# 5 More Than One Mediator

In this chapter, I extend the principles of mediation analysis introduced in Chapter 3 to models with more than one mediator. Such models allow a variable's effect to be transmitted to another through multiple mechanisms simultaneously. Two forms of multiple mediator models are introduced here that differ from each other by whether mediators operate in parallel, without affecting one another, or in series, with mediators linked together in a causal chain. By including more than one mediator in a model simultaneously, it is possible to pit theories against each other by statistically comparing indirect effects that represent different theoretical mechanisms.

In Chapter 3, I introduced the fundamentals of statistical mediation analysis. In the context of a model with a single mediator, I illustrated how the total effect of a causal antecedent $X$ on consequent $Y$ can be partitioned into direct and indirect components, and I described various means of statistically testing hypotheses about total, direct, and indirect effects. As noted at the beginning of that chapter, the simple mediation model is frequently used by researchers, but it often oversimplifies the kinds of phenomena that researchers study. Specifically, because it is based on only a single mediator variable, it doesn't allow the investigator to model multiple mechanisms simultaneously in a single integrated model.

This limitation of the simple mediation model is important for at least four reasons (see, e.g., Preacher & Hayes, 2008a; MacKinnon, 2000, 2008). First, most effects and phenomena that scientists study probably operate through multiple mechanisms at once. Of course, all models are wrong to some extent, and no model will completely and accurately account for all influences on some variable of interest (cf. MacCallum, 2003). But some models are more wrong than others. If you have reason to believe that an antecedent variable's effect on a consequent may or does operate through multiple mechanisms, a better approach is to estimate a model that allows for multiple processes at work simultaneously.

Second, related to this first limitation, it is frequently possible to propose, if not also theoretically likely, that a specific causal influence in a simple mediation model is itself mediated. For instance, the direct effect in a simple mediation model estimates the effect of $X$ on $Y$ independent of $M$. But there may be identifiable mechanisms responsible for the transmission of this effect. In other words, a direct effect could be interpreted as an estimate of the influence of one or more mechanisms that link $X$ to $Y$ other than the mediator already included in the model. Similarly, in a simple mediation model, the $a$ path estimates the *total* effect of $X$ on $M$, and the $b$ path estimates the *total* effect of $M$ on $Y$ controlling for $X$. Each of these total effects could, in principle, be partitioned into direct and indirect components through one or more mediators, just as can the total effect of $X$ on $Y$. Doing so requires the addition of at least one mediator to the simple mediation model.

Third, a proposed mediator could be related to an outcome not because it causes the outcome but because it is correlated with another variable that is causally influencing the outcome. This is the noncausal alternative explanation for an association I referred to in Chapter 2 as *epiphenomenality*. For example, recall the simple mediation analysis of the economic stress study presented in Chapter 3. This model proposed that economic stress influences withdrawal intentions through business-related depressed affect, with depressed affect increased through the experience of economic stress, which in turn enhances desire to withdraw from entrepreneurship. But suppose that in fact it is not depressed business-related affect that is the mediator but role conflict. Perhaps economic stress leads entrepreneurs to have to spend more time at work, away from family and friends, in order to keep their business afloat. This conflict between roles (e.g., role as business leader, provider for the family, spouse, or father or mother) may enhance the desire to change occupations as a means of bringing the demands of competing roles into better balance. If business-related depressed affect were correlated with feelings of role conflict, then a failure to include role conflict in the model as a mediator could result in the mistaken claim that depressed affect is the mediator transmitting the effect of stress on withdrawal intentions.

Finally, the inclusion of multiple mediators between an antecedent and a consequent allows one to pit competing theories of mechanisms against each other. For instance, theory A may postulate that the effect of $X$ on $Y$ is transmitted primarily through mediator A, whereas theory B stipulates that a different mediator B is the conduit through which $X$ affects $Y$. Inclusion of mediators A and B in an integrated model allows for a formal comparison of the size of the indirect effects of $X$ through them, giving you a means of determining which indirect effect is the stronger of the two (or three, or four, depending on the complexity of the model).

In this chapter, I extend the principles of path analysis and inference described in Chapter 3 to models with more than one mediator. I focus on two forms of the multiple mediator model defined by whether the mediators are linked together in a causal chain (the *serial* multiple mediator model) or are merely allowed to correlate but not causally influence another mediator in the model (the *parallel* multiple mediator model). I also discuss models that blend parallel and serial processes.

## 5.1 The Parallel Multiple Mediator Model

In a parallel multiple mediator model, antecedent variable $X$ is modeled as influencing consequent $Y$ directly as well as indirectly through two or more mediators, with the condition that no mediator causally influences another. For example, Teixeira et al. (2010) simultaneously examined three potential mediators of the effectiveness of a 30-session, 1-year, experimental weight loss intervention among middle-aged women. These mediators included emotional eating (e.g., eating to placate a negative mood), restrained eating (e.g., not eating after feeling full), and perceived barriers to exercise. Figure 5.1 depicts this model in conceptual form. They found that relative to women randomly assigned to a control weight loss program, those who experienced the experimental method did lose more weight over the year. The mediation analysis suggested that the intervention reduced frequency of emotional eating and increased restraint while eating, which in turn resulted in greater weight loss. But independent of these two mechanisms, there was no evidence that the intervention influenced weight loss by changing perceived barriers to exercise.

A statistical diagram of a parallel multiple mediator model with $k$ mediators is depicted in Figure 5.2. There are other forms that a multiple mediator model can take. A defining feature of the parallel multiple mediator model that distinguishes it from an alternative multiple mediator model, the serial multiple mediator model described in section 5.4, is the constraint that no mediator is modeled as influencing another mediator in the model. This constraint is apparent in Figure 5.2 by the absence of any unidirectional arrows linking any mediator to any other mediator. This is not to say that the mediators are assumed to be independent. In fact, in most circumstances, the mediators are likely to be correlated. Even if they are not, there still may be some advantage to estimating a parallel multiple mediator model with $k$ mediators rather than $k$ simple mediation models. Doing so could result in a power boost for tests of indirect effects if the

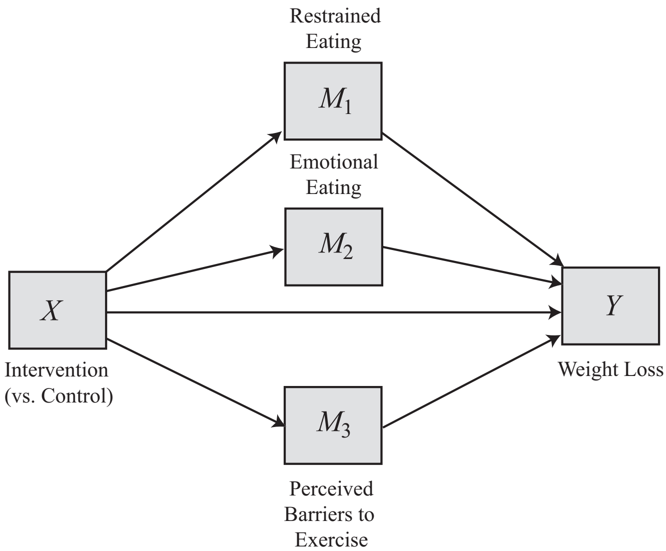


**FIGURE 5.1.** A conceptual diagram of a parallel multiple mediator model.

mediators are highly correlated with $Y$ but weakly correlated with each other, and doing so affords the ability to compare the sizes of the indirect effects through different mediators.

In principle, the number of mediators one can include in a parallel multiple mediator model is limited only by the number of cases in one's data file and the number of variables one has the foresight to measure as possible mediators. In practice, models with two mediators are most commonly estimated (e.g., Gurmen & Rohner, 2014; Kurti & Dallery, 2014; Quintana-Orts, Rey, Chamizo-Nieto, & Worthington, 2020; Pitts, Safer, Castro-Chapman, & Russell, 2018; Spinhoven, Penninx, Krempeniou, van Hemert, & Elzinga, 2015; Scogin, Morthland, DiNapoli, LaRocca, & Chaplin, 2015). But parallel multiple mediator models can be found with three (e.g., Charalambous, Giannakopoulou, Bozas, & Paikousis, 2019; D. A. Jones, Willness, & Madey, 2014; Merino, Senra, & Ferreiro, 2016; Vraga, Johnson, Carr, Bode, & Bard, 2014), four (e.g., Alvarez & Juang, 2010; Goldman, Goodboy, & Weber, 2016; Kirby, Jones, & Copello, 2014; Klimmt et al., 2019; Peréz, Abrams, López-Martínez, & Asmundson, 2012), five (e.g., Brandt & Reyna, 2010; Osberg, Billingsley, Eggert, & Insana, 2012; Zadeh, Farnia, & Ungerleider, 2010), six (e.g., Bemister, Brooks, Dyck, & Kirton, 2015; Billard, 2019; Goldman & Goodboy, 2016; Veilleux, Skinner, Reese, & Shaver, 2014; Weiss, 2015), and even as many as seven mediators in a model simultaneously (e.g., Anagnostopoulos, Slater, & Fitzsimmons, 2010; Hsu et al., 2012; Lecheler, Bos, & Vliegenthart, 2015) .

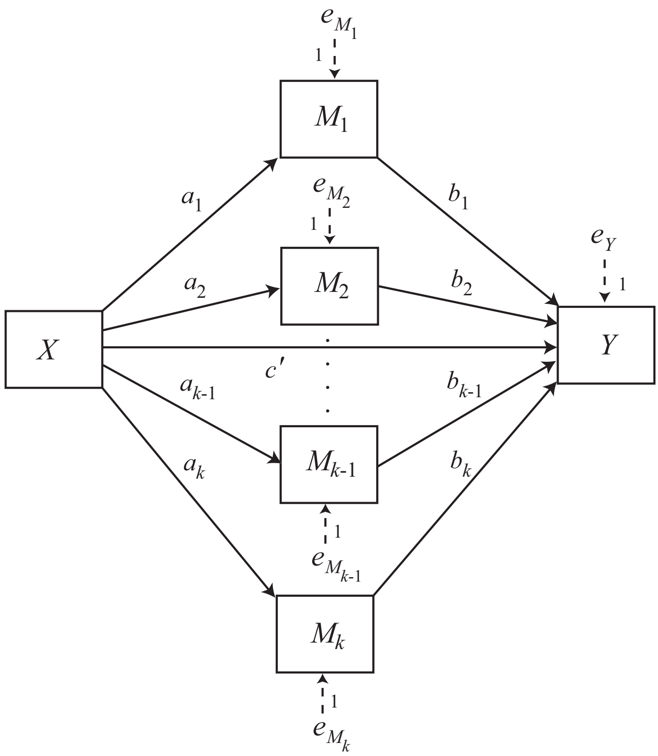


**FIGURE 5.2.** A statistical diagram representing a parallel multiple mediator model with *k* mediators.

As can be seen in Figure 5.2, a parallel multiple mediator model with $k$ mediators has $k + 1$ consequent variables (one for each of the $k$ mediators $M$ and one for $Y$) and so requires $k + 1$ equations to estimate all the effects of $X$ on $Y$. These equations are

$$M_i = i_{M_i} + a_i X + e_{M_i} \quad \text{for all } i = 1 \text{ to } k \tag{5.1}$$

$$Y = i_Y + c'X + \sum_{i=1}^{k} b_i M_i + e_Y \tag{5.2}$$

In this set of equations, $a_i$ estimates the effect of $X$ on $M_i$, $b_i$ estimates the effect of $M_i$ on $Y$ controlling for $X$ and the other $k - 1$ $M$ variables, and $c'$ estimates the effect of $X$ on $Y$ holding all $k$ $M$ variables constant.

Consider a parallel multiple mediator with three mediators, like the weight loss example introduced earlier. With $k = 3$ mediators, four equations are needed:

$$M_1 = i_{M_1} + a_1X + e_{M_1} \quad (5.3)$$
$$M_2 = i_{M_2} + a_2X + e_{M_2} \quad (5.4)$$
$$M_3 = i_{M_3} + a_3X + e_{M_3} \quad (5.5)$$
$$Y = i_Y + c'X + b_1M_1 + b_2M_2 + b_3M_3 + e_Y \quad (5.6)$$

In equations 5.3, 5.4, and 5.5, $a_1$, $a_2$, and $a_3$ quantify the amount by which two cases that differ by one unit on $X$ are estimated to differ on $M_1$, $M_2$, and $M_3$, respectively. In equation 5.6, $b_1$ estimates the amount by which two cases that differ by one unit on $M_1$ differ on $Y$ holding $M_2$, $M_3$, and $X$ constant. Similarly, $b_2$ estimates the amount by which two cases that differ by one unit on $M_2$ differ on $Y$ holding $M_1$, $M_3$, and $X$ constant, and $b_3$ estimates the amount by which two cases that differ by one unit on $M_3$ differ on $Y$ holding $M_1$, $M_2$, and $X$ constant. Finally, $c'$ estimates the amount by which two cases that differ by one unit on $X$ differ on $Y$ holding $M_1$, $M_2$, and $M_3$ constant.

The interpretations of $a_i$ and $c'$ are not dependent on the scale of measurement of $X$. Whether $X$ is a dichotomous variable or a continuum, the interpretation is the same. However, when $X$ is a dichotomous variable with the two groups coded by a one-unit difference, these can be interpreted as estimated mean differences. For instance, suppose the two groups are coded with $X = 0$ or $X = 1$. In that case, $a_i = [\overline{M}_i \mid (X = 1)] - [\overline{M}_i \mid (X = 0)]$, and $c' = [\overline{Y}^* \mid (X = 1)] - [\overline{Y}^* \mid (X = 0)]$, where $\overline{Y}^*$ is an adjusted mean as defined on page 92, with all mediators set to their sample means: $\overline{Y}^* = i_Y + c'X + \sum_{i=1}^{k} b_i\overline{M}_i$.

## Direct and Indirect Effects in a Parallel Multiple Mediator Model

In a parallel multiple mediator as in Figure 5.2, $X$ is modeled to exert its effect on $Y$ through $k + 1$ pathways. One pathway is direct, from $X$ to $Y$ without passing through any of the proposed mediators, and the other $k$ pathways are indirect, each through a single mediator. In a multiple mediator model, the indirect effects are referred to as *specific indirect effects*. Thus, a model with $k$ mediators has $k$ specific indirect effects, one through $M_1$ ($X \rightarrow M_1 \rightarrow Y$), one through $M_2$ ($X \rightarrow M_2 \rightarrow Y$), and so forth, up through $M_k$ ($X \rightarrow M_k \rightarrow Y$).

As in a simple mediation model, the indirect effect of $X$ on $Y$ through a given mediator $M_i$ is quantified as the product of paths linking $X$ to $Y$ through $M_i$. In a parallel multiple mediator model, only two paths link $X$

to $Y$ through $M_i$. The first of these paths is the effect of $X$ to $M_i$, and the second is the path from $M_i$ to $Y$. The regression coefficients corresponding to these paths, when multiplied together, yield the specific indirect effect of $X$ on $Y$ through $M_i$. So consider the three-mediator parallel multiple mediator model estimated with equations 5.3 through 5.6. In this model, the specific indirect of $X$ on $Y$ through $M_1$ is $a_1b_1$, the specific indirect effect through $M_2$ is $a_2b_2$, and the specific indirect effect of $X$ through $M_3$ is $a_3b_3$. Most generally, regardless of the number of mediators, the specific indirect effect of $X$ on $Y$ through $M_i$ is estimated as $a_ib_i$ from equations 5.1 and 5.2.

A specific indirect effect is interpreted just as in the simple mediation model, except with the addition of "controlling for all other mediators in the model." Thus, the specific indirect effect of $X$ on $Y$ through $M_i$ is the estimated amount by which two cases that differ by one unit on $X$ are estimated to differ on $Y$ as a result of the effect of $X$ on $M_i$, which in turn affects $Y$, holding all other mediators constant.

When added together, the specific indirect effects yield the *total indirect effect* of $X$ on $Y$ through all mediators in the model. In a model with $k$ mediators,

$$\text{Total indirect effect of } X \text{ on } Y = \sum_{i=1}^{k} a_ib_i$$

For example, in a parallel multiple mediator model with three mediators represented by equations 5.3 through 5.6, the total indirect effect of $X$ on $Y$ is $a_1b_1 + a_2b_2 + a_3b_3$.

The direct effect of $X$ quantifies how much two cases that differ by one unit on $X$ are estimated to differ on $Y$ independent of all mediators. As discussed earlier, this is $c'$ in the model of $Y$ from $X$ and all mediators (e.g., equation 5.6 for the three-mediator model, or equation 5.2 more generally).

As in the simple mediation model, the sum of the direct and indirect effects is the total effect of $X$. In a model with $k$ mediators, from the coefficients in equations 5.1 and 5.2,

$$c = c' + \sum_{i=1}^{k} a_ib_i \tag{5.7}$$

where $c$ is the total effect of $X$. The total effect can also be estimated by regressing $Y$ on $X$ alone (as in equation 3.4). For instance, in the three-mediator model, $c = c' + a_1b_1 + a_2b_2 + a_3b_3$. Isolation of the total indirect effect in equation 5.7 shows that the total indirect effect is equal to the difference between the total and the direct effects of $X$:

$$\sum_{i=1}^{k} a_ib_i = c - c'$$

## 5.2 Example Using the Presumed Media Influence Study

In Chapter 3, I illustrated a simple mediation analysis using the data from a study conducted in Israel in which participants' reactions to a newspaper article about a likely sugar shortage were assessed (Tal-Or et al., 2010). Recall that half of the participants read an article they were told would be published on the front page of Israel's largest daily newspaper, whereas the other half were told it would appear in an internal economic supplement. After reading the article, their beliefs about how others would be influenced were measured (i.e., the extent to which the general public would be prompted to go buy sugar as a result of the article). The model in that chapter placed these beliefs, presumed media influence (PMI in the data file), as the mechanism or mediator intervening between the experimental manipulation of article location (COND in the data file: 1 for those assigned to the front page condition, 0 to the interior page condition) and intentions to buy sugar (REACTION in the data file). That is, people who thought the article was about to be published on the front page would be more inclined to believe that the public would be influenced relative to those told the article would appear in an economic supplement, so they themselves should go out and buy more sugar before it was all gone.

As described at the beginning of this chapter, establishing an indirect effect of $X$ on $Y$ through $M$ through a simple mediation analysis does not imply that $M$ is the only mechanism at work linking $X$ to $Y$ (cf. Rucker et al., 2011). Furthermore, the indirect effect could be due to an epiphenomenal association between the $M$ in a simple mediation model and the "true" mediator or mediators causally between $X$ and $Y$. Any variable correlated with presumed media influence and also affected by the experimental manipulation of article location could be the actual mediator transmitting the effect of location on intentions to buy sugar.

Fortunately, Tal-Or et al. (2010) recognized this and had the foresight to measure a variable related to another possible mechanism—perceived issue importance. Perhaps people infer, from where an article is published in the newspaper, the extent to which the issue is something worthy of attention, of local or national significance, and thereby potentially something one should think about and perhaps act upon. So they measured people's beliefs about how important the potential sugar shortage was using two questions that were aggregated to form a perceived importance measure (IMPORT in the data file). Significant to the point made earlier, issue importance is correlated with presumed media influence ($r = 0.282, p < .01$). Those relatively more likely to believe others would be influenced to

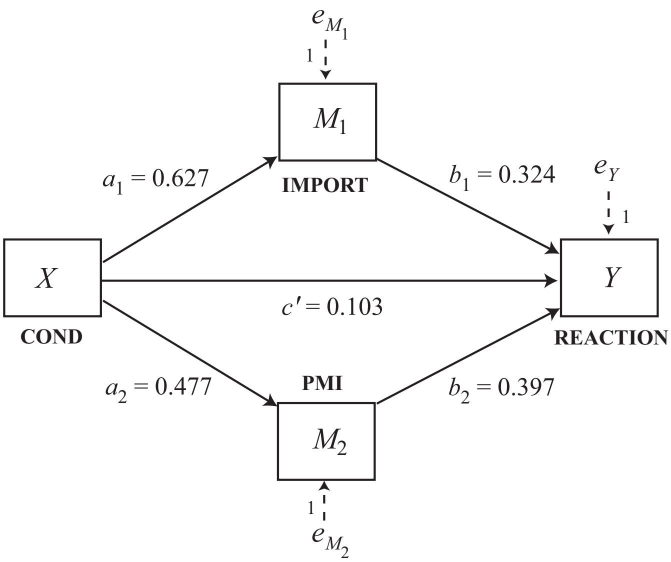


**FIGURE 5.3.** A statistical diagram of the parallel multiple mediator model for the presumed media influence study.

buy sugar as a result of reading the article also perceived the sugar shortage as relatively more important. Thus, it is conceivable that presumed media influence only appears to be functioning as a mediator of the effect of article location on peoples' reactions and it is perceptions of importance that is the real mediator.

Estimation of indirect effects in a parallel multiple mediator model with both presumed media influence and perceived importance as mediators would allow for a simultaneous test of each mechanism while accounting for the association between them. Figure 5.3 provides a statistical diagram of the model. As can be seen, it contains three consequent variables, so it requires three equations to estimate all the effects, one for each of the mediators ($M_1$ and $M_2$), and one for the outcome $Y$. The equations for the mediators contain article location ($X$) as the only predictor, whereas the equation for intentions to buy sugar ($Y$) includes both article location and the two mediators.[1]

[1]Readers familiar with SEM might interpret Figure 5.3 to mean that we are assuming no correlation between the errors in estimation of $M_1$ and $M_2$. In the regression framework that is the topic of this book, it is not necessary to make a distinction at the modeling phase between a fixed and freely estimated error covariance in a model such as this. The regression math allows for the estimation of this correlation, which would take the form of a partial correlation between the residuals from the models of $M_1$ and $M_2$. See section 5.4 for an example and discussion.

In SPSS, the coefficients of this model are estimated with three regression commands:

```
regression/dep=import/method=enter cond.
regression/dep=pmi/method=enter cond.
regression/dep=reaction/method=enter cond import pmi.
```

The corresponding commands in SAS and R are

```
proc reg data=pmi;
model import=cond;model pmi=cond;model reaction=cond import pmi;
run;
```

```
summary(lm(import~cond,data=pmi))
summary(lm(pmi~cond,data=pmi))
summary(lm(reaction~cond+import+pmi,data=pmi))
```

The regression coefficients, standard errors, and other statistics pertinent to the model are summarized in Table 5.1, and the path coefficients are superimposed on the statistical diagram in Figure 5.3.

PROCESS greatly simplifies the estimation process by conducting all these regressions in one command, while also generating various additional statistics and inferential tests discussed in section 5.3 but not available in the OLS regression routines built into SPSS, SAS, and R. The PROCESS commands below estimate the model and generate output pertinent to statistical inference as well as some additional things I discuss later.

```
process y=reaction/x=cond/m=import pmi/total=1/contrast=1/model=4/
    modelres=1/seed=31216.
```

```
%process (data=pmi,y=reaction,x=cond,m=import pmi,total=1,contrast=1,
    model=4,modelres=1,seed=31216);
```

```
process (data=pmi,y="reaction",x="cond",m=c("import","pmi"),total=1,
    contrast=1,model=4,modelres=1,seed=31216)
```

This PROCESS command looks identical to the command for the simple mediation model in Chapter 3, with a few exceptions. First, because the model contains more than one mediator, more than one variable is provided following **m=**. Notice that the inclusion of an additional mediator does not require a different model number; **model=4** is used for both simple

**TABLE 5.1.** Regression Coefficients, Standard Errors, and Model Summary Information for the Presumed Media Influence Parallel Multiple Mediator Model Depicted in Figure 5.3

| | Consequent | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $M_1$ (IMPORT) | | | | $M_2$ (PMI) | | | | $Y$ (REACTION) | | |
| Antecedent | | Coeff. | *SE* | *p* | | Coeff. | *SE* | *p* | | Coeff. | *SE* | *p* |
| $X$ (COND) | $a_1$ | 0.627 | 0.310 | .045 | $a_2$ | 0.477 | 0.236 | .045 | $c'$ | 0.103 | 0.239 | .666 |
| $M_1$ (IMPORT) | | — | — | — | | — | — | — | $b_1$ | 0.324 | 0.071 | < .001 |
| $M_2$ (PMI) | | — | — | — | | — | — | — | $b_2$ | 0.397 | 0.093 | < .001 |
| Constant | $i_{M_1}$ | 3.908 | 0.213 | < .001 | $i_{M_2}$ | 5.377 | 0.162 | < .001 | $i_Y$ | −0.150 | 0.530 | .778 |
| | | $R^2 = 0.033$ | | | | $R^2 = 0.033$ | | | | $R^2 = 0.325$ | | |
| | | $F(1, 121) = 4.094, p = .045$ | | | | $F(1, 121) = 4.088, p = .045$ | | | | $F(3, 119) = 19.112, p < .001$ | | |

mediation models and parallel multiple mediator models. PROCESS automatically detects the number of variables listed in the **m=** list and estimates a parallel multiple mediator model if it sees more than one variable in the list. The order of the variables in this list is not consequential in model 4 for estimation purposes, although it does influence the order in which information about the models and effects is displayed in the output. The second difference is the addition of the **contrast=1** command, which requests PROCESS to conduct a test of differences between specific indirect effects. This test is described in section 5.3.

From Table 5.1 or Figure 5.4, the three best-fitting OLS regression models that define this parallel multiple mediator model are

$$\hat{M}_1 = 3.908 + 0.627X \quad (5.8)$$

$$\hat{M}_2 = 5.377 + 0.477X \quad (5.9)$$

$$\hat{Y} = -0.150 + 0.103X + 0.324M_1 + 0.397M_2 \quad (5.10)$$

Thus, $a_1 = 0.627$, $a_2 = 0.477$, $b_1 = 0.324$, $b_2 = 0.397$, $c' = 0.103$. The use of the **total** option in PROCESS also generates the total effect, $c = 0.496$, from estimating $Y$ from $X$ alone. Very little of the variance in perceived media influence or issue importance is explained by the manipulation of article location (both $R^2 = 0.033$), but about a third of the variance in intentions to buy sugar is accounted for by both proposed mediators and article location, $R^2 = 0.325$.

The most relevant information pertinent to the process being modeled is the direct and indirect effects of article location on participants' reactions to the article. Starting first with the indirect effect through issue importance, this indirect effect is estimated as $a_1b_1 = 0.627(0.324) = 0.203$. PROCESS does the multiplication automatically and displays the indirect effect in the section of output on page 172 labeled "Indirect effect of X on Y" in the row labeled "import." Two cases that differ by one unit on $X$ (i.e., COND, coding the front vs. the interior page condition in this dataset) are estimated to differ by 0.203 units in their intention to buy sugar through perceived importance, with those assigned to the front page condition having higher intentions (because the indirect effect is positive). This positive indirect effect results from two positive constituent effects. Those assigned to the front-page condition have stronger intentions to buy sugar as a result of the tendency for those told the article was to be published on the front page to perceive the sugar shortage as more important than those told it would be published in an interior supplement (because $a_1$ is positive), which in turn was positively related to their own intentions to purchase sugar (because $b_1$ is positive). Because the two experimental groups are coded by a one-unit difference on $X$, this indirect effect is equal to the

```
Model  : 4
    Y  : reaction
    X  : cond
   M1  : import
   M2  : pmi

Sample
Size:  123

Custom
Seed:     31216    <------ Random number seed

**************************************************************************
OUTCOME VARIABLE:
 import

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .1809      .0327     2.9411     4.0942     1.0000   121.0000      .0452     OLS regression
a1                                                                                output (eq. 5.8)
Model
              coeff         se          t          p       LLCI       ULCI
constant     3.9077      .2127    18.3704      .0000     3.4866     4.3288
cond          .6268      .3098     2.0234      .0452      .0135     1.2401

**************************************************************************
OUTCOME VARIABLE:
 pmi

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .1808      .0327     1.7026     4.0878     1.0000   121.0000      .0454     OLS regression
a2                                                                                output (eq. 5.9)
Model
              coeff         se          t          p       LLCI       ULCI
constant     5.3769      .1618    33.2222      .0000     5.0565     5.6973
cond          .4765      .2357     2.0218      .0454      .0099      .9431

**************************************************************************
OUTCOME VARIABLE:
 reaction

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5702      .3251     1.6628    19.1118     3.0000   119.0000      .0000     OLS regression
c'                                                                                output (eq. 5.10)
Model
              coeff         se          t          p       LLCI       ULCI
constant     -.1498      .5298     -.2828      .7778    -1.1989      .8993
cond          .1034      .2391      .4324      .6662     -.3701      .5768
b1 -> import  .3244      .0707     4.5857      .0000      .1843      .4645
pmi           .3965      .0930     4.2645      .0000      .2124      .5806

************************** TOTAL EFFECT MODEL ****************************
b2
OUTCOME VARIABLE:
 reaction

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .1603      .0257     2.3610     3.1897     1.0000   121.0000      .0766     OLS regression
c                                                                                 output
Model
              coeff         se          t          p       LLCI       ULCI
constant     3.2500      .1906    17.0525      .0000     2.8727     3.6273
cond          .4957      .2775     1.7860      .0766     -.0538     1.0452
```

(*continued*)

**FIGURE 5.4.** Output from the PROCESS procedure for SPSS for a parallel multiple mediator model of the presumed media influence data.

```
****************** CORRELATIONS BETWEEN MODEL RESIDUALS *******************

                import        pmi   reaction
import          1.0000      .2578      .0000
pmi              .2578     1.0000      .0000
reaction         .0000      .0000     1.0000

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
   Effect        se         t          p       LLCI      ULCI
    .4957     .2775    1.7860      .0766    -.0538    1.0452

Direct effect of X on Y
   Effect        se         t          p       LLCI      ULCI
    .1034     .2391     .4324      .6662    -.3701     .5768

Indirect effect(s) of X on Y:
              Effect     BootSE   BootLLCI   BootULCI
TOTAL          .3923      .1645      .0908      .7387
import         .2033      .1140      .0063      .4550
pmi            .1890      .1050      .0051      .4267
(C1)           .0144      .1449     -.2675      .3097

Specific indirect effect contrast definition(s):
(C1)          import     minus     pmi

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for bootstrap confidence intervals:
  5000
```

Correlations between regression residuals

$c$ → Total effect; $c'$ → Direct effect; $a_1b_1 + a_2b_2$ → TOTAL; $a_1b_1$ → import; $a_2b_2$ → pmi; $a_1b_1$ - $a_2b_2$ → (C1)

Percentile bootstrap confidence intervals

**FIGURE 5.4** continued.

mean difference in perceived importance multiplied by the partial effect of perceived importance on reactions: $a_1b_1 = ([\overline{M}_1 \mid (X = 1)] - [\overline{M}_1 \mid (X = 0)])b_1 = (4.535 - 3.908)0.324 = 0.203$.

A second indirect effect of article location on intention to buy sugar is modeled through presumed media influence, estimated as $a_2b_2 = 0.477(0.397) = 0.189$ and provided in the PROCESS output. Those assigned to the front-page condition have stronger intentions to buy sugar (by 0.189 units) as a result of the tendency for those told the article was to be published on the front page to perceive others would be influenced by the story more so than those told it would be published in an interior supplement (because $a_2$ is positive), which in turn was positively related to their own intentions to purchase sugar (because $b_2$ is positive). This is equivalent to the mean difference in perceived media influence multiplied by the partial effect of presumed media influence on reactions: $a_2b_2 = ([\overline{M}_2 \mid (X = 1)] - [\overline{M}_2 \mid (X = 0)])b_2 = (5.853 - 5.377)0.397 = 0.189$.

In a parallel multiple mediator model, it is possible to talk about the indirect effect of $X$ on $Y$ summed across all mediators. This is the total indirect effect, defined here as $a_1b_1 + a_2b_2 = 0.627(0.324) + 0.477(0.397) = 0.392$. The total indirect effect is positive, meaning that those assigned to the front-page condition were, on average, 0.392 units higher in their intention to buy sugar than those assigned to the interior page condition as a result of the effect of article location on the mediators, which in turn influence intentions. The total indirect effect often is not of much interest in a multiple mediator model, and sometimes it will be small even when the specific indirect effects are large, which seems paradoxical. More on this in section 5.6.

The direct effect, $c' = 0.103$, quantifies the effect of the manipulation of article location on intentions to buy sugar independent of the effect of the proposed mediators on those intentions. Irrespective of differences between the groups in their perceived media influence and issue importance, and how those mediators relate to intentions to buy sugar, those told the article was to be published on the front page expressed stronger intentions to buy sugar (because $c'$ is positive) than those told it would be published in the interior supplement. Due to the coding of groups by a difference of one unit, $c'$ is equivalent to the difference between adjusted means, as defined and described on page 92. In this case, $c' = [\overline{Y}^* \mid (X = 1)] - [\overline{Y}^* \mid (X = 0)] = 3.538 - 3.435 = 0.103$, where $\overline{Y}^* = -0.150 + 0.103X + 0.324(4.203) + 0.397(5.603)$ from the model of $Y$.

The total effect of article location on intentions to buy sugar is not determined at all by the mediators proposed as intervening between $X$ and $Y$. As it was in the simple mediation model, $c = 0.496$. As promised, this total effect partitions cleanly into the direct effect plus the sum of the specific indirect effects:

$$c = c' + a_1b_1 + a_2b_2 = 0.103 + 0.203 + 0.189 = 0.496$$

meaning that the total indirect effect of $X$ (i.e., the sum of the specific indirect effects) is the difference between the total and direct effects of $X$:

$$c - c' = a_1b_1 + a_2b_2 = 0.496 - 0.103 = 0.203 + 0.189 = 0.392$$

## 5.3 Statistical Inference

In the prior section, I illustrated the estimation of the equations defining a multiple mediator model using the OLS regression procedures built into SPSS, SAS, and R, as well as the PROCESS procedure. The discussion thus far has been purely descriptive in nature. Statistical inference allows for generalization to the process generating the data or the population from which the sample was derived. The inferential procedures available for effects in the parallel multiple mediator model are similar to those in the simple mediation model. The inclusion of multiple mediators also allows for a formal test of the difference between specific indirect effects. I describe such a test in this section.

## Inference about the Direct and Total Effects

As in the simple mediation model, inference about the total and direct effects of $X$ on $Y$ is straightforward. A test of the null hypothesis that ${}_Tc' = 0$ is available in the output from any statistical package that can estimate equation 5.2 using OLS regression. This test is available in two locations on the PROCESS output in Figure 5.4. As can be seen, $c' = 0.103, t(119) = 0.432, p = .666$. The null hypothesis cannot be rejected. Alternatively, a confidence interval can be constructed using equation 2.17, implemented automatically by PROCESS. From the PROCESS output, $-0.370 \leq {}_Tc' \leq 0.577$. Regardless of which method is used, we cannot claim that participants' reactions to the article differ as a function of article location when presumed media influence and perceived importance are statistically controlled.

The total effect of article location on reactions is the sum of the direct and indirect effects. In this parallel multiple mediator model, the total effect $c$ can be estimated by regressing $Y$ on $X$ alone using any OLS regression program. The coefficient for $X$ is the total effect of $X$ in this regression. The **`total`** option in PROCESS generates the relevant output. As can be seen in Figure 5.4, $c = 0.496, p = .077$, with a 95% confidence interval between $-0.054$ and 1.045. This is identical to the total effect of $X$ in the simple mediation example in section 3.3 because the total effect won't be influenced by the number of mediators you place between $X$ and $Y$.

## Inference about Specific Indirect Effects

The normal theory approach for the indirect effect in a simple mediation model described in section 3.4 can be used for statistical inference about specific indirect effects in a parallel multiple mediator model, though for reasons outlined in Chapter 3, I don't recommend this approach. For the specific indirect effect of $X$ on $Y$ through $M_i$, the second-order standard error estimator is

$$se_{a_ib_i} = \sqrt{a_i^2 se_{b_i}^2 + b_i^2 se_{a_i}^2 + se_{a_i}^2 se_{b_i}^2}$$

where $se_{a_i}^2$ and $se_{b_i}^2$ are the squared standard errors of $a_i$ and $b_i$. A test of the null hypothesis that ${}_Ta_{iT}b_i = 0$ is constructed by dividing $a_ib_i$ by the estimated standard error and deriving a $p$-value from the standard normal distribution. Alternatively, a $ci$% confidence interval can be constructed as

$$a_ib_i - Z_{ci\%}se_{a_ib_i} \leq {}_Ta_{iT}b_i \leq a_ib_i + Z_{ci\%}se_{a_ib_i}$$

where $ci$ is the confidence desired (e.g., 95) and $Z_{ci\%}$ is the value in the standard normal distribution that cuts off the upper $(100 - ci)/2\%$ of the distribution from the rest.

Rounding errors and other inaccuracies are nearly inevitable if these computations are done by hand. PROCESS provides normal theory hypothesis tests for specific indirect effects in a parallel multiple mediator model through the use of the **normal** option.

Bootstrap confidence intervals are the better approach to inference when the original data are available for analysis. No assumptions about the shape of the sampling distribution of $a_i b_i$ are made, and bootstrap confidence intervals tend to be more powerful than competing methods such as the normal theory approach (see Williams & MacKinnon, 2008, for simulation results specific to the multiple mediator model). Using the same procedure described on page 100, a bootstrap confidence interval for a specific indirect effect is constructed by taking a random sample with replacement of size $n$ from the sample, estimating each specific indirect effect $a_i b_i^*$ in the resulting data, and repeating this resampling and estimation many times. With several thousand bootstrap estimates of each specific indirect effect, endpoints of the confidence interval are calculated. If zero is outside of a $ci$% confidence interval, then ${}_Ta_{iT}b_i$ is declared different from zero with $ci$% confidence, whereas if the confidence interval straddles zero, the conclusion is that there is insufficient evidence that $X$ affects $Y$ through $M_i$.

Bootstrap confidence intervals for the specific indirect effects generated by PROCESS using the percentile method can be found in Figure 5.4 under the section of the output that reads "Indirect effect(s) of X on Y." By default, 5,000 bootstrap samples are generated. Notice that contrary to the conclusion reached using the normal theory approach, the bootstrap confidence intervals support the claim, with 95% confidence, that article location influences reactions indirectly through both perceived importance (0.006 to 0.455) and presumed media influence (0.005 to 0.427), as both confidence intervals are entirely above zero.

Bootstrapping requires the original data. Although this is not usually a problem, there are occasions when the data may not be available. Monte Carlo confidence intervals are a good substitute for bootstrapping in such a circumstance. The estimation of a Monte Carlo confidence interval for a specific indirect effect proceeds similarly to the estimation procedure in the simple mediation model. The major difference in the procedure relates to the fact that there are multiple $a$ and $b$ distributions to simulate in a multiple mediator model. For a multiple mediator model with $k$ mediators, one could simply use the Monte Carlo method described in section 3.4 $k$ times, once for each specific indirect effect, plugging the values of $a_i$, $b_i$, $se_{a_i}$, and $se_{b_i}$ into a Monte Carlo sampling procedure. An alternative and better approach would acknowledge that the paths from each $M$ to $Y$ in a multiple mediator model are not necessarily independent, and so the Monte Carlo sampling procedure should accommodate this. Preacher and Selig (2012) describe the construction of Monte Carlo confidence intervals in a multiple mediator model and provide R code that does the computation.

### Pairwise Comparisons between Specific Indirect Effects

In a multiple mediator model, it is sometimes of interest to test whether one indirect effect is statistically different from another. For instance, is the specific indirect effect of article location on reactions through perceived importance different from the specific indirect effect through presumed media influence? If the indirect effect of $X$ through mediator $i$ (i.e., $a_i b_i$) is pertinent to the mechanism postulated by one theory and the indirect effect of $X$ through mediator $j$ (i.e., $a_j b_j$) quantifies the mechanism relevant to a second theory, an inference about whether ${}_T a_{iT} b_i = {}_T a_{jT} b_j$ affords a claim as to whether one mechanism accounts for more of the effect of $X$ on $Y$ than the other mechanism, with an important caveat described below. For examples of such questions in the literature about difference between indirect effects, answered using the approach described here, see Goldman et al. (2016), Hart (2011), Merino et al. (2016), Peréz et al. (2012), and Scogin et al. (2015).

Although it might seem that such a comparison between specific indirect effects would be impossible if the mediators are measured on different metrics, it turns out this is not a problem. A specific indirect effect is interpreted as the amount by which two cases differing by one unit on $X$ are estimated to differ on $Y$ through the intervening variable independent of the other intervening variables. This interpretation does not include the metric of the intervening variable. Specific indirect effects are scaled entirely in terms of the metrics of $X$ and $Y$ (see MacKinnon, 2000, 2008; Preacher & Hayes, 2008a), so two specific indirect effects of the same antecedent on the same consequent can be meaningfully compared even if the mediator variables are measured on different scales. Thus, standardization or other forms of arithmetic gymnastics applied to the measurement scales is not necessary to conduct an inferential test of the equality of specific indirect effects from $X$ to $Y$ in a multiple mediator model.

Two inferential approaches have been most widely discussed and disseminated in the literature. A normal theory approach is described by Preacher and Hayes (2008a) and MacKinnon (2000) based on dividing $a_i b_i - a_j b_j$ by an estimate of its standard error. One estimator of the standard error of the difference is

$$se_{a_i b_i - a_j b_j} = \sqrt{\begin{array}{l} b_i^2 se_{a_i}^2 - 2 b_i b_j COV_{a_i a_j} + b_j^2 se_{a_j}^2 + \\ a_j^2 se_{b_j}^2 - 2 a_i a_j COV_{b_i b_j} + a_i^2 se_{b_i}^2 \end{array}}$$

where $COV_{a_i a_j}$ is the covariance between $a_i$ and $a_j$, and $COV_{b_i b_j}$ is the covariance between $b_i$ and $b_j$. MacKinnon (2000) offers a different standard error estimator that does not require the covariance between $a_i$ and $a_j$ by assuming it is zero, which is equivalent to constraining the correlation between the residuals in the models of $M_i$ and $M_j$ to be zero:

$$se_{a_i b_i - a_j b_j} = \sqrt{b_i^2 se_{a_i}^2 + b_j^2 se_{a_j}^2 + a_j^2 se_{b_j}^2 - 2a_i a_j COV_{b_i b_j} + a_i^2 se_{b_i}^2}$$

The ratio of the difference to its standard error is then calculated and a $p$-value for a test of the null hypothesis that ${}_T a_{iT} b_i = {}_T a_{jT} b_j$ can be derived using the standard normal distribution. Alternatively, a 95% confidence interval for the difference can be computed as

$$(a_i b_i - a_j b_j) \pm 1.96 se_{a_i b_i - a_j b_j} \tag{5.11}$$

In this expression, 1.96 can be replaced with an appropriate critical $Z$ from a table of normal probabilities for different confidence levels (e.g., 1.645 for 90% or 2.57 for 99% confidence).

Like all normal theory approaches discussed thus far, this method requires the assumption that the sampling distribution of the difference between specific indirect effects is normal. It turns out that this is a fairly reasonable assumption, but since an assumption can never be proven true, bootstrapping offers an alternative without requiring this assumption. A bootstrap confidence interval is derived by estimating the difference between specific indirect effects over repeated bootstrap sampling and model estimation. Using the resulting empirical approximation of the sampling distribution of the difference between specific indirect effects, a bootstrap confidence interval for the difference can be constructed with the same procedure described thus far.

PROCESS offers bootstrap confidence intervals for pairwise comparisons between specific indirect effects with the addition of **contrast=1** to the PROCESS command. In a model with $k$ mediators, PROCESS will conduct $k(k-1)/2$ pairwise comparisons, one for each possible difference between specific indirect effects. A confidence interval that does not contain zero provides evidence that the two indirect effects are statistically different from each other, whereas a confidence interval that straddles zero supports the claim of no difference between the specific indirect effects.

The output this option generates for the parallel multiple mediator model of the presumed media influence study can be found in Figure 5.4 in the indirect effects section in the row labeled "(C1)." There is only one comparison listed, because in a parallel multiple mediator model with two mediators, there are only two specific indirect effects, so only one pairwise comparison is possible. The PROCESS output provides a key for the meaning of (C1) at the bottom of Figure 5.4, which in this case is the specific indirect effect through importance minus the specific indirect effect through presumed media influence (i.e., $a_1b_1 - a_2b_2$). The point estimate of the difference between specific indirect effects is $0.203 - 0.189 = 0.014$, but a 95% confidence interval straddles zero ($-0.268$ to $0.310$). So we can't say definitively these specific indirect effects are different from each other.

It is tempting to interpret this as a test of the difference in *strength* of the mechanisms at work linking $X$ to $Y$, or that one indirect effect is larger than another in an absolute sense. However, such an interpretation is justified only if the two specific indirect effects being compared are of the same sign. Consider, for instance, the case where $a_ib_i = -0.30$ and $a_jb_j = 0.30$. A test of the difference between these specific indirect effects may lead to the claim that their difference is not zero, but this does not mean the mechanisms are of different strength or that one indirect effect is bigger. The point estimates suggest one mechanism results in a positive difference in $Y$ as a result of $X$, whereas the other yields a negative difference of equal magnitude. In an absolute sense, they are equal in size by the point estimates, yet statistically different by an inferential test that considers their sign. But one indirect effect is not *stronger* than the other. Nor can we say that $X$ exerts a larger effect on $Y$ through one of the mediators relative to the other.

But what if you find yourself in a situation where you want to compare the strength of two indirect effects that are different in sign? The literature is largely silent on this, but here are a few options. Rather than defining the contrast as $a_ib_i - a_jb_j$ and then bootstrapping this difference, instead define the contrast as

$$|a_ib_i| - |a_jb_j| \tag{5.12}$$

and bootstrap this difference, which ignores whether a specific indirect effect is positive or negative. A confidence interval for this difference that does not include zero suggests that the indirect effects are different when you ignore sign, meaning that they differ in strength. But if the confidence interval contains zero, then one cannot definitely claim that the indirect effects are different in strength.

PROCESS implements this approach to comparing the strength of two specific indirect effects by constructing a bootstrap confidence interval for the difference using equation 5.12. To get this output, use 2 rather than 1 in the argument of the **contrast** command (i.e., **contrast=2**).

An alternative approach, used by Ter Hoeven, Van Vianen, and Fonner (2016), is based on the recognition that if two indirect effects are of the same size but opposite in sign, then their sum is zero. So a confidence interval for the sum of two indirect effects can be used as a test of equality of strength of two indirect effects that are different in sign. If a confidence interval for the sum of those specific indirect effects includes zero, then the two specific indirect effects can be deemed equal in strength, whereas if the confidence interval excludes zero, then that is interpreted as a difference in the strength of the two indirect effects. Of course, in a two-mediator parallel model, the sum of the two specific indirect effects is just the total indirect effect, and PROCESS will generate this test automatically, as discussed below. However, it should only be interpreted as a test of the equality of the strength of the two specific indirect effects when the two indirect effects being compared are different in sign.

In mediation models with more than two specific indirect effects, this test of equality of strength based on the sum of specific indirect effects opposite in sign can be conducted in PROCESS using a variation on the **`contrast`** option. As documented in Appendix A, PROCESS can construct a confidence interval for a linear combination of specific indirect effects, which a sum of two specific indirect effects is. The weights for each specific indirect effect in the model that define the linear combination are provided using the **`contrast`** option, and PROCESS will construct a bootstrap confidence interval for that linear combination. See page 592 for an example.

A simulation study conducted by Coutts (2020) compared these two approaches to testing the equality of the strength of two specific indirect effects that are opposite in sign. The results of this study suggest that both approaches can work fairly well, but the approach using the sum is better than the difference in absolute values when the two indirect effects are close to zero. In that scenario, the test based on differences in absolute values doesn't perform particularly well in smaller samples. The greater the distance from zero the two specific indirect effects and the larger the sample size, the more comparable the two methods are in performance. These results lead me to recommend using a bootstrap confidence interval for the sum of the specific indirect effects rather than the difference in the absolute values of those indirect effects.

## Inference about the Total Indirect Effect

A multiple mediator model also contains a *total indirect effect*, defined as the sum of all specific indirect effects. It is possible to conduct an inferential test of the total indirect effect using either the normal theory approach, a bootstrap confidence interval, or a Monte Carlo confidence interval. The normal theory approach requires an estimate of the standard error of the total indirect effect, but the formula for constructing it is quite complicated, even in multiple mediator models with only two mediators. Given such complicated expressions and the fact that I do not recommend the normal theory approach to inference about indirect effects, I don't present the details here. They can be found in Preacher and Hayes (2008a) or MacKinnon (2008). Good SEM programs can conduct a normal theory test of the total indirect effect. PROCESS does not provide this test.

The Monte Carlo approach is available for the total indirect effect in a multiple mediator model using code provided by Preacher and Selig (2012), and PROCESS provides a bootstrap confidence interval. As I discuss in section 5.6, the total indirect effect is often not of much interest, and I generally deemphasize it when interpreting a multiple mediator model. As can be seen in the PROCESS output in Figure 5.4, we can be 95% confident that the total indirect effect of article location through both mediators simultaneously is somewhere between 0.091 and 0.739. This supports the claim that perceived importance and presumed media influence collectively mediate the effect of article location on intentions to buy sugar.

## 5.4 The Serial Multiple Mediator Model

Examples of the parallel multiple mediator model like that described in the prior section are abundant in the literature. A distinguishing feature of this model is the assumption that no mediator causally influences another. In practice, mediators will be correlated, but this model specifies that they are not causally so. In the *serial* multiple mediator model, the assumption of no causal association between two or more mediators is not only relaxed, but it is also rejected outright a priori. The goal when an investigator estimates a serial multiple mediator model is to investigate the direct and indirect effects of $X$ on $Y$ while modeling a process in which $X$ causes $M_1$, which in turn causes $M_2$, and so forth, concluding with $Y$ as the final consequent.

Though less common than the parallel multiple mediator model, it is not hard to find exemplars of such models in the literature. For instance, Casciano and Massey (2012) compared the anxiety of residents living in a low-income housing development located in a middle-class neighborhood to a matched group that applied to live in the housing development but remained on the waiting list. They argued that life in a middle-class housing development would reduce exposure to neighborhood disorder (e.g., crime, homeless people, drugs and drug use, violence) relative to those living elsewhere, which would in turn reduce the number of stressful life experiences, which in turn would translate into fewer anxiety symptoms. Their analysis supported the environment → disorder exposure → stressful experiences → anxiety symptoms causal sequence. Other examples in the literature in which a causal process is modeled as operating with mediators linked in series include Aragón, Clark, Dyer, and Bargh (2015), Chugani et al. (2015), Critcher and Lee (2018), Dunning et al. (2021), Feldman (2011), Gramszlo, Geronimi, Arellano, and Woodruff-Borden (2018), Brown-Iannuzzi, Dotsch, Cooley, and Payne (2017), Kan, Lichtenstein, Grant, and Janiszwski (2014), Knobloch-Westerwick and Hoplamazian (2012), Krieger and Sarge (2013), A. Li, Shaffer, and Bagger (2016), Oishi and Diener (2014), Leyva and Hill (2018), Schrift and Moty (2015), Tomfohr, Pung, and Dimsdale (2016), Traut-Mattausch, Wagner, Pollatos, and Jones (2015), Tsang, Carpenter, Robers, Frisch, and Carlisle (2014), Valentine, Li, Penki, and Perrett (2014), and van Jaarsveld, Walker, and Skarlicki (2010).

Serial multiple mediator models can grow in complexity quite rapidly as the number of mediators increases, as increasing the number of mediators increases the number of paths that one can draw between causes and effects. In this section, I restrict discussion to a form of serial mediation in which variables presumed as causally prior are modeled as affecting all variables later in the causal sequence. In a sense, this is the most complex serial mediator model possible because it maximizes the number of paths that need to be estimated. Variations on this model are described in section 5.5 that impose constraints on what variables earlier in the causal sequence affect what variables later.

Two serial multiple mediator models can be found in Figure 5.5 in the form of statistical diagrams. The diagram in panel A depicts a two-mediator model in which $X$ is modeled as affecting $Y$ through four pathways. One pathway is indirect and runs from $X$ to $Y$ through $M_1$ only, a second indirect path runs through $M_2$ only, and a third indirect influence passes through both $M_1$ and $M_2$ in series, with $M_1$ affecting $M_2$. The remaining effect of $X$ is direct from $X$ to $Y$ without passing through either $M_1$ or $M_2$.

This statistical model translates into three equations, because the model contains three consequent variables:

$$M_1 = i_{M_1} + a_1X + e_{M_1} \tag{5.13}$$
$$M_2 = i_{M_2} + a_2X + d_{21}M_1 + e_{M_2} \tag{5.14}$$
$$Y = i_Y + c'X + b_1M_1 + b_2M_2 + e_Y \tag{5.15}$$

Notice in this set of equations that each consequent has all variables assumed to be causally prior as antecedents. So $M_1$ is estimated from $X$ alone, $M_2$ is estimated from $X$ and $M_1$, and $Y$ is estimated from $X$, $M_1$, and $M_2$.

Figure 5.5, panel B, is a serial multiple mediator model with three mediators representing eight distinct effects of $X$ on $Y$, seven indirect and one direct (for examples, see Charalambous et al., 2019; Tomfohr et al.,

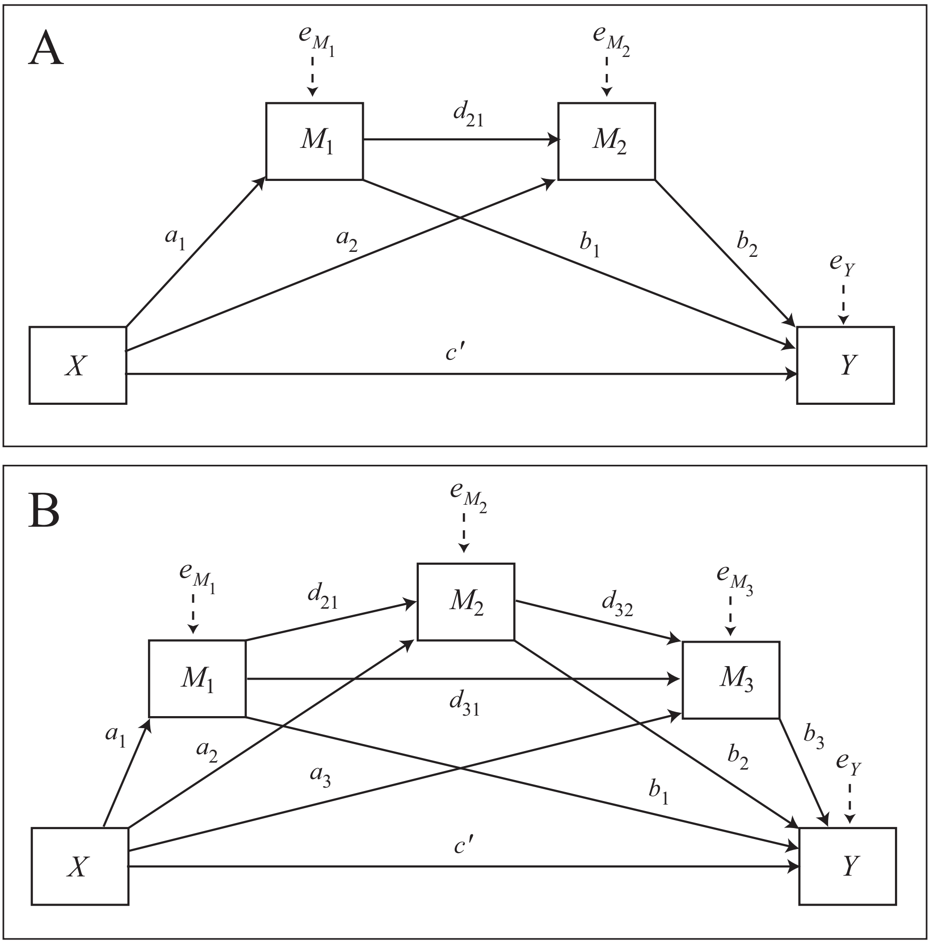


**FIGURE 5.5.** Two serial multiple mediator models in statistical diagram form with two (panel A) and three (panel B) mediators.

2016) The seven indirect paths are found by tracing every possible way of getting from $X$ to $Y$ through at least one $M$. The possibilities include three passing through only a single mediator ($X \rightarrow M_1 \rightarrow Y; X \rightarrow M_2 \rightarrow Y; X \rightarrow M_3 \rightarrow Y$), three passing through two mediators in series ($X \rightarrow M_1 \rightarrow M_2 \rightarrow Y; X \rightarrow M_1 \rightarrow M_3 \rightarrow Y; X \rightarrow M_2 \rightarrow M_3 \rightarrow Y$), and one through all three mediators in series ($X \rightarrow M_1 \rightarrow M_2 \rightarrow M_3 \rightarrow Y$). As always, the direct effect does not pass through any mediators. The four equations (one for each of the four consequent variables) representing the three-mediator serial multiple mediator model are

$$\begin{aligned}
M_1 &= i_{M_1} + a_1X + e_{M_1} \\
M_2 &= i_{M_2} + a_2X + d_{21}M_1 + e_{M_2} \\
M_3 &= i_{M_3} + a_3X + d_{31}M_1 + d_{32}M_2 + e_{M_3} \\
Y &= i_Y + c'X + b_1M_1 + b_2M_2 + b_3M_3 + e_Y
\end{aligned}$$

Most generally, a serial multiple mediator model with $k$ mediators requires $k+1$ equations to estimate because there are $k+1$ consequent variables (one for each of the $k$ mediators, plus one for $Y$):

$$\begin{aligned}
M_1 &= i_{M_1} + a_1X + e_{M_1} \\
M_i &= i_{M_i} + a_iX + \textstyle\sum_{j=1}^{i-1} d_{ij}M_j + e_{M_i} \quad \text{for all } i = 2 \text{ to } k \\
Y &= i_Y + c'X + \textstyle\sum_{i=1}^{k} b_iM_i + e_Y
\end{aligned}$$

## Direct and Indirect Effects in a Serial Multiple Mediator Model

In a serial multiple mediator model, the total effect of $X$ on $Y$ partitions into direct and indirect components, just as it does in the simple and parallel multiple mediator models. Regardless of the number of mediators in the model, the direct effect is $c'$ and interpreted as always—the estimated difference in $Y$ between two cases that differ by one unit on $X$ but that are equal on all mediators in the model. The indirect effects, of which there may be many depending on the number of mediators in the model, are all constructed by multiplying the regression weights corresponding to each step in an indirect pathway. And they are all interpreted as the estimated difference in $Y$ between two cases that differ by one unit on $X$ through the causal sequence from $X$ to mediator(s) to $Y$. Regardless of the number of mediators, the sum of all the specific indirect effects is the total indirect effect of $X$, and the direct and indirect effects sum to the total effect of $X$. I illustrate below for two serial multiple mediator models with either two or three mediators, but the procedure generalizes to serial mediator models with any number of mediators.

**Two Mediators in Series**. Consider the serial multiple mediator model with two mediators. This model has three specific indirect effects and one direct effect. The three specific indirect effects are each estimated as the product of the regression weights linking $X$ to $Y$ through at least one $M$. From Figure 5.5 panel A, the specific indirect effect of $X$ on $Y$ through only $M_1$ is $a_1b_1$, the specific indirect effect through $M_2$ only is $a_2b_2$, and the specific indirect effect through both $M_1$ and $M_2$ in serial is $a_1d_{21}b_2$. Combined, these three indirect effects sum to the total indirect effect of $X$:

$a_1b_1 + a_2b_2 + a_1d_{21}b_2$. When the total indirect effect of $X$ is added to the direct effect of $X$, the result is $c$, the total effect of $X$, which can be estimated from a regression estimating $Y$ from $X$ only, as in equation 3.4. That is,

$$c = c' + a_1b_1 + a_2b_2 + a_1d_{21}b_2$$

As in the simple and parallel multiple mediator models, the total indirect effect of $X$ on $Y$ in the serial multiple mediator model is the difference between the total effect of $X$ on $Y$ and direct effect of $X$ on $Y$:

$$c - c' = a_1b_1 + a_2b_2 + a_1d_{21}b_2$$

**Three Mediators in Series**. These same definitions, rules, and relationships apply to the serial multiple mediator model with three mediators. Considering the three-mediator model in Figure 5.5, there are seven indirect effects estimated as products of regression coefficients. For example, the specific indirect effect of $X$ on $Y$ through $M_2$ only is $a_2b_2$. Through $M_1$ and $M_3$ in serial, the specific indirect effect is $a_1d_{31}b_3$. And the specific indirect effect through $M_1$, $M_2$, and $M_3$ in serial is $a_1d_{21}d_{32}b_3$. Using this same procedure, following all pathways and multiplying coefficients as you go, all seven specific indirect effects can be derived. These sum to the total indirect effect of $X$ on $Y$ through all three mediators: $a_1b_1 + a_2b_2 + a_3b_3 + a_1d_{21}b_2 + a_1d_{31}b_3 + a_2d_{32}b_3 + a_1d_{21}d_{32}b_3$. When the total indirect effect is added to the direct effect, the result is $c$, the total effect of $X$ on $Y$:

$$c = c' + a_1b_1 + a_2b_2 + a_3b_3 + a_1d_{21}b_2 + a_1d_{31}b_3 + a_2d_{32}b_3 + a_1d_{21}d_{32}b_3$$

which means the total indirect effect of $X$ on $Y$ is the difference between the total effect of $X$ on $Y$ and the direct effect of $X$ on $Y$:

$$c - c' = a_1b_1 + a_2b_2 + a_3b_3 + a_1d_{21}b_2 + a_1d_{31}b_3 + a_2d_{32}b_3 + a_1d_{21}d_{32}b_3$$

## Statistical Inference

Inferential tests of direct and indirect effects are analogous to methods described already for the simple and parallel multiple mediator model. A test of the null hypothesis that the direct effect ${}_Tc'$ is equal to zero is available in the output of any OLS regression routine, and an interval estimate is constructed as described in section 5.3.

A comparable normal theory approach for inference about the indirect effects in a serial multiple mediator model proceeds as usual by dividing the indirect effect by an estimate of the standard error and then deriving the $p$-value using the standard normal distribution in order to test the null hypothesis that the indirect effect is zero in the population. The same formulas for the standard errors for indirect effects through a single mediator provided in section 5.3 can be used in the serial multiple mediator model for the $a_ib_i$ indirect effects. With two mediators linked in serial, A. B. Taylor, MacKinnon, and Tein (2008) provide the standard error of the indirect effect of $a_1d_{21}b_2$ as

$$se_{a_1d_{21}b_2} = \sqrt{a_1^2d_{21}^2se_{b_2}^2 + a_1^2b_2^2se_{d_{21}}^2 + d_{21}^2b_2^2se_{a_1}^2}$$

where $se_{a_1}^2$, $se_{d_{21}}^2$, and $se_{b_2}^2$ are the squared standard errors of $a_1$, $d_{21}$, and $b_2$, respectively. The formula for the standard error of the indirect effect involving three or more mediators in serial is complicated and described in Sobel (1982).

Computation of these standard errors by hand is certain to produce inaccuracies, so let a computer do the work for you if you are going to use this approach.[2] But whether computed by hand or by computer, I don't recommend the normal theory approach for the same reasons I don't recommend it in simple or parallel multiple mediation models. It assumes normality of the sampling distribution of the indirect effect—an unrealistic assumption and not necessary to make these days, because simulation research (A. B. Taylor et al., 2008) shows that bootstrap confidence intervals generally perform better without making this assumption.

No modifications to the logic or method of bootstrapping is required to apply this method to the indirect effects in a serial multiple mediator model. Bootstrap confidence intervals for indirect effects (specific, total, or pairwise comparisons between) are calculated by repeatedly resampling from the data with replacement, estimating the model in each bootstrap sample, calculating the indirect effects, and deriving the endpoints of a confidence interval for each as described already. An indirect effect (or a difference between two indirect effects) can be deemed different from zero with *ci*% confidence if zero is outside of a *ci*% confidence interval. If the confidence interval straddles 0, this supports the claim that the indirect effect (or difference between) is not statistically different from zero.

In principle, Monte Carlo confidence intervals can be constructed for all indirect effects in a serial multiple mediator model. As noted earlier, Preacher and Selig (2012) describe Monte Carlo confidence interval construction for specific indirect effects through a single mediator in a parallel multiple mediator model as well as for the total indirect effect. The method and code they illustrate could be adapted without too much difficulty to indirect effects through multiple mediators chained in serial as well.

[2]Some SEM programs can generate standard errors for complex indirect effects.

## Example from the Presumed Media Influence Study

The parallel multiple mediator model of the presumed media influence study estimated and interpreted in sections 5.2 and 5.3 assumes no causal association between the mediators. This does not mean it assumes the mediators are uncorrelated. Mediators in a multiple mediator model typically would be correlated, and the estimation and inference for effects discussed in sections 5.1 and 5.2 take into account the correlation between mediators. The assumption of no causal association between mediators is merely a commitment being made at the modeling stage. The absence of any mediator on the right-hand side of equations 5.8 and 5.9 is a mathematical instantiation of the assumption that neither mediator influences the other mediator. Although plausible in this example, it is perhaps more plausible that people's beliefs about how others are going to be influenced by the media are determined at least in part by perceived issue importance. That is, perhaps those who perceive a particular article pertains to an issue of local, national, or international importance are more likely to believe that others will be affected by what they read about that important topic, then go out and act based on this information. The psychological logic would go something like this: "This article will be published on the front page, so it must be important, and people will take notice of such an important matter and act by buying sugar to stock up. Therefore, I should go out and buy sugar before supplies are all gone."

This process predicts that even after accounting for the effect of article location on both perceived media influence and perceived importance, there should be some association remaining between these mediators. In a parallel multiple mediator model, the partial correlation between $M_1$ and $M_2$ controlling for $X$ is an index of association between mediators remaining after accounting for the effect of $X$ on both. In these data, this partial correlation is $0.258, p < .01$. This partial correlation (though not its $p$-value), requested in the PROCESS command on page 168 with the use of **`modelres=1`** in the command line, can be found in Figure 5.4 under the heading "CORRELATIONS BETWEEN MODEL RESIDUALS." So after statistically adjusting for the effect of the experimental manipulation of article location on both perceived importance and presumed media influence, those who perceive the sugar shortage as relatively more important also presume relatively more media influence. Of course, this correlation remaining after accounting for $X$ could be due to other causes outside of the system being modeled, but it may reflect a misspecification resulting from assuming no causal association between $M_1$ and $M_2$.

A statistical diagram of a serial multiple mediator model consistent with this proposed process can be found in Figure 5.6. This model contains

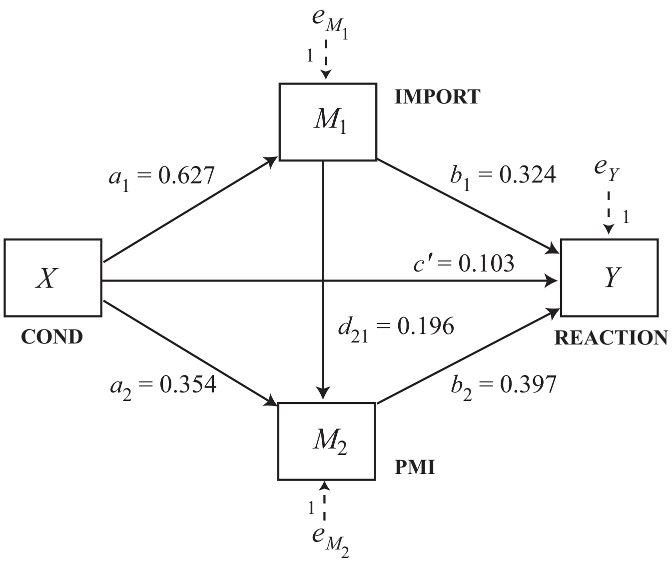


**FIGURE 5.6.** A statistical diagram of the serial multiple mediator model for the presumed media influence data.

one direct and three indirect effects of article location on intentions to buy sugar, pieced together by estimating the regression coefficients in equations 5.13, 5.14, and 5.15. In SPSS, the commands are

```
regression/dep=import/method=enter cond.
regression/dep=pmi/method=enter cond import.
regression/dep=reaction/method=enter cond import pmi.
```

In SAS or R, use

```
proc reg data=pmi;
model import=cond;model pmi=cond import;model reaction=cond import pmi;
run;
```

```
summary(lm(import~cond,data=pmi))
summary(lm(pmi~cond+immport,data=pmi))
summary(lm(reaction~cond+import+pmi,data=pmi))
```

However, the OLS routine built into SPSS, SAS, and R will not calculate any of the indirect effects for you, nor will it provide any inferential tests of the indirect effects such as bootstrap confidence intervals. Better to use PROCESS, which estimates the coefficients and provides additional information needed for inference all in one fell swoop. In SPSS, try the command below.

```
process y=reaction/x=cond/m=import pmi/total=1/contrast=1/model=6/
    seed=031216.
```

The equivalent PROCESS command in SAS is

```
%process (data=pmi,y=reaction,x=cond,m=import pmi,total=1,contrast=1,
    model=6,seed=031216);
```

and in R, use

```
process (data=pmi,y="reaction",x="cond",m=c("import","pmi"),total=1,
    contrast=1,model=6,seed=31216)
```

Notice that this PROCESS command looks very similar to the PROCESS command for the parallel multiple mediator model. The major difference is the specification of **model=6**, which tells PROCESS this is a serial multiple mediator model (see Appendix A). When model 6 is specified, the order of the variables listed in the **m=** list matters, unlike in model 4 where order is ignored. The order of the variables in the list of mediators is taken literally as the causal sequence, with the first mediator variable in the list causally prior to the second in the list, and so forth. This PROCESS command will also generate bootstrap confidence intervals for all indirect effects, as well as all possible pairwise comparisons between indirect effects using 5,000 bootstrap samples. PROCESS does not provide normal theory tests for indirect effects in a serial multiple mediator model.

PROCESS output can be found in Figure 5.7, and the various model coefficients and other assorted statistics are summarized in Table 5.2. The model coefficients have also been superimposed on the statistical diagram for this model in Figure 5.6. Whether extracted from the summary table, the PROCESS output, or the statistical diagram, the model expressed in equation form is

$$\hat{M}_1 = 3.908 + 0.627X \quad (5.16)$$

$$\hat{M}_2 = 4.610 + 0.354X + 0.196M_1 \quad (5.17)$$

$$\hat{Y} = -0.150 + 0.103X + 0.324M_1 + 0.397M_2 \quad (5.18)$$

The direct effect of the manipulation in this serial multiple mediator model is exactly the same as in the parallel multiple mediator model because whether the mediators are modeled as causally influencing each other or not does not change the model of $Y$. That is, the equation for $Y$ is the same in both models, as they each contain only $X$, $M_1$, and $M_2$ as antecedents. This direct effect is positive but not statistically significant, $c' = 0.103, t(119) = 0.432, p = .666$. As we learned from the parallel multiple

**TABLE 5.2.** Regression Coefficients, Standard Errors, and Model Summary Information for the Presumed Media Influence Serial Multiple Mediator Model Depicted in Figure 5.6

| | Consequent | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | $M_1$ (IMPORT) | | | | $M_2$ (PMI) | | | | $Y$ (REACTION) | | |
| Antecedent | | Coeff. | $SE$ | $p$ | | Coeff. | $SE$ | $p$ | | Coeff. | $SE$ | $p$ |
| $X$ (COND) | $a_1$ | 0.627 | 0.310 | .045 | $a_2$ | 0.354 | 0.233 | .131 | $c'$ | 0.103 | 0.239 | .666 |
| $M_1$ (IMPORT) | | — | — | — | $d_{21}$ | 0.196 | 0.067 | .004 | $b_1$ | 0.324 | 0.071 | < .001 |
| $M_2$ (PMI) | | — | — | — | | — | — | — | $b_2$ | 0.397 | 0.093 | < .001 |
| Constant | $i_{M_1}$ | 3.908 | 0.213 | < .001 | $i_{M_2}$ | 4.610 | 0.306 | < .001 | $i_Y$ | −0.150 | 0.530 | .778 |
| | | $R^2 = 0.033$ | | | | $R^2 = 0.097$ | | | | $R^2 = 0.325$ | | |
| | | $F(1, 121) = 4.094, p = .045$ | | | | $F(2, 120) = 6.443, p = .002$ | | | | $F(3, 119) = 19.112, p < .001$ | | |

```
Model  : 6
    Y  : reaction
    X  : cond
   M1  : import
   M2  : pmi

Sample
Size:  123

Custom
Seed:     031216   <---- Random number seed

**************************************************************************
OUTCOME VARIABLE:
 import

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .1809      .0327     2.9411     4.0942     1.0000   121.0000      .0452   OLS regression
                                                                              output (eqs. 5.13
a1                                                                            and 5.16)
Model
              coeff         se          t          p       LLCI       ULCI
constant     3.9077      .2127    18.3704      .0000     3.4866     4.3288
cond          .6268      .3098     2.0234      .0452      .0135     1.2401

**************************************************************************
OUTCOME VARIABLE:
 pmi

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .3114      .0970     1.6027     6.4428     2.0000   120.0000      .0022   OLS regression
                                                                              output (eqs. 5.14
a2                                                                            and 5.17)
Model
              coeff         se          t          p       LLCI       ULCI
constant     4.6104      .3057    15.0836      .0000     4.0053     5.2156
cond          .3536      .2325     1.5207      .1310     -.1068      .8139
import        .1961      .0671     2.9228      .0041      .0633      .3290

**************************************************************************
d21
OUTCOME VARIABLE:
 reaction

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .5702      .3251     1.6628    19.1118     3.0000   119.0000      .0000   OLS regression
                                                                              output (eqs. 5.15
c'                                                                            and 5.18)
Model
              coeff         se          t          p       LLCI       ULCI
constant     -.1498      .5298     -.2828      .7778    -1.1989      .8993
cond          .1034      .2391      .4324      .6662     -.3701      .5768
b1 -> import  .3244      .0707     4.5857      .0000      .1843      .4645
pmi           .3965      .0930     4.2645      .0000      .2124      .5806

************************** TOTAL EFFECT MODEL ****************************
b2
OUTCOME VARIABLE:
 reaction

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      .1603      .0257     2.3610     3.1897     1.0000   121.0000      .0766   OLS regression
                                                                              output
c
Model
              coeff         se          t          p       LLCI       ULCI
constant     3.2500      .1906    17.0525      .0000     2.8727     3.6273
cond          .4957      .2775     1.7860      .0766     -.0538     1.0452
```

(*continued*)

**FIGURE 5.7.** Output from the PROCESS procedure for a serial multiple mediator analysis of the presumed media influence data.

```
************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Total effect of X on Y
    Effect       se         t         p      LLCI      ULCI
     .4957    .2775    1.7860     .0766    -.0538    1.0452

Direct effect of X on Y
    Effect       se         t         p      LLCI      ULCI
     .1034    .2391     .4324     .6662    -.3701     .5768

Indirect effect(s) of X on Y:
              Effect     BootSE   BootLLCI   BootULCI
TOTAL          .3923      .1645      .0908      .7387
Ind1           .2033      .1140      .0063      .4550
Ind2           .1402      .1013     -.0410      .3633
Ind3           .0488      .0354      .0001      .1367
(C1)           .0631      .1573     -.2333      .3855
(C2)           .1546      .0988     -.0005      .3827
(C3)           .0915      .1095     -.1221      .3169

Specific indirect effect contrast definition(s):
(C1)          Ind1      minus    Ind2
(C2)          Ind1      minus    Ind3
(C3)          Ind2      minus    Ind3

Indirect effect key:
Ind1 cond        ->    import      ->    reaction
Ind2 cond        ->    pmi         ->    reaction
Ind3 cond        ->    import      ->    pmi         ->    reaction

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95.0000

Number of bootstrap samples for bootstrap confidence intervals:
  5000
```

$c$ → Total effect; $c'$ → Direct effect; $a_1b_1$ → Ind1; $a_2b_2$ → Ind2; $a_1d_{21}b_2$ → Ind3

TOTAL ← $a_1b_1 + a_2b_2 + a_1d_{21}b_2$

(C1) ← $a_1b_1 - a_2b_2$

(C2) ← $a_1b_1 - a_1d_{21}b_2$

(C3) ← $a_2b_2 - a_1d_{21}b_2$

Bootstrap confidence intervals

**FIGURE 5.7** continued.

mediator model, location of the article in the newspaper is unrelated to intentions to buy sugar independent of the effect of perceived importance and presumed media influence.

This serial multiple mediator model contains four indirect effects estimated as products of regression coefficients linking $X$ to $Y$. These indirect effects can be found in the PROCESS output along with 95% bootstrap confidence intervals based on 5,000 bootstrap samples. Because an indirect effect in a serial mediation model may pass through several mediators, a complete label can be quite lengthy, so PROCESS uses a shorthand notation to label them, along with a key with a lengthier and more descriptive label.

The first indirect effect is the specific indirect effect of article location on reactions through perceived importance of the sugar shortage ($X \rightarrow M_1 \rightarrow Y$), estimated as $a_1b_1 = 0.627(0.324) = 0.203$ and found in the output in the row labeled "Ind1." This indirect effect can be interpreted as significantly positive because the bootstrap confidence interval is entirely above zero (0.006 to 0.455). Those told the article would appear on the front page of the newspaper perceived the sugar shortage as more important (because $a_1$ is positive), and this increased importance was associated with an increased intention to buy sugar (because $b_1$ is positive) independent of presumed media influence.

The second specific indirect effect, labeled "Ind2," is the indirect effect of article location on reactions through only presumed media influence ($X \rightarrow M_2 \rightarrow Y$). Estimated as the product of the effect of article location on presumed media influence ($a_2$) and the effect of presumed media influence on reactions ($b_2$), this indirect effect is 0.354(0.397) = 0.140. However, this path of influence cannot be claimed as definitively different from zero because the bootstrap confidence interval straddles zero (−0.041 to 0.363).

The third indirect effect is found in the output labeled "Ind3." This is the specific indirect effect of article location on reactions through perceived importance and presumed media influence in series, with importance modeled as affecting presumed media influence, which in turn influences intentions to buy sugar (i.e., $X \rightarrow M_1 \rightarrow M_2 \rightarrow Y$). Estimated as $a_1 d_{21} b_2 = 0.627(0.196)0.397 = 0.049$, this specific indirect effect is significantly positive because the bootstrap confidence interval is above zero (0.0001 to 0.137). Relative to those assigned to the interior-page condition, those told the article would appear in the front page perceived the sugar shortage as more important (as $a_1$ is positive), which in turn was associated with a greater perception that others would be influenced by the article (because $d_{21}$ is positive) and this greater perception of influence on others translated into a greater intention to buy sugar (because $b_2$ is positive).

A serial multiple mediator model also contains a total indirect effect, estimated as the sum of all the specific indirect effects. As can be seen in the PROCESS output in the row labeled "Total," the total indirect effect is 0.392 and different from zero as determined by a bootstrap confidence interval that does not contain zero (0.091 to 0.739).

The contrast option of PROCESS, specified by adding **`contrast=1`** to the command line, calculates all possible pairwise comparisons between specific indirect effects. These comparisons are found in the PROCESS output in the rows labeled "(C1)," "(C2)," and so forth, along with a corresponding key toward the bottom. From the PROCESS output, the three differences are

$$
\begin{aligned}
C1 &= a_1b_1 - a_2b_2 = 0.203 - 0.140 = 0.063 \\
C2 &= a_1b_1 - a_1d_{21}b_2 = 0.203 - 0.049 = 0.155 \\
C3 &= a_2b_2 - a_1d_{21}b_2 = 0.140 - 0.049 = 0.091
\end{aligned}
$$

When used in conjunction with the bootstrapping option in PROCESS, confidence intervals for the comparison are also provided for inference about the difference between specific indirect effects. Notice in the PROCESS output that all of the confidence intervals contain zero. The interpretation is that no specific indirect effect is statistically different than any other specific indirect effect.

If you have been following along closely, you might have noticed what seems like a conflict in results here. Earlier, we saw that the specific indirect effect of article location on reactions through presumed media influence *alone* is not definitively different from zero, because the bootstrap confidence interval for this specific indirect effect includes zero. The other two specific indirect effects we could claim are different from zero, as their bootstrap confidence intervals are entirely above zero. If you think of these results in terms of the logic of hypothesis testing, you would say that there is no indirect effect through presumed media influence only, but a positive indirect effect through perceived importance only, as well as through perceived importance and then presumed media influence in series. Yet the bootstrap confidence intervals for differences between any two specific indirect effects all include zero. In hypothesis testing terms, you would conclude from these comparisons that none of the indirect effects differ from each other. Yet how can that be true if some of the indirect effects are different from zero while others are not?

The apparent conflict results from three things you should always keep in mind when interpreting a set of inferential tests in mediation analysis (and, indeed, in any analytical context). First, a test as to whether an effect is different from zero is not the same as a test of whether one effect differs from another effect. They test different hypotheses, and there is no mathematical law that says the result of one test must be consistent with the results of another test of a different hypothesis. Second, difference in significance does not mean statistically different (Gelman & Stern, 2006), just as similarity in significance does not imply statistical equivalence. If an inferential test leads to the conclusion that one thing is different from zero but another is not, that does not mean that those things are necessarily different from each other. This *would* be a conflict if inferential tests were always accurate. But we know that inferential procedures can lead us astray. A failure to reject a null hypothesis doesn't mean the null hypothesis is necessarily true, and rejecting a null hypothesis doesn't mean the null hypothesis is certainly false. Third, there is always uncertainty in our estimates of unknown quantities. A confidence interval that includes zero doesn't mean that thing we are estimating is zero. The confidence intervals for the difference between the specific indirect effect through presumed media influence alone and either of the other two specific indirect effects includes nonzero values. This means that these specific indirect effects *could be* different. We just can't say definitively that they are because the confidence interval includes zero as a possibility.

## 5.5 Models with Parallel and Serial Mediation Properties

In a model with two mediators, the only difference between a serial and a parallel multiple mediator model is the inclusion of a causal path from $M_1$ to $M_2$. The serial model estimates this effect, whereas the parallel model assumes it is zero, which is equivalent to leaving it out of the model entirely. With more than three mediators, a model can be a blend of parallel and serial mediation processes, depending on which paths between mediators are estimated and which are fixed to zero through their exclusion from the model.

Consider the mediation model in statistical form in Figure 5.8, panel A. This model has three mediators, but only $M_1$ has a pathway of influence to the two other mediators, $M_2$ and $M_3$. More complex versions of such a model would include additional mediators stacked in the parallel process operating between $M_1$ and $Y$. Some examples in the literature of a mediation model taking this form include Bombay, Matheson, and Anisman (2012), Gratz, Bardeen, Levy, Dixon-Gordon, and Tull (2015), and Liao, Ho, and Yang (2016).

Using regression analysis, the direct and indirect effects of $X$ on $Y$ in this model can be estimated using four equations, one for each of the three mediators and one for the final consequent $Y$:

$$\begin{aligned}
M_1 &= i_{M_1} + a_1X + e_{M_1} \\
M_2 &= i_{M_2} + a_2X + d_{21}M_1 + e_{M_2} \\
M_3 &= i_{M_3} + a_3X + d_{31}M_1 + e_{M_3} \\
Y &= i_Y + c'X + b_1M_1 + b_2M_2 + b_3M_3 + e_Y
\end{aligned}$$

This model has five specific indirect effects of $X$ on $Y$, discovered by finding all the ways one can trace from $X$ to $Y$ passing through at least one mediator. Each of these specific indirect effects is quantified as the product of the pathways that link $X$ to $Y$. Three of these specific indirect effects pass through only one mediator ($a_1b_1$, $a_2b_2$, and $a_3b_3$) and two pass through two mediators ($a_1d_{21}b_2$ and $a_1d_{31}b_3$). The sum of the specific indirect effects is the total indirect effect. The direct effect of $X$ is $c'$. The specific indirect effects and the direct effect of $X$ sum to produce the total effect of $X$, which can also be estimated by regressing $Y$ on $X$ alone.

If $X$ feeds immediately into a parallel mediation process, with the parallel process then sending pathways to a common additional mediator, the result is a model such as depicted in Figure 5.8, panel B. This model includes three mediators stacked in parallel, but variations on this model exist in the literature with as few as two mediators in the parallel process to as many as six (see, e.g., Krieger, Katz, Kam, & Roberto, 2012; Moyer-Guse, Chung, & Jain, 2011; Leyva & Hill, 2018; Richard & Purnell, 2017; Robertson & Barling, 2013; Schriesheim & Liu, 2018; Valdesolo & Graham, 2014).

The direct and indirect effects of $X$ for the model in Figure 5.8, panel B, can be estimated using five equations, one for each of the four mediators and one for the final consequent:

$$\begin{aligned}
M_1 &= i_{M_1} + a_1X + e_{M_1} \\
M_2 &= i_{M_2} + a_2X + e_{M_2} \\
M_3 &= i_{M_3} + a_3X + e_{M_3} \\
M_4 &= i_{M_4} + a_4X + d_{41}M_1 + d_{42}M_2 + d_{43}M_3 + e_{M_4} \\
Y &= i_Y + c'X + b_1M_1 + b_2M_2 + b_3M_3 + b_4M_4 + e_Y
\end{aligned}$$

This model has seven specific indirect effects, four passing through only one mediator ($a_1b_1, a_2b_2, a_3b_3$, and $a_4b_4$), and three passing through two mediators ($a_1d_{41}b_4, a_2d_{42}b_4$, and $a_3d_{43}b_4$). These sum to produce the total indirect effect. The direct effect of $X$ is $c'$, and the direct and indirect effects sum to produce the total effect of $X$ on $Y$. In this model, as in the others discussed in this chapter, the total effect can also be estimated by regressing $Y$ on $X$ without any of the mediators in the model.

Inference about the total and direct effects come from the regression output for the models of $Y$ (one with all the mediators in the model for the direct effect, and one without the mediators for the total effect) just as in other mediation analyses described thus far. And any of the methods for inference about an indirect effect in sections 5.1 and 5.4 can be used in models such as these. PROCESS simplifies the analysis considerably, as it has each of these two forms of a "parallel–serial" model preprogrammed (in Appendix A, models 80 and 81; also see model 82 for an interesting model blending parallel and serial processes). The output will include all regression coefficients with standard errors, $t$- and $p$-values, and confidence intervals, as well as bootstrap confidence intervals for all the indirect effects. And the **`contrast`** option can be used to conduct all possible pairwise comparisons between specific indirect effects.

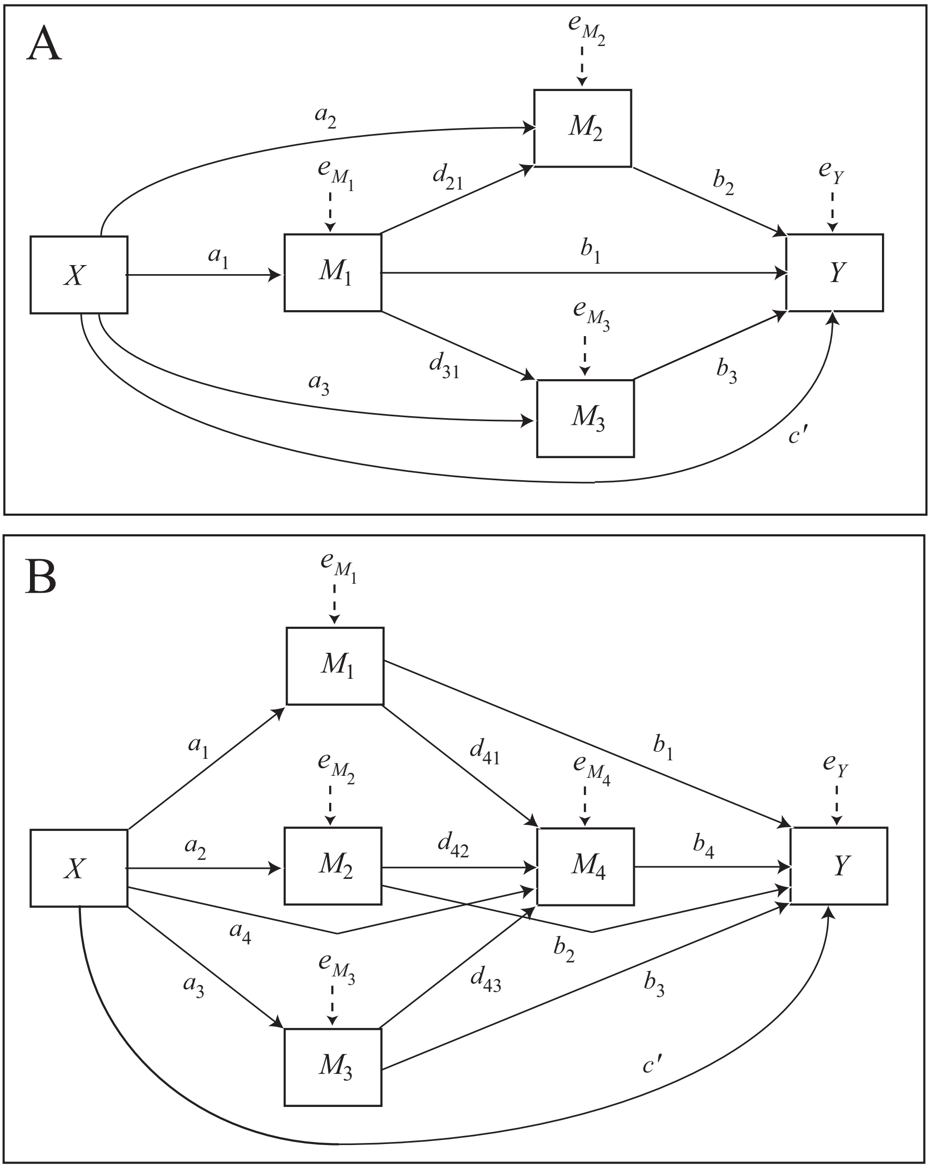


**FIGURE 5.8.** Some models that combine properties of parallel and serial mediation.

## 5.6 Complementarity and Competition among Mediators

This chapter has been dedicated to mediation models containing more than one mediator. At this point, the benefits of estimating multiple mechanisms of influence in a single model are no doubt apparent. But the inclusion of more than one mediator in a model does entail certain risks as well, and at times the results of multiple mediator model may appear to contradict the results obtained when estimating a simpler model with a single mediator. Some of the risks, paradoxes, and contradictions that sometimes can occur are worth some acknowledgment and discussion.

First, a specific indirect effect quantifies the influence of $X$ on $Y$ through a particular mediator while holding constant other mediators. This means it is possible that a simple mediation analysis reveals evidence of an indirect effect of $X$ on $Y$ through $M_1$ when $M_1$ is the sole mediator in the model, but no such indirect effect when $M_1$ is included in a model along with $M_2$, $M_3$, and so forth. This will occur with greater likelihood when the mediators are somewhat correlated, which is precisely the circumstance in which a multiple mediator model is most useful. But when the intercorrelation between mediators becomes too large, the usual problems with collinearity in regression models begin to take hold and muddle the results, as the paths from each mediator to the outcome are estimated controlling for all other mediators. Collinearity between predictors increases sampling variance in estimates of their partial relationships with an outcome (J. Cohen et al., 2003; Darlington & Hayes, 2017; Fox, 1991), and such sampling variance will propagate throughout the estimates of indirect effects and increase the width of confidence intervals for both asymmetric and symmetric confidence intervals or increase $p$-values from normal theory tests for specific indirect effects.

With evidence of an indirect effect when a mediator is considered in isolation but not when considered in a model with multiple mediators, it is reasonable to ask which result is correct. But there is no good answer to this question. In fact, they could both be correct because the specific indirect effect in a multiple mediator model estimates something different than the indirect effect in a simple mediation model. The indirect effect in a model with a single mediator confounds influence through that sole mediator and other mediators it may be correlated with but that are excluded from the model. Including correlated mediators in the model allows you to disentangle spurious and epiphenomenal association from potential causal association, but this comes at the cost of greater sampling variance and reduced power for tests of indirect effects.

Second, remember that the total indirect effect of $X$ quantifies how differences in $X$ relate to differences in $Y$ through all mediators at once. Evidence that the total indirect effect is different from zero supports the claim that, taken together, $X$ influences $Y$ indirectly in some fashion through one or more of these mechanisms these mediators represent. However, because the indirect effect is a sum over all specific indirect effects, some seemingly paradoxical results are possible.

One possibility is when the total indirect effect is not different from zero according to the outcome of an inferential test, even though one or more of the specific indirect effects is. Two scenarios can produce such an apparent paradox. Because the total indirect effect is a sum of all specific indirect effects, if those indirect effects differ in sign but are of similar magnitude, their sum very well may be zero or nearly so (see, e.g., MacKinnon, 2008; Hayes, 2009). For instance, people who attend more highly or frequently to political campaign advertisements may be more likely to vote because such exposure leads people to believe that the outcome of the election is consequential to the future, which in turn facilitates turnout. On the other hand, such advertisements often are highly negative in tone, which may reduce trust in government and politicians, which could suppress the likelihood of showing up at the ballot box. Such push-and-pull processes could be at work simultaneously, but because the specific indirect effects are opposite in sign (i.e., a positive effect through perceptions of consequence, but a negative effect through trust in government), they may sum to zero. See Pitts et al. (2018) for a published example of such opposing indirect effects.

Such a paradox can also result in models with several specific indirect effects that differ in size, even if those specific indirect effects are the same sign. For instance, an investigator might fit a parallel multiple mediator model with four mediators, only one of which is actually transmitting $X$'s effect on $Y$. The inclusion of a bunch of potential mediators in the model that actually do nothing to carry $X$'s effect on $Y$ can increase the sampling variance of the estimate of the total indirect effect, rendering it not statistically different from zero when subjected to an inferential test.

The opposite is also possible—evidence of a total indirect effect in spite of absence of compelling evidence from inferential tests that any of the specific indirect effects are different from zero. Consider a variation on the example just presented in which *all* of the specific indirect effects are small in size but are of the same sign. If the sample size is relatively small or the mediators highly correlated, sampling variance will rule the day, making it hard to detect a weak signal (i.e., a small specific indirect effect) amid all the sampling noise. But a few weak signals, when added up (i.e., the total indirect effect), may be strong enough to detect with an inferential test because, all other things being equal, power is higher when the effect size is larger.

Such apparently paradoxical inconsistencies between inferential tests for total and specific indirect effects result not so much from the statistics but, rather, from our minds by thinking of these effects in binary terms, as either zero or not zero. One escape, which is admittedly difficult given how deeply ingrained the logic of hypothesis testing is in the consciousness of scientists, is to acknowledge the uncertainty inherent in our estimates as communicated through confidence intervals. The fact that a confidence interval for an effect contains zero does not mean the effect is zero. It merely means that zero is in the realm of possibility, or that one cannot say with certainty what the direction of the effect is.

A second escape is to discount the relevance of the total indirect effect when interpreting the results. Although this may not be possible, in some situations, the total indirect effect will have little substantive or theoretical value. The total indirect effect and the outcome of an inferential test thereof are similar to the squared multiple correlation in a regression model or an omnibus test of the equality of several means in ANOVA. Rejection of the null hypothesis that a regression model fits no better than chance or that all group means are equal in analysis of variance says nothing about the size or statistical significance of the individual predictors in the model or the outcome of various pairwise comparisons between means. One could have a statistically significant $R^2$ or $F$-ratio with no significant predictors or pairwise mean comparisons. Conversely, one could find one or more statistically significant predictor variables in a regression model, or two or more statistically significant pairwise comparisons between means even if one is not able to reject the null hypothesis that a model fits no better than chance or that a set of group means are the same using an omnibus test. The total indirect effect is a sum of all specific indirect effects, some of which may be large, others small, some positive, some negative. We often estimate multiple mediator models because we are interested in specific mechanisms at work, not the aggregate of all mechanisms. With a few exceptions, such as small specific indirect effects that are too small to detect with the data available but sum to a large total indirect effect, or in a serial multiple mediator model with data collected over time on the same mediator (see, e.g., D. A. Cole & Maxwell, 2003, pp. 571–572), inference and interpretation of a multiple mediator model would usually focus more on the direct and specific indirect effects, not the total indirect effect.

## 5.7 Chapter Summary

In this chapter, I have extended the principles of simple mediation analysis introduced in Chapter 3 to models with more than one mediator. Acknowledging and explicitly modeling the multiple mechanisms or pathways of influence between $X$ and $Y$ opens the door to more interesting analytical opportunities and tests. Specific indirect effects estimated in models with mediators operating either in parallel or series estimate causal influences independent of other processes in the model. Tests that compare specific indirect effects provide a means of pitting competing mechanisms or theories against each other in a single integrated process model.