**Losing our way?**

A critical examination of path analysis in accounting research [[1]](#footnote-1)\*

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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 practice makes it difficult for a 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 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).

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

**1. Introduction**

Path analysis was invented more than one hundred years ago by Sewall Wright (Wright 1921) as a tool to disentangle direct and indirect causal effects.[[2]](#footnote-2) The methodology adopts a structural equations approach whereby a mediator variable serves as a channel through which an exogenous variable is hypothesized to affect a dependent variable *indirectly*. This has generally been done while allowing the exogenous variable to also affect the dependent variable *directly*. Thus, path analysis attempts to decompose a variable’s total effect into a direct effect and an indirect effect through a mediator variable.

Since its invention, path analysis has been adopted by various disciplines, including biology, sociology, psychology, political science, education, and business. Consistent with Wright’s (1921) original claims, many researchers say they use path analysis to identify causal relations and to disentangle direct and indirect causal effects (e.g., Lleras 2005). Indeed, many published studies refer to the path analysis methodology as “causal modeling” (Dennis and Legerski 2006). However, there is disagreement regarding the usefulness of path analysis for obtaining causal inferences. In fact, some researchers assert that path analysis is *not* a method for discovering causal effects (e.g., Duncan 1966). In this study, we seek to reconcile these contrary views by explaining how the path analysis methodology works and what assumptions underpin it. We discuss the limitations and pitfalls of path analysis and evaluate how well the methodology has been implemented in the accounting literature.

We begin in Section 2 by highlighting the links between path analysis, ordinary least squares (OLS), and instrumental variable (IV) estimation. Highlighting these connections is important because archival researchers tend to be familiar (less familiar) with IV estimation (path analysis), whereas experimental researchers tend to be familiar (less familiar) with path analysis (IV estimation). We explain that path analysis and IV estimation are similar in that both methods employ a structural equations approach where an exogenous (instrumental) variable indirectly affects a dependent variable through a mediator. The major difference between IV and path analysis is that IV estimation requires one or more exclusion restrictions on the instruments for the purpose of identification, whereas path analysis does not. 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 the excluded instrument has no direct effect on the main dependent variable). Path analysis is different because it does not require the assumption of no direct effect. Instead, path analysis allows the total effect of a variable to be decomposed into 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 that the error terms in the different equations (the mediator equation and the dependent variable equation) are uncorrelated for the coefficients to be identified. Specifically, the researcher must assume that the unobservables affecting the mediator variable are uncorrelated with the unobservables affecting the main dependent variable. We explain that the assumption of uncorrelated errors is equivalent to assuming away the endogeneity problem. Therefore, path analysis is the same as OLS when the researcher assumes uncorrelated errors, whereas path analysis is the same as IV when the researcher imposes exclusion restrictions on one or more of the exogenous covariates.

In Section 3, we survey the ways in which path analysis is used in the accounting literature. We find that 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 has surged over the past 25 years, with a marked increase in usage during the past decade. The number of studies using path analysis averaged just 2 per year between 1995 and 2009 but increased to an average of 13 per year after 2010 and reached an all-time high of 29 in 2022. Of the studies that use path analysis, we find that most claim to use the method to strengthen their causal inferences. We examine whether such causal claims are justified given the assumptions that are explicitly or, more often, implicitly imposed in the studies.

We find that most path analysis studies assume uncorrelated errors; that is, they assume away the endogeneity problem. 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 endogeneity by assuming uncorrelated errors. Thus, it is difficult to have confidence in the causal claims of many of the path analysis results within our surveyed studies. We also find that most studies fail to disclose whether they assume the errors to be correlated or uncorrelated. The lack of full disclosure can make it 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 document that path analysis is widely used in both the archival and experimental literatures. Given the nature of archival data, the variables used in archival path analyses are nearly always endogenous. An important strength of the experimental approach, relative to the archival approach, is that random assignment of participants to treatment and control groups ensures that the study’s manipulated variables are exogenous. Crucially, however, we find that the mediator variables in most experimental studies are measured rather than manipulated. Measured mediator variables in experiments (i.e., post-experimental questionnaire responses or observed participant behaviors) are endogenous (Pirlott and MacKinnon 2016; Asay et al. 2022). This means that while some paths in the system of equations may be estimated without bias in isolation (i.e., the effect of the main manipulated variable on the mediator), the use of non-manipulated mediators leads to similar endogeneity concerns as seen in archival studies. This is because the inclusion of an endogenous mediator in a system of equations biases not only the coefficient for the mediator variable but also the other coefficients in the system of equations. Consequently, our criticisms of the path analysis methodology apply to experimental studies that employ endogenous (i.e., measured) mediator variables as well as to the archival studies that do so.

We find that, in both the archival and experimental literatures, studies typically do not disclose whether they assume correlated or uncorrelated errors. Moreover, of the studies that assume uncorrelated errors, most do not attempt to defend this assumption. That is, they do not explain why it is reasonable to assume that the unobservables affecting the endogenous mediator are uncorrelated with the unobservables affecting the main dependent variable. We illustrate these criticisms with examples from both the archival and experimental literatures.

 We provide five recommendations for future research. First, authors need to explicitly disclose whether they are assuming correlated or uncorrelated errors because altering this assumption can completely flip a study’s inferences. Second, when assuming uncorrelated errors, authors should explain why they consider the assumption to be reasonable. That is, if authors assume uncorrelated errors, they should explain why the unobservables affecting the mediator variable are uncorrelated with the unobservables affecting the main dependent variable. Although many studies provide sound theoretical explanations for the posited effects of mediation, they fail to provide a similar defense for their assumption of uncorrelated errors. Third, when assuming uncorrelated errors, authors should not claim (or suggest) that path analysis provides stronger causal inferences than OLS. In fact, OLS and path analysis generate identical coefficient estimates when the errors are assumed to be uncorrelated because the assumption of uncorrelated errors is equivalent to ignoring the endogeneity problem. Fourth, when the errors are allowed to be correlated, authors should explicitly disclose and justify the assumed exclusion restrictions on the exogenous instruments (as allowing for correlated errors is 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. Finally, we recommend that authors consider whether path analysis or instrumental variable estimation is more appropriate for their setting. We further recommend that authors discuss the plausibility of the assumptions that underpin this decision. Specifically, is it more reasonable to assume that the unobservables affecting the mediator variable are uncorrelated with the unobservables affecting the main dependent variable, or is it more reasonable to impose one or more exclusion restrictions on the independent variables? If neither assumption is justifiable, authors should acknowledge the endogeneity concern and refrain from making causal inferences.

Our study has important implications for both archival and experimental research. For archival researchers, it must be understood that path analysis is not an alternative to OLS or IV estimation. Instead, path analysis is equivalent to OLS when the researcher assumes uncorrelated errors, while path analysis is equivalent to IV estimation when the researcher imposes exclusion restrictions on one or more of the exogenous covariates. Thus, path analysis does not offer a “third” option that is meaningfully different from OLS or IV estimation. Archival researchers must decide whether it is more reasonable to assume uncorrelated errors (as in OLS) or to impose exclusion restrictions (as in IV). If neither assumption is plausible, then archival researchers should consider other ways to strengthen their causal inferences, such as using difference-in-differences estimation or regression discontinuity designs.

Turning to the experimental literature, it is important to appreciate that path analysis can provide unreliable causal inferences when the mediators are measured (i.e., endogenous) instead of manipulated (i.e., exogenous). Methodological studies in the psychology literature also highlight the problem of using measured mediators (e.g., Spencer et al. 2005; Pirlott and MacKinnon 2016; Bullock and Green 2021). Pirlott and MacKinnon (2016) recommend that experimental researchers use manipulated mediators. For example, they suggest that experimental researchers first establish a causal relationship between Y and X in experiment #1 before manipulating a mediator variable in experiment #2 to test the causal channel through which X affects Y. In our survey of the accounting literature, we find that most experimental studies do not use manipulated mediators or the multi-experiment approach. Similar to Pirlott and MacKinnon (2016) and Spencer et al. (2005), we recommend that experimental researchers use manipulated rather than measured mediators.[[3]](#footnote-3)

Regardless of whether the mediator is manipulated or measured, it is important for path analysis studies to fully disclose and defend their key assumptions; i.e., their assumption of uncorrelated errors or their assumed exclusion restrictions.[[4]](#footnote-4) It is also important for researchers to consider the relevant tradeoffs between assuming uncorrelated errors (i.e., OLS estimation) versus imposing exclusion restrictions (i.e., IV estimation). Bullock and Green (2021) argue that, in many psychology studies, it may be more convincing for experimental researchers to impose exclusion restrictions rather than assume uncorrelated errors especially in cases where the manipulated mediator is believed to be the only channel though which X affects Y. Therefore, experimental researchers should consider whether IV estimation might be preferable to OLS (or ANOVA).[[5]](#footnote-5)

Our study contributes to a recent stream of literature that considers a variety of methodological issues in accounting research. Prior studies examine issues relating to 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; DeFond et al. 2017; Lawrence et al. 2017), robust regression (Leone et al. 2019), the (over) use of control variables (Whited et al. 2022), and experimental designs (Asay et al. 2022). Our study is the first to critically evaluate how path analysis is used in accounting. This evaluation is important because path analysis is rarely covered in Ph.D. 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 resolve this apparent contradiction. Moreover, we provide a set of practical recommendations to help researchers who wish to continue using path analysis.

**2. Path analysis and instrumental variable (IV) estimation**

*2.1. Path analysis*

Without loss of generality, consider a system of equations with two dependent variables (Y1 and Y2) and two exogenous covariates (X and Z).[[6]](#footnote-6)

Y1 = α1 + α2 Y2 + α3 X + u1 (1)

Y2 = β1 + β2 Z+ β3 X + u2 (2) [[7]](#footnote-7)

In path analysis, the Y2 variable is typically called a mediator because it acts as an indirect channel though which the exogenous X variable affects Y1. The direct and indirect effects of X on Y1 are found by substituting (2) into (1), which gives the reduced form model for Y1.

Y1 = α1 + α2 (β1 + β2 Z+ β3 X + u2) + α3 X + u1 (3)

Eq. (3) shows that the total effect of X on Y1 is α3 + α2 β2, which comprises a direct effect (α3) and an indirect effect (α2 β2). A fundamental objective of path analysis is to separate this total effect into the direct effect and indirect effect through the mediator (Y2).

*2.2. The relationships between path analysis, instrumental variables (IV) estimation, and OLS*

A key insight from our study is that the estimated path coefficients are identical to those from IV estimation if the researcher allows the error terms in (1) and (2) to be correlated (i.e., cov (u2 u1) ≠ 0). On the other hand, the estimated path coefficients are identical to those from OLS if the researcher assumes uncorrelated errors (i.e., cov (u2 u1) = 0). The purpose of this section is to explain these equivalences. In doing so, we answer the question as to whether path analysis can be relied upon to generate causal inferences.[[8]](#footnote-8)

 While the Y2 variable is typically called a “mediator” in path analysis, it is typically called an endogenous regressor in econometrics. The textbook IV solution to endogeneity bias is to find one or more exogenous variables that have a powerful effect on Y2 but no direct effect on Y1. The Z variable in (2) performs this function because Z is exogenous and is assumed to have no direct effect on Y1. The exclusion of Z from (1) is commonly known as an exclusion restriction.[[9]](#footnote-9)

Note that Y2 is comprised of both an exogenous component (β1 + β2 Z+ β3 X) that is uncorrelated with u1 (because Z and X are exogenous) and an unobserved component (u2) that is potentially correlated with u1. In (1), the presence (or absence) of endogeneity bias therefore hinges on whether u2 is correlated with u1. If u2 and u1 are uncorrelated (i.e., cov (u2 u1) = 0), then Y2 is exogenous in (1) even though Y2 is an endogenous dependent variable in (2). In this situation, OLS estimates of (1) are unbiased because all the independent variables (including Y2) are exogenous in (1). On the other hand, if u2 and u1 are correlated (i.e., cov (u2 u1) ≠ 0), then Y2 is correlated with u1 and OLS estimates of (1) are biased because Y2 is endogenous. 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 u2 from (1) and (3) by replacing the actual value of Y2 with its predicted value ($\hat{Y}$2). $ \hat{Y}$2 is obtained in a first-stage regression of (2):

$\hat{Y}$2 = $\hat{β}$1 + $\hat{β}$2 Z+ $\hat{β}$3 X.

Next, the endogeneity bias is removed by plugging $\hat{Y}$2 into the Y1 model to remove u2.

Y1 = α1 + α2 ($\hat{β}$1 + $\hat{β}$2 Z+ $\hat{β}$3 X) + α3 X + u1 (4)

With u2 removed, the 2SLS coefficients in (4) are estimated without bias because $\hat{Y}$2 is uncorrelated with u1.[[10]](#footnote-10)

 It is important to understand the key role that the exclusion restriction plays in identifying the causal effect of Y2 on Y1. To see this, consider what would happen if there were no exclusion restriction, i.e., Z is included in the Y1 model as well as the Y2 model. In this case, the Y1 model becomes:

Y1 = α1 + α2 Y2 + α3 X + α4 Z + u1 (5).

Note that (5) allows Z to affect Y1 directly (i.e., α4 ≠ 0), whereas (1) assumes that Z has no direct effect on Y1 (i.e., α4 = 0). In other words, (1) imposes an exclusion restriction on Z and (5) does not. Now, suppose a researcher replaces Y2 with $\hat{Y}$2 from (5). The reduced form model for Y1 then becomes:

Y1 = α1 + α2 ($\hat{β}$1 + $\hat{β}$2 Z+ $\hat{β}$3 X) + α3 X + α4 Z + u1 (6).

Rearranging terms:

Y1 = α1 + α2 $\hat{β}$1 + (α4 + α2 $\hat{β}$2) Z+ (α3 + α2 $\hat{β}$3) X + u1 (7).

Note that (7) is under-identified because, although the researcher has an estimate of $\hat{β}$2 from (2), this estimate is insufficient to determine whether the total effect of Z on Y1 (α4 + α2 $\hat{β}$2) is attributable to a direct effect (α4) or an indirect effect (α2 $\hat{β}$2), or both. Therefore, the causal effect of Y2 on Y1 (as captured by α2) cannot be estimated without imposing an exclusion restriction on Z (i.e., α4 = 0).

When the exclusion restriction is imposed (i.e., α4 = 0), (5) becomes (1). In this case, the α2 coefficient can be inferred from the indirect effect (α2 $\hat{β}$2) together with the Z coefficient in the Y2 model ($\hat{β}$2); i.e., α2 = (α2 $\hat{β}$2 / $\hat{β}$2). When the exclusion restriction is not imposed (α4 ≠ 0), the α2 coefficient cannot be estimated because the total effect of Z on Y1 comes from both a direct effect (α4) and an indirect effect (α2 $\hat{β}$2). In the absence of any restriction, it is impossible to disentangle the direct and indirect causal effects; i.e., α2 ≠ (α4 + α2 $\hat{β}$2 / $\hat{β}$2) when α4 ≠ 0. 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 Y1 (i.e., α4 = 0) or by assuming away the endogeneity problem by imposing the assumption of uncorrelated errors (i.e., cov (u2 u1) = 0).[[11]](#footnote-11)

 Most path analysis studies do not have exclusion restrictions on the covariates and thus rely on the assumption of uncorrelated errors for identification. The assumption of uncorrelated errors implies that Y2 is assumed to be exogenous (i.e., cov (Y2 u1) = 0), which is equivalent to assuming away the endogeneity problem. To put it an alternative way, Y2 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. Incorrectly imposing the assumption of uncorrelated errors gives rise to a classical endogeneity problem. Endogeneity biases the estimated direct effect of the mediator variable (Y2) on the main outcome variable (Y1) (i.e., the estimate of α2 is biased). Importantly, endogeneity also biases the estimated indirect effect of the exogenous variable (Z). Specifically, the indirect channel through which Z affects Y1 (i.e., α2 $\hat{β}$2) is estimated with bias because the direct effect of the mediator (α2) is estimated with bias, even though Z is an exogenous variable (i.e., $\hat{β}$2 is unbiased but α2 $\hat{β}$2 is biased because α2 is biased). Indeed, endogeneity can bias *all* the coefficients in (1), including the coefficients on the exogenous variables.

*2.3. The advantage of path analysis (or OLS) versus 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. These three conditions are onerous as it is often difficult for a researcher to find an instrument (Z) that is uncorrelated with the unobservables (u1 and u2), has a large impact on Y2,and affects Y1 only indirectly through Y2.[[12]](#footnote-12) The main advantage of path analysis (and OLS) relative to IV is that the system of equations can be estimated *without* imposing exclusion restrictions. That is, the researcher can allow Z to affect Y1 directly (α4 ≠ 0) as well as indirectly. However, as shown above, 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 (u1 u2) = 0). This assumption is far from innocuous because it is equivalent to assuming that the Y2 mediator is exogenous even though it is an endogenous dependent variable elsewhere in the system. The assumption of uncorrelated errors is reasonable if the mediator variable (Y2) is manipulated in an experiment but not in other situations if there are unobservables that affect both the mediator (Y2) and the main dependent variable (Y1).

The assumption of uncorrelated errors (cov (u1 u2) = 0) is different than assuming an exclusion restriction (i.e., α4 = 0). An explicit consideration of the relative merits of each assumption (i.e., cov (u1 u2) = 0 or α4 = 0) will help the researcher determine which approach is more appropriate. IV estimation is generally used when a researcher is interested in the effect of the endogenous mediator (Y2) on the main dependent variable (Y1). The exclusion restriction (Z) is used in this case for the purposes of identification and causal inference. With IV, the researchers should focus on evaluating the plausibility of the onerous conditions outlined above. Path analysis is generally used when the researcher is interested in the effect of the independent variable (Z) on the main dependent variable (Y1). Path analysis attempts to separate this total effect into direct and indirect effects through the mediator (Y2). Here, researchers should focus on evaluating whether the error terms in the systems of equations are likely to be correlated or uncorrelated.

In short, researchers should consider the following questions: Is it more reasonable to assume that the unobservables affecting the mediator are uncorrelated with the unobservables affecting the main dependent variable (i.e., cov (u1 u2) = 0)? Or is it more reasonable to assume there is at least one exogenous variable that directly affects the mediator but has no effect on the main dependent variable (i.e., α4 = 0)?

As an example, an experimental researcher may decide to construct a manipulated (i.e., exogenous) mediator by running a second experiment (Pirlott and MacKinnon 2016) to defend the assumption of uncorrelated errors (i.e., cov (u1 u2) = 0). In doing so, the experimental researcher can relax the assumption of no direct effect (i.e., α4 ≠ 0), thereby allowing the total effect of a manipulated variable to be decomposed into both direct and indirect causal effects.

An archival researcher may decide that neither assumption is justifiable (i.e., cov (u1 u2) ≠ 0 and α4 ≠ 0). In this case, the archival researcher may opt for an alternative approach to strengthen their causal inferences—such as using difference-in-differences estimation or a regression discontinuity design—or acknowledge the endogeneity concern and refrain from making causal inferences.

*2.4. Path diagrams*

Studies often outline their path analyses using diagrams that show hypothesized relations between variables while omitting critical parts of the path diagram (as discussed later). However, using diagrams can be an efficient way to communicate estimation assumptions. Similar to path analysis, the IV method can also be illustrated in a path diagram. Figure 1 shows the posited causal relationships in (1) and (2) under IV estimation.

[Insert Figure 1 here]

Figure 1 uses straight-line arrows to show the implied causal relations in (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 Y1, Y2 to Y1, u1 to Y1, X to Y2, Z to Y2, and u2 to Y2. Recall that the effect of Y2 on Y1 is identified by either imposing an exclusion restriction on Z (i.e., α4 = 0) or by assuming uncorrelated errors (i.e., cov (u2 u1) = 0).[[13]](#footnote-13) In Figure 1, the researcher relies on an exclusion restriction. Specifically, the exclusion restriction on Z is indicated by the absence of an arrow connecting Z to Y1, implying that Z affects Y1 only indirectly through Y2. Figure 1 also depicts a curved double-headed arrow connecting u1 and u2 to denote that the errors are allowed to be correlated, making explicit that the unobservables affecting Y1 are allowed to correlate with the unobservables affecting Y2.[[14]](#footnote-14) With the exclusion restriction in place (α4 = 0), the researcher can control for the endogeneity in Y2 that arises from the correlated errors.

 If a researcher is unable to assume a valid exclusion restriction on Z (α4 ≠ 0), the researcher can obtain identification by instead assuming that the errors are uncorrelated (i.e., cov (u1 u2) = 0). Figure 2 shows a diagram representative of the typical path analysis design under the scenario of uncorrelated errors. Note that, in contrast to Figure 1, Figure 2 has a straight-line arrow connecting Z to Y1, indicating that Z affects Y1 directly (i.e., α4 ≠ 0) as well as indirectly. Also, note that there is no curved arrow connecting u1 and u2 in Figure 2, meaning that the error terms are assumed to be uncorrelated (cov (u1 u2) = 0). That is, Y2 is assumed to be exogenous in (1) despite being an endogenous dependent variable in (2). Including error terms in path diagrams is thus an easy way to tell a reader whether the errors are assumed to be correlated or not.

[Insert Figure 2 here]

*2.5. The historical origins and proliferation of path analysis*

The path analysis method is credited to the geneticist Sewall Wright, who presented his new methodology in a 1921 study titled “*Correlation and Causation.*” Unfortunately, the limitations of Wright’s (1921) methodology were present from the beginning. His system of equations lacked exclusion restrictions (see Appendix A), which means that causality was determined and causal inferences were drawn while assuming uncorrelated errors (i.e., cov (u1 u2) = 0). This was done despite the assumption of uncorrelated errors being implausible in his empirical setting.[[15]](#footnote-15) Furthermore, the assumption of uncorrelated errors is not immediately obvious to the casual reader of Wright (1921) because his path diagram fails to include the error terms and his article does not explicitly state its assumption of uncorrelated errors.

To be fair to Wright, his article was written before IV was introduced as a method to address endogeneity concerns.[[16]](#footnote-16) Thus, the full ramifications of assuming uncorrelated errors were not well understood at the time. Towards the end of his life, Wright acknowledged that researchers ought to disclose the error terms to make clear whether they are assumed to be correlated or uncorrelated. Three years before his death, Wright 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).

Unfortunately, many studies fail to follow Wright’s 1985 recommendation as they do not show the error terms in their path diagrams.[[17]](#footnote-17) The lack of disclosure makes it difficult for readers to determine whether a study is assuming away endogeneity (as in Fig. 2) or instead 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, but 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 or attempting to control for endogeneity by imposing exclusion restrictions. We view this lack of disclosure as the most egregious aspect of the path analysis literature, particularly when studies that assume away endogeneity concerns say they use path analysis to strengthen their causal inferences.

After Wright’s introduction of path analysis in 1921, the methodology lay dormant for four decades. Hubert M. Blalock popularized the method in sociology in the 1960s (Blalock 1964).[[18]](#footnote-18) 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 articles across many disciplines, including accounting. The language used in published studies often serves to reinforce the notion that path analysis is somehow synonymous with causation (see Appendix A). Indeed, many studies explicitly refer to path analysis as “casual modeling” (Dennis and Legerski 2006). Such language reflects the historical connection that Wright had incorrectly made between his methodology and causation. Academic publications are partly a teaching tool for researchers to learn what methods are accepted by reviewers and journal editors as appropriate (e.g., Petersen 2009), so it is important for publications to reflect the proper usage and interpretations of statistical methods.

 One reason for the misunderstanding could be the way 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* […] *“chains” of influence, in that variable A influences variable B, which in turn affects variable C. Despite its previous name of “causal modelling”, path analysis cannot be used to establish causality*.” (Streiner 2005, p. 115; emphases added).

With respect to the accounting literature, we focus on two limitations with the way path analysis is used. First, studies often assume uncorrelated errors, which is equivalent to assuming away the endogeneity problem.[[19]](#footnote-19) 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 errors are uncorrelated or correlated. In effect, such studies fail to disclose whether they are assuming away the endogeneity problem or acknowledging an endogeneity problem and trying to address it.[[20]](#footnote-20)

*2.6. Summary*

We have discussed two ways researchers can estimate a system of recursive equations. The first approach (IV) is to impose one or more exclusion restrictions on the exogenous covariates (α4 = 0). The second approach is to assume uncorrelated errors (cov (u1 u2) = 0). If neither approach is adopted, the Y1 model is under-identified and the direct effect of the endogenous mediator (Y2) on the main dependent variable (Y1) cannot be estimated. The choice between imposing exclusion restrictions or assuming uncorrelated errors is far from innocuous because the coefficient estimates depend on which approach is taken. Moreover, the IV coefficients can vary depending on whether a system of equations is just-identified or over-identified. Therefore, there are three possible situations, which we summarize as follows:

Approach #1): The researcher assumes uncorrelated errors (cov (u1 u2) = 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 (or ANOVA). This equivalence reinforces our point that assuming uncorrelated errors is the same as assuming away the endogeneity problem.

Approach #2): The researcher allows correlated errors (cov (u1 u2) ≠ 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 the endogeneity concern by imposing exclusion restrictions equal to the number of endogenous regressors.

Approach #3): The researcher allows correlated errors (cov (u1 u2) ≠ 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 generalized method of moments. We explain in Appendix B why the coefficients differ across these alternative estimation methods when the system is over-identified (whereas the coefficients are identical when the system is just identified). Next, we present the findings from our survey of the accounting literature. Our survey reveals that relatively few accounting studies fall into the over-identified category, which is why we relegate this third case to an Appendix.[[21]](#footnote-21)

**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 Appendix C. Figure 3 shows the number of studies in each year. [[22]](#footnote-22) 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 after 2010, reaching an all-time high of 29 in 2022.

[Insert Figure 3 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.[[23]](#footnote-23) Path analysis is employed in all the major topic areas in accounting. We partition the studies into seven topics: 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 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 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 identifying assumptions. We code such studies as “unclear” due to the lack of full disclosure.

We find that in most studies the system of equations is identified by assuming uncorrelated errors rather than by imposing exclusion restrictions on the covariates. As shown in Table 2, 130 studies (67.4%) lack exclusion restrictions on the covariates, whereas 22 studies only impose exclusion restrictions. We code 22 (11.4%) studies as unclear because we are unable to infer from the article whether exclusion restriction(s) are imposed or the errors are assumed to be uncorrelated. The remaining 19 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 154 studies (79.8%) make causal claims based on the results of their path analysis. Causal inferences are prevalent (76.9%) even among the 130 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 (50.6%) say 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 (i.e., they assume uncorrelated errors instead of imposing 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) motivates the use of path analysis as follows: “*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 determine whether each study uses path analysis for its main findings or as a robustness or supplementary analysis (Q3 in Table 2). We find that 155 studies (78.2%) implement path analysis as their main analysis, whereas only 42 studies (21.8%) 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 path analysis studies fully disclose their key assumptions. First, we read each study to determine if it discloses its assumption about uncorrelated or correlated errors. Of the 130 studies that lack exclusion restrictions on the covariates, only 3 (2.31%) explicitly disclose that they are assuming uncorrelated errors.

[Insert Table 3 here]

 There are 41 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 41 studies that impose exclusion restrictions, one discloses that they are assuming uncorrelated errors, three disclose that the errors are allowed to be correlated, while 37 are unclear because they do not disclose their assumption. There are another 22 studies where we are unable to determine whether exclusion restrictions are imposed on the covariates. Of these 22 studies, none disclose that they assume uncorrelated errors, three disclose that the error terms are allowed to be correlated, while 19 studies are unclear because they do not disclose their assumption.

Next, for the 130 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 130 studies include language that acknowledges the implications of assuming uncorrelated errors (Q2 in Table 3). Thus, 130 studies assume away the endogeneity problem, yet 128 studies do not acknowledge that this is an 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 defend their exclusion restrictions using theory or economic reasoning (e.g., Larcker and Rusticus 2010). Of the 41 studies that impose exclusion restrictions, Q3 shows that only 11 (26.8%) offer a theoretical or intuitive 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 do not disclose they are making this key assumption and do not disclose 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 obtained from OLS, with the problem of endogeneity being assumed away instead of being addressed.

*3.4. Path diagram disclosures*

Following Wright (1921), many studies include path diagrams to show the hypothesized and assumed relations. Of the 193 studies in our survey, 172 (89.1%) 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 172 studies with path diagrams, we find that only one study shows error terms in their 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 107 studies with both path diagrams and covariates, we find that only 41 studies (38.3%) 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.[[24]](#footnote-24)

[Insert Table 4 here]

*3.5. Experimental studies*

Path analysis is particularly popular in 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 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 and 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 employ measured (i.e., non-manipulated) mediator variables (Y2) that are endogenously determined during the experiment or after the experiment has ended. Measured mediators are 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 measured mediator variables are obtained after the experiment has ended by providing survey questionnaires to the research participants. For less obtrusive mediator variables, endogeneity concerns can arise because the mediator is determined by the choices or behaviors of participants during the experiment. If the unobservable factors affecting the endogenous mediator (Y2) are correlated with the unobservable factors affecting the main dependent variable (Y1), then it is incorrect to assume uncorrelated errors. For mediator variables obtained through post-experimental questionnaires, an additional concern of reverse causality may be present because the mediator (Y2) is measured after the main dependent variable (Y1) is measured (Asay et al. 2022).[[25]](#footnote-25) Thus, the main dependent variable (Y1) could affect the mediator (Y2,), rather than Y2 serving as the indirect channel through which the manipulated variable (Z) affects Y1.[[26]](#footnote-26) 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 the concern of correlated unobservables.

When a mediator variable is not manipulated, it is endogenous. In this situation, the assumption of uncorrelated errors can be problematic for the same reasons as in archival studies. Specifically, the estimated effect of the measured mediator on the main dependent variable (α2) is subject to endogeneity bias. Moreover, the estimated effect of the exogenous manipulated variable working indirectly through the measured mediator (α2 $\hat{β}$2) is also subject to bias. Both biases arise because the mediator is endogenous. We therefore investigate whether the experimental studies in our survey utilize endogenous (i.e., measured) mediators 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 the archival and experimental fields draw causal inferences from their path analysis findings (Q1), many state that they use 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. Most studies do not acknowledge that the assumption of uncorrelated errors is equivalent to assuming away the endogeneity problem. In fact, we find no experimental studies that discuss this 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, we find that only one study employs an exogenous (i.e., manipulated) mediator variable. The remaining 137 studies employ measured (i.e., endogenous) mediators. Thus, the statistical inferences of most experimental studies with respect to the mediator’s effect (α2) and the mediated effect of the manipulated variable (α2 $\hat{β}$2) are subject to potential endogeneity concerns, just as in archival research. This evidence emphasizes the recommendation in the psychology literature for experimental researchers to employ manipulated, rather than measured, mediators whenever possible (e.g., Spencer et al. 2005; Pirlott and MacKinnon 2016; Bullock and Green 2021).

Of the 137 studies that employ measured 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 measured mediators, 31 obtain their mediators by observing participant behavior during the experiment. For these 31 studies, there is a potential concern that the unobservables affecting the mediator (Y2) could be correlated with the unobservables affecting the main dependent variable (Y1). The remaining 106 studies use mediators from post-experimental questionnaires. In these studies, there is an additional reverse causality concern given that the mediator (Y2) is measured after the main dependent variable (Y1); i.e., Y1 could have a causal impact on Y2. [[27]](#footnote-27)

Thus, our criticisms of path analysis are not confined to archival studies but apply to the experimental literature as well. In both streams of the literature, mediators are typically endogenous, studies provide inadequate disclosures about the error term assumptions, and studies do not explain the implications of their assumptions for causal inferences.

*3.6. An example from the experimental literature*

We illustrate our points by discussing Bhaskar, Hopkins, and Schroeder (2019), which is one of the experimental studies in our survey.[[28]](#footnote-28) A notable strength of their study is that it provides a well-grounded theoretical explanation for a mediation effect. Further, the study manipulates some of the independent variables which helps to strengthen some of their causal inferences. In common with most studies in our survey, however, the Bhaskar et al. (2019) study employs an endogenous mediator. Accordingly, the estimated effect of the measured mediator (α2) is potentially biased, as is the estimated indirect effect of the manipulated variable working through the mediator (α2 $\hat{β}$2).

Bhaskar et al. (2019) specifically tests 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. Client pressures are manipulated and therefore exogenous, whereas the mediator variable (directional goals) is measured and therefore endogenous. The mediator is measured as the composite score of a participant’s answers to five survey questions related to the participant’s goals. These answers 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.

Endogeneity bias could come through various unobservable factors that jointly affect both the mediator (directional goals) and the main dependent variable (acceptance of aggressive accounting). Both variables could be affected by unobservables such as: i) a participant’s propensity to please others, ii) how much the participant identifies with their career as an auditor, or iii) the participant’s personal ethical standards. Taking the first example from this list, a participant’s propensity to please others could drive their goal to support management (i.e., the mediator, Y2) while also driving the participant’s decision to not recommend accounting adjustments (i.e., the main dependent variable, Y1). Consequently, this unobservable could cause the errors to be correlated, which would bias both the estimated effect of the measured mediator (i.e., α2) and the estimated mediating effect of the manipulated variable (i.e., α2 $\hat{β}$2). Thus, the indirect effect of the manipulated variable could be biased even though the manipulated variable is exogenous due to random assignment of participants.

*3.7. An example from the archival literature*

To highlight the importance of the error term assumption, we provide an example from the archival literature. In this example, we estimate the same system of equations varying only the error term assumption (i.e., correlated or uncorrelated errors). Specifically, we replicate one of the path analyses in Li et al. (2021). We choose this study for a couple of reasons. First, the system of equations is over-identified (i.e., there are more exclusion restriction than endogenous mediators), which means we are able to examine how varying the assumption of correlated versus uncorrelated errors affects the estimated coefficients. Second, the study uses publicly available (or readily available) datasets.[[29]](#footnote-29)

Li et al. (2021) tests whether market liquidity is affected by mandatory IFRS adoption and whether this effect is mediated by disclosure quality. Using the notation adopted earlier, market liquidity is the main dependent variable (Y1), disclosure quality is the mediator (Y2), and IFRS adoption is an exogenous variable (X). The study has a set of exogenous variables (Z) that affect disclosure quality but that are assumed to have no direct effect on market liquidity. Thus, their system of equations is over-identified.

Similar to most path analysis studies, Li et al. (2021) do not disclose whether they assume correlated or uncorrelated errors. Further, Li et al. (2021) do not attempt to justify their exclusion restrictions. We take their exclusion restrictions as given and explore the implications of assuming correlated or uncorrelated errors. *A priori*, we note that the assumption of uncorrelated errors may be questionable as unobservable factors could affect both market liquidity and disclosure quality. For example, audit quality could affect both market liquidity and disclosure quality. To the extent that audit quality is not entirely observable, the unobservables affecting market liquidity are potentially correlated with the unobservables affecting disclosure quality.

Following Li et al. (2021), we estimate the following system of equations:

*Ln(PRC\_IMPACT)* = β1 + β2 *DQ* + *ControlsPRC* + *Country FE* + *Industry FE* + u1 (8)

*DQ* = α1 + *ControlsDQ* + *Country FE* + *Industry FE* + u2 (9)

The market liquidity variable (Y1) is *Ln(PRC\_IMPACT)*, which is the natural log of the median Amihud (2002) illiquidity measure over the fiscal year. The mediator variable (Y2) is *DQ*, which captures the number of line items reported in the financial statements (following Chen et al. (2015) but altered for Compustat Global). The exogenous variables in (10) are represented by *ControlsPRC* while the exogenous variables in (11) are represented by *ControlsDQ*. The variables in *ControlsPRC* are: *POST* (an indicator equal to one in the years after *IFRS* adoption and zero otherwise), IFRS (an indicator equal to one if the firm is in a country that mandatorily adopted IFRS and zero otherwise), *POST × IFRS*, the lagged number of zero returns days in the fiscal year, lagged size, and the lagged natural log of return volatility over the previous fiscal year. The variables in *ControlsDQ* are: *POST*, *IFRS*, *POST × IFRS*, size, leverage, sales growth, ROA, an M&A indicator, a Big 4 indicator, a qualified audit opinion indicator, the natural log of return volatility over the fiscal year, the natural log of a country’s GDP per capita, and the natural log of a country’s market capitalization per capita. Notice that *ControlsDQ* contains several variables that are not in *ControlsPRC*. These variables, therefore, serve as exclusion restrictions. We do not attempt to justify the exclusion restrictions chosen by Li et al. (2021) as our objective is to highlight the importance of the error term assumption. Finally, (10) and (11) include country fixed effects and industry fixed effects following Campbell (1996). In each equation, the exogenous variable of interest is *POST × IFRS*, which captures mandatory IFRS adoption.

We estimate equations (8) and (9) twice, once under the assumption of uncorrelated errors (i.e., cov (u1 u2) = 0) and once under the assumption of correlated errors (i.e., cov (u1 u2) ≠ 0). The results are shown in Panels A and B of Figure 4.

[Insert Figure 4 here]

Consistent with Li et al. (2021), the *POST × IFRS* coefficients are positive and statistically significant in both the *Ln(PRC\_IMPACT)* and *DQ* regressions. However, the coefficient magnitudes are rather different across Panels A and B, suggesting that the results are sensitive to the assumption of correlated or uncorrelated errors. More importantly, the sign on the *DQ* coefficient in the *Ln(PRC\_IMPACT)* equationflips when going from the uncorrelated to correlated error term assumption. Specifically, the *DQ* coefficient is significantly positive in Panel A, suggesting that disclosure quality is associated with an increase in illiquidity.[[30]](#footnote-30) In contrast, the *DQ* coefficient is significantly negative in Panel B, suggesting that disclosure quality is associated with a decrease in illiquidity.[[31]](#footnote-31) Thus, varying only the error term assumption results in opposite conclusions for the sign of the effect of the endogenous mediator (disclosure quality) on the main outcome variable (market liquidity). We do not claim that every system of equations will see a sign flip when altering the error term assumption. However, this example illustrates the importance of the error term assumption by showing that altering the assumption can flip the sign of the coefficient on the mediator and can dramatically impact the coefficient magnitudes.

**4. Conclusion and recommendations for future research**

Causal inferences do not become stronger when a study simply assumes away the endogeneity problem. However, this is what many path analysis studies have done as they assume (sometimes explicitly but usually implicitly) that the errors in their system of equations are uncorrelated. Typically, studies do not disclose or attempt to defend their assumption of uncorrelated errors. 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. Accordingly, our criticisms of the path analysis methodology apply to studies in the experimental field as well as the archival literature.

We conclude with five 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.

1. *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 (Y2) are uncorrelated with the unobservables affecting the main outcome variable (Y1)? When there exists substantial doubt about the validity of this assumption, the study should note the limitation 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 to strengthen their causal inferences. In fact, OLS and path analysis generate identical coefficient estimates in the equation with the endogenous regressor 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 causal estimates. 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, the coefficient estimates can be different depending on whether the researcher is estimating the path analysis equations using FIML or an alternative IV approach (i.e., 2SLS, LIML, or GMM). In this situation, the study can report sensitivity tests to check whether its inferences are sensitive to the estimation method employed.

5) *Consider whether path analysis or instrumental variable estimation is more appropriate.*

When researchers employ a mediation analysis, they should carefully explain whether path analysis or instrumental variable estimation is more appropriate for their setting. Moreover, researchers should discuss the plausibility of the assumptions that underpin the choice. Specifically, researchers should discuss whether it is more reasonable to assume uncorrelated errors or it is more reasonable to assume exclusion restrictions. If neither assumption is plausible then the endogeneity problem has not been resolved, in which case researchers should avoid drawing causal inferences from the estimated regressions.

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X

Y1

u1

Z

Y2

u2

**Figure 1**

A diagrammatic representation of the Y1 and Y2 equations.

Y1 = α1 + α2 Y2 + α3 X + u1

Y2 = β1 + β 2 Z+ β3 X + u2

The error terms are assumed to be correlated (i.e., cov (u1 u2 ) ≠ 0) as shown by the curved double-headed arrow connecting u1 and u2. The Z variable is assumed to have no direct impact on Y1 as shown by the absence of a straight-line arrow connecting Z to Y1.

X

Y1

u1

Z

Y2

u2

**Figure 2**

A diagrammatic representation of the Y1 and Y2 equations.

Y1 = α1 + α2 Y2 + α3 X + α4 Z + u1

Y2 = β1 + β2 Z+ β3 X + u2

The error terms are assumed to be uncorrelated (cov (u1 u2 ) = 0) as shown by the absence of a curved double-headed arrow connecting u1 and u2. The Z variable is assumed to have a direct impact on Y1 as shown by the straight-line arrow connecting Z to Y1.



**Figure 3**

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*).

**0.231\*\*\***

*Controls*DQ

u2

*Controls*PRC

u1

**4.48\*\*\***

**0.045\*\*\***

*DQ*

*POST×IFRS*

*Ln(PRC\_IMPACT)*

**Panel A: Uncorrelated errors**

**0.977\*\*\***

*Controls*DQ

u2

*POST×IFRS*

*DQ*

u1

*Controls*PRC

**-12.78\*\*\***

*Ln(PRC\_IMPACT)*

**0.044\*\*\***

**Panel B: Correlated errors**

**Figure 4**

*Ln(PRC\_IMPACT)* = β1 + β2 *DQ* + *ControlsPRC* + *Country FE* + *Industry FE* + u1

*DQ* = α1 + *ControlsDQ* + *Country FE* + *Industry FE* + u2

Panel A assumes uncorrelated errors (as shown by the absence of a curved arrow connecting u1 and u2), whereas Panel B allows the error terms to be correlated (as shown by the curved arrow connecting u1 and u2).

*Ln(PRC\_IMPACT)* is the natural log of the median Amihud (2002) illiquidity measure. *DQ* captures the number of line items in the financial statements following Chen et al. (2015). The variables in *ControlsPRC* are: *POST* (an indicator equal to one in the years after *IFRS* adoption and zero otherwise), IFRS (an indicator equal to one if the firm is in a country that mandatorily adopted IFRS and zero otherwise), *POST × IFRS*, the lagged number of zero returns days in the fiscal year, lagged size, and the lagged natural log of return volatility over the previous fiscal year. The variables in *ControlsDQ* are: *POST*, IFRS, *POST × IFRS*, size, leverage, sales growth, ROA, M&A indicator, a Big 4 indicator, a qualified audit opinion indicator, the natural log of return volatility over the fiscal year, the natural log of a country’s GDP per capita, and the natural log of a country’s market capitalization per capita.

\*\*\* indicates statistical significance at the 1% level (two-tailed).

**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 | 130 | 22 | 22 | 19 | 193 |
| Q1. Do the authors draw causal inferences from their path analysis findings? | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No |
|  | 100 | 30 | 18 | 4 | 17 | 5 | 19 | 0 | 154 | 39 |
| 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 |
|  | 51 | 49 | 13 | 5 | 10 | 7 | 7 | 12 | 78 | 76 |
| 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 |
|  | 103 | 27 | 19 | 3 | 14 | 8 | 15 | 4 | 151 | 42 |
| 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 | 130 | 22 | 22 | 19 |
| Q1. Do the authors assume uncorrelated errors? | Yes b | No | Yes | No | Unclear c | Yes | No | Unclear c | Yes | No | Unclear c |
|  | 130  | N/A | 1 | 2 | 19 | 0 | 3 | 19 | 0 | 1 | 18 |
| 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 | 128 | 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 |  |
|  |  |  | 7 | 15 |  |  |  |  | 4 | 15 |  |
| 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 130 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 | 130 | 22 | 22 | 19 |
| Q1. Do the authors include one or more path diagrams to illustrate their system of equations? | Yes | No | Yes | No | Yes | No | Yes | No |
|  | 111 | 19 | 22 | 0 | 21 | 1 | 18 | 1 |
| 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 | 110 | 0 | 22 | 0 | 21 | 0 | 18 |
| 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 |
|  | 25 | 38 | 6 | 13 | 5 | 9 | 5 | 6 |
|  |  |  |  |  |  |  |  |  |
| 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 | No |  | Yes | No |  |
|  | 113 | 25 |  | 41 | 14 |  |
| 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 |  |
|  | 52 | 61 |  | 31 | 10 |  |
| Q3. Do the authors impose exclusion restrictions on the covariates? | Yes a | No | Unclear b | Yes  | No | Unclear b |
|  | 29 | 90 | 19 | 12 | 40 | 3 |
| Q4. Do the authors assume uncorrelated errors? | Yes | No | Unclear c | Yes | No | Unclear c |
|  | 90 | 5 | 43 | 40 | 2 | 13 |
| 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 | No |  | Yes | No |  |
|  | 0 | 90 |  | 2 | 38 |  |
| Q6. Is the mediator in the experimental study an exogenous (i.e., manipulated) variable? | Yes | No |  |  |  |  |
|  | 1 | 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 | No |  |  |  |  |
|  | 118 | 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 A**

**The historical origins of path analysis, early criticisms, and subsequent proliferation**

To illustrate the path analysis methodology, Wright (1921) utilizes an empirical example of guinea pigs. Specifically, he estimates how the weight of guinea pigs at their age of weaning (33 days old) (*Weight 33*) is affected by: the guinea pig’s weight at birth (*Weight birth*), external conditions (*External*), heredity (*Heredity*), and litter size (*Litter size*). The *Weight birth* variable is a 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*).[[32]](#footnote-32) The path diagram in Figure A shows Wright’s system. It 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*.

*Weight birth*

*Weight 33*

*Gestation*

*period*

*Condition of Dam*

*Litter size*

*Heredity of Dam*

*Heredity*

*External*

**Figure A**

Wright (1921) does not formally state the system of estimated equations; nor does it not disclose anything about the error terms. Nevertheless, the equations can be indirectly inferred from the path diagram, as shown in (1A) to (4A).

*Weight 33* = α1 + α2 *Weight birth* + α3 *External* + α4 *Heredity* + α5 *Litter* + u1 (1A)

*Weight birth* = β1 + β2 *Gestation* + β3 *Dam Condition* + β4 *Heredity* + β5 *Litter* + u2  (2A)

*Gestation* = γ1 + γ2 *Litter* + γ3 *Dam Condition* + u3 (3A)

*Dam Condition* = δ1 + δ2 *Heredity of Dam* + δ3 *External* + u4 (4A)

Note that (2A) has two exogenous covariates (*Heredity* and*Litter*), which are included as covariates in (1A) as well. Thus, (1A) lacks any exclusion restrictions. In the absence of exclusion restrictions, (1A) is identified by assuming that the errors in (1A) and (2A) are uncorrelated (i.e., cov (u1 u2) = 0).

The assumption of uncorrelated errors is far from innocuous in this setting. Effectively, Wright (1921) assumes that the unobservable factors affecting a guinea pig’s weight at birth (the mediator variable in (1A)) are uncorrelated with the unobservable factors that affect that same guinea pig’s weight at 33 days (the main dependent variable in (1A)). In other words, Wright (1921) implicitly assumes uncorrelated errors (i.e., cov (u1 u2) = 0). In our view, the assumption of uncorrelated errors is not very plausible because one would expect similar unobservable factors to affect both weight variables. For example, a guinea pig could be born with health defects that affect its weight at birth and its weight at 33 days. Such birth defects may not be genetically linked to the guinea pig’s mother, in which case they would reside in the error terms. To the casual reader, Wright’s assumption of uncorrelated errors may not be immediately obvious because his path diagram fails to include the error terms and his article does not explicitly state that it assumes uncorrelated errors.

The usefulness of the path analysis methodology was strongly disputed in the 1920s by a fellow geneticist, Henry Niles, who described Wright’s claims about causality as fallacious. Like us, Niles’ primary objection rests with Wright’s presumption that causality can be inferred by simply positing a system of causal relations in a path diagram and then estimating the set of statistical correlations implied by the diagram.[[33]](#footnote-33)

*“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 statistical 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 popular. Starting with sociology in the 1960s, path analysis spread quickly to other disciplines including psychology, education, political science, and business (Wolfle 2003). Many studies in these disciplines use language that reinforces the notion that path analysis is somehow synonymous with 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).

**APPENDIX B**

**Some estimation issues in over-identified systems**

Path analysis models are sometimes estimated using Full Information Maximum Likelihood (FIML) instead of OLS.[[34]](#footnote-34) The FIML path coefficients in the equation with the endogenous regressor are identical to the OLS coefficients when the researcher assumes uncorrelated errors. When the researcher allows the errors to be correlated, 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 other IV estimators. Moreover, the coefficients in an over-identified system are different across alternative IV estimators as well. In Appendix B, we briefly explain why FIML, LIML, 2SLS and GMM generate different coefficient estimates in systems that are over-identified.

 Consider an over-identified system with correlated errors (cov (u1 u2) ≠ 0).

Y1 = α1 + α2 Y2 + α3 X + u1 (1B)

Y2 = β1 + β2 Z+ β3 X + β4 W + u2 (2B)

This system should not be estimated using OLS because the errors are correlated, raising concerns about bias in (1B) due to the presence of the endogenous mediator, Y2. Instead, the system must be estimated using IV by imposing one or more exclusion restrictions on the exogenous covariates. The above system is over-identified because (1B) has a single endogenous mediator (Y2) 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.[[35]](#footnote-35) Thus, in LIML, the over-identifying restrictions in the other equation (2B) are not considered when estimating the coefficients of the equation with the endogenous mediator (1B). In FIML, the over-identifying restrictions are taken into account when estimating the system. Imposing an additional exclusion restriction in the other equation (2B) 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.[[36]](#footnote-36) 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.

 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).[[37]](#footnote-37) K-class estimators are IV estimators in which the actual and predicted values of the endogenous regressor (Y2) take a special form:

$Y\_{2}^{\*}=\left(1-k\right)Y\_{2}+k\hat{Y\_{2}}$ where 0 ≤ k ≤ 1.

In the 2SLS approach, k is assumed to equal one. That is, 2SLS employs the predicted value of the endogenous regressor ($\hat{Y\_{2}}$) (see the earlier discussion in Section 2.1). In OLS, k is assumed to equal zero (i.e., OLS uses the actual value of Y2 rather than the predicted value of Y2 because Y2 is assumed to be exogenous). LIML generates an estimated value of k somewhere between these two extremes (0 ≤ k ≤ 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 coefficient estimates, with the matrix also being estimated. Consequently, the GMM coefficients are different from other estimation methods (2SLS, LIML, FIML) when the system of equations is over-identified.

**Appendix C**

**Studies using path analysis (sorted by accounting journal)**

|  |  |  |
| --- | --- | --- |
| *Journal of Accounting & Economics* |  | *Journal of Accounting Research* |
| Authors | Year |  | Authors | Year |
| Barton & Mercer | 2005 |  | Phillips | 1999 |
| Landsman, Maydew, & Thornock | 2012 |  | Bushee & Noe | 2000 |
| Jackson, Keune, & Salzsieder | 2013 |  | Ittner, Lanen, & Larcker | 2002 |
| Hilary, Hsu, Segal, & Wang | 2016 |  | Hatfield, Agoglia, & Sanchez | 2008 |
| Schoenfeld | 2017 |  | Koonce & Lipe | 2010 |
| Adhikari, Agrawal, & Malm | 2019 |  | Rennekamp | 2012 |
| Nagar, Schoenfeld, & Wellman | 2019 |  | Brown | 2014 |
| Tan, Wang, & Yoo | 2019 |  | Clor-Proell & Maines | 2014 |
| WheelerBonsall IV, Green, & Muller III | 20192020 |  | Griffith, Hammersley, Kadous, & Young | 2014 |
| Hills, Kubic, & Mayew | 2021 |  | Cardinaels & Yin | 2015 |
| Hung, Kraft, Wang, & Yu | 2022 |  | Ham, Lang, Seybert, & Wang | 2017 |
| Yue, Zhang, & Zhong | 2022 |  | Bonner, Majors, & Ritter | 2018 |
|  |  |  | Elliott, Grant, & Hodge | 2018 |
|  |  |  | Bhaskar, Hopkins, & Schroeder | 2019 |
|  |  |  | Brown, Gale, & Grant | 2021 |
|  |  |  | Bochkay, Markov, Subasi, Weisbrod | 2022 |
|  |  |  | Commerford, Dennis, Joe, & Ulla | 2022 |
|  |  |  |  |  |
|  |  |  |  |  |
| *The Accounting Review* |
| Authors | Year |  | Authors | Year |
| Cloyd & Spilker | 1999 |  | Hales, Venkataraman, & Wilks | 2012 |
| Towry | 2003 |  | Kadous, Koonce, & Thayer | 2012 |
| MercerJackson | 20052008 |  | Masschelein, Cardinaels, & Van den Abbeele | 2012 |
| Kadous, Magro, & Spilker | 2008 |  | Schloetzer | 2012 |
| Clor-Proell | 2009 |  | Pike, Curtis, & Chui | 2013 |
| Denison | 2009 |  | Presslee, Vance, & Webb | 2013 |
| Maas & Matějka | 2009 |  | Tafkov | 2013 |
| Wolfe, Mauldin, & Diaz | 2009 |  | Choi | 2014 |
| Ahn, Hwang, & Kim | 2010 |  | Arnold | 2015 |
| Hatfield, Houston, Stefaniak, & Usrey | 2010 |  | BaileyBowlin, Hobson, & Piercey | 20152015 |
| Reffett | 2010 |  | Lo | 2015 |
| Rose, Norman, & RoseTayler | 20102010 |  | Mayew, Sethuraman, & Venkatachalam | 2015 |
| Agoglia, Doupnik, & Tsakumis | 2011 |  | Tan, Wang, & Zhou | 2015 |
| Huelsbeck, Merchant, & Sandino | 2011 |  | Brasel, Doxey, Grenier, & Reffett | 2016 |
| Bhattacharya, Ecker, Olsson, & Schipper | 2012 |  | Brazel, Jackson, Schaefer, & StewartChoi, Hecht, Tafkov, & Towry | 20162016 |
| Bushee & MillerChrist, Sedatole, & Towry | 20122012 |  | DeFond, Lim, & ZangGimbar, Hansen, & Ozlanski | 20162016 |
| Elliott, Hodge, & Sedor | 2012 |  | Humphreys, Gary, & Trotman | 2016 |
|  |  |  |  |  |
| *The Accounting Review – Continued* |
| Authors | Year |  | Authors | Year |
| Nelson, Proell, & Randel | 2016 |  | Bhaskar | 2020 |
| Cannon & Bedard | 2017 |  | Elliott, Fanning, & Peecher | 2020 |
| Erickson, Hewitt, & Maines | 2017 |  | Hecht, Hobson, & Wang | 2020 |
| Farrell, Grenier, & Leiby | 2017 |  | Kunz & Staehle | 2020 |
| Koch & Salterio | 2017 |  | Liu, Huang, Jiang, & Messier Jr. | 2020 |
| Maksymov & NelsonArnold, Hannan, & Tafkov | 20172018 |  | Mayew, Sethuraman, & Venkatachalam | 2020 |
| Asay & Hales | 2018 |  | Mendoza | 2020 |
| Bochkay, Chychyla, Sankaraguruswamy, & Willenborg | 2018 |  | Murphy & SandinoBauer, Fang, & PittmanBochkay & Joos | 202020212021 |
| Bonsall IV, Green, & Muller III | 2018 |  | Hobson, Sommerfeldt, & Wang | 2021 |
| Cardinaels, Chen, & Yin | 2018 |  | McAllister, Blay, & Kadous | 2021 |
| Commerford, Hatfield, & Houston | 2018 |  | YoungAnderson, Cheng, Phua | 20212022 |
| Griffith | 2018 |  | Blum, Hatfield, & Houston | 2022 |
| Haesebrouck, Cools, & Van den Abbeele | 2018 |  | Bogdani, Causholli, & KnechelBrazel, Leiby, & Schaefer | 20222022 |
| Loftus & Tanlu | 2018 |  | Cao, Duh, Tan, & Xu | 2022 |
| Tang & Venkataraman | 2018 |  | Chang | 2022 |
| Badertscher, Shanthikumar, & Teoh | 2019 |  | Douthit, Martin, & McAllisterGale | 20222022 |
| Bentley | 2019 |  | Hong | 2022 |
| Brown & Fanning | 2019 |  | Mendoza & Winn | 2022 |
| Church, Jiang, Kuang, & Vitalis | 2019 |  | Schuhmacher, Towry, & Zureich | 2022 |
| Dyreng, Hanlon, & Maydew | 2019 |  | Tan & Yeo | 2022 |
| Tsang, Xie, & Xin | 2019 |  |  |  |
| Bauer, Bucaro, & Estep | 2020 |  |  |  |
|  |  |  |  |  |
|  |  |  |  |  |
| *Contemporary Accounting Research* |
| Authors | Year |  | Authors | Year |
| Kadous & Magro | 2001 |  | Hobson | 2011 |
| Kadous & Sedor | 2004 |  | Lu, Richardson, & Salterio | 2011 |
| Webb | 2004 |  | Asare & Wright | 2012 |
| Wilks & Zimbelman | 2004 |  | Clor-Proell, Proell, & Warfield | 2014 |
| Blay | 2005 |  | Koonce, Miller, & Winchel | 2015 |
| Jackson & Hatfield | 2005 |  | Winchel | 2015 |
| Kadous, Koonce, & Towry | 2005 |  | Bhattacharjee & Moreno | 2017 |
| Sawers | 2005 |  | Capps, Koonze, & White | 2017 |
| Hodge, Martin, & Pratt | 2006 |  | Elliott, Grant, & Rennekamp | 2017 |
| Banker & Mashruwala | 2007 |  | Koonce & Lipe | 2017 |
| Brazel & Agoglia | 2007 |  | Rupar | 2017 |
| Glover, Prawitt, & Wood | 2008 |  | Asay | 2018 |
| Williamson | 2008 |  | Bol & Leiby | 2018 |
| Tan & Trotman | 2010 |  | Wright & Bhattacharjee | 2018 |
|  |
| *Contemporary Accounting Research – Continued* |
| Authors | Year |  | Authors | Year |
| Arnold, Gillenkirch, & Hannan | 2019 |  | Dunn, Lundstrom, & Wilkins | 2021 |
| Arnold & Tafkov | 2019 |  | Fanning, Williams, & Williamson | 2021 |
| Bratten, Causholli, & Omer | 2019 |  | Gimbar & Mercer | 2021 |
| Commerford, Hermanson, Houston, & Peters | 2019 |  | Grasser, Majerczyk, Staehle, & YangGriffith, Kadous, & Young | 20212021 |
| Garrett, Livingston, & Tayler | 2019 |  | He, Li, Liu, & Pittman | 2021 |
| Kadous & ZhouAlderman & Jollineau | 20192020 |  | Hurley, Mayhew, Obermire, & Tegeler | 2021 |
| Bauer, Fang, Pittman, Zhang, & Zhao | 2020 |  | Li, Siciliano, & VenkatachalamPickerd & Piercey | 20212021 |
| Bucaro, Jackson, & Lill | 2020 |  | Rennekamp & Witz | 2021 |
| Demere, Donohoe, & Lisowsky | 2020 |  | Anderson, Hobson, & Sommerfeldt | 2022 |
| Demerjian, Donovan, & Lewis-Western | 2020 |  | Files & LiuGillette & Stinson | 20222022 |
| Hayes & Reckers | 2020 |  | Helikum, Tan, & Xu | 2022 |
| Hewitt, Hodge, & Pratt | 2020 |  | Joe, Luippold, & Sanderson | 2022 |
| Johnson, Theis, Vitalis, & Young | 2020 |  | Klassen & Ruiz | 2022 |
| Kachelmeier, Rimkus, Schmidt, & Valentine | 2020 |  | Tafkov, Towry, & ZhouWaddoups | 20222022 |
| Kang, Piercey, & Trotman | 2020 |  |  |  |
| Newman, Tafkov, & Zhou | 2020 |  |  |  |
| Tang, Wang, & Zhou | 2020 |  |  |  |
| Dezoort, Doxey, & Pollard | 2021 |  |  |  |
|  |  |  |  |  |
|  |  |  |  |  |
| *Review of Accounting Studies* |  |  |  |
| Authors | Year |  |  |  |
| Elliott, Rennekamp, & White | 2015 |  |  |  |
| Mattei & Platikanova | 2017 |  |  |  |
| Cardinaels, Hollander, & White | 2019 |  |  |  |
| Chapman, Drake, Schroeder, & Seidel | 2021 |  |  |  |
| Cho & Krishnan | 2021 |  |  |  |
| Fox & Wilson | 2022 |  |  |  |
| Huang, Shen, & Zang | 2022 |  |  |  |
| Kim, McGuire, Savoy, & Wilson | 2022 |  |  |  |
| Li, Maydew, Willis, & Xu | 2022 |  |  |  |
| Pham, Merkoulova, & Veld | 2022 |  |  |  |
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1. \* We appreciate helpful comments from Patricia Dechow, Ed deHaan, Mark DeFond, Kristin Diehl, Shelley Li, Miguel Minutti-Meza, Matt Shaffer, Sarah Bonner, Tim Seidel, Jonathan Shipman, Richard Sloan, Quinn Swanquist, Dan Taylor, Chenqi Zhu (discussant), and workshop participants at the Illinois Symposium on Auditing Research, the 16th Annual Bauer Accounting Research Symposium (University of Houston), the Western Region AAA Doctoral Student-Faculty Interchange, and the University of Southern California. [↑](#footnote-ref-1)
2. The introduction to Wright’s (1921) article leaves the reader in little doubt that he considers path analysis to be a causal methodology (page 557): *“The present paper is an attempt to present a method of measuring the direct influence along each separate path in such a system and thus of finding the degree to which variation of a given effect is determined by each particular cause.”* [↑](#footnote-ref-2)
3. Spencer et al. (2005, page 846) observes that *“by manipulating* ***both*** *the independent variable* ***and*** *the mediating variable we can make strong inferences about the causal chain of events”*. [↑](#footnote-ref-3)
4. Bullock and Green (2021, page 16) criticize path analysis studies in the psychology literature for failing to defend their assumption of uncorrelated errors. The authors note: “*We are unaware of published articles in psychology in which authors argued persuasively that cov(e1, e2) is zero for their application.*” [↑](#footnote-ref-4)
5. ANOVA and OLS are identical when the researcher uses categorical independent variables. When the independent variables are not categorical, ANOVA is not appropriate (researchers can instead use OLS). [↑](#footnote-ref-5)
6. A covariate is exogenous if it is uncorrelated with the unobservables that affect the endogenous variables (Y1 and Y2). Thus, the assumption that X and Z are exogenous is equivalent to assuming that cov (X u1) = 0, cov (X u2) = 0, cov (Z u1) = 0, and cov (Z u2) = 0. [↑](#footnote-ref-6)
7. Eqs. (1) and (2) show a recursive system in which Y2 affects Y1 but Y1 does not affect Y2. We present a recursive system because all the accounting studies in our survey estimate 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 Y2 affects Y1 *and* Y1 affects Y2. 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. [↑](#footnote-ref-7)
8. IV estimation has been discussed in Larcker and Rusticus (2010), but there is no similar work on path analysis and there is no work showing the connections between path analysis and IV estimation. [↑](#footnote-ref-8)
9. The exclusion restriction is sometimes called the “only-through condition” (e.g., Atanasov and Black 2021) because it is assumed that Z affects Y1 only indirectly through Y2, i.e., Z does not affect Y1 directly. [↑](#footnote-ref-9)
10. 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). [↑](#footnote-ref-10)
11. A researcher cannot test the assumption of uncorrelated errors by examining the correlation between the estimated residuals (cov ($\hat{u}$1 $\hat{u}$2)). Such a test would be invalid because endogeneity causes $\hat{u}$1 to be a biased estimate of u1. Hence, cov ($\hat{u}$1 $\hat{u}$2) ≠ cov (u2 u1) when endogeneity bias is present. The only way to test the assumption of uncorrelated errors is to use a Hausman test for endogeneity bias after estimating the system of equations using IV estimation. The Hausman test requires the researcher to assume that Z has no direct effect on Y1 (i.e., α4 = 0) because otherwise the IV system would be under-identified. [↑](#footnote-ref-11)
12. 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)). [↑](#footnote-ref-12)
13. The regression R2 cannot be used to infer whether an endogeneity problem is present or absent. For example, eq. (1) could have a high R2 if α2 is biased upwards due to the endogeneity in Y2. Similarly, eq. (1) could have a low R2 if α2 is biased towards zero due to the endogeneity in Y2. In general, a regression R2 provides no information about whether the estimated coefficients are biased or unbiased (e.g., Cramer 1987; Gu 2007). [↑](#footnote-ref-13)
14. Figure 1 also allows the exogenous variables to correlate as denoted by the curved double-headed arrow that connects X and Z. [↑](#footnote-ref-14)
15. As explained in Appendix A, Wright (1921) assumes that the unobservable factors affecting a guinea pig’s weight at birth are uncorrelated with the unobservable factors that affect that same guinea pig’s weight at 33 days. This assumption is implausible because one would expect similar unobservable factors to affect both weight variables. For example, a guinea pig could be born with health defects that affect its weight at birth and its weight at 33 days. Such birth defects may not be genetically linked to the guinea pig’s mother, in which case they would reside in the error terms as unobservables. [↑](#footnote-ref-15)
16. Coincidentally, the IV method was introduced by Sewall’s father, Phillip Wright, a few years later in 1928 (P. Wright 1928). [↑](#footnote-ref-16)
17. 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, we often don’t bother to draw it, to keep the drawing simpler, but if it’s not explicitly drawn, it’s implicitly present.”* Streiner (2005, p. 117; emphasis added). [↑](#footnote-ref-17)
18. 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.*” [↑](#footnote-ref-18)
19. 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 (Y1 <- Y2 X) (Y2 <- X Z)*. A researcher can override the default option and allow the errors to be correlated by modifying the command as follows: *sem (Y1 <- Y2 X) (Y2 <- X Z), cov(e. Y1\*e. Y2)*. [↑](#footnote-ref-19)
20. 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. [↑](#footnote-ref-20)
21. Upon publication of this manuscript, we will provide a link to a co-author’s website which provides teaching notes, sample data, STATA code, and STATA output to illustrate the three approaches discussed in this section. We do not provide the link currently because we wish to preserve the anonymity of the authors in the review process. The materials at the website demonstrate the following: 1) the coefficients and standard errors are the same in path analysis and OLS when the researcher assumes uncorrelated errors, 2) the coefficients and standard errors are the same in path analysis and IV estimation when the researcher assumes correlated errors and a just-identified system, and 3) the coefficients and standard errors are different in path analysis and IV estimation when the researcher assumes correlated errors and an over-identified system. [↑](#footnote-ref-21)
22. 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. [↑](#footnote-ref-22)
23. Section 3.5 provides a detailed discussion of path analysis in experimental accounting research. [↑](#footnote-ref-23)
24. Creating and thinking about causal diagrams can benefit a paper’s hypotheses development and empirical tests by bringing focus to theoretical underpinnings of the predictions made. Gow et al. (2016) therefore recommend that researchers use path diagrams when estimating structural equation systems. We agree with their recommendation. Our point is simply that many of the path diagrams in published research fail to disclose the key elements of these diagrams that assist in the reader in drawing correct conclusions from the results. [↑](#footnote-ref-24)
25. While the manipulation of the main independent variable (Z) forces it to come before the mediator (Y2) and main dependent variable (Y1), the mediator could still be subject to reverse causality concerns with respect to the dependent variable (Y1). [↑](#footnote-ref-25)
26. 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. [↑](#footnote-ref-26)
27. 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, 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.”* [↑](#footnote-ref-27)
28. It is beyond the scope of our review to discuss all 193 studies that use path analysis. The Bhaskar et al. (2019) study is fairly typical of most studies in our survey. [↑](#footnote-ref-28)
29. Our purpose is not to refute the findings in Li et al. (2021) nor to exactly replicate their results. That said, we follow their research design as closely as we can. [↑](#footnote-ref-29)
30. *Ln(PRC\_IMPACT)* is constructed such that negative coefficients indicate an increase in market liquidity (i.e., a decrease in illiquidity). [↑](#footnote-ref-30)
31. The coefficient signs in Panel B are consistent with Li et al. (2021) although the coefficient magnitudes are rather different. [↑](#footnote-ref-31)
32. The mother of a guinea pig is called a dam. [↑](#footnote-ref-32)
33. Similar to Niles (1922), Pirlott and MacKinnon (2016, page 30) note in the context of the experimental literature that “*providing statistical evidence of a mediation relationship fails to provide causal evidence of the mediation relationship.*” [↑](#footnote-ref-33)
34. Some researchers, especially in the experimental field, use the PROCESS macro in SPSS to estimate the path analysis equations. The PROCESS macro relies on OLS for estimation. Other researchers, especially in the archival field, use the *sem* command in STATA to estimate path analysis equations. The *sem* command relies on FIML rather than OLS. [↑](#footnote-ref-34)
35. 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. [↑](#footnote-ref-35)
36. See chapter 4 of Angrist and Pischke (2009). [↑](#footnote-ref-36)
37. 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>. [↑](#footnote-ref-37)