim W|\mathbf{X}}^2$  and  $R_{Y \sim W|Z,\mathbf{X}}^2$  in terms of the relative strength parameters  $k_Z$  and  $k_Y$ . [Cinelli and Hazlett \(2020\)](#) derived bounds considering the part of  $W$  not linearly explained by  $\mathbf{X}$ . These are particularly useful when contemplating  $X_j$  and  $W$  both *confounders* of  $Z$  (violations of the ignorability of the instrument). In the IV setting, however,  $W$  and  $X_j$  may be *side-effects* of  $Z$ , instead of causes of  $Z$ . In such cases, it may be more natural to reason about the orthogonality of  $\mathbf{X}$  and  $W$  after conditioning on  $Z$ . Therefore, here we additionally provide bounds under the condition  $R_{W \sim X_j|Z,\mathbf{X}_{-j}}^2 = 0$ .

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**THEOREM 6 (RELATIVE BOUNDS ON THE STRENGTH OF  $W$ ).** *Under Assumption 1, for fixed  $k_Z$  and  $k_Y$  as defined in (18), if  $R_{W \sim X_j|Z,\mathbf{X}_{-j}}^2 = 0$  then*

$$R_{Z \sim W|\mathbf{X}}^2 \leq \eta^2 f_{Z \sim X_j|\mathbf{X}_{-j}}^2, \quad R_{Y \sim W|Z,\mathbf{X}}^2 = k_Y f_{Y \sim X_j|Z,\mathbf{X}_{-j}}^2, \quad (19)$$

where,  $\eta = \left( \frac{\sqrt{k_Z} + \sqrt{R_{Z \sim X_j|\mathbf{X}_{-j}}^3}}{\sqrt{1 - k_Z R_{Z \sim X_j|\mathbf{X}_{-j}}^4}} \right)$ .

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These results allow investigators to leverage knowledge of *relative importance* of variables (Kruskal and Majors, 1989) when making plausibility judgments regarding sensitivity parameters, by setting  $R_{Y \sim W|Z, \mathbf{X}}^{2 \max} = k_Y f_{Y \sim X_j|Z, \mathbf{X}_{-j}}^2$ ,  $R_{Z \sim W|Z, \mathbf{X}}^{2 \max} = \eta^2 f_{Z \sim X_j|Z, \mathbf{X}_{-j}}^2$  in  $\text{CI}_{1-\alpha, \mathbf{R}^2}^{2 \max}(\lambda)$ .

#### 4. AN OMITTED VARIABLE BIAS FRAMEWORK FOR THE SENSITIVITY OF IV

##### 4.1. A suite of sensitivity analysis tools for instrumental variables

We are now ready to develop a suite of sensitivity analysis tools for instrumental variable regression. In what follows, we first show how separate sensitivity analysis of the reduced form and first stage is sufficient to draw many valuable conclusions regarding the sensitivity of the instrumental variable estimate. We then construct a complete omitted variable bias framework for sensitivity analysis of instrumental variables within the Anderson-Rubin approach.

##### 4.2. What can be learned from the reduced form and first stage?

The critical examination of the first stage and the reduced form plays an important role for supporting the causal story behind a particular instrumental variable (Angrist and Krueger, 2001; Angrist and Pischke, 2009; Imbens, 2014). While investigating these separate regressions, all sensitivity analysis results discussed in the previous section can be readily deployed. Fortunately, such sensitivity analyses also answer many pivotal questions regarding the IV estimate itself. First, if the investigator is interested in assessing the strength of confounders or side-effects needed to bring the effect estimate to zero, or to not reject the null hypothesis of zero effect, the results of the sensitivity analysis of the reduced form is all that is needed. Second, the sensitivity of the first stage (to confounding that could change its sign) reveals whether the IV estimate could be arbitrarily large in either direction (in the context of randomization inference, similar observations have been noted by Imbens and Rosenbaum, 2005; Small and Rosenbaum, 2008; Keele et al., 2017). We elaborate on these claims below.

Starting with the point estimate, all estimators under consideration here equal to the ratio of the reduced-form and the first-stage regression coefficients,  $\hat{\tau} := \hat{\lambda}/\hat{\theta}$ . This simple algebraic fact leads to two immediate and practically important conclusions regarding the sensitivity of  $\hat{\tau}$  from the sensitivity of  $\hat{\lambda}$  and  $\hat{\theta}$  alone. First, residual biases can bring the IV point estimate to zero if and only if they can bring the reduced-form point estimate to zero. Therefore, if sensitivity analysis of the reduced form reveals that omitted variables are not strong enough to explain away  $\hat{\lambda}$ , then they also cannot explain away  $\hat{\tau}$ . Or, more worrisome, if analysis reveals that it takes weak confounding or side-effects to explain away  $\hat{\lambda}$ , the same holds for  $\hat{\tau}$ . Second, if we cannot rule out confounders or side-effects able to change the sign of the first stage, we cannot rule out that  $\hat{\tau}$  could be arbitrarily large in either direction. This can be immediately seen by letting  $\hat{\theta}$  approach zero on either side of the limit. Thus, whenever we are interested in biases as large or larger than a certain amount, the robustness of the first stage to the zero null puts an upper bound on the robustness of the IV point estimate.

Moving to inferential concerns, the Anderson-Rubin test for the null hypothesis  $H_0 : \tau = \tau_0$  is based on the test of  $H_0 : \phi_{\tau_0} = 0$ . By the FWL theorem, the point estimate and (estimated) standard error for  $\hat{\phi}_{\tau_0}$  can be expressed in terms of the first-stage and reduced-form estimates, namely,  $\hat{\phi}_{\tau_0} = \hat{\lambda} - \tau_0 \hat{\theta}$  and,  $\hat{\text{se}}(\hat{\phi}_{\tau_0}) = \sqrt{\widehat{\text{var}}(\hat{\lambda}) + \tau_0^2 \widehat{\text{var}}(\hat{\theta}) - 2\tau_0 \widehat{\text{cov}}(\hat{\lambda}, \hat{\theta})}$ . Testing  $H_0 : \phi_{\tau_0} = 0$  requires comparing the t-value for  $\hat{\phi}_{\tau_0}$  with a critical threshold  $t_{\alpha, \text{df} - 1}^*$ , and the null hypothesis is not rejected if  $|t_{\hat{\phi}_{\tau_0}}| \leq t_{\alpha, \text{df} - 1}^*$ . Squaring and rearranging terms we obtain the quadratic inequal-

ity,

$$\underbrace{(\hat{\theta}^2 - \widehat{\text{var}}(\hat{\theta})t_{\alpha,\text{df}-1}^{*2})\tau_0^2}_{a} + \underbrace{2(\widehat{\text{cov}}(\hat{\lambda}, \hat{\theta})t_{\alpha,\text{df}-1}^{*2} - \hat{\lambda}\hat{\theta})\tau_0}_{b} + \underbrace{(\hat{\lambda}^2 - \widehat{\text{var}}(\hat{\lambda})t_{\alpha,\text{df}-1}^{*2})}_{c} \leq 0. \quad (20)$$

When considering the null hypothesis  $H_0 : \tau_0 = 0$ , only the term  $c$  remains, and  $c$  is less or equal to zero if and only if one cannot reject the null hypothesis  $H_0 : \lambda = 0$  in the reduced-form regression. Also note that arbitrarily large values for  $\tau_0$  will satisfy the inequality in Equation (20) if, and only if,  $a < 0$ , meaning that we cannot reject the null hypothesis  $H_0 : \theta = 0$  in the first-stage regression. Within the Anderson-Rubin framework, we thus reach analogous conclusions regarding hypothesis testing as those regarding the point estimate: (i) when interest lies in the zero null hypothesis, the sensitivity of the reduced form is exactly the sensitivity of the IV—no other analyses are needed; and, (ii) if one is interested in biases of a certain amount, or larger, then the sensitivity of the first stage to the zero null hypothesis needs also to be assessed.

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#### 4.3. Sensitivity analysis for a specific null hypothesis

Within the Anderson-Rubin approach, a sensitivity analysis for the null hypothesis  $H_0 : \tau = \tau_0$ , for any arbitrary value  $\tau_0$  can be performed as follows.

*Algorithm 1.* Sensitivity analysis for a specific null hypothesis.

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- (1) Set  $H_0 : \tau = \tau_0$ ,  $\alpha$ , and  $\mathbf{R}^2 = \{R_{Z \sim W|\mathbf{X}}^2, R_{Y_{\tau_0} \sim W|Z, \mathbf{X}}^2\}$ ;
- (2) Construct  $Y_{\tau_0} = Y - \tau_0 D$ ;
- (3) Fit the Anderson-Rubin regression  $Y_{\tau_0} = \hat{\phi}_{\text{res}, \tau_0} Z + \mathbf{X} \hat{\beta}_{\text{res}, \tau_0} + \hat{\varepsilon}_{\tau_0, \text{res}}$ ;
- (4) Compare the t-value for testing  $H_0 : \phi_{\text{res}, \tau_0} = 0$  against the critical value  $t_{\alpha, \text{df}-1, \mathbf{R}^2}^{\dagger \max}$ ;
- (5) Compute  $\text{XRV}_{q^*=1, \alpha}(\phi_{\tau_0})$  and  $\text{RV}_{q^*=1, \alpha}(\phi_{\tau_0})$ ;
- (6) Report the results of (4) and (5).

The procedure above tells us how omitted variables no worse than  $\mathbf{R}^2 = \{R_{Z \sim W|\mathbf{X}}^2, R_{Y_{\tau_0} \sim W|Z, \mathbf{X}}^2\}$  would alter inferences regarding the null  $H_0 : \tau = \tau_0$ , as well as the minimal strength of  $\mathbf{R}^2$  required to not reject the null  $H_0 : \tau = \tau_0$ , as given by the RV or XRV. Note the bounds on  $\mathbf{R}^2$  can be chosen to reflect the assumption that the omitted variables are no stronger than certain observed covariates, as per Section 3.6.

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#### 4.4. Compatible inferences for IV given bounds on partial $R^2$

More broadly, analysts can recover the set of inferences compatible with plausibility judgments on the maximum strength of  $W$ . For a critical threshold  $t_{\alpha, \text{df}-1}^*$ , the confidence interval for  $\tau$  in the Anderson-Rubin framework is given by  $\text{CI}_{1-\alpha}(\tau) = \{\tau_0; t_{\phi_{\tau_0}}^2 \leq t_{\alpha, \text{df}-1}^{*2}\}$ . Thus, consider bounds on sensitivity parameters  $R_{Y_{\tau_0} \sim W|Z, \mathbf{X}}^2 \leq R_{Y_0 \sim W|Z, \mathbf{X}}^{2 \max}$  (which should be judged to hold *regardless* of the value of  $\tau_0$ ) and  $R_{Z \sim W|\mathbf{X}}^2 \leq R_{Z \sim W|\mathbf{X}}^{2 \max}$ . Let  $t_{\alpha, \text{df}-1, \mathbf{R}^2}^{\dagger \max}$  denote the maximum bias-adjusted critical value under the posited bounds on the strength of  $W$ . The set of compatible inferences for the IV estimate  $\text{CI}_{1-\alpha, \mathbf{R}^2}^{\max}(\tau)$  is then defined as

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$$\text{CI}_{1-\alpha, \mathbf{R}^2}^{\max}(\tau) := \left\{ \tau_0; t_{\hat{\phi}_{\text{res}, \tau_0}}^2 \leq \left( t_{\alpha, \text{df}-1, \mathbf{R}^2}^{\dagger \max} \right)^2 \right\}. \quad (21)$$

This interval can be found analytically using the same inequality as in Equation (20), but now with the parameters of the restricted regression actually run, and  $t_{\alpha, \text{df}-1}^*$  replaced by  $t_{\alpha, \text{df}-1, \mathbf{R}^2}^{\dagger \max}$ . Note that users can easily obtain  $\text{CI}_{1-\alpha, \mathbf{R}^2}^{\max}(\tau)$  with any software that computes Anderson-Rubin

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or Fieller's confidence intervals by simply providing the modified critical threshold  $t_{\alpha, \text{df} - 1, \mathbf{R}^2}^{\dagger \max}$ . Armed with the notion of a set of compatible inferences for IV,  $\text{CI}_{1-\alpha, \mathbf{R}^2}^{\max}(\tau)$ , we are now able to formally define and derive (extreme) robustness values for instrumental variable estimates.

#### 4.5. Extreme robustness values for IV

The extreme robustness value  $\text{XRV}_{q^*, \alpha}(\tau)$  for the instrumental variable estimate is defined as the minimum strength of association of omitted variables with the instrument so that we cannot reject a reduction of  $(100 \times q^*)\%$  of the original estimate; that is,

$$505 \quad \text{XRV}_{q^*, \alpha}(\tau) := \inf \{ \text{XRV}; (1 - q^*)\hat{\tau}_{\text{res}} \in \text{CI}_{1-\alpha, 1, \text{XRV}}^{\max}(\tau) \}. \quad (22)$$

The  $\text{XRV}_{q^*, \alpha}(\tau)$  computes the minimal strength of  $W$  required to not reject a particular null hypothesis of interest. However, we might be interested, instead, in asking about the minimal strength of omitted variables to not reject a specific value *or worse*. When confidence intervals are connected, such as the case of standard OLS, the two notions coincide. But in the Anderson-Rubin case, confidence intervals can sometimes consist of disjoint intervals. Therefore, let the upper and lower limits of  $\text{CI}_{1-\alpha, \mathbf{R}^2}^{\max}(\tau)$  be  $\text{LL}_{1-\alpha, \mathbf{R}^2}^{\max}(\tau)$  and  $\text{UL}_{1-\alpha, \mathbf{R}^2}^{\max}(\tau)$  respectively. The extreme robustness value  $\text{XRV}_{\geq q^*, \alpha}(\tau)$  for the IV estimate is defined as the minimum strength of association that confounders or side-effects need to have with the instrument so that we cannot reject a change of  $(100 \times q^*)\%$  *or worse* of the original estimate,

$$515 \quad \text{XRV}_{\geq q^*, \alpha}(\tau) := \inf \{ \text{XRV}; (1 - q^*)\hat{\tau}_{\text{res}} \in [\text{LL}_{1-\alpha, 1, \text{XRV}}^{\max}(\tau), \text{UL}_{1-\alpha, 1, \text{XRV}}^{\max}(\tau)] \}. \quad (23)$$

Both quantities can be obtained via the Anderson-Rubin and first-stage regressions as follows.

**THEOREM 7 (EXTREME ROBUSTNESS VALUE—IV).** *Under Assumption 1, for given  $q^*$  and  $\alpha$ , the extreme robustness values for IV are given by*

$$520 \quad \text{XRV}_{q^*, \alpha}(\tau) = \text{XRV}_{1, \alpha}(\phi_{\tau^*}), \quad \text{and}, \quad (24)$$

$$\text{XRV}_{\geq q^*, \alpha}(\tau) = \min \{ \text{XRV}_{1, \alpha}(\phi_{\tau^*}), \text{XRV}_{1, \alpha}(\theta) \}, \quad (25)$$

where  $\tau^* = (1 - q^*)\hat{\tau}_{\text{res}}$ .

**Remark 3.** Theorem 7 corroborates the discussion of Section 4.2. The robustness of IV estimates against biases as large or larger than a certain amount is bounded by the robustness of the first stage assessed at the zero null. Moreover, for the special case of the null hypothesis of zero effect,  $H_0 : \tau = 0$ , we obtain  $\text{XRV}_{\geq 1, \alpha}(\tau) = \min \{ \text{XRV}_{1, \alpha}(\lambda), \text{XRV}_{1, \alpha}(\theta) \}$ , that is, the XRV of the IV estimate, against biases that bring it to zero or worse, is equal to the minimum of the XRV of the first stage and the reduced form, both evaluated at the zero null ( $q^* = 1$ ).

**Remark 4.** Note that the XRV of the first stage  $\text{XRV}_{1, \alpha}(\theta)$  can be arbitrarily different from traditional metrics of instrument strength. For a simple numerical example, consider  $\text{df} = 100,000$  and suppose the first stage F statistic is  $F = t^2 \approx 100$ , which could be considered a strong instrument for statistical inference purposes. In this case, we still have  $\text{XRV}_{1, \alpha}(\theta) \approx 0.001$ .

#### 4.6. Robustness values for IV

The definitions of the robustness value for instrumental variables follow the same logic discussed above, but now considering both bounds on  $\text{CI}_{1-\alpha, \mathbf{R}^2}^{\max}(\tau)$  varying simultaneously. That is, the RV for not rejecting a bias of exactly  $q^*$  is defined as

$$535 \quad \text{RV}_{q^*, \alpha}(\tau) := \inf \{ \text{RV}; (1 - q^*)\hat{\tau}_{\text{res}} \in \text{CI}_{1-\alpha, \text{RV}, \text{RV}}^{\max}(\tau) \}, \quad (26)$$

and the RV for not rejecting the null of a reduction of  $(100 \times q^*)\%$  or worse is defined as,

$$RV_{\geq q^*, \alpha}(\tau) := \inf \{RV; (1 - q^*)\hat{\tau}_{\text{res}} \in [\text{LL}_{1-\alpha, \text{RV}, \text{RV}}^{\max}(\tau), \text{UL}_{1-\alpha, \text{RV}, \text{RV}}^{\max}(\tau)]\}. \quad (27)$$

We then have analogous results for robustness values, and similar discussion applies.

**THEOREM 8 (ROBUSTNESS VALUE—IV).** *Under Assumption 1, for given  $q^*$  and  $\alpha$ , the robustness values for IV are given by*

$$RV_{q^*, \alpha}(\tau) = RV_{1, \alpha}(\phi_{\tau^*}), \quad \text{and,} \quad (28)$$

$$RV_{\geq q^*, \alpha}(\tau) = \min\{RV_{1, \alpha}(\phi_{\tau^*}), RV_{1, \alpha}(\theta)\}, \quad (29)$$

where  $\tau^* = (1 - q^*)\hat{\tau}_{\text{res}}$ .

#### 4.7. Conservative bounds on the strength of omitted variables

When testing a specific null hypothesis  $H_0: \tau = \tau_0$  in the Anderson-Rubin regression, we have  $k_Z$  as in Section 3.6, and instead of  $k_Y$  we now have  $k_{Y_{\tau_0}} := R_{Y_{\tau_0} \sim W|Z, \mathbf{X}_{-j}}^2 / R_{Y_{\tau_0} \sim X_j|Z, \mathbf{X}_{-j}}^2$ . The plausibility judgment one is making here is thus under the null  $H_0: \tau = \tau_0$ . Since the judgment is made under a specific null, the bounds will be different when testing different hypotheses. Therefore, it is useful to compute bounds under a slightly more *conservative* assumption. We can posit that the omitted variables are no stronger than (a multiple of) the *maximum* explanatory power of an observed covariate, regardless of the value of  $\tau_0$ , i.e.,  $k_{Y_{\tau_0}}^{\max} := \frac{\max_{\tau_0} R_{Y_{\tau_0} \sim W|Z, \mathbf{X}_{-j}}^2}{\max_{\tau_0} R_{Y_{\tau_0} \sim X_j|Z, \mathbf{X}_{-j}}^2}$ . This has the useful property of providing a unique bound for any null hypothesis, and can be used to place bounds on the sensitivity contours of the lower and upper limit of the Anderson-Rubin confidence intervals, as we show next.

## 5. USING THE OMITTED VARIABLE BIAS FRAMEWORK FOR THE SENSITIVITY OF IV

We return to our running example of Section 2 and show how the tools developed here can be deployed to assess the robustness of the original findings to violations of the IV assumptions. Throughout, we focus the discussion on violations of the ignorability of the instrument due to confounders, as this is the main threat of the study under investigation. Readers should keep in mind, however, that mathematically all analyses performed here can be equally interpreted as assessing violations of the exclusion restriction (or both).

Table 2 shows our proposed minimal sensitivity reporting for IV estimates. It starts by replicating the usual statistics, such as the point estimate (0.132), as well as the lower and upper limits of the Anderson-Rubin confidence interval [0.025, 0.285], and the t-value against the null hypothesis of zero effect (2.33). Next, we propose researchers report the extreme robustness value ( $XRV_{\geq q^*, \alpha} = 0.05\%$ ) and the robustness value ( $RV_{\geq q^*, \alpha} = 0.67\%$ ) required to bring the lower limit of the confidence interval to or beyond zero (or another meaningful threshold), at the 5% significance level. We also show these same statistics for the first stage and reduced form. As derived in Theorems 7 and 8, the (extreme) robustness value of the IV estimate required to bring the lower limit of the confidence interval to *zero or below* is the *minimum* of the (extreme) robustness value of the reduced form and the (extreme) robustness value of the first stage evaluated at the zero null. In our running example, the reduced form is more fragile, thus the sensitivity of the IV hinges critically on the sensitivity of the reduced form (see Supplementary Material for separate detailed analyses of the robustness of the reduced form and first stage).

The RV reveals that confounders explaining 0.67% of the residual variation both of *proximity* and of (log) *Earnings* are already sufficient to make the instrumental variable estimate

Model	Param.	Estimate	LL <sub>1-<math>\alpha</math></sub>	UL <sub>1-<math>\alpha</math></sub>	t-value	XRV <sub><math>\geq q^*, \alpha</math></sub>	RV <sub><math>\geq q^*, \alpha</math></sub>
Inst. Variable	$\tau$	0.132	0.025	0.285	2.33	0.05%	0.67%
First Stage	$\theta$	0.320	0.148	0.492	3.64	0.31%	3.02%
Reduced Form	$\lambda$	0.042	0.007	0.078	2.33	0.05%	0.67%

Bound (1x SMSA):  $R^2_{Y \sim W|Z, \mathbf{X}} = 2\%$ ,  $R^2_{W \sim Z| \mathbf{X}} = 0.6\%$ ,  $t_{\alpha, df-1, R^2}^{\dagger \max} = 2.55$ .

**Note:** df = 2994,  $q^* = 1$ ,  $\alpha = 0.05$ .

Table 2: Minimal sensitivity reporting.

statistically insignificant. Further, the XRV shows that, if we are not willing to impose constraints on the partial  $R^2$  of confounders with the outcome, they need only explain 0.05% of the residual variation of the instrument to be problematic. To aid users in making plausibility judgments, the note of the table provides bounds on the maximum strength of unobserved confounding if it were as strong as *SMSA* (an indicator variable for whether the individual lived in a metropolitan region) along with the bias-adjusted critical value for a confounder with such strength,  $t_{\alpha, df-1, R^2}^{\dagger \max} = 2.55$ . Since the observed t-value (2.33) is less than the adjusted critical threshold of 2.55, this immediately reveals that confounding as strong as *SMSA* (e.g. residual geographic confounding) is already sufficiently strong to be problematic.

It will often be valuable to assess the sensitivity of the instrumental variable estimate against hypothesis *other than zero*. To that end, investigators may wish to examine sensitivity contour plots showing the whole range of adjusted lower and upper limits of the Anderson-Rubin confidence interval against various strengths of the omitted variables  $W$ . These contours are shown in Figure 1. Here the horizontal axis indicates the bounds on  $R^2_{Z \sim W| \mathbf{X}}$  and the vertical axis indicates the bounds on  $R^2_{Y_{\tau_0} \sim W|Z, \mathbf{X}}$ . Under a constant treatment effects model,  $R^2_{Y_{\tau_0} \sim W|Z, \mathbf{X}}$  has a simple interpretation—it stands for how much residual variation confounders explain of the untreated potential outcome. For simplicity, of exposition, we adopt this interpretation here. The contour lines show the worst lower (or upper) limit of the  $CI_{1-\alpha, R^2}^{\max}(\tau)$ , with omitted variables bounded by such strength. Red dashed lines shows a critical contour line of interest (such as zero) as well as the boundary beyond confidence intervals become unbounded. The red diamonds places bounds on strength of  $W$  as strong as *Black* (an indicator for race) and, again, *SMSA*, as per Section 4.7. As the plot reveals, both confounding as strong as *SMSA*, or as strong as *black*, could lead to an interval for the target parameter of  $CI_{1-\alpha, R^2}^{\max}(\tau) = [-0.02, 0.40]$ , which includes not only implausibly high values (40%), but also negative values (-2%), and is thus too wide for any meaningful conclusions. Since it is not very difficult to imagine residual confounders as strong or stronger than those (e.g., parental income, finer grained geographic location, etc), these results call into question the strength of evidence provided by this study.

## 6. DISCUSSION

Sensitivity analysis tools, such as those introduced in this paper, provide logical deductions aimed at: (i) revealing the consequences of varying degrees of violation of identifying assumptions (e.g., via bias-adjusted critical values), and (ii) determining the minimal degree of violation of those assumptions necessary to overturn certain conclusions (e.g., via robustness values).

This shifts the scientific debate from arguing whether, say, latent confounders of an instrumental variable have exactly zero strength—an indefensible claim in most settings—to a more realistic discussion about whether we can confidently rule out strengths that are shown to be problematic.

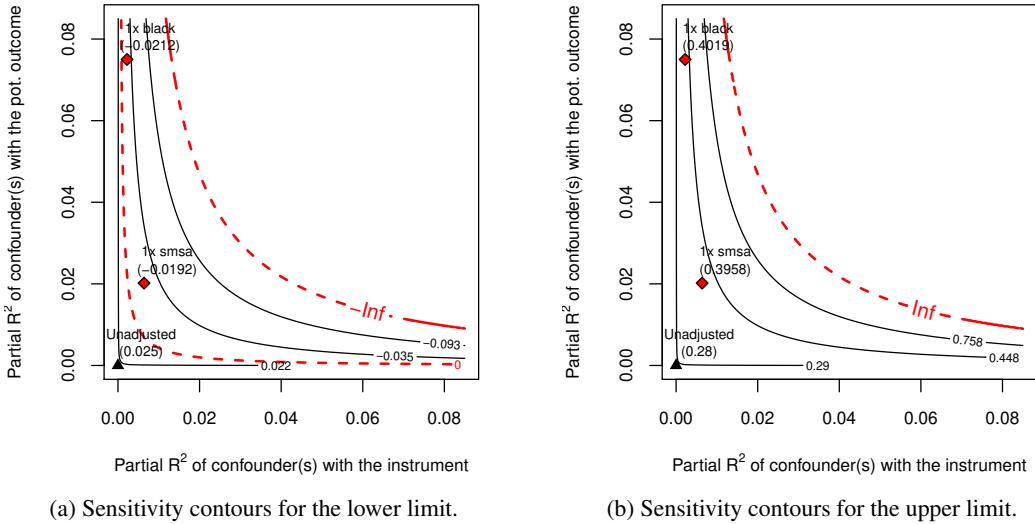


Figure 1: Sensitivity contours of the Anderson-Rubin confidence interval.

The results of sensitivity analyses are not always self-evident and can often be surprising. They may reveal that certain studies are highly sensitive to plausible perturbations of identifying assumptions, while others remain robust despite such perturbations. Even when results fall in between these two extremes, sensitivity analyses still represent an improvement over simply assuming away the problem. They clarify what one needs to know, by transparently revealing how vulnerable the results are to violations of the exclusion and independence restrictions. This provides policymakers a better understanding of what remains unknown about an estimated effect, and offers researchers a roadmap for improving their analyses in future inquiries.

It is important to emphasize that plausibility judgments on the maximum strength of latent variables inevitably depend on expert knowledge and can thus vary substantially across scientific disciplines, fields of study, and the quality of the research design. For that reason, we do not propose any universal thresholds for the sensitivity statistics we propose here. For instance, in an observational study without randomization nor a rich set of measured confounders, it would be hard to rule out latent confounders that explain, say, 1% of the residual variation of the instrument. This indeed seems to be the case in our running example (Card, 1993), where residual geographic confounders could plausibly attain such strength. In other scientific contexts, however, a value of 1% may in fact be large. For example, in a Mendelian randomization study where the main concern is pleiotropy, it may be defensible to argue against genetic variants explaining 1% of the variation of a latent complex pleiotropic trait (Cinelli et al., 2022).

Finally, in this paper we focused on the traditional instrumental variable estimand, consisting of the ratio of two regression coefficients. We chose to do so because this reflects current practices for IV analysis and encompasses the vast majority of applied work. These tools can thus be immediately put to use to improve the robustness of current research, without requiring any additional assumptions, beyond those that already justified the traditional IV analysis in the first place. Recent papers, however, have usefully questioned the causal interpretation of this estimand, as it relies on strong parametric assumptions (Słoczyński, 2020; Blandhol et al., 2022). Extending the sensitivity tools we present here to the nonparametric case is possible by lever-

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640 aging recent results in [Chernozhukov et al. \(2022\)](#), and offers an interesting direction for future work.

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#### SUPPLEMENTARY MATERIAL

The Supplementary Material provides proofs for all results, compares our proposal with alternative approaches, and includes additional analyses of the empirical example.

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