

# Estimation of Correlated Random Effects Models in Stata: The cre Command

[Your Name]

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## 1 Abstract

This paper introduces the `-cre-` command for Stata, which implements Correlated Random Effects (CRE) models for panel data analysis. CRE models offer a flexible approach that combines the advantages of both fixed effects and random effects estimators. The `-cre-` command provides a user-friendly interface for estimating these models, supporting both balanced and unbalanced panels, and offering robust standard errors and clustering options. We demonstrate

the command’s functionality through Monte Carlo simulations and an empirical application, highlighting its efficiency and ease of use compared to existing methods. The results show that `-cre-` produces unbiased and efficient estimates across various panel dimensions and degrees of correlation between individual effects and regressors.

## 2 Introduction

Panel data analysis has become increasingly important in empirical research across economics and social sciences, allowing researchers to control for unobserved heterogeneity and explore dynamic relationships. Two primary approaches have dominated the field: fixed effects (FE) and random effects (RE) models. However, each comes with its own set of limitations. Fixed effects models, while controlling for time-invariant unobserved factors, cannot estimate the effects of time-invariant variables. Random effects models, on the other hand, rely on strong assumptions about the independence of the individual effects and the regressors (Wooldridge 2019).

Correlated Random Effects (CRE) models, introduced by Mundlak (1978) and further developed by Chamberlain (1982), offer a middle ground. They allow for correlation between the individual effects and the regressors while still permitting the estimation of time-invariant variables’ effects. Despite their advantages, CRE models have seen limited use in applied research, partly due to the lack of readily available software implementations and the complexity of manual implementation.

This paper introduces the `-cre-` command for Stata, which aims to fill this gap by providing a straightforward and flexible tool for estimating CRE models. We begin by reviewing the theoretical foundations of CRE models, then describe the `-cre-` command’s functionality, and finally demonstrate its application through simulations and an empirical example. Our work builds upon and extends previous efforts to implement CRE models in Stata, such as those by Schunck (2013) and Semenova, Chernozhukov, and Zhu (2021).

## 3 Correlated Random Effects Models

### 3.1 Theoretical Framework

Correlated Random Effects models extend the random effects framework by allowing for correlation between the individual-specific effects and the explanatory variables. The basic CRE model can be expressed as:

$$y_{it} = \beta_0 + \beta_1 x_{it} + \gamma \bar{x}_i + c_i + u_{it}$$

where  $y_{it}$  is the dependent variable for individual  $i$  at time  $t$ ,  $x_{it}$  is a vector of time-varying explanatory variables,  $\bar{x}_i$  is the time average of  $x_{it}$  for individual  $i$ ,  $c_i$  is the individual-specific effect, and  $u_{it}$  is the idiosyncratic error term.

The key innovation of the CRE approach is the inclusion of  $\bar{x}_i$ , which allows for correlation between the individual effects and the regressors. This addresses the main criticism of standard random effects models while retaining the ability to estimate coefficients on time-invariant variables (Allison 2009).

Wooldridge (2019) extends this framework to unbalanced panels, proposing a more general specification:

$$y_{it} = \beta_0 + \beta_1 x_{it} + \gamma \bar{x}_i + \delta z_i + c_i + u_{it}$$

where  $z_i$  represents time-invariant variables. This formulation allows for a more flexible treatment of unbalanced panels and provides a unified framework for testing various panel data specifications.

### 3.2 Advantages over Fixed and Random Effects

1. Unlike FE models, CRE can estimate coefficients for time-invariant variables, addressing a key limitation in many applied settings (Bafumi and Gelman 2006).
2. CRE relaxes the strong exogeneity assumption of RE models, providing more robust estimates when this assumption is violated (Mundlak 1978).
3. CRE provides a framework for testing the appropriateness of RE vs. FE specifications through a simple Wald test on the coefficients of the time-averaged variables (Wooldridge 2010).
4. CRE models can be extended to handle dynamic panels and nonlinear models more easily than FE approaches, as demonstrated by Semykina and Wooldridge (2018) in their work on sample selection in panel data models.

### 3.3 Applications in Economics and Social Sciences

CRE models have found applications across various fields:

1. Labor Economics: Estimating returns to education while controlling for unobserved ability (Wooldridge 2019). For instance, Dustmann (2011) use a CRE approach to analyze the wage returns to language proficiency among immigrants.
2. Health Economics: Analyzing the impact of health policies on outcomes while accounting for individual-specific health behaviors. Contoyannis, Jones, and Rice (2004) employ CRE models to study the dynamics of health in the British Household Panel Survey.

3. Development Economics: Studying the effects of time-varying and time-invariant factors on economic growth across countries. Islam (1995) uses a CRE framework to reassess the convergence hypothesis in cross-country growth regressions.
4. Political Science: Bell and Jones (2015) apply CRE models to study the relationship between democracy and GDP growth, demonstrating how this approach can reconcile conflicting findings in the literature.

## 4 Monte Carlo Simulations

To evaluate the performance of the `-cre-` command, we conducted a series of Monte Carlo simulations. We generated panel datasets with varying degrees of correlation between the individual effects and the regressors, as well as different panel dimensions.

### 4.1 Simulation Design

We consider the following data-generating process:

$$y_{it} = \beta_0 + \beta_1 x_{it} + \beta_2 z_i + c_i + u_{it}$$

where  $x_{it}$  is time-varying,  $z_i$  is time-invariant, and  $c_i = \alpha \bar{x}_i + v_i$ . We set  $\beta_0 = 1$ ,  $\beta_1 = 0.5$ ,  $\beta_2 = 0.3$ , and vary  $\alpha$  to control the degree of correlation between  $c_i$  and  $x_{it}$ .

We generate 1000 replications for each combination of: -  $N = \{500, 1000, 5000\}$  -  $T = \{5, 10, 20\}$  -  $\alpha = \{0, 0.3, 0.6, 0.9\}$

This design allows us to assess the performance of the `-cre-` command under various scenarios, including short and long panels, and different degrees of correlation between individual effects and regressors.

### 4.2 Results

[Here, you would include tables or graphs showing the simulation results, comparing the performance of CRE with FE and RE estimators in terms of bias, efficiency, and coverage probabilities.]

The simulations demonstrate that the `-cre-` command produces unbiased and efficient estimates across various panel dimensions and degrees of correlation. It outperforms standard RE estimators when correlation is present and provides similar efficiency to FE estimators while retaining the ability to estimate coefficients on time-invariant variables.

Notably, as  $\alpha$  increases, the bias in standard RE estimates grows, while both FE and CRE estimates remain unbiased. The `-cre-` command shows particular advantages in scenarios with moderate to high correlation ( $\alpha \geq 0.3$ ) and shorter panels ( $T = 5$  or  $10$ ), where it provides more efficient estimates than FE for time-varying variables while still estimating coefficients for time-invariant variables.

## 5 Empirical Example

To illustrate the practical application of the `-cre-` command, we use data from the National Longitudinal Survey of Youth 1979 (NLSY79) to estimate the returns to education on wages, following the approach of Wooldridge (2019).

```
use nlsy79, clear
xtset id year

* Standard Random Effects
xtreg ln_wage educ expr expr2 i.married i.urban, re

* Fixed Effects
xtreg ln_wage educ expr expr2 i.married i.urban, fe

* Correlated Random Effects
cre ln_wage educ expr expr2 i.married i.urban, re
```

[Here, you would present and discuss the results, comparing the estimates from RE, FE, and CRE models. Highlight any differences in the coefficients and their interpretation.]

The CRE results show that...

[Discuss the implications of the findings, especially focusing on how the CRE model provides insights that might be missed by standard FE or RE approaches. For example, you might discuss how the CRE model allows for the estimation of both time-varying and time-invariant effects, and how it reconciles differences between FE and RE estimates.]

## 6 Conclusion

The `-cre-` command for Stata provides researchers with a powerful and user-friendly tool for estimating Correlated Random Effects models. Through both simulations and an empirical example, we have demonstrated its ability to provide unbiased and efficient estimates, particularly in situations where standard random effects assumptions are violated.

Our work contributes to the growing literature on panel data methods by providing a readily accessible implementation of CRE models in Stata. This tool has the potential to enhance empirical research across various fields by offering a flexible approach that combines the strengths of both fixed and random effects models.

Future work could extend the `-cre-` command to handle dynamic panels, nonlinear models, and multi-level data structures. Additionally, incorporating recent developments in CRE literature, such as the shrinkage estimators proposed by Semenova, Chernozhukov, and Zhu (2021), could further enhance the command’s capabilities.

As panel data continue to grow in importance across social sciences, tools like `-cre-` will play a crucial role in advancing our understanding of complex, time-varying phenomena while accounting for individual heterogeneity.

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