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Conducting a difference-in-differences analysis with PLS-SEM: The classic 2x2 approach

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Abstract

Difference-in-differences analyses often employ a classic 2x2 scenario, which involves two conditions, control and treatment; and two points in time, before and after an intervention that may be tied to one of the conditions. In our analysis, we assess the impact on labor productivity of being in a more technology-intensive US state, instead of a more manufacturing-intensive one. Consistently with the difference-in-differences analysis scenario, we also assess the full latent growth effect of a government-driven age discrimination crackdown, in the technology-intensive state, on the previous effect – of being in a technology-intensive state on labor productivity. We do this by employing a model analyzed in the context of structural equation modeling via partial least squares (PLS-SEM). We also discuss advantages of using PLS-SEM in this scenario; which include assessments of causality, common method bias, and endogeneity.

Keywords: Difference-in-Differences; Full Latent Growth; Structural Equation Modeling; Partial Least Squares; WarpPLS.

Introduction

The classic 2x2 scenario for a difference-in-differences analysis involves two conditions, control and treatment; and two points in time, before and after an intervention that may be tied to one of the conditions. The simulated case discussed here, inspired by Card & Krueger's (1994) famous study, involved two US states and two points in time. One of the US states was manufacturing-intensive, because of the predominance of manufacturing companies in it; this state was used as the control condition. The other was a technology-intensive state, with a predominance of technology firms; this state was used as the treatment condition. The two points in time stood approximately one year apart, and were before or after the year in which the technology-intensive state's government unleashed an age discrimination crackdown, to prevent ageism amongst its technology firms.

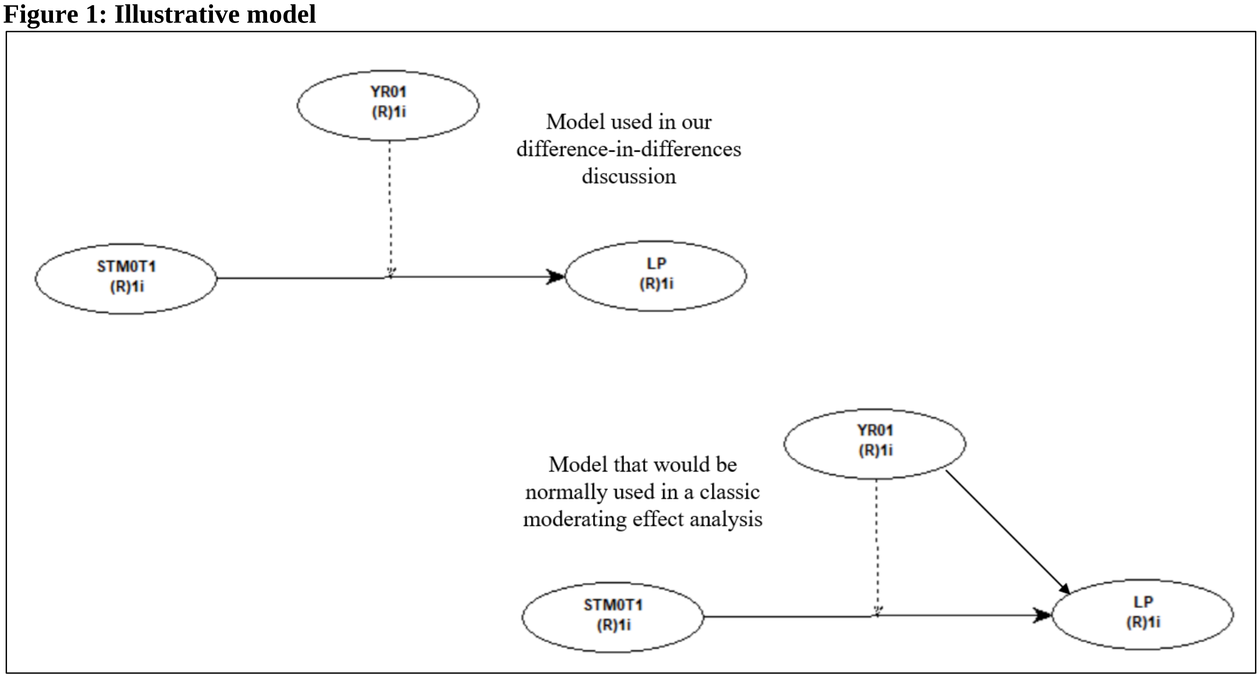
In our analysis, we assess the impact of being technology-intensive, as opposed to manufacturing-intensive, on labor productivity. Consistently with the difference-in-differences analysis scenario, we also assess the latent growth effect of the government-driven age discrimination crackdown, in the technology-intensive state, on the effect of being technology-intensive on labor productivity. We do this by employing a model with latent variables (LVs), and analyzed in the context of structural equation modeling via partial least squares (PLS-SEM). In our study, the LVs are implemented through single indicators, which makes ours a robust path analysis. Nevertheless, our example can be easily generalized to the case where LVs are measured through multiple indicators, which is more common in SEM studies.

Our discussion is based on an illustrative model analyzed with the software WarpPLS, Version 8.0 (Kock, 2022a). WarpPLS is a widely utilized SEM software tool that implements both classic composite-based as well as more advanced factor-based PLS-SEM algorithms (Kock, 2019a; 2019b), where LVs can be estimated through various algorithms, among other features that can be valuable in innovative SEM analyses (Amora, 2021; 2023; Canatay et al., 2022; Cox, 2024; Hubona & Belkhamza, 2021; Kock, 2015a; 2015b; 2015c; 2016; 2019a; 2019b; 2020a; 2020b; 2020c; 2021a; 2021b; 2021c; 2022a; 2022b; 2022c; 2023a; 2023b; 2024; Kock & Gaskins, 2016; Kock & Lynn, 2012; Ma & Zhang, 2023; Moqbel et al., 2020; Morrow & Conger, 2021; Rasoolimanesh, 2022; Samak et al., 2024; Tarkom & Gopal, 2024).

Difference-in-differences versus moderation analyses

The illustrative model shown in Figure 1, at the top left, is the one that should be used for a difference-in-differences analysis, and is the one where the LV pointing at the link (dashed arrow) is modelled as a full latent growth LV (Hubona & Belkhamza, 2021; Kock, 2020a). This is contrasted with the model shown at the bottom right, which is the one that would normally be used in a traditional moderating effect analysis. The key distinguishing characteristic between these two models is that in the one at the top left the LV pointing at the link does not compete, outside of the interaction effect to which it contributes, with the structural predictor LV for the variance explained in the criterion LV. This is what makes it a full latent growth model.

Figure 1: Illustrative model



Notes: STM0T1 = 0 or 1 respectively for manufacturing or technology state; YR01 = 0 or 1 for before or after age discrimination crackdown in technology state; LP = labor productivity (revenues per employee); notation under LV acronym describes measurement approach and number of indicators, e.g., (R)1i = reflective measurement with 1 indicator.

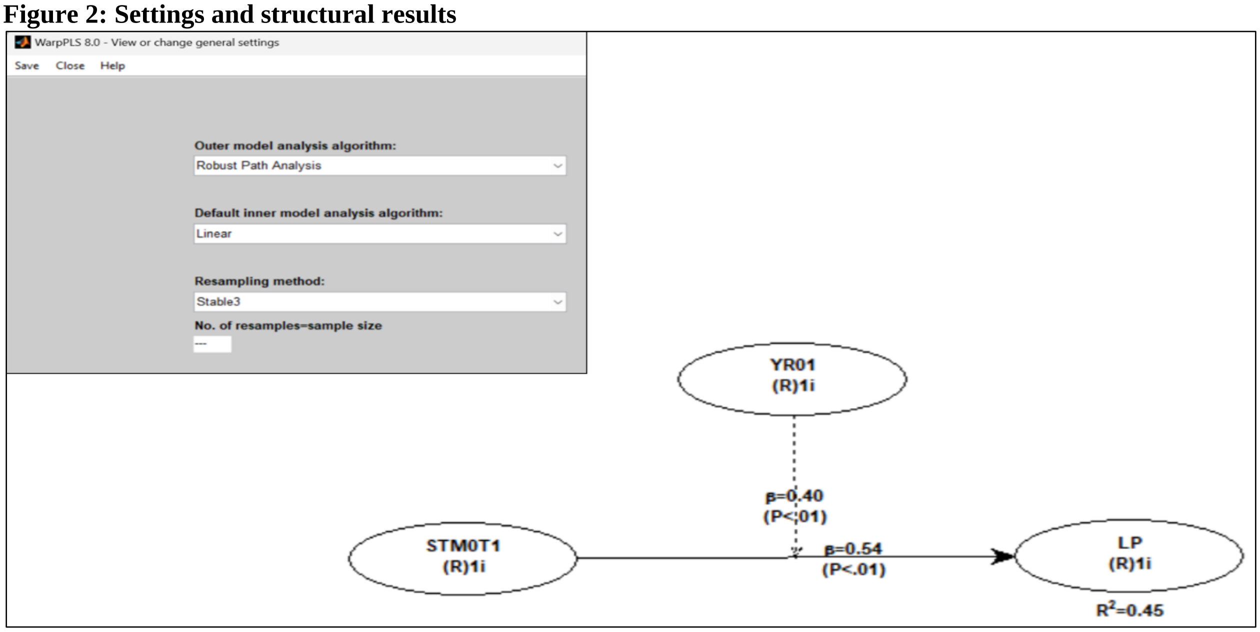
The illustrative model contains two exogenous LVs, namely STM0T1 and YR01, with the latter used as a full latent growth LV; and one endogenous LV, indicated as LP. STM0T1 stores one of the values 0 or 1, respectively to refer to the manufacturing-intensive or technology-intensive state. Similarly, YR01 stores one of the values 0 or 1, respectively to refer to a point in time before or after the year in which the government of the technology-intensive state launched an age discrimination crackdown to prevent ageism among its technology companies. LP stores a measure of labor productivity, which refers to the mean revenues per employee in each company.

The illustrative model served as the basis for the creation of a simulated dataset, through the Monte Carlo method (Kock, 2016), with a sample size of 500. The unit of analysis for LP in our dataset is the company, meaning that each row of the dataset refers to one company in a given state at a given point in time. The assumption here is that the dataset contains panel data, by comprising data collected at two points in time, or YR01 = 0 or 1. These refer to points in time before and after the age discrimination crackdown in the technology-intensive state.

Settings and structural results

Figure 2 shows the settings employed in our analysis, which were selected through the "View or change general settings" menu option, and the structural model results. The Robust Path Analysis algorithm is a simplified algorithm in which LV scores are produced by averaging the scores of the indicators associated with the LVs. That is, in this algorithm, weights are not estimated though an iterative process. This algorithm is called "robust" path analysis, because a standard path analysis (where all LVs are measured through single indicators) can be conducted through it, and the P values can be calculated through the nonparametric resampling or stable methods implemented through the software. If all LVs are measured with single indicators (as in our study), the Robust Path Analysis algorithm will yield LV scores and various parameters that are identical to those generated through the other algorithms, but with greater computational efficiency (which yields greater statistical power).

Figure 2: Settings and structural results

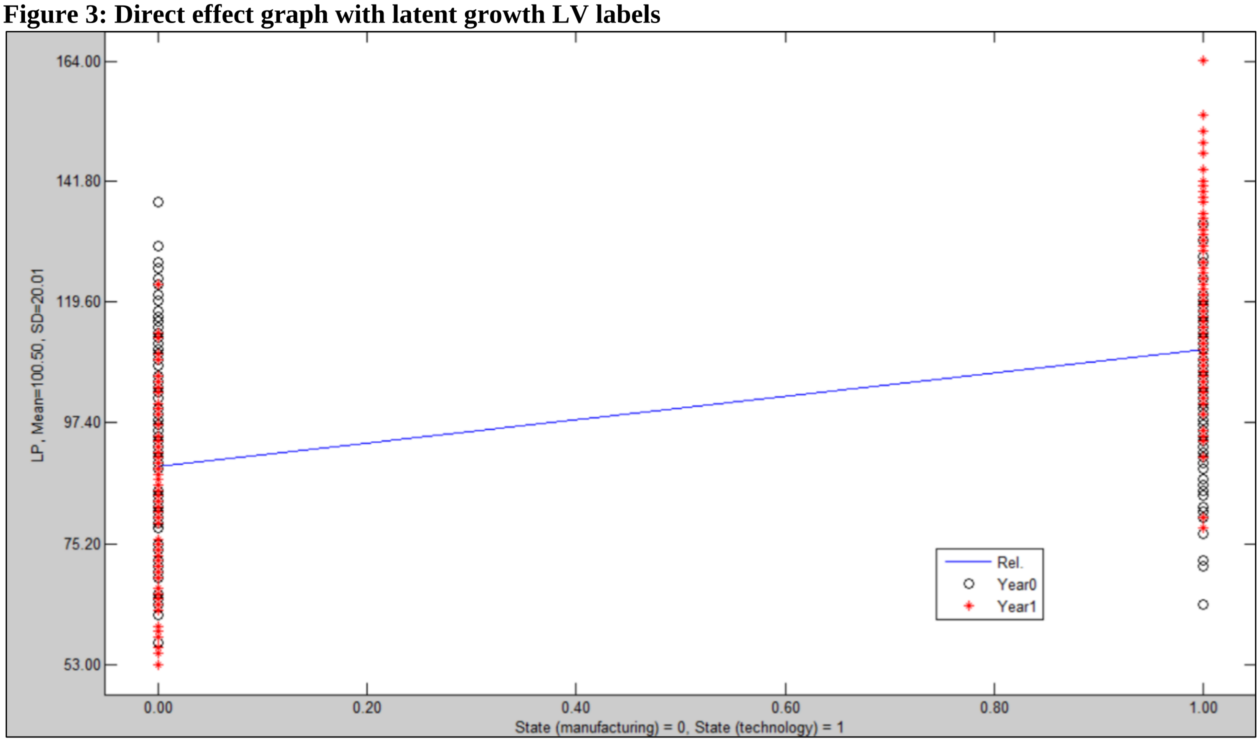


As we can see from the structural results, being in the technology-intensive state was found to be significantly associated with increased labor productivity (β=.54, P<.01, STM0T1 > LP). This is consistent with the expectation of generally higher revenues per employee in technology companies, when compared with manufacturing firms. And, this relationship became stronger after the year in which the government of the technology-intensive state launched an age discrimination crackdown to prevent ageism among the state's technology companies. [β=.40, P<.01, YR01 > (STM0T1 > LP)]. This could be seen as a surprising result, given that it goes against the idea that older employees will be underperformers in technology companies. Past research, however, has shown that this idea is erroneous (Kock et al., 2018).

Difference-in-differences graph patterns

In this section we show two types of graphs that exemplify the significant difference-in-differences effect discussed in this paper through latent growth patterns. In Figure 3, we can see that being in the technology-intensive state was associated with increased labor productivity, which is illustrated by the positive inclination of the best fitting line passing through the data points. It can also be noticed that this relationship became stronger after the age discrimination crackdown in the technology-intensive state, which is illustrated by the different distributions of data points in Year 1 and Year 0, actually adding to the positive inclination.

Figure 3: Direct effect graph with latent growth LV labels



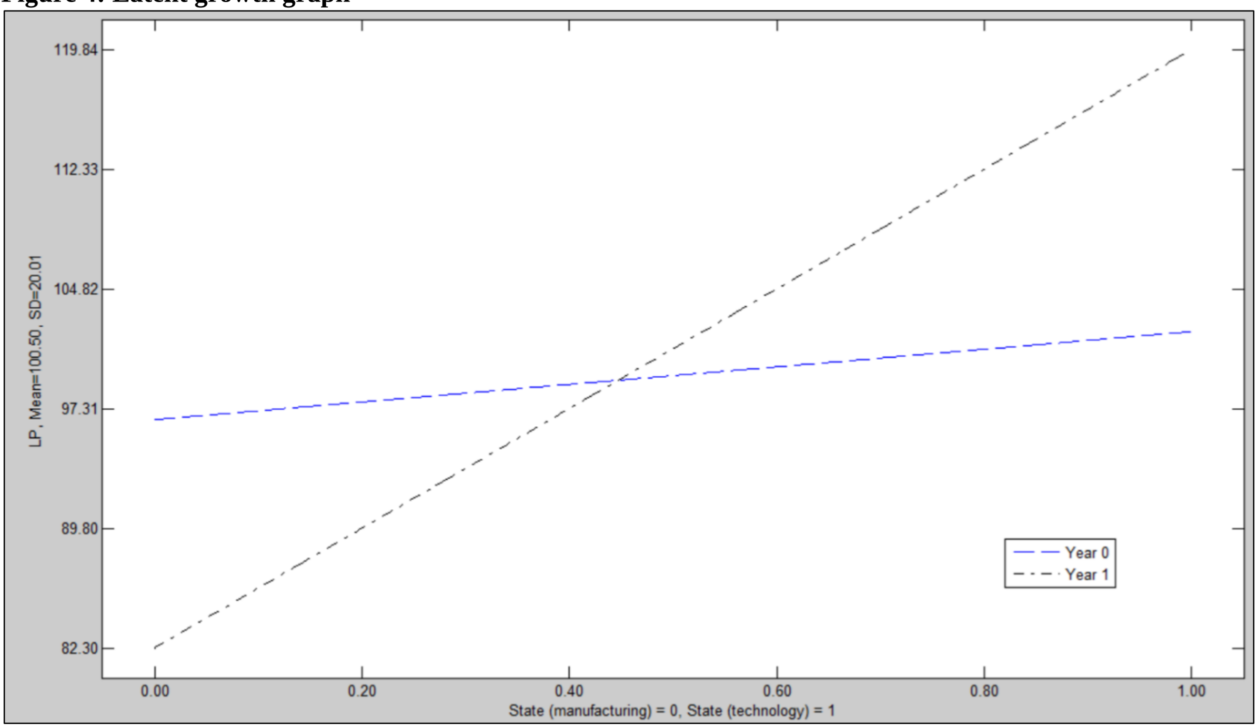
Notes: Being in the technology state was associated with increased labor productivity (positive inclination), and this relationship became stronger after age discrimination crackdown in technology state (Year 1 versus Year 0 points add to the positive inclination).

Shown in Figure 3 are data labels as part of the legend for the graph. The menu options "Add data labels from clipboard" and "Add data labels from file" allow you to add data labels into the project file. Data labels are text identifiers that are entered by you through these options, one column at a time. Like the original numeric dataset, the data labels are stored in a table. Each column of this table refers to one data label, and each row to the corresponding row of the original numeric dataset.

Data labels can be read from the clipboard or from a file, but only one column of labels can be read at a time. Data label cells cannot be empty, contain spaces, or contain only numbers; they must be combinations of letters, or of letters and numbers. Valid examples are the following: “Age>17”, “Y2001”, “AFR”, and “HighSuccess”. These would normally be entered without the quotation marks, which are used here only for clarity. Some invalid examples: “123”, “Age > 17”, and “Y 2001”.

In Figure 4, we can see that being in the technology-intensive state was associated with increased labor productivity, which is illustrated by the positive inclinations in both Year 0 and Year 1. It can also be noticed that this relationship became stronger after the year in which the government of the technology-intensive state launched the age discrimination crackdown to prevent ageism among its technology companies, which is illustrated by the steeper positive inclination for Year 1 than for Year 0.

Figure 4: Latent growth graph



Notes: Being in the technology state was associated with increased labor productivity (positive inclination in both Year 0 and Year 1), and this relationship became stronger after age discrimination crackdown in technology state (steeper positive inclination for Year 1 than for Year 0).

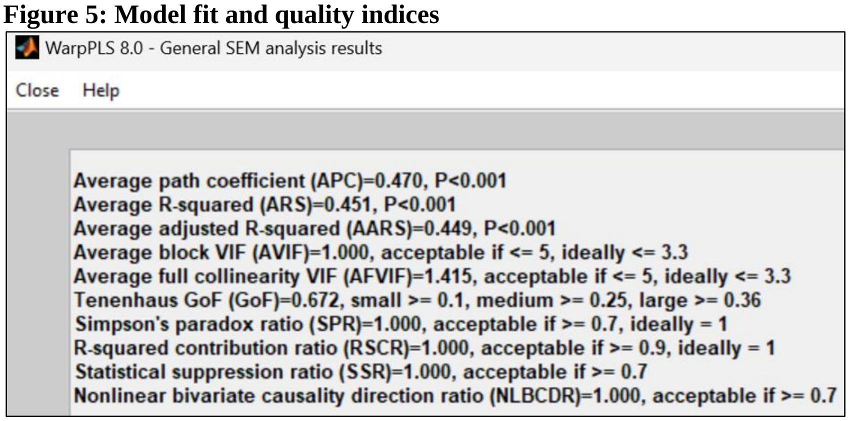
The “View moderating relationship in one focused graph” options allow users to view 2D graphs like the one in Figure 4, which focus on the best-fitting lines or curves for high and low values of the latent growth LV, and that exclude data points to provide the effect of zooming in on the area comprising the best-fitting lines or curves. The sub-option used was “View focused graph with low-high values of moderating variable (unstandardized scales)”.

One interesting possible scenario, slightly different from the one above, would have been inclinations of different signs for Year 1 and Year 0. For example, for Year 0 the inclination could have been negative, and positive for Year 1. That would mean that the age discrimination crackdown in the technology-intensive state would have been even more impactful, because in that case ageism might have been decreasing labor productivity – possibly by preventing the hiring of older and more experienced professionals in key technology company positions (for example, see: Kock et al., 2018).

Conclusion

As demonstrated in the previous sections, there are advantages associated with employing PLS-SEM in difference-in-differences analyses, such as the more intuitive graph-based interpretations of the effects. One additional advantage is that model fit and quality indices can be used. Several of these are shown in Figure 5. Both the average R-squared (ARS) and the average adjusted R-squared (AARS) suggest fairly high levels of variance explained in connection with the model's endogenous variables. Since the average path coefficient (APC) is also high, we can conclude that the high levels of variance explained are not due to the inclusion of redundant LVs in the model.

Figure 5: Model fit and quality indices



The variance inflation factor (VIF) indices, namely the average block VIF (AVIF) and average full collinearity VIF (AFVIF), were both below 3.3, suggesting low levels of vertical and lateral collinearity. This essentially means that the LVs used in the model measure different underlying constructs. These indices also suggest that the model is generally free from common method bias. Additionally, the Tenenhaus GoF (GoF) suggests a large level of goodness-of-fit between the model and the data.

Finally, the last four indices shown at the bottom of Figure 5 allow for causality and endogeneity assessments, which are arguably quite important in difference-in-differences analyses (Card & Krueger, 1994). The Simpson's paradox ratio (SPR), R-squared contribution ratio (RSCR), and statistical suppression ratio (SSR) all equal 1. These values suggest that the model is largely sound in terms of its causality assumptions; i.e., the directions of causality implied by the links connecting the variables appear to be correct. The nonlinear bivariate causality direction ratio (NLBCDR) also equals 1. This index is a measure of the extent to which bivariate nonlinear coefficients of association provide support for the hypothesized directions of the causal links in a model. The value of 1 suggests not only sound causality assumptions, but the absence of significant endogeneity in the model.

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