LINEAR PANEL ANALYSIS pdf

1: Fixed effects model - Wikipedia

Linear Panel Analysis: Models of Quantitative Change focuses on the use of linear models in the analysis of change data measured on a sample of individuals over multiple time points. This book is organized into 12 chapters.

Advanced Search Abstract The analysis of repeated measures or panel data allows control of some of the biases which plague other observational studies, particularly unmeasured confounding. When this bias is suspected, and the research question is: Epidemiologists familiar with using mixed models may initially presume that specifying a random effect intercept for every individual in the study is an appropriate method. Variation between individuals may introduce confounding bias into mixed model estimates, if unmeasured time-invariant factors are associated with both the exposure and the outcome. Fixed effects estimators rely only on variation within individuals and hence are not affected by confounding from unmeasured time-invariant factors. The reduction in bias using a fixed effects model may come at the expense of precision, particularly if there is little change in exposures over time. Neither fixed effects nor mixed models control for unmeasured time-varying confounding or reverse causation. The problem with observational studies Epidemiology is concerned with discovering and understanding the causal relationships between exposures and health outcomes. Therefore, the exposed and non-exposed groups are likely to be different in important ways, due to self-selection and other processes, and this may bias estimation of the exposure-outcome relationship e. However, these require that appropriate data is collected during the experiment, including suitable, valid exogenous variables which are not determined by any other variables of interest 6 that can be used in instrumental variable analyses. Thus true natural experiments are rare and many give results that are not widely generalizable. Modelling the within-individual component opens the door to removing all time-invariant confounding, as each individual acts as their own control. Although it is well established that people with lower socioeconomic position have worse health outcomes, the recommendation that often follows from this observation, that interventions to raise socioeconomic position will improve health, are based on limited evidence. However, within-individual changes in income and health can be used to give an estimate of the exposure income â€”outcome health association that is not affected by time-invariant confounding biasâ€”provided the estimator used is unbiased and consistent. This usage is quite distinct from that of the statistical literature, where it is often met in the context of random effects or mixed models. In statistical jargon, a fixed effect is a parameter associated with an entire population to be estimated and a random effect is a parameter describing the variability of experimental units e. In what follows we focus on methods for estimating effects of changes over time at an individual level. Where estimates averaged over the population in question are sought, population average models e. This is the really remarkable promise of the fixed effects model, and one that makes it so attractive for social epidemiology, where exposures are often heavily confounded by myriad contextual, behavioural and attitudinal quantities that would be difficult to assess exhaustively. To demonstrate how a fixed effects model controls for time-invariant confounding when applied to longitudinal data, consider a causal linear model where outcome yit for the ith of N individuals measured at time t is predicted by time-varying xit and time-invariant Zi exposures. Figure 1 View large Download slide Results of simulation showing the difference between random effects RE, dotted line and fixed effects FE, stepped line models using five observations each on two individuals: A dots and B bold dots and relationship to estimator from a pooled model P, dashed line using data from all simulated points cloud of small dots Figure 1 View large Download slide Results of simulation showing the difference between random effects RE, dotted line and fixed effects FE, stepped line models using five observations each on two individuals: A dots and B bold dots and relationship to estimator from a pooled model P, dashed line using data from all simulated points cloud of small dots An alternative and computationally less demanding way to calculate the linear fixed effects model is the mean-centring approach. The time-invariant terms which are not independently identifiable are eliminated in the mean-centring Equation 2 , and only parameters associated with time-varying covariates can be estimated by the model. In fact many software packages e. SAS, STATA do this automatically, and also provide a variety of adjustments to standard errors for heteroscedasticity and serial correlation to improve inference. The linear fixed effects model has found wide application in the econometrics literature, and we have used it here to illustrate key concepts. However, in epidemiology, outcomes are often categorical, and non-linear models assume greater importance. In general non-linear fixed effects models are more challenging but, for several non-linear models important to epidemiologists, relatively straightforward methods are available. These include conditioning the parameter representing time-invariant confounding out of the likelihood logistic models or explicitly modelling within-individual changes in a multilevel group-mean-centred mixed model ordinal models. In particular, if heteroscedasticity is suspected, parameter estimates may be biased, and providing robust standard errors as in the linear case for a biased estimate makes little sense. If such unobserved variables are important confounders, mixed model estimates will not remove the significant bias introduced by those confounders. This applies particularly where the number of individuals N is large but the number of data collection points T relatively small, as in most longitudinal data analyses. Where T is also large, the mixed model estimate will be dominated by within-individual variation and the difference between estimates from fixed effects and simple random intercept mixed models is reduced. The cloud of data points represent the full simulated longitudinal dataset to which the pooled model is fitted. The pooled Pâ€"dashed line estimator does not model individual-specific effects to account for unmeasured confounding or account for serial correlation where random disturbances across time for the same individual are correlated. All of these factors increase the error in the RE estimator. In this simulation, the mixed random intercept regression model RE correctly treats longitudinal data as grouped at the individual level , but does not control for unmeasured confounders and therefore does not provide a reliable estimate of causal interest the average of the within-individual slopes, given by FE. Limitations of fixed effects models The main advantage of the fixed effects model is that it only uses within-individual variation, but this can lead to lack of precision mixed models are potentially more efficient, with narrower confidence intervals. Another major disadvantage is that parameters for time-invariant variables, such as sex and ethnicity, are not estimated since they do not change in individuals over time. However, time-invariant covariates may be interacted with time-varying exposures of interest, e. Basic fixed effects models work under the assumption of strict exogeneity, which prohibits some types of feedback from past outcomes to current covariates and current outcome to future covariates. Under this assumption, having controlled for a given set of possibly lagged covariates at each time point, past values of the selected covariates cannot independently modify the current outcome and past outcomes cannot independently modify future values of those covariates. However, this assumption may be problematic in some situations of interest to epidemiologist. Figure 2 presents a simple directed acyclic graph of one exposure and outcome over two time periods, highlighting departures from the strict exogeneity assumption in dashed lines. These include unobserved time-varying confounding Figure 2 , pathway B, e. Accounting for this bias by including endogenous observed initial outcomes requires additional assumptions about the static nature of processes occurring before the study genesis, which may not be sound. Similar remarks apply to conditioning unobserved initial outcomes out of the model likelihood.

2: Econometric Analysis of Panel Data: Class Notes

We will begin with a development of the standard linear regression model, then extend it to panel data settings involving 'fixed' and 'random' effects. The asymptotic distribution theory necessary for analysis of generalized linear and nonlinear models will be reviewed or developed as we proceed.

The estimated value based on the fitted regression model for the new observation at is: The prediction interval values calculated in this example are shown in the figure below as Low Prediction Interval and High Prediction Interval, respectively. The columns labeled Mean Predicted and Standard Error represent the values of and the standard error used in the calculations. Measures of Model Adequacy It is important to analyze the regression model before inferences based on the model are undertaken. The following sections present some techniques that can be used to check the appropriateness of the model for the given data. These techniques help to determine if any of the model assumptions have been violated. Coefficient of Determination R2 The coefficient of determination is a measure of the amount of variability in the data accounted for by the regression model. As mentioned previously, the total variability of the data is measured by the total sum of squares,. The amount of this variability explained by the regression model is the regression sum of squares,. The coefficient of determination is the ratio of the regression sum of squares to the total sum of squares. For the yield data example, can be calculated as: It may appear that larger values of indicate a better fitting regression model. However, should be used cautiously as this is not always the case. The value of increases as more terms are added to the model, even if the new term does not contribute significantly to the model. Therefore, an increase in the value of cannot be taken as a sign to conclude that the new model is superior to the older model. Adding a new term may make the regression model worse if the error mean square, , for the new model is larger than the of the older model, even though the new model will show an increased value of. In the results obtained from the DOE folio, is displayed as R-sq under the ANOVA table as shown in the figure below , which displays the complete analysis sheet for the data in the preceding table. These values measure different aspects of the adequacy of the regression model. For example, the value of S is the square root of the error mean square, , and represents the "standard error of the model. The values of S, R-sq and R-sq adj indicate how well the model fits the observed data. Residual Analysis In the simple linear regression model the true error terms, , are never known. The residuals, , may be thought of as the observed error terms that are similar to the true error terms. Since the true error terms, , are assumed to be normally distributed with a mean of zero and a variance of , in a good model the observed error terms i. Thus the residuals in the simple linear regression should be normally distributed with a mean of zero and a constant variance of. Residuals are usually plotted against the fitted values, , against the predictor variable values, , and against time or run-order sequence, in addition to the normal probability plot. Plots of residuals are used to check for the following: Residuals follow the normal distribution. Residuals have a constant variance. Regression function is linear. A pattern does not exist when residuals are plotted in a time or run-order sequence. There are no outliers. Examples of residual plots are shown in the following figure. Such a plot indicates an appropriate regression model. Such a plot indicates increase in variance of residuals and the assumption of constant variance is violated here. Transformation on may be helpful in this case see Transformations. If the residuals follow the pattern of c or d , then this is an indication that the linear regression model is not adequate. Addition of higher order terms to the regression model or transformation on or may be required in such cases. A plot of residuals may also show a pattern as seen in e , indicating that the residuals increase or decrease as the run order sequence or time progresses. This may be due to factors such as operator-learning or instrument-creep and should be investigated further. Example Residual plots for the data of the preceding table are shown in the following figures. One of the following figures is the normal probability plot. It can be observed that the residuals follow the normal distribution and the assumption of normality is valid here. In one of the following figures the residuals are plotted against the fitted values, , and in one of the following figures the residuals are plotted against the run order. Both of these plots show that the 21st observation seems to be an outlier. Further investigations are needed to study the cause of this outlier. This perfect model will give us a zero error sum of squares. Thus, no error exists for the perfect model. However, if you record the response values for the same values of for a second time, in conditions maintained as strictly identical as possible to the first time, observations from the second time will not all fall along the perfect model. The deviations in observations recorded for the second time constitute the "purely" random variation or noise. The sum of squares due to pure error abbreviated quantifies these variations.

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3: Simple Linear Regression Analysis - ReliaWiki

This chapter discusses the casual analysis of change. In experimental research, spuriousness and direction of causality are evaluated by randomization and manip.

This blog July 15, Books on Multilevel, Longitudinal, and Panel Analysis Here lies my current list of books on multilevel, longitudinal, and panel data modeling. Applications and data analysis methods. Gelman, Andrew, and Jennifer Hill. Routledge Snijders, Tom AB. Generalized linear mixed models: Rabe-Hesketh, Sophia, and Anders Skrondal. Multilevel and Longitudinal Modeling Using Stata. Multilevel Modeling Using R: Panel Data Nerlove, M. An essay on the history of panel data econometrics. Econometric analysis of panel data. Analysis of panel data. Longitudinal Analysis Singer, J. Applied longitudinal data analysis: Modeling Change and Event Occurrence. Modeling Within-Person Fluctuation and Change. The econometrics of panel data: Handbook of multilevel analysis. Hox, Joop, and J. Handbook of advanced multilevel analysis. The SAGE handbook of multilevel modeling: Advances in Multilevel Modeling for Educational Research: Generalized latent variable modeling: Multilevel, longitudinal, and structural equation models. Generalized linear models with random effects: Nonparametric regression methods for longitudinal data analysis: Mixed effects models for complex data: Applied Bayesian hierarchical methods: Richly parameterized linear models: Multilevel Network Analysis for the Social Sciences. Spatial Analysis for the Social Sciences. Foundations, Methods, and Models.

4: Panel data - Wikipedia

guide for substantive social scientists new to the area of panel data analysis, but who have a working knowledge of generalized linear models. The Advantages of Panel Data.

5: Panel zones - Technical Knowledge Base - Computers and Structures, Inc. - Technical Knowledge Base

Linear analysis: When the deformations of structures are linear combinations of applied loads, it is called linear. So, purpose of the linear analysis is to identify the transformation and inverse transformation between these two set of quantities.

6: Books on Multilevel, Longitudinal, and Panel Analysis â€“ About Methods

Longitudinal and Panel Data: Analysis and Applications for the Social Sciences Brief Table of Contents Chapter 1. Introduction PART I - LINEAR MODELS.

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