Losing our way?

A critical examination of path analysis in accounting research

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Abstract: Many scholars view path analysis as a tool to disentangle direct and indirect causal effects. Path analysis has become increasingly popular in the accounting literature with the number of papers using this methodology surging over the past decade. We provide two criticisms of the way path analysis is used in practice. First, although many studies say they use path analysis to strengthen causal inferences, they are instead assuming away potential endogeneity problems by imposing the restriction of uncorrelated errors. Second, many studies fail to explicitly state their assumptions, including the assumption of uncorrelated errors. This makes it difficult for the reader to determine whether potential endogeneity problems are being assumed away or, instead, necessary steps are being taken to address those problems. We conclude with several recommendations to improve the literature's implementation of the path analysis method.

"Path analysis focuses on the problem of interpretation and does not purport to be a method for discovering causes." (Duncan 1966, page 1).

*"Path analysis is a methodological tool that helps researchers using quantitative (correlational) data to disentangle the various (causal) processes underlying a particular outcome." (*Lleras 2005, p. 25).

1. Introduction

Path analysis was invented more than one hundred years ago by Sewall Wright (Wright 1921). Since its invention, path analysis has been adopted by various disciplines, including biology, sociology, psychology, political science, education, and business. Many researchers say they use path analysis to identify causal relations and to disentangle direct and indirect causal effects (e.g., Lleras 2005). However, as illustrated by the above quotations, disagreement is present regarding the potential benefits of path analysis. Some researchers assert that path analysis is synonymous with causation, an idea reinforced by some published studies referring to the method as "causal modeling" (Dennis and Legerski 2006). Other researchers disagree, stating that path analysis is not a method for discovering causal effects (e.g., Duncan 1966).

We provide a critical examination of the way in which path analysis has been used in 193 studies published from 1995 to 2022 in five leading accounting journals (*Journal of Accounting and Economics, Journal of Accounting Research, The Accounting Review, Contemporary Accounting Research,* and *Review of Accounting Studies*). Our analysis is timely and important because path analysis usage in accounting studies has surged over the past 25 years, with a marked increase during the past decade. Of the studies that use path analysis, we find that most claim to use the method to strengthen causal inferences. We examine whether the causal claims are justified given the assumptions that are explicitly or implicitly imposed. We also discuss the limitations and pitfalls of using path analysis and provide an evaluation of how well the methodology has been implemented in the accounting literature.

Instrumental variable (IV) estimation is an alternative tool that scholars can use to estimate causal effects. In Section 2, we explain the similarities and differences between IV and path analysis. IV and path analysis are similar in that both methods employ a mediator variable, which acts as a channel through which an exogenous (instrumental) variable indirectly affects the main dependent variable. The major difference between IV and path analysis is that IV estimation requires one or more exclusion restrictions on the instrumental variables for the purpose of identification, whereas exclusion restrictions are not required in path analysis. In IV estimation, causal effects are identified by assuming that the excluded instrument affects the dependent variable only indirectly through the mediator (i.e., it is assumed that there is no direct effect). Path analysis is different because path analysis does not require the assumption of only having an indirect effect. Instead, path analysis allows the total effect of a variable to be decomposed into both direct and indirect effects. The primary limitation of path analysis, however, is that when there are insufficient exclusion restrictions to permit IV estimation, the researcher must assume uncorrelated errors for the system of equations to be identified. Crucially, we explain that the assumption of uncorrelated errors is equivalent to assuming away the endogeneity problem.

In Section 3, we survey the way in which path analysis has been used in the accounting literature. We find that most path analysis studies assume uncorrelated errors. That is, most studies assume away the endogeneity problem rather than attempt to solve it. Nevertheless, most studies draw causal inferences from the results of their path analysis. A majority of studies explicitly state that they use path analysis to strengthen their causal inferences even though the same studies implicitly assume away the endogeneity problem by assuming uncorrelated errors.

Thus, it is difficult to have confidence in the causal claims of many path analysis studies. We also find that most studies fail to disclose whether they are assuming the errors to be correlated or uncorrelated. The lack of full disclosure means that it can be difficult (although not always impossible) for a reader to determine whether a study is assuming away the endogeneity problem or taking steps to address it.

We conclude by providing four recommendations for future research. First, authors need to explicitly disclose whether they are assuming correlated or uncorrelated errors. Second, when assuming uncorrelated errors, authors should explain why they consider the assumption to be reasonable. That is, authors should explain why the unobservables affecting the mediator variable are uncorrelated with the unobservables affecting the main dependent variable. Third, when assuming uncorrelated errors, authors should not claim (or suggest) that path analysis provides stronger causal inferences than Ordinary Least Squares (OLS). In fact, we highlight that OLS and path analysis generate identical coefficient estimates when the errors are assumed to be uncorrelated. Finally, when the errors are allowed to be correlated, authors should explicitly disclose and justify the assumed exclusion restrictions on the exogenous instruments (as correlated errors are only possible in path analysis when imposing exclusion restrictions on the covariates). The recommendation of justifying exclusion restrictions was made over a decade ago by Larcker and Rusticus (2010), but some studies still do not disclose this crucial information.

Our study contributes to a recent stream of literature that considers a variety of methodological issues in accounting research. Prior studies examine issues affecting IV estimators (Larcker and Rusticus 2010; Lennox et al. 2012; Gow et al. 2016; Armstrong et al. 2021), difference-in-difference estimators (Barrios 2021; Baker et al. 2022; Armstrong et al. 2022), fixed effects estimators (deHaan 2021; Jennings et al. 2022), propensity score matching (Shipman et al.

2017), robust regression (Leone et al. 2019), and the (over-) use of control variables (Whited et al. 2022). Our study is the first to provide a critical evaluation of the path analysis methodology. This evaluation is important because the method of path analysis is rarely covered in PhD-level econometrics courses or econometrics textbooks. Path analysis is discussed in the statistical textbooks of some disciplines outside of economics (e.g., psychology and sociology), but the researchers in those disciplines provide conflicting messages about the benefits of using path analysis. Some claim that path analysis allows researchers to disentangle causal effects from statistical correlations (e.g., Lleras 2005) whereas others say the opposite (e.g., Duncan 1966). Our study helps to resolve this apparent contradiction. Moreover, we provide a set of practical recommendations to help future researchers who wish to continue using path analysis.

2. Instrumental variable (IV) estimation and path analysis

IV estimation and path analysis are two alternative methods that researchers use to estimate causal effects. In this section, we first describe the IV approach with the aim of highlighting the conceptual linkages between IV and path analysis. Further, we explain how the IV and path analysis methods differ from each other.[1]

2.1. Instrumental variables (IV) estimation

[1] IV and path analysis are sometimes used to address the problem of measurement error bias (e.g., Bollen 1989). The accounting studies in our survey use path analysis to address causality issues rather than measurement error bias. Therefore, our discussion focuses on causality rather than measurement errors.

Without loss of generality, consider a system of equations with two dependent variables (Y_1 and Y_2) and two exogenous covariates (X and Z).[2]

$$Y_1 = \alpha_1 + \alpha_2 Y_2 + \alpha_3 X + u_1 \tag{1}$$

$$Y_2 = \beta_1 + \beta_2 X + \beta_3 Z + u_2 \tag{2}$$

A covariate is said to be exogenous if it is uncorrelated with the unobservables that affect the endogenous variables (Y_1 and Y_2). Thus, the assumption that X and Z are exogenous is equivalent to assuming that cov ($X\ u_1$) = 0, cov ($X\ u_2$) = 0, cov ($Z\ u_1$) = 0, and cov ($Z\ u_2$) = 0.

OLS estimation of (2) generates unbiased coefficients because there are no endogenous regressors in (2). In contrast, an endogenous regressor (Y_2) is present in (1), raising potential concerns of endogeneity bias. The textbook IV solution to endogeneity is to find one or more exogenous variables that have a powerful effect on the endogenous regressor (Y_2) but no direct effect on Y_1. The Z variable in (2) performs this function because Z is exogenous and is assumed to have no direct effect on Y_1. The exclusion of Z from (1) is commonly known as an exclusion restriction.[3]

Substituting (2) into (1) gives the reduced form model for Y_1.

$$Y_1 = \alpha_1 + \alpha_2 (\beta_1 + \beta_2 Z + \beta_3 X + u_2) + \alpha_3 X + u_1 \tag{3}$$

[2] Eqs. (1) and (2) show a recursive system in which Y_2 affects Y_1 but Y_1 does not affect Y_2. We present a recursive system because all the accounting studies in our survey assume recursive systems. In addition, some researchers regard a recursive system as the only type of model that can properly be called a path analysis (e.g., Lleras 2005). A non-recursive system is one in which Y_2 affects Y_1 *and* Y_1 affects Y_2. An important difference between recursive and non-recursive systems is that recursive systems must be estimated using IV (e.g., three-stage-least-squares) even if the error terms are assumed to be uncorrelated. In contrast, non-recursive systems can be estimated using OLS rather than IV if the researcher is willing to assume that the error terms are uncorrelated.

[3] The exclusion restriction is sometimes called the "only-through condition" (e.g., Atanasov and Black 2021) because it is assumed that Z affects Y_1 only indirectly through Y_2.

In (3), the Y_2 term is shown in parentheses ($\beta_1 + \beta_2 Z + \beta_3 X + u_2$). Note that Y_2 has an exogenous component ($\beta_1 + \beta_2 Z + \beta_3 X$) that is uncorrelated with u_1 and an endogenous component (u_2) that is potentially correlated with u_1. In (1), the presence (or absence) of endogeneity bias therefore hinges on whether u_2 is uncorrelated with u_1. If u_2 and u_1 are uncorrelated (i.e., cov (u_2 u_1) = 0), then Y_2 is an exogenous regressor in (1) even though Y_2 is an endogenous dependent variable in (2). In this situation, OLS estimates of (1) are unbiased because all of the independent variables are exogenous. On the other hand, if u_2 and u_1 are correlated (i.e., cov (u_2 u_1) ≠ 0), then Y_2 is correlated with u_1 and OLS estimates of (1) are biased because Y_2 is an endogenous regressor. Thus, we can see from the above discussion that correlated errors are the source of the endogeneity bias in (1).

The intuition for two-stage-least squares (2SLS) is to remove u_2 from (1) and (3) by replacing the actual value of Y_2 with its predicted value ($\hat{Y}_2$). $\hat{Y}_2$ is obtained in a first-stage regression of (2):

$$\hat{Y}_2 = \alpha_1 + \alpha_2 (\hat{\beta}_1 + \hat{\beta}_2 Z + \hat{\beta}_3 X).$$

Next, the endogeneity bias is removed by plugging $\hat{Y}_2$ into the Y_1 model to remove u_2.

$$Y_1 = \alpha_1 + \alpha_2 (\hat{\beta}_1 + \hat{\beta}_2 Z + \hat{\beta}_3 X) + \alpha_3 X + u_1 \tag{4}$$

With u_2 removed, the OLS coefficients in (4) are estimated without bias because $\hat{Y}_2$ is uncorrelated with u_1.[4]

[4] 2SLS generates unbiased coefficient estimates when the researcher employs valid exclusion restrictions. However, the standard errors from the second-stage regression must be corrected to account for the uncertainty in the first-stage regression. This correction is done automatically in most software packages (e.g., STATA).

It is important to understand the key role that the exclusion restriction plays in identifying the causal effect of Y_2 on Y_1. To see this, consider what would happen if there were no exclusion restriction; i.e., Z is included in the Y_1 model as well as the Y_2 model. In this case, the Y_1 model becomes:

$$Y_1 = \alpha_1 + \alpha_2 Y_2 + \alpha_3 X + \alpha_4 Z + u_1 \qquad (5).$$

Note that (5) allows Z to affect Y_1 directly (i.e., $\alpha_4 \neq 0$), whereas (1) assumes that Z has no direct effect on Y_1 (i.e., $\alpha_4 = 0$), i.e., (1) imposes an exclusion restriction on Z. Now, suppose a researcher replaces Y_2 with $\hat{Y}_2$ in (5). The reduced form model for Y_1 then becomes:

$$Y_1 = \alpha_1 + \alpha_2 (\hat{\beta}_1 + \hat{\beta}_2 Z + \hat{\beta}_3 X) + \alpha_3 X + \alpha_4 Z + u_1 \qquad (6).$$

Rearranging terms:

$$Y_1 = \alpha_1 + \alpha_2 \hat{\beta}_1 + (\alpha_4 + \alpha_2 \hat{\beta}_2) Z + (\alpha_3 + \alpha_2 \hat{\beta}_3) X + u_1 \qquad (7).$$

Eq. (7) shows that the total effect of Z on Y_1 is captured by $\alpha_4 + \alpha_2 \hat{\beta}_2$. These two terms comprise a direct effect and an indirect effect. The direct effect is captured by α_4. The indirect effect of Z on Y_1 occurs through Y_2 and is captured by $\alpha_2 \hat{\beta}_2$. Note that (7) is under-identified because, although the researcher has an estimate of $\hat{\beta}_2$ from (2), this estimate is insufficient to determine whether the total effect ($\alpha_4 + \alpha_2 \hat{\beta}_2$) is attributable to a direct effect (α_4) or an indirect effect ($\alpha_2 \hat{\beta}_2$), or both. Therefore, the causal effect of Y_2 on Y_1 (as captured by α_2) cannot be estimated without imposing an exclusion restriction on Z (i.e., $\alpha_4 = 0$).

When the exclusion restriction is imposed (i.e., $\alpha_4 = 0$), (5) becomes (1). In this case, the α_2 coefficient can be inferred from the indirect effect ($\alpha_2 \hat{\beta}_2$) together with the Z coefficient in the Y_2 model ($\hat{\beta}_2$); i.e., $\alpha_2 = (\alpha_2 \hat{\beta}_2 \,/\, \hat{\beta}_2)$. When the exclusion restriction is not imposed ($\alpha_4 \neq 0$), the α_2

coefficient cannot be estimated because the total effect of Z on Y_1 is assumed to come from both a direct effect (α_4) and an indirect effect ($\alpha_2 \hat{\beta}_2$). In the absence of any other restriction, it is not possible to disentangle the direct and indirect effects. In this situation, we say that (7) is under-identified. The under-identification problem can be avoided by assuming either that Z has no direct effect on Y_1 (i.e., $\alpha_4 = 0$) or by assuming away the endogeneity problem through imposing the assumption of uncorrelated errors (i.e., cov (u_2 u_1) = 0).

2.2. Path diagrams

The IV method can be illustrated in a path diagram. Figure 1 shows the posited causal relationships in (1) and (2).

$$Y_1 = \alpha_1 + \alpha_2 Y_2 + \alpha_3 X + u_1 \tag{1}$$

$$Y_2 = \beta_1 + \beta_2 X + \beta_3 Z + u_2 \tag{2}$$

[Insert Figure 1 here]

Figure 1 uses straight-line arrows to show the causal relations implied by (1) and (2) and curved double-headed arrows to show non-causal correlations. There are six causal relations and, thus, six straight-line arrows, which connect X to Y_1, Y_2 to Y_1, u_1 to Y_1, X to Y_2, Z to Y_2, and u_2 to Y_2. Recall that the effect of Y_2 on Y_1 is identified by either imposing an exclusion restriction on Z (i.e., $\alpha_4 = 0$) or by assuming uncorrelated errors (i.e., cov (u_2 u_1) = 0). Figure 1 shows an instance where a researcher relies on an exclusion restriction instead of assuming uncorrelated errors. Specifically, the exclusion restriction on Z (i.e., $\alpha_4 = 0$) is indicated by the absence of an arrow connecting Z to Y_1, implying that Z affects Y_1 only indirectly through Y_2. Figure 1 depicts a curved double-headed arrow connecting u_1 and u_2, implying that the errors are allowed to be correlated.[5] With the exclusion restriction in place ($\alpha_4 = 0$), the researcher can control for the endogeneity in Y_2 that arises from these correlated errors. Thus, Figure 1 makes explicit that the unobservables affecting Y_1 are allowed to correlate with the unobservables affecting Y_2. In the verbiage of path analysis Y_2 is called a "mediator" variable, whereas in the verbiage of IV estimation Y_2 is called an endogenous regressor. Despite the differences in semantics, it is clear from the above discussion that IV and path analysis are conceptually related to each other.

If a researcher is unable to assume a valid exclusion restriction on Z ($\alpha_4 \neq 0$), the IV approach cannot be used because (5) would be under-identified. In this situation, the researcher can obtain identification by instead assuming that the errors are uncorrelated (i.e., cov (u_1 u_2) = 0). The assumption of uncorrelated errors implies that Y_2 is assumed to be exogenous (i.e., cov (Y_2 u_1) = 0), which is equivalent to assuming away the endogeneity problem. To put this an alternative way, Y_2 is assumed to be exogenous in (1) even though it is an endogenous dependent variable in (2) because the unobservables in the two equations are assumed to be unrelated. In this situation, 2SLS collapses to simple OLS.

Figure 2 shows the path analysis diagram under this alternative scenario of uncorrelated errors. Note that, in contrast to Figure 1, Figure 2 has a straight-line arrow connecting Z to Y_1, indicating that Z affects Y_1 directly (i.e., $\alpha_4 \neq 0$) as well as indirectly. Note that there is no curved arrow connecting u_1 and u_2 in Figure 2, because the error terms are assumed to be uncorrelated (cov (u_1 u_2) = 0). That is, Y_2 is assumed to be an exogenous regressor in (1) despite being an endogenous variable in (2).

[5] Figure 1 also allows the exogenous variables to correlate as denoted by the curved double-headed arrow that connects X and Z.

[Insert Figure 2 here]

In summary, there are alternative options for estimating the Y_1 model in (1). One option (Fig. 1) is to impose an exclusion restriction on the Z covariate ($\alpha_4 = 0$), which allows the researcher to use IV estimation to control for the endogeneity bias that arises from correlated errors (cov (u_1 u_2) $\neq 0$). Another option (Fig. 2) is to assume uncorrelated errors (cov (u_1 u_2) = 0), which is equivalent to assuming away the endogeneity problem and using OLS. Under this second option, the researcher can allow Z to have a direct effect on Y_1 (i.e., $\alpha_4 \neq 0$) but the researcher must assume that Y_2 is exogenous in (1). A third option is to impose both the exclusion restriction ($\alpha_4 = 0$) and the assumption of uncorrelated errors (cov (u_1 u_2) = 0), which also is equivalent to OLS. With the above discussion in mind, we now discuss the path analysis method.

2.3. The advantage of using path analysis instead of IV

Three conditions are needed for IV estimation to be appropriate: a) the chosen instruments must be exogenous, b) the instruments must be powerful, and c) the researcher must impose valid exclusion restrictions on one or more instruments for the system to be identified. In terms of our earlier equations, the first condition (exogeneity) requires the instrument (Z) to be uncorrelated with the error terms in the system (i.e., cov (Z u_1) = 0 and cov (Z u_2) = 0). The second condition (power) requires the instrument (Z) to have a large impact on the mediator variable (Y_2).[6] The third condition (exclusion restriction) requires the instrument to have no direct impact on the main dependent variable (i.e., Z affects Y_1 only indirectly through Y_2).

[6] Stock et al. (2002) presents some rules of thumb for assessing the power of the chosen instruments. When the number of instruments is 1, 2, 3, 5, 10, the suggested critical F-statistics are 8.96, 11.59, 12.83, 15.09, and 20.88, respectively.

These three conditions are onerous as it is often difficult for a researcher to find an instrument (Z) that is uncorrelated with the unobservables (u_1 and u_2), has a large impact on Y_2, and affects Y_1 only indirectly.[7] The main advantage of path analysis (relative to IV) is that the system of equations can be estimated *without* imposing exclusion restrictions on the covariates. That is, the researcher can allow Z to affect Y_1 directly ($\alpha_4 \neq 0$) as well as indirectly through the mediator variable, Y_2. However, doing so raises an identification issue because, in the absence of exclusion restrictions on the covariates, the system of equations is identified by assuming uncorrelated errors (cov (u_1 u_2) = 0). This assumption is far from innocuous because it is equivalent to assuming that the Y_2 mediator variable is exogenous even though it is endogenous elsewhere in the system.

2.4. The historical origins of path analysis

The path analysis method is generally credited to the geneticist Sewall Wright. Wright presented his new methodology in a 1921 study titled "*Correlation and Causation.*" In the introduction to his article, Wright leaves the reader in little doubt that he considers path analysis to be a causal methodology.

[7] There exist statistical tests for instrument validity when the system of equations is over-identified. The logic for such tests is that different subsets of instruments should generate approximately the same coefficient estimates if all the chosen instruments are valid. However, the tests of instrument validity have two significant limitations. First, a test for instrument validity is not available when the system of equations is just-identified because a just-identified system can only be estimated using all the chosen instruments. Such a system cannot be estimated using subsets of instruments because the system would then be under-identified. Second, the statistical tests for instrument validity are only valid if at least one of the chosen instruments is valid. When all the instruments are invalid, different subsets of instruments can generate approximately the same coefficient estimates, causing the researcher to incorrectly conclude that the chosen instruments are valid when in fact they are all invalid. Given these two limitations, researchers should avoid relying only on statistical tests to assess the validity of the chosen instruments (e.g., see the discussion in Larcker and Rusticus (2010)).

"The present paper is an attempt to present a method of measuring the <u>*direct influence*</u> *along each separate path in such a system and thus of finding the degree to which variation of a given* <u>*effect*</u> *is determined by each* <u>*particular cause.*</u>*"* (Wright, 1921, page 557: emphases added).

To illustrate the methodology, Wright (1921) utilizes an empirical example of guinea pigs. He estimates how the weight of guinea pigs at their age of weaning (33 days old) (*Weight 33*) is affected by four variables: the guinea pig's weight at birth (*Weight birth*), external conditions (*External*), heredity (*Heredity*), and litter size (*Litter size*). The *Weight birth* variable is an endogenous regressor (or mediator) that is determined by the length of gestation (*Gestation*), heredity (*Heredity*), the size of the litter (*Litter*), and the condition of the dam (*Dam Condition*).[8] Wright's path analysis system is shown in Figure 3. His path diagram assumes that: 1) *Weight 33* is affected by *Weight birth*, *External*, *Heredity* and *Litter*; 2) *Weight birth* is affected by *Gestation*, *Dam Condition*, *Heredity* and *Litter*; 3) *Gestation* is affected by *Litter* and *Dam Condition*; and 4) *Dam Condition* is affected by *Heredity of Dam* and *External*.[9]

[Insert Figure 3 here]

It is important to note that Wright's path diagram does not show error terms. The error terms are not mentioned anywhere else in the article, and Wright (1921) does not formally write out the system of estimated equations. Nevertheless, the estimated equations with the error terms can be indirectly inferred from his path diagram, as shown in (8) to (11).

$$\textit{Weight 33} = \alpha_1 + \alpha_2 \textit{Weight birth} + \alpha_3 \textit{External} + \alpha_4 \textit{Heredity} + \alpha_5 \textit{Litter} + u_1 \quad (8)$$

$$\textit{Weight birth} = \beta_1 + \beta_2 \textit{Gestation} + \beta_3 \textit{Dam Condition} + \beta_4 \textit{Heredity} + \beta_5 \textit{Litter} + u_2 \quad (9)$$

$$\textit{Gestation} = \gamma_1 + \gamma_2 \textit{Litter} + \gamma_3 \textit{Dam Condition} + u_3 \quad (10)$$

[8] The mother of a guinea pig is called a dam.

[9] The diagram in Wright (1921) includes two additional relations that are mathematical identities rather than causal: 1) weight at 33 days (*Weight 33*) depends on how quickly the guinea pig grows after it is born, and 2) birth weight (*Weight birth*) depends on how quickly the guinea pig grows inside the dam. Figure 3 omits these two mathematical identities because they have no bearing on the estimated coefficients.

$$\textit{Dam Condition} = \delta_1 + \delta_2\,\textit{Heredity of Dam} + \delta_3\,\textit{External} + u_4 \tag{11}$$

Note that (9) has two exogenous covariates (*Heredity* and *Litter*), which are included as covariates in (8) as well. Thus, (8) lacks any exclusion restrictions on the exogenous covariates. In the absence of exclusion restrictions, (8) is identified by assuming that the errors in (8) and (9) are uncorrelated (i.e., cov (u_1 u_2) = 0). The assumption of uncorrelated errors is far from innocuous for estimating (8) and (9). Effectively, Wright (1921) is assuming that the unobservable factors affecting a guinea pig's weight at birth (u_2) are uncorrelated with the unobservable factors that affect the guinea pig's weight at 33 days (u_1). In our view, this assumption is not very plausible because one would expect similar unobservable factors to affect both weight variables. In effect, Wright (1921) is implicitly assuming away any endogeneity for the *Weight birth* regressor in (8) even though *Weight birth* is an endogenous dependent variable in (9).

To be fair to Sewall Wright, his article was written before IV was introduced as a method to address endogeneity concerns and estimate causal effects.[10] Thus, the full ramifications of assuming uncorrelated errors were not well understood at the time. Towards the end of his life, Sewall acknowledged that the error terms ought to be shown in the path diagrams in order to make clear to the reader whether the errors are assumed to be correlated or uncorrelated. Three years before his death, Sewall wrote:

> *"The necessary formal completeness of the diagram requires the introduction of a symbol for the array of unknown residual factors among those back of each variable that is not represented as one of the ultimate factors, unless it can safely be assumed that there is complete determination by the known factors. Such a residual factor can be assumed by definition to be uncorrelated with any of the other factors immediately back of the same variable but cannot be assumed to be independent of other variables in the system without careful consideration."* (S. Wright, Chapter 3 in Blalock (1985); emphasis added).

[10] Coincidentally, the IV method was introduced by Sewall's father, Phillip Wright, a few years later in 1928 (P. Wright 1928).

Unfortunately, many studies fail to follow Wright's 1985 recommendation as they do not show the error terms in their path diagrams and do not explicitly disclose whether the error terms are assumed to be correlated or uncorrelated. One reason for the lack of disclosure could be that researchers are trying to make their path figures simpler by not including the error terms.

> *"Because every endogenous variable must have a disturbance term associated with it, <u>we often don't bother to draw it, to keep the drawing simpler</u>, but if it's not explicitly drawn, it's implicitly present."* Streiner (2005, p. 117; emphasis added).

Omitting the error terms from the path diagram may help to make the figure simpler, but it comes at the cost of making it more difficult for readers to determine whether the endogeneity problem is being assumed away (as in Fig. 2), or instead the study is allowing for endogeneity and attempting to address it (as in Fig. 1). Not only do studies routinely fail to disclose this crucial information in their path diagrams, many studies also fail to disclose it elsewhere in their articles. In the absence of an explicit disclosure, it can be difficult (and sometimes impossible) for readers to determine whether a study is assuming away the endogeneity problem by assuming uncorrelated errors or attempting to control for endogeneity by imposing exclusion restrictions on one or more of the exogenous covariates. We view this lack of disclosure as the most egregious aspect of the path analysis literature, particularly when the same studies assert that they are using path analysis to strengthen their causal inferences.

2.5. The proliferation of path analysis despite early criticisms

The usefulness of Sewall's methodology was strongly disputed in the 1920s by a fellow geneticist, Henry Niles, who described Sewall's claims about causality as fallacious. Like us, Henry's primary objection rests with the notion that causality can be inferred by simply positing a system of causal relations in a path diagram and then estimating the set of correlations implied by the diagram.

> *"To find flaws in a method that would be of such great value to science if only it were valid is certainly disappointing. The basic fallacy of the method appears to be the assumption that it is possible to set up a priori a comparatively simply graphic system which will truly represent the lines of action of several variables upon each other, and upon a common result" (Niles, 1922; p. 261).*

In an article one year later, Niles clarified that he disputed only the implicit assumptions embedded within Wright's path diagram, not the mathematics of the correlations that Wright had estimated.

> *"I have never attacked the mathematics of the method of 'path coefficients' because it seems sound enough when the preliminary assumptions regarding the basis of the method are granted, but I do not grant them" (Niles, 1923, p. 256).*

In his criticisms, Niles did not explicitly mention the error terms, perhaps because he was also writing at a time before the IV methodology was introduced to address endogeneity concerns.

It took a few decades for path analysis to become popularized. In fact, four decades after Wright (1921) first introduced the methodology, Hubert M. Blalock helped to popularize path analysis in the sociology discipline with a book that would later be regarded as a classic (Blalock 1964).[11] Path analysis then spread quickly to other disciplines including psychology, education, political science, and business (Wolfle 2003). The method is now frequently found in published academic articles across many disciplines, including accounting.

[11] Wolfle (2003) notes that the first applications of path analysis in sociology were statistically unsophisticated (page 2): "*The early applications of path analysis in sociology glossed over the niceties of statistical inference; indeed, neither Duncan and Hodge (1963) or Duncan (1966) reported standard errors.*"

Academic publications are partly a teaching tool for researchers to learn what methods are accepted by reviewers and journal editors as appropriate and in which situations they are acceptable (e.g., Petersen 2009). Therefore, it is important for published papers to accurately reflect the proper usage and interpretations of statistical methods. The language used in published studies often serves to reinforce the notion that path analysis is somehow synonymous with causation. Indeed, many studies explicitly refer to path analysis as "casual modeling" (Dennis and Legerski 2006). Such language reflects the historical connection that Sewall Wright had incorrectly made between his methodology and causation. Consider for example, the following published papers in non-accounting disciplines which all use causal verbiage—such as "causes", "consequences", and "effects"—in their titles.

"Causes and effects of teacher conflict inducing attitudes towards pupils: A path analysis model" (Sava 2002).

"A path analysis of causes and consequences of salespeople's perceptions of role clarity" (Teas et al. (1979).

"*The effects of credibility, reliance, and exposure on media agenda-setting: A path analysis model*" (Wanta and Hu, 1994).

"*Factors affecting the use of market research information: A path analysis*" (Deshpande and Zaltman, 1982).

"A path analysis model of the antecedents and consequences of organizational commitment" (DeCotiis and Summers 1987).

"The effects of governmental and individual predictors on COVID-19 protective behaviors in China: A path analysis model" (Dai et al. 2020).

"A path analysis model for explaining unsafe behavior in workplaces: the effect of perceived work pressure" (Ghasemi et al. 2018).

Our study is not the first to point out the limitations of using path analysis to estimate causal effects (Niles 1922, 1923; James 1980; Dennis and Legerski 2006). For example, Dennis and Legerski (2006) offer the following criticism:

> *"Misuses and misrepresentations of path analysis center on adopting the causal semantics of Wright's method, without, in most cases, reasonable a priori justification* […] *without a "causal context" required for substantiating causal claims, path analysis is simply an enhanced and powerful statistical procedure more analogous to multiple regression, and should be interpreted void of causal verbiage." (*Dennis and Legerski 2006, p. 3*).*

Unfortunately, this message has not been fully appreciated. One reason for the misunderstanding could be the way in which some textbooks and articles present the path analysis method. For example, some statistical textbooks (outside of econometrics) interweave an explanation of path analysis with a philosophical discussion of causation (e.g., see Chapter 18 of Pedhazur 1997). This co-mingling can lead an unsuspecting reader to conclude that path analysis and causation are somehow synonymous. Some methodology articles acknowledge that path analysis cannot be used to establish causality but, at the same time, they dilute this cautionary message by including equivocating language that suggests the exact opposite. Consider, for instance, the following mixed messages in Streiner's (2005) review of path analysis in the psychiatry field.

> "*Path analysis can examine situations in which there are* […] *<u>"chains" of influence</u>, in that variable A <u>influences</u> variable B, which in turn <u>affects</u> variable C. Despite its previous name of "causal modelling", <u>path analysis cannot be used to establish causality</u>.*" (Streiner 2005, p. 115; emphases added).

With respect to the accounting literature, we focus on two major limitations with the way path analysis is used. First, studies often assume uncorrelated error terms, which is equivalent to assuming away the endogeneity problem.[12] Nevertheless, the same studies often claim they are using path analysis to estimate causal effects. Second, most path analysis studies provide incomplete disclosure. That is, they fail to explicitly disclose whether the error terms are assumed to be uncorrelated or correlated. In effect, such studies are failing to disclose whether they are assuming away the endogeneity problem or acknowledging an endogeneity problem and trying to address it.[13]

2.6. Identification

We have discussed two ways researchers can identify causal effects in a system of equations. The first approach (IV) is to impose one or more exclusion restrictions on the exogenous covariates ($\alpha_4 = 0$). The second approach is to assume uncorrelated errors ($cov\ (u_1\ u_2) = 0$). If neither approach is adopted, the Y_1 model is under-identified and the direct causal effect of the endogenous Y_2 variable on Y_1 cannot be estimated. The choice between imposing exclusion restrictions or assuming uncorrelated errors is far from innocuous because the coefficient estimates can be the same or different depending on which approach is taken. Moreover, the IV coefficients can vary depending on whether the researcher chooses to estimate a system that is just-identified or over-identified. Therefore, there are three possible situations, which we summarize as follows:

[12] The assumption of uncorrelated errors is the default option in STATA, which may explain why most studies assume uncorrelated errors. The STATA command for estimating (1) and (2) with uncorrelated errors is *sem* $(Y_1$ <- Y_2 $X)$ $(Y_2$ <- X $Z)$. A researcher can override the default option and allow the errors to be correlated by modifying the command as follows: *sem* $(Y_1$ <- Y_2 $X)$ $(Y_2$ <- X $Z)$, *cov(e.* Y_1*e. $Y_2)$.

[13] Although most studies fail to disclose whether the errors are assumed to be correlated or uncorrelated, we are often able to back out the assumption by examining whether there are any exclusion restrictions on the covariates. When no explicit disclosure is made, we infer that a study assumes uncorrelated errors when the system of equations would otherwise be under-identified.

Approach #1): The researcher assumes uncorrelated errors (cov (u_1 u_2) = 0).

In this first case, irrespective of whether exclusion restrictions are imposed on the exogenous covariates, the estimated coefficients from path analysis are identical to the coefficients from OLS.[14] This equivalence reinforces our point that assuming uncorrelated errors is the same as assuming away the endogeneity problem. In our survey of the accounting literature, we find that most path analysis studies fall into this first category, i.e., they assume away the endogeneity problem (cov (u_1 u_2) = 0). Yet, those same studies often draw strong causal inferences from the estimated path coefficients.

Approach #2): The researcher allows for correlated errors (cov (u_1 u_2) ≠ 0) in a just-identified system.

In this second case, the estimated coefficients from path analysis are identical to the coefficients from IV estimation (e.g., Burgess et al. 2015) because the researcher addresses endogeneity through imposing exclusion restrictions equal to the number of endogenous regressors. This fact reinforces our point that IV and path analysis are conceptually very similar.

Approach #3): The researcher allows for correlated errors (cov (u_1 u_2) ≠ 0) in an over-identified system.

In this third case, the estimated coefficients from path analysis are generally different from the coefficients in IV estimation. Moreover, the IV coefficients in an over-identified system are different depending on whether the system is estimated using 2SLS, maximum likelihood, or the

[14] Although the coefficients are identical, the standard errors are slightly different. Software packages such as STATA use the degrees of freedom when calculating the variance-covariance matrix for the OLS model, whereas it uses the total number of observations for the path analysis model. In studies with large samples, the degrees of freedom are similar to the sample size and so OLS and path analysis often produce very similar standard errors.

generalized method of moments. We explain in Section 4 why the coefficients differ across these alternative estimation methods when the system is over-identified (whereas the coefficients are the same when the system is just-identified). Before covering that material, which is a bit more technical, we first present the findings from our survey of the accounting literature. Our survey reveals that relatively few accounting studies fall into this third category, which is why we give this third case less emphasis.

3. A survey of the accounting literature

3.1. *How often is path analysis used in the accounting literature?*

We first investigate how many studies in the accounting literature use path analysis. We then examine how many studies impose the assumption of uncorrelated errors, or alternatively obtain identification by imposing exclusion restrictions on one or more exogenous covariates.

We find 193 path analysis studies in five leading accounting journals (*Journal of Accounting and Economics, Journal of Accounting Research, The Accounting Review, Contemporary Accounting Research,* and *Review of Accounting Studies*) between 1995 and 2022. The studies are listed in the Appendix, and Figure 4 shows the number of studies in each year. [15] We see a strong upward trend over time, especially in the period since 2011. The average number of studies using path analysis was only 2 per year between 1995 and 2009 but increased to an average of 13 per year between 2010 and 2022.

[15] We identify candidate studies by searching for the terms "path analysis," "mediation," "mediate," "indirect effects," and "path model." After performing this initial search, we carefully read each study to ensure that it does in fact use path analysis. Any studies that do not directly state the use of "path analysis" or a "path model" must include a path diagram to be kept in our sample.

[Insert Figure 4 here]

Path analysis is commonly employed in psychology research. Many experimental papers in accounting test psychological theories, so we expect a relatively high frequency of path analysis usage among experimental studies. Consistent with this expectation, Table 1 shows that path analysis is used in 138 experimental studies and 55 archival studies.[16] However, path analysis is employed in all the major topic areas in accounting. We partition the studies into seven topic areas: 1) disclosure (*DISC*), 2) earnings management and earnings quality (*EQ*), 3) contracting and corporate governance (*GOV*), 4) other financial accounting (*FIN*), 5) auditing (*AUD*), 6) tax (*TAX*), and 7) management accounting (*MGR*). We find that path analysis is used by 29 *DISC* studies, 12 *EQ* studies, 5 *GOV* studies, 31 *FIN* studies, 59 *AUD* studies, 10 *TAX* studies, and 47 *MGR* studies. Most of the *AUD* and *MGR* studies are experimental whereas most of the *FIN* studies are archival.

3.2. Path analysis and causal inferences

We carefully read each study to determine whether the system of equations is identified by imposing exclusion restrictions on the exogenous covariates or by assuming uncorrelated errors (or both). The coding for these research design choices is not straightforward because most studies fail to explicitly disclose whether the errors are assumed to be correlated or uncorrelated, and some studies also fail to disclose whether they impose exclusion restrictions. Nevertheless, when a study lacks exclusion restrictions, we are able to indirectly infer the study's assumption of uncorrelated errors, because the system would be under-identified (and therefore not

[16] Section 3.5 provides a detailed discussion of path analysis in experimental accounting research.

estimable) without this assumption. In some cases, when studies have exclusion restrictions or do not disclose whether they have exclusion restrictions, we are unable to infer the implicit assumptions used to identify the causal effects. We code such studies as "unclear."

In most studies, we find that the system is identified by assuming uncorrelated errors rather than by imposing exclusion restrictions on the covariates. As shown in Table 2, 144 studies (74.6%) lack exclusion restrictions on the covariates, whereas 9 studies only impose exclusion restrictions. We code 24 (12.4%) studies as unclear because we are unable to infer from the article whether exclusion restriction(s) are imposed or errors are assumed to be uncorrelated. The remaining 16 studies report some specifications with exclusion restrictions and some specifications without exclusion restrictions.

[Insert Table 2 here]

Next, we investigate the causal claims that studies make. We first determine whether studies draw causal inferences from the results of their path analysis (Q1 in Table 2). We find that 148 studies (76.7%) make causal claims based on the results of their path analysis. Causal inferences are prevalent (75.7%) even among the 144 studies that lack exclusion restrictions. Thus, most studies claim to estimate causal effects even while (implicitly) ignoring endogeneity by assuming uncorrelated errors. Recall that the path coefficients in these studies are identical to the coefficients that would be obtained using OLS.

Next, we examine each study's stated rationale for using path analysis (see Q2 in Table 2). Of the studies that draw causal inferences from the results of their path analysis, most (52.3%) assert they use path analysis to estimate causal effects. For example, an archival study by Hilary et al. (2016, page 56) states: "*We perform a path analysis to better understand the mechanisms through which past success (MBSTR) influences over-optimism and over-optimism influences firm performance.*

Path analysis uses a structural equation model to answer how a source variable affects an outcome variable via their direct paths and indirect paths through mediating variables (e.g., Baron and Kenny, 1986)."

Some authors state that they use path analysis to estimate causal effects even when they assume away the endogeneity problem by not imposing any exclusion restrictions on the covariates. For example, an experimental study by Tan et al. (2019: pages 418 & 424) states: "*To understand the underlying causal mechanism, we conduct a mediation analysis and find that jargon reduces these investors' investment willingness because it decreases their understanding* […] *We conduct a mediation analysis to test the underlying causal mechanism predicted in H1*." Similarly, an experimental study by Tang and Venkataraman (2018, pages 329 and 344) states: "*Our causal path model shows that investors attribute inconsistent guidance patterns to managerial opportunism, as suggested by theory, particularly when guidance frequency is low*. […] *Overall, our path model provides supportive evidence that the results for our primary dependent variables—investors' confidence in their EPS estimates and their willingness to invest—are driven by the causal mechanism we posit*."

Finally, we code whether each study uses path analysis as part of its main findings or as a robustness or supplementary analysis (Q3 in Table 2). We find that 155 studies (80.3%) implement path analysis as their main analysis, whereas only 48 studies (19.7%) use path analysis as a robustness test or as a supplementary analysis. Therefore, path analysis is a key research design choice in the majority of the surveyed studies.

3.3. Do the studies assume uncorrelated or correlated errors?

It is important for authors to fully disclose their key assumptions so that other researchers can replicate and possibly extend their findings. We therefore examine whether the path analysis studies fully disclose their key assumptions. First, we read each study to determine if it explicitly discloses its assumption about uncorrelated or correlated errors. Of the 144 studies that lack exclusion restrictions on the covariates, only 4 (2.78%) explicitly disclose that they are assuming uncorrelated errors.

[Insert Table 3 here]

There are 25 studies that impose exclusion restrictions on the covariates (Q1 in Table 3). In these studies, it is particularly important for the authors to disclose whether the errors are assumed to be correlated or uncorrelated, because there is no way for a reader to infer if the study is attempting to address endogeneity concerns otherwise. Of the 25 studies that impose exclusion restrictions, none disclose that they are assuming uncorrelated errors, one discloses that the errors are allowed to be correlated, while 24 are unclear because they do not disclose their assumption. There are another 24 studies where we are unable to determine whether exclusion restrictions are imposed on the covariates. Of these 24 studies, none disclose that they assume uncorrelated errors, four disclose that the error terms are allowed to be correlated, while 20 studies are unclear because they do not disclose their assumption.

Next, for the 144 studies that assume uncorrelated errors, we investigate whether they acknowledge that this assumption is equivalent to assuming away the endogeneity problem. Only 2 of the 144 studies include language that acknowledges the implications of this assumption (Q2 in Table 3). Thus, 144 studies assume away the endogeneity problem by imposing the assumption of uncorrelated errors, yet 142 studies do not acknowledge this implication of their assumption. Instead, they typically draw causal inferences from their path analysis findings (Q1 in Table 2).

Finally, we examine the relatively small number of studies that impose exclusion restrictions on the covariates. It is important for such studies to carefully justify their exclusion restrictions using theory or economic reasoning (e.g., Larcker and Rusticus 2010). Of the 25 studies that impose exclusion restrictions, Q3 shows that only 7 (25.2%) offer a justification for their chosen exclusion restrictions.

In summary, there are two main conclusions from Table 3. First, most path analysis studies assume away the endogeneity problem by assuming uncorrelated errors. Second, most studies fail to explicitly disclose they are making this key assumption or the implications that follow from it. Overall, many studies promote the path analysis method as a tool to estimate causal effects, but their path coefficients are identical to what they would have been obtained from OLS, with the problem of endogeneity being assumed away instead of being addressed.

3.4. Path diagram usage

Following Wright (1921), many studies include path diagrams to show the assumed relations. Of the 193 studies in our survey, we find that 174 (90.2%) include one or more path diagrams (Q1 in Table 4). However, most diagrams are incomplete as they fail to include the error terms. Of the 174 studies with path diagrams, we find that only two studies show error terms in the diagrams (Q2 in Table 4). Likewise, the path diagrams typically omit the covariates, which means they do not show whether exclusion restrictions are imposed on the covariates. Of the 104 studies with both path diagrams and covariates, we find that only 39 studies (37.5%) show the covariates in the path diagram (Q3 in Table 4). Overall, these disclosure patterns make it challenging for a reader to determine whether a study is trying to address endogeneity and, if so, what assumptions are being imposed to achieve this objective.[17]

[Insert Table 4 here]

3.5. Experimental studies

Path analysis is particularly popular among experimental studies (see Table 1). This finding is perhaps unsurprising given that path analysis is often used in the psychology literature and many experimental studies in accounting are grounded in psychological theories.

An important advantage of the experimental method is that researchers can randomly assign participants to treatment conditions. The variables manipulated in the experiment are exogenously determined (X, Z in our previous example from Section 2), allowing experimental researchers to draw causal inferences as to the effects of the manipulated variables on the dependent variable(s).

Crucially, however, not all the independent variables in experimental studies are exogenous. Many experimental studies have mediator variables (Y_2) that are endogenously determined either during the experiment or after the experiment has ended. Endogenous mediator variables are sometimes obtained during an experiment by passively observing participant behaviors (e.g., their eye movements, mouse clicks, time taken to read an item, etc.). More obtrusive mediator variables are obtained after the experiment has ended by providing survey questionnaires to the research participants. For less obtrusive mediator variables, endogeneity concerns could arise because the mediator is determined by the choices or behaviors

[17] Gow et al. (2016) recommend that researchers use path diagrams to show the key elements of a system of equations. We agree with their recommendation. Our point is simply that many path diagrams fail to disclose the key elements.

of participants during the experiment. If the unobservable factors affecting the mediator (Y_2) are correlated with the unobservable factors affecting the main measured dependent variable (Y_1), the assumption of uncorrelated errors is problematic. For mediator variables obtained through post-experimental questionnaires, an additional concern of potential reverse causality may be present because the mediator (Y_2) is measured after the main dependent variable (Y_1) is measured (Asay et al. 2022). Thus, the mediator (Y_2) could have a direct causal effect on Y_1, rather than Y_2 serving as the indirect channel through which the manipulated variable (Z) affects Y_1.[18] Interestingly, most experimental studies use post-experimental questionnaires rather than unobtrusive mediator variables (Asay et al. 2022). Thus, their inferences are subject to potential reverse causality concerns as well as concerns about endogenous mediators.

When the mediator is not a manipulated (i.e., exogenous) variable, it is determined endogenously, either during the experiment or afterwards. In this situation, the assumption of uncorrelated errors can be problematic in the same way as archival studies. We therefore investigate whether the experimental studies in our survey utilize endogenous mediator variables or exogenous (i.e., manipulated) mediators.

Table 5 presents our findings after partitioning the studies into experimental and archival. Table 5 confirms that most studies in both the archival and experimental fields draw causal inferences from their path analysis findings (Q1), many state that they are using path analysis to estimate causal effects (Q2), only a minority impose exclusion restrictions on the covariates (Q3), and most assume (either implicitly or explicitly) that the error terms are uncorrelated (Q4) while a substantial number are unclear on this point. Similar to the archival literature, most

[18] In a survey of 76 experimental papers that use mediator variables, Asay et al. (2022) document that 87% use post-experimental questionnaires whereas only 16% use unobtrusive mediator variables.

experimental studies do not acknowledge that the assumption of uncorrelated errors is equivalent to assuming away the endogeneity problem. In fact, we are unable to find any experimental studies that discuss the ramifications of assuming uncorrelated errors and only two archival studies that do so (Q5 in Table 5).

[Insert Table 5 here]

Q6 is our main question of interest: *In the experimental studies, is the mediator an exogenous (i.e., manipulated) variable?* Of the 138 experimental studies, only one study employs an exogenous (i.e., manipulated) mediator variable. The remaining 137 studies employ endogenous mediators. Thus, the statistical inferences of most experimental studies with respect to the mediator's effect on the main dependent variable are subject to endogeneity concerns just as in archival research. Of the 137 studies that employ endogenous mediators, 11 include mediators from both post-experimental questionnaires and by observing participant behavior during the experiment. The other 126 studies use mediators of only one type (mainly from post-experimental questionnaires) (see Q7 of Table 5). Of the 137 studies that use endogenous mediators, 31 measure mediators by observing participant behavior during the experiment. For these 31 studies, there is a concern that the unobservables affecting the mediator (Y_2) could be correlated with the unobservables affecting the main dependent variable (Y_1). The remaining 106 studies use mediators from post-experimental questionnaires. In these studies, there is an additional reverse causality concern given that the mediator (Y_2) is measured after the experiment has ended (i.e., Y_2 could have a causal impact on Y_1). [19]

[19] Our findings for Q6 and Q7 are consistent with Asay et al. (2022) who advise experimental researchers to be careful about drawing causal inferences when using endogenous mediator variables. Asay et al. (2022: page 28) state: "*Because mediation designs often do not satisfy the temporal precedence requirement or manipulate M* [the mediator variable]*, these designs are unable to provide causal evidence beyond the XY relationship. That is, because M and Y are measured* [i.e., endogenous]*, mediation designs can identify correlational, but not causal,*

For example, Bhaskar, Hopkins, and Schroeder (2019) study whether the association between client pressures in auditing and an auditor's propensity to accept a client's aggressive accounting is mediated by an auditor's directional goals. These directional goals represent the extent to which the participant has the goal of building a case to justify management's seemingly aggressive tax provision as reasonable or appropriate. This mediator variable is measured as the composite score of a participant's answers to five survey questions related to the participant's goals. Endogeneity could come through various omitted variables that jointly affect the mediator variable (the participant's goals) and the outcome variable (the participant's acceptance of aggressive accounting). Both variables could be affected by a participant's propensity to please others, how much the participant identifies with their career as an auditor, and the participant's personal ethical standards, to name a few examples. Taking the first example from our list, a participant's propensity to please others could drive their goals to support management (the mediator variable) while also driving the participant's decision to not recommend adjustments to the accounting numbers (the outcome variable).

We conclude that our criticisms of the path analysis literature are not confined to archival studies but apply to the experimental literature as well, given that the mediators are typically generated endogenously rather than through experimental manipulations. Both experimental and archival studies provide inadequate disclosures about the error terms and the implications of assuming uncorrelated errors for their causal inferences.

relationships involving M. In addition, participants are not randomly assigned to levels of the mediator, and alternative explanations may remain plausible. As a consequence, mediation designs are subject to a number of validity threats."

4. Estimation issues

4.1. When are the path analysis coefficients different from the OLS and IV coefficients?

Path analysis models are often estimated using Full Information Maximum Likelihood (FIML). Under the assumption of uncorrelated errors, the FIML path coefficients are identical to the OLS coefficients. Under the alternative assumption of correlated errors, the FIML coefficients can differ from the IV coefficients depending on whether the system is just-identified or over-identified. In a just-identified system, the path coefficients from FIML are identical to the IV coefficients from 2SLS, Limited Information Maximum Likelihood (LIML), or the generalized method of moments (GMM). In other words, the choice of IV estimator makes no difference to the estimated coefficients in a system that is just-identified. The situation is more complicated in an over-identified system because, in this situation, the path coefficients from FIML are generally different from the traditional IV coefficients. Moreover, the coefficients in an over-identified system are different across alternative IV estimators as well. In the next section, we briefly explain why FIML, LIML, 2SLS and GMM generate different coefficient estimates in systems that are over-identified.

4.2. *An over-identified system with correlated errors*

Consider an over-identified system with correlated errors ($\text{cov}\ (u_1\, u_2) \neq 0$).

$$Y_1 = \alpha_1 + \alpha_2\, Y_2 + \alpha_3\, X + u_1 \tag{12}$$

$$Y_2 = \beta_1 + \beta_2\, X + \beta_3\, Z + \beta_4\, W + u_2 \tag{13}$$

This system should not be estimated using OLS because the errors are correlated, raising concerns about bias in (12) due to the presence of the endogenous mediator, Y_2. Instead, the system must be estimated using one or more exclusion restrictions on the exogenous covariates. The above system is over-identified because (12) has a single endogenous mediator (Y_2) while it has exclusion restrictions on two exogenous covariates (Z and W). This system can be estimated using traditional IV approaches (2SLS, LIML, GMM) or path analysis (FIML) but should not be estimated using OLS due to the endogeneity concern.

We begin by explaining why the coefficients are different between LIML and FIML, which are both maximum likelihood estimators. Under LIML each equation in the system is estimated individually, whereas under FIML the equations are estimated jointly.[20] Thus, in LIML, the over-identifying restrictions in the other equation (13) are not considered when estimating the coefficients of the equation with the endogenous mediator (12). In FIML, the over-identifying restrictions are taken into account when estimating the system. Imposing an additional exclusion restriction in the other equation (13) allows FIML to use more information from which to generate the coefficient estimates. Consequently, FIML estimates are different from and asymptotically more efficient than the coefficient estimates from LIML. Despite this advantage, some researchers prefer LIML to FIML because the median LIML estimate is close to unbiased even when the chosen instruments (W and Z) are weak.[21] When the instruments are strong, the exclusion restrictions on them yield more information for the purposes of identification, and the coefficients in LIML and FIML diverge by more. Conversely, when the instruments (W and Z) are weak, the exclusion restrictions yield less information content, and so the LIML and FIML coefficients are more similar.

[20] FIML is similar to 3SLS in that the entire system of equations is estimated simultaneously whereas each equation is estimated separately in LIML and 2SLS.
[21] See chapter 4 of Angrist and Pischke (2009).

Unlike FIML, the 2SLS and LIML methods are both single-equation estimators. They belong to what is known as the k-class suite of estimators (Nagar 1959).[22] K-class estimators are IV estimators in which the actual and predicted values of the endogenous regressor (Y_2) take a special form:

$$Y_2{}^* = (1-k)Y_2 + k\widehat{Y_2} \text{ where } 0 \leq k \leq 1.$$

In the 2SLS approach, k is assumed to equal one. That is, 2SLS employs the predicted value of the endogenous regressor ($\widehat{Y_2}$) (see the earlier discussion in Section 2.1). In OLS, k is assumed to equal zero (i.e., OLS uses the actual value of Y_2 rather than the predicted value of Y_2 because Y_2 is assumed to be exogenous). LIML generates an estimated value of k somewhere between these two extremes ($0 \leq k \leq 1$) based on the specific features of the system. In a just-identified LIML system, k equals one, which is why LIML and 2SLS produce the same coefficient estimates. In an over-identified system, the estimated value of k deviates from one, which is why LIML generates different coefficient estimates from 2SLS.

GMM, on the other hand, is a separate class of estimator based on moment functions. In just-identified systems, GMM has moment conditions that exactly align to those of 2SLS. Therefore, in just-identified systems, the GMM coefficients are identical to 2SLS (as well as LIML and FIML). However, in over-identified systems, GMM relies on a weighting matrix to generate parameter estimates, which itself is estimated. Consequently, the GMM coefficients are different from other estimation methods (2SLS, LIML, FIML) when the system of equations is over-identified.

[22] See also https://www.sfu.ca/sasdoc/sashtml/ets/chap19/sect32.htm and http://www.eviews.com/help/helpintro.html#page/content/gmmiv-Limited_Information_Maximum_Likelihood_and_K-Cla.html.

5. Conclusion and recommendations for future research

Causal inferences do not become stronger when a study assumes away the endogeneity problem. However, this is what many path analysis studies have done because they assume (sometimes explicitly but usually implicitly) that the errors in their system of equations are uncorrelated. There may be some situations in which the assumption of uncorrelated errors is appropriate, for example when the mediator variable in an experiment is manipulated and therefore exogenous. However, the mediator variables in most experimental studies are not manipulated. Instead, they are endogenous variables obtained by observing participant behavior during the experiment or by giving participants a post-experimental questionnaire. Accordingly, our criticisms of the path analysis methodology apply to many studies in both the archival and experimental fields.

We conclude by providing four recommendations for researchers to implement if they wish to continue using the path analysis method.

1) *Disclose whether the errors are assumed to be correlated or uncorrelated.*

Researchers should explicitly disclose whether they are assuming correlated or uncorrelated errors. This disclosure can be provided in the path diagram, the main text of the paper, or preferably both.

2) *Justify the assumption of uncorrelated errors.*

When authors assume uncorrelated errors, they should explain why they consider this assumption to be reasonable. In other words, why is it reasonable to assume that the unobservables affecting the mediator variable (Y_2) are uncorrelated with the unobservables affecting the main outcome variable (Y_1)? When there exists substantial doubt about the validity of assuming uncorrelated errors, the study should acknowledge the endogeneity concern and refrain from drawing causal inferences.

3) Do not over-claim the benefits of using path analysis.

When authors assume uncorrelated errors, they should avoid claiming that they use path analysis as a means to strengthen their causal inferences. In fact, OLS and path analysis generate identical coefficient estimates when the errors are assumed to be uncorrelated. In such studies, the reported results should be interpreted as merely correlational rather than causal unless the authors can make a strong case for the mediator variable being exogenous.

4) Disclose whether exclusion restrictions are imposed on the covariates.

When authors allow the errors to be correlated, they should carefully explain which exclusion restrictions are imposed on the covariates to identify the estimated causal effects. In this situation, the study can clarify that the path analysis method is conceptually very similar to IV. Indeed, path analysis and IV estimation generate identical coefficient estimates when the system is just-identified. When the system is over-identified, there can be differences in the coefficient estimates depending on whether the researcher is using path analysis (FIML) or a traditional IV approach (2SLS, LIML, GMM). In this situation, the study can report sensitivity tests to check whether its inferences are sensitive to the estimation method employed.

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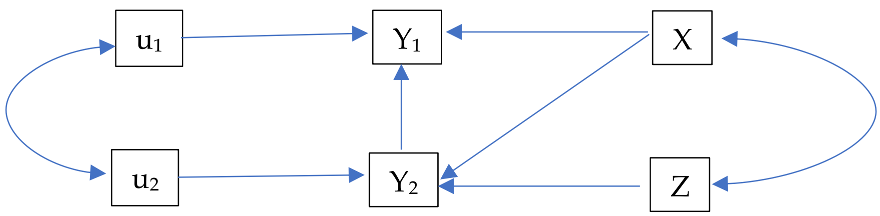

Figure 1

A diagrammatic representation of the Y_1 and Y_2 equations.

$Y_1 = \alpha_1 + \alpha_2 Y_2 + \alpha_3 X + u_1$

$Y_2 = \beta_1 + \beta_2 Z + \beta_3 X + u_2$

The error terms are assumed to be correlated (i.e., cov ($u_1 u_2$) $\neq 0$) as shown by the curved double-headed arrow connecting u_1 and u_2. The Z variable is assumed to have no direct impact on Y_1 as shown by the absence of a straight-line arrow connecting Z to Y_1.

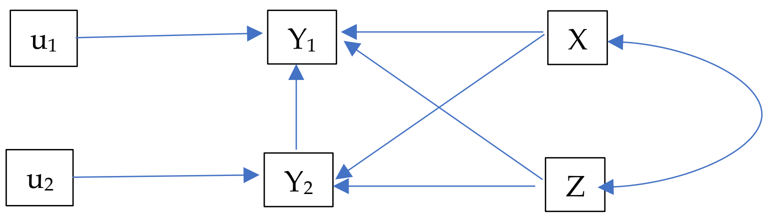

Figure 2

A diagrammatic representation of the Y_1 and Y_2 equations.

$Y_1 = \alpha_1 + \alpha_2 Y_2 + \alpha_3 X + \alpha_4 Z + u_1$

$Y_2 = \beta_1 + \beta_2 X + \beta_3 Z + u_2$

The error terms are assumed to be uncorrelated ($\text{cov}(u_1 u_2) = 0$) as shown by the absence of a curved double-headed arrow connecting u_1 and u_2. The Z variable is assumed to have a direct impact on Y_1 as shown by the straight-line arrow connecting Z to Y_1.

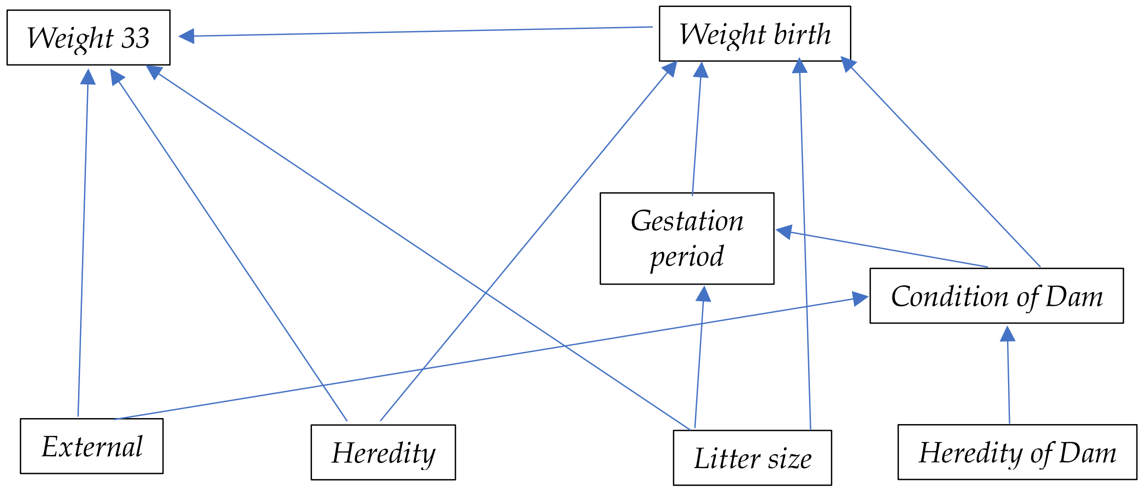

Figure 3

A diagrammatic representation of the system of equations estimated by Wright (1921).

Weight 33 = $\alpha_1 + \alpha_2$ *Weight birth* + α_3 *External* + α_4 *Heredity* + α_5 *Litter* + u_1

Weight birth = $\beta_1 + \beta_2$ *Gestation* + β_3 *Dam Condition* + β_4 *Heredity* + β_5 *Litter* + u_2

Gestation = $\gamma_1 + \gamma_2$ *Litter* + γ_3 *Dam Condition* + u_3

Dam Condition = $\delta_1 + \delta_2$ *Heredity of Dam* + δ_3 *External* + u_4

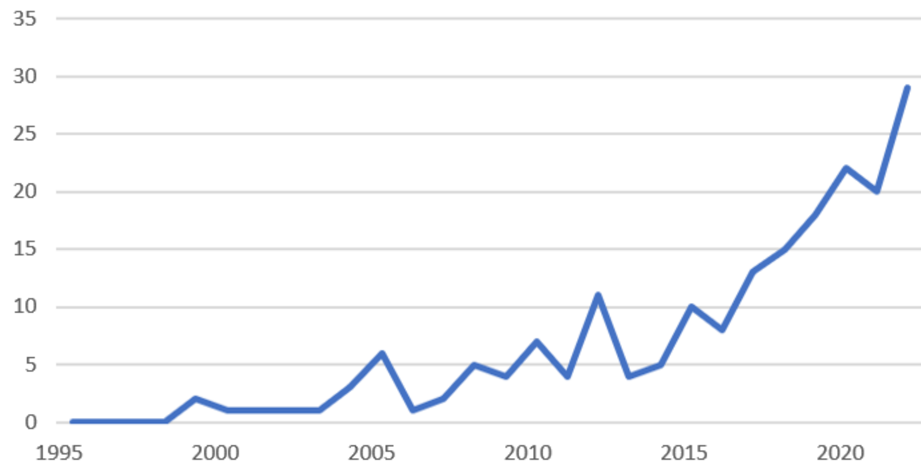

Figure 4

The usage of path analysis (1995-2022) among studies published in five leading accounting journals (*Journal of Accounting and Economics*, the *Journal of Accounting Research*, *The Accounting Review, Review of Accounting Studies, and Contemporary Accounting Research*).

Table 1

Path analysis studies (sorted by methodology and topic)

	Topic							
Methodology	*DISC*	*EQ*	*GOV*	*FIN*	*AUD*	*TAX*	*MGR*	**Total**
Archival	**11**	**3**	**1**	**17**	**8**	**5**	**10**	**55**
Experimental	**18**	**9**	**4**	**14**	**51**	**5**	**37**	**138**
Total	**29**	**12**	**5**	**31**	**59**	**10**	**47**	**193**

The topic categories are disclosure (*DISC*), earnings management and earnings quality (*EQ*), contracting and corporate governance (*GOV*), other financial accounting (*FIN*), auditing (*AUD*), taxation (*TAX*), and management accounting (*MGR*).

The path analysis studies are identified by searching for the terms "path analysis," "mediation," "mediate," "indirect effects," and "path model" in articles published by the *Journal of Accounting and Economics*, the *Journal of Accounting Research*, *The Accounting Review, Review of Accounting Studies, and Contemporary Accounting Research*.

Table 2

Causal inferences

	No exclusion restrictions imposed on the covariates		*Exclusion restrictions imposed on the covariates*		*Unclear if exclusion restrictions are imposed on the covariates* [a]		*Study includes some specifications with exclusion restrictions and some specifications without exclusion restrictions*		*Total*	
Total studies	144		9		24		16		193	
Q1. Do the authors draw causal inferences from their path analysis findings?	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
	109	35	7	2	18	6	14	2	148	45
Q2. For the studies in which the answer to (1) is "Yes", do the authors state that they use path analysis to provide causal inferences?	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
	57	52	6	1	10	8	4	10	77	71
Q3. Do the authors implement path analysis as part of their main tests (rather than as robustness or supplementary tests)?	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
	116	38	7	2	16	8	16	0	155	48

[a] Studies are coded as "Unclear" if they do not reveal whether they impose any exclusion restrictions on the covariates and if we cannot infer from their system of equations whether any exclusion restriction(s) were imposed.

Table 3

The assumption of uncorrelated errors

	No exclusion restrictions imposed on the covariates		*Exclusion restrictions imposed on the covariates*			*Unclear if exclusion restrictions are imposed on the covariates* [a]			*Study includes some specifications with exclusion restrictions and some specifications without exclusion restrictions*		
Total studies	144		9			24			16		
Q1. Do the authors assume uncorrelated errors?	Yes [b]	No	Yes	No	Unclear [c]	Yes	No	Unclear [c]	Yes	No	Unclear [c]
	144	N/A	0	1	8	0	4	20	0	0	16
Q2. For studies in which the answer to (1) is "Yes", do the authors acknowledge that assuming uncorrelated errors is equivalent to assuming away endogeneity concerns?	Yes	No	Yes	No		Yes	No		Yes	No	
	2	142	0	0		0	0		0	0	
Q3. For studies in which exclusion restrictions are imposed on the covariates, do the authors attempt to justify the imposed exclusion restrictions?			Yes	No					Yes	No	
			4	5					3	13	

[a] Studies are coded as "Unclear" if they do not disclose whether they impose any exclusion restrictions on the covariates and if we cannot infer from their system of equations whether any exclusion restriction(s) are imposed.
[b] We infer that all 144 studies must have assumed uncorrelated errors because otherwise their system of equations would have been under-identified due to the absence of exclusion restrictions on the covariates.
[c] Studies that impose exclusion restrictions on the covariates are coded as "Unclear" if the authors do not disclose whether they assume correlated or uncorrelated errors.

Table 4

Path diagrams

	No exclusion restrictions imposed on the covariates		*Exclusion restrictions imposed on the covariates*		*Unclear if exclusion restrictions are imposed on the covariates* [a]		*Study includes some specifications with exclusion restrictions and some specifications without exclusion restrictions*	
Total studies	144		9		24		16	
Q1. Do the authors include one or more path diagrams to illustrate their system of equations?	Yes	No	Yes	No	Yes	No	Yes	No
	127	17	9	0	22	2	16	0
Q2. For studies in which the answer to (1) is "Yes", do the path diagram(s) include the error terms?	Yes	No	Yes	No	Yes	No	Yes	No
	1	126	1	8	0	22	0	16
Q3. For studies that include covariates in the path model and in which the answer to (1) is "Yes", do the path diagram(s) include the covariates?	Yes	No	Yes	No	Yes	No	Yes	No
	31	45	1	4	4	9	3	7

[a] Studies are coded as "Unclear" if they do not disclose whether they impose any exclusion restrictions on the covariates and if we cannot infer from their system of equations whether any exclusion restriction(s) were imposed.

Table 5

Experimental and Archival Studies

	Experimental Studies			*Archival Studies*		
Total Studies	138			55		
Q1. Do the authors draw causal inferences from their path analysis findings?	Yes 106	No 32		Yes 42	No 13	
Q2. For the studies in which the answer to (1) is "Yes", do the authors state that they use path analysis to provide causal inferences?	Yes 48	No 58		Yes 29	No 13	
Q3. Do the authors impose exclusion restrictions on the covariates?	Yes [a] 24	No 95	Unclear [b] 19	Yes 1	No 49	Unclear [b] 5
Q4. Do the authors assume uncorrelated errors?	Yes 95	No 5	Unclear [c] 38	Yes 49	No 2	Unclear [c] 4
Q5. For studies in which the answer to (4) is "Yes", do the authors acknowledge that assuming uncorrelated errors is equivalent to assuming away endogeneity concerns?	Yes 0	No 95		Yes 2	No 47	
Q6. Is the mediator in the experimental study an exogenous (i.e., manipulated) variable?	Yes 1	No 137				
Q7. For experimental studies in which the mediator variable is not exogenous (i.e., not manipulated), is the mediator variable obtained from a post-experimental questionnaire?	Yes 118	No 31 [d]				

[a] This column includes studies that report specifications with exclusion restrictions and specifications without exclusion restrictions.

[b] Studies are coded as "Unclear" if they do not disclose whether they impose any exclusion restrictions on the covariates and if we cannot infer from their system of equations whether any exclusion restriction(s) were imposed.
[c] Studies that impose exclusion restrictions on the covariates are coded as "Unclear" if the authors do not disclose whether they assume correlated or uncorrelated errors.
[d] Many studies have multiple mediator variables. Therefore, the sum for Q7 is greater than 137.

Appendix

Studies using path analysis (sorted by accounting journal)

Journal of Accounting & Economics Authors	Year
Barton & Mercer	2005
Landsman et al.	2012
Jackson et al.	2013
Hilary et al.	2016
Schoenfeld	2017
Adhikari et al.	2019
Nagar et al.	2019
Tan et al.	2019
Wheeler	2019
Bonsall et al.	2020
Hills et al.	2021
Hung et al.	2022
Yue et al.	2022

Journal of Accounting Research Authors	Year
Phillips	1999
Bushee & Noe	2000
Ittner et al.	2002
Hatfield et al.	2008
Koonce & Lipe	2010
Rennekamp	2012
Brown	2014
Clor-Proell & Maines	2014
Griffith et al.	2014
Cardinaels & Yin	2015
Ham et al.	2017
Bonner et al.	2018
Elliott et al.	2018
Bhaskar et al.	2019
Brown et al.	2021
Bochkay et al.	2022
Commerford et al.	2022

The Accounting Review

Authors	Year	Authors	Year
Cloyd & Spilker	1999	Hales et al.	2012
Towry	2003	Kadous et al.	2012
Mercer	2005	Masschelein et al.	2012
Jackson	2008	Schloetzer	2012
Kadous et al.	2008	Pike et al.	2013
Clor-Proell	2009	Presslee et al.	2013
Denison	2009	Tafkov	2013
Maas & Matějka	2009	Choi	2014
Wolfe et al.	2009	Arnold	2015
Ahn et al.	2010	Bailey	2015
Hatfield et al.	2010	Bowlin et al.	2015
Reffett	2010	Lo	2015
Rose et al.	2010	Mayew et al.	2015
Tayler	2010	Tan et al.	2015
Agoglia et al.	2011	Brasel et al.	2016
Huelsbeck et al.	2011	Brazel et al.	2016
Bhattacharya et al.	2012	Choi et al.	2016
Bushee & Miller	2012	DeFond et al.	2016
Christ et al.	2012	Gimbar et al.	2016

The Accounting Review – Continued			
Authors	Year	Authors	Year
Elliott et al.	2012	Bhaskar	2020
Nelson et al.	2016	Elliott et al.	2020
Cannon & Bedard	2017	Hecht et al.	2020
Erickson et al.	2017	Kunz & Staehle	2020
Farrell et al.	2017	Liu et al.	2020
Koch & Salterio	2017	Mayew et al.	2020
Maksymov & Nelson	2017	Mendoza	2020
Arnold et al.	2018	Murphy & Sandino	2020
Asay & Hales	2018	Bauer et al.	2021
Bochkay et al.	2018	Bochkay & Joos	2021
Bonsall et al.	2018	Hobson et al.	2021
Cardinaels et al.	2018	McAllister et al.	2021
Commerford et al.	2018	Young	2021
Griffith	2018	Anderson et al.	2022
Haesebrouck et al.	2018	Blum et al.	2022
Loftus & Tanlu	2018	Bogdani et	2022
Tang & Venkataraman	2018	Brazel et al.	2022
Badertscher et al.	2019	Cao et al.	2022
Bentley	2019	Chang	2022
Brown & Fanning	2019	Douthit et al.	2022
Church et al.	2019	Gale	2022
Dyreng et al.	2019	Hong	2022
Tsang et al.	2019	Mendoza & Winn	2022
Humphreys et al.	2016	Schuhmacher et al.	2022
Bauer et al.	2020	Tan & Yeo	2022

Contemporary Accounting Research			
Authors	Year	Authors	Year
Kadous & Magro	2001	Hobson	2011
Kadous & Sedor	2004	Lu et al.	2011
Webb	2004	Asare & Wright	2012
Wilks & Zimbelman	2004	Clor-Proell et al.	2014
Blay	2005	Koonce et al.	2015
Jackson & Hatfield	2005	Winchel	2015
Kadous et al.	2005	Bhattacharjee & Moreno	2017
Sawers	2005	Capps et al.	2017
Hodge et al.	2006	Elliott et al.	2017
Banker & Mashruwala	2007	Koonce & Lipe	2017
Brazel & Agoglia	2007	Rupar	2017
Glover et al.	2008	Asay	2018
Williamson	2008	Bol & Leiby	2018
Tan & Trotman	2010	Wright & Bhattacharjee	2018

Contemporary Accounting Research – Continued			
Authors	Year	Authors	Year
Arnold et al.	2019	Dunn et al.	2021
Arnold & Tafkov	2019	Fanning et al.	2021
Bratten et al.	2019	Gimbar & Mercer	2021
Commerford et al.	2019	Grasser et al.	2021
Garrett et al.	2019	Griffith et al.	2021
Kadous & Zhou	2019	He et al.	2021
Alderman & Jollineau	2020	Hurley et al.	2021
Bauer et al.	2020	Li et al.	2021
Bucaro et al.	2020	Pickerd & Piercey	2021
Demere et al.	2020	Rennekamp & Witz	2021
Demerjian et al.	2020	Anderson et al.	2022
Hayes & Reckers	2020	Files & Liu	2022
Hewitt et al.	2020	Gillette & Stinson	2022
Johnson et al.	2020	Helikum et al.	2022
Kachelmeier et al.	2020	Joe et al.	2022
Kang et al.	2020	Klassen & Ruiz	2022
Newman et al.	2020	Tafkov et al.	2022
Tang et al.	2020	Waddoups	2022
Dezoort et al.	2021		

Review of Accounting Studies	
Authors	Year
Elliott et al.	2015
Mattei & Platikanova	2017
Cardinaels et al.	2019
Chapman et al.	2021
Cho & Krishnan	2021
Fox & Wilson	2022
Huang et al.	2022
Kim et al.	2022
Li et al.	2022
Pham et al.	2022