FISCAL EQUALIZATION TRANSFERS AND PROVINCIAL INCOME DISPARITIES IN CANADA: AN ECONOMETRIC REASSESSMENT

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ABSTRACT

This paper uses the panel data method and data from 1982 to 2006 to examine the effect of federal equalization transfers on provincial income disparities in Canadian. Estimation problems of weak instruments and endogenous regressors are addressed by the use of a system generalized method of moment estimator. The results from the empirical analysis indicate that the current rate of convergence of personal income in Canada is 4.48 percent per year. This rate is considerably higher than the range of 1.80 and 2.41 percent per year that previous studies using least square estimators have reported. The findings from the policy analysis show that the fiscal transfers, which are part of the federal equalization program, have reduced provincial income disparities by accelerating the speed of convergence for Canadian provinces.

JEL Classification Numbers: *O18; O38; O41; O51*

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1 INTRODUCTION

Provincial income disparities in Canada have received a lot of attention in the convergence literature for two important reasons. First, Canada is a large country, characterized by geographic disparities in resource base and industries. The industrial base of the country is highly concentrated in the Great Lakes-Saint Laurent River area, with economic activities in the remaining regions largely based on the exploitation of various natural resources. Second, the Constitution Act of 1982, Section 36 re-enforces federal responsibilities in the area of provincial disparities and equalization. As a result, the federal and provincial governments have embarked on a comprehensive fiscal transfer program particularly aimed at bridging the gap between the poor and rich provinces. The program involves unconditional federal transfers to provinces with low per capita revenues in order to raise their fiscal capacities to a standard level. This policy shift has sparked a lot of debates and research to determine its effectiveness. The goal of this paper is to analyze the effect of the fiscal transfers on provincial income inequalities in Canada using the neoclassical growth framework and a new empirical methodology.

According to the neoclassical growth theory, if different regions are at different points relative to their steady state growth paths, then poorer regions will grow faster than the rich ones. Barro (1991), Barro and Sala-i-Martin (1991 and 1992), and Sala-i-Martin (1996) have used cross section regression analysis to provide empirical evidence of this "catch-up" effect. They found that convergence occurred for US States and the regions of Europe and Japan at a rate of about 2 percent per year. Studies using Canadian provinces as units of analysis have also provided a stock of empirical evidence that establishes the nature of the evolution of provincial income disparities and some evidence on how the federal government policies have affected it. Coulombe and Lee (1995, 1998) and Coulombe (1996, 2000) found that there is convergence among Canadian provinces for different measurements of per capita output and income. They concluded that the terms of trade and governments transfers and taxes are two key factors that have helped the provinces to converge at a rate similar to earlier studies on regions within the United States, Japan, and Europe. Lee and Coulombe (1995) approached the issue differently. They analyzed the convergence pattern in earnings, labour productivity, and unemployment rates and concluded that there has been provincial convergence in earnings and labour productivity, but not in the unemployment rates. Warkerly (2002) conducted a different analysis. Using the evolving distribution approach first used by Quah (1993), and data on provinces and industries, he found that the growth process in Canada has not reduced income disparities among the provinces.[6]

All the studies discussed above and others such as Coulombe and Day (1999) and Coulombe (1997) used least square estimators for their estimate of the convergence parameter. The central argument of this study is that these estimation

[6] Other notable studies using Canadian data are: Lee and Coulombe (1995), Coulombe (2003), Lee (1995) Milne and Tucker (1992), Mansell and Copithorne (1985) and Gunderson (1996).

techniques have some potential econometric problems which may lead to biased estimates of the convergence parameter, and invalidate any empirical analysis, especially those by Coulombe and Lee (1995, 1998) and Coulombe (1996, 2000) which analyze the effect of government policy changes on provincial income disparities in Canada. For instance, the least square techniques pay little or no attention to the problem of unobserved province specific effects which has considerable implications with regards to the estimation of unbiased convergence rate. In addition, the techniques neglect the potential problem of endogeneity of regressors in the growth equation which may give rise to dynamic bias problems. The main objective of this paper, therefore, is to analyze the effect of the fiscal transfers on income convergence in Canada by using the panel data approach. The panel data analysis by using both cross-sectional and time series variability is well equipped to deal with these problems. Specifically, we will address the above econometric issues by using the Arellano-Bond (1991) and Blundell-Bond (1998) linear generalized method of moment estimators, which address the potential endogeneity of the regressors, and incorporate, albeit implicitly, fixed effects to analyze the effect of fiscal transfers on income convergence in Canada.

Our findings are relatively easy to report. First, we find that the System GMM (SYS-GMM) estimator yields the best results, in terms of finite sample performance, because it addresses the estimation problems of weak instruments and endogenous regressors. Second, the results indicate that the current rate of convergence of personal income in Canada is 4.48 percent per year which is considerably higher than the range of 1.80 and 2.41 percent per year that previous studies using least square estimators have reported. Third, the equalization program, which is part of the overall federal government transfers in Canada, have accelerated the speed of convergence in income in Canada.

The rest of the paper is organized as follows. Section 2 presents an overview of the Solow neoclassical growth model that provides the framework for the empirical analysis of income convergence. Section 3 discusses problems associated with applying least square estimators to panel data set. The section also discusses the Difference GMM (DIFF-GMM) and SYS-GMM estimators and shows how they address the problems of endogenous regressors and weak instruments. Section 4 conducts the empirical analysis to determine the effect of the fiscal equalization transfers on conditional income convergence among Canadian provinces. Section 5 concludes the paper.

2 THE SOLOW GROWTH FRAMEWORK

The Solow growth model provides the theoretical basis for a large number of studies on income convergence (Barro and Sala-i-Martin, 1992; Quah, 1993; Islam, 1995; Weeks and Yao, 2003; Coulombe and Tremblay, 2001; and Coulombe and Lee, 1995). Though most of these studies have used either pooled time series or simple cross section data approach to estimate the convergence rate, Islam (1995) and Weeks and Yao (2003) have provided a good background to a panel data approach to the convergence hypothesis. In this section, we use a summarized version of their models. Using standard notation, we assume a Cobb-Douglas production function with labour augmenting technological process:

$$Y(t) = K(t)^{\alpha}\left[A(t)L(t)\right]^{1-\alpha}, \tag{1}$$

where $0<\alpha<1, Y$ is output, K is capital, L is labor and A is the level of technology. Labour force and technology are assumed to grow exogenously at the rate n and g respectively:

$$L(t) = L(0)e^{nt}, \tag{2}$$

$$A(t) = A(0)e^{gt}. \tag{3}$$

Define $\hat{y} = Y/AL,\ \hat{k} = K/AL,\ \delta$ as a constant rate of depreciation, and s as a constant fraction of output that is saved and invested. Then the dynamic equation for $\hat{k}$ is given by:

$$\dot{\hat{k}}(t) = s\hat{y}(t) - (n+g+\delta)\hat{k}(t), \tag{4}$$

$$= s\hat{k}(t)^{\alpha} - (n+g+\delta)\hat{k}(t). \tag{4'}$$

From equation (4') $\hat{k}$ converges to its steady state value:

$$\hat{k}^* = \left(\frac{s}{n+g+\delta} \right)^{\frac{1}{(1-\alpha)}}. \tag{5}$$

Substituting (5) into (1) and taking logs, the steady state income per capita is:

$$\ln\left[\frac{Y(t)}{L(t)}\right] = \ln A(0) + gt + \frac{\alpha}{1-\alpha}\ln(s) - \frac{\alpha}{1-\alpha}\ln(n+g+\delta). \tag{6}$$

Most conditional convergence studies such as Barro and Sala-i-Martin (1995), Coulombe and Lee, (1995, 1998) and Coulombe (2000, 2003) have paid little attention to $\ln A(0)$ and gt. Specifically, they have almost invariably relegated them into the error or the constant terms of their regression models with the assumption that they are independent of the s and $(n+g+\delta)$ variables. Our main argument is that a panel data framework that explicitly controls for the technological shift term ($\ln A(0)$) is the appropriate approach. Following Weeks and Yao (2003), we write an autoregressive form of the growth model (equation 6) as:

$$\begin{aligned} \ln y(t_2) &= \zeta \ln y(t_1) + (1-\zeta)\ln A(0) + g(t_2 - \zeta t_1) + (1-\zeta)\frac{\alpha}{1-\alpha}\ln s \\ &- (1-\zeta)\frac{\alpha}{1-\alpha}\ln(n+g+\delta), \end{aligned} \tag{7}$$

where $y(t) = Y(t)/L(t)$ is the per capita income and $\zeta = e^{-\beta_1}(t_2 - t_1)$. Equation (7) represents the transitional growth dynamics of an economy towards its steady state income path and represents the general dynamic framework within which income convergence is examined. The equation can be viewed as a dynamic panel data model with $(1-\zeta)\ln A(0)$ as the time invariant individual unit/regional effect term and the $g(t_2 - t_1)$ as the time specific effect. Using standard notation of the panel data literature and adding a disturbance term we may re-write equation (7) as:

$$y_{it} = \gamma y_{it-1} + \sum_{j=2}^{3} \beta_j x_{it}^j + \eta_t + \mu_i + v_{it}, \tag{8}$$

where $y_{it} = \ln y(t_2)$, $y_{it-1} = \ln y(t_1)$, $\gamma = e^{-\beta_1}(t_2 - t_1)$, β_1 measures the rate of convergence, $\beta_2 = (1-\zeta)\alpha/(1-\alpha)$, $\beta_3 = -(1-\zeta)\alpha/(1-\alpha)$, $x_{it}^1 = \ln(s)$, $x_{it}^2 = \ln(n+g+\delta)$, $\mu_i = (1-\zeta)\ln A(0)$, $\eta_t = g(t_2 - t_1)$, and v_{it} is the usual transitory error term that varies across units/regions and time periods and has mean equal zero. In our empirical analysis, we will allow provinces to have differences in the initial state of technology $A(0)$, and assume that g (technological growth rate) is homogeneous across provinces. Hence equation (8) becomes:[7]

$$y_{it} = \gamma y_{it-1} + \sum_{j=2}^{3} \beta_j x_{it}^j + \mu_i + v_{it} \tag{9}$$

3 ECONOMETRIC ISSUES AND DATA

It is a well known fact in the convergence literature that the lagged dependent variable (y_{it-1}) is endogenous to the fixed effect μ_i (Arellano and Bond, 1991, and Blundell and Bond, 1998). Hence, OLS estimation of equation (6) without the fixed effect gives rise to dynamic panel bias.[8] This is because the lagged dependent variable is positively related to the fixed effect which violates an assumption necessarily for the consistency of OLS. In particular, OLS inflates the coefficient estimate of the lagged dependent variable by attributing predictive power to it that actually belongs to the fixed effect.[9] One of the non panel

[7] The $A(0)$ term reflects not just technology but resources endowments, climate, and institutions. As earlier mentioned these factors differ across the Canadian provinces.

[8] This is also known in the literature as the endogeneity problem.

[9] Hsiao (1986) Sevestre and Trongnon (1996) and Weeks and Yao (2003) make the same argument.

data approaches to solving the endogeneity problem is the within group (WG) estimator. The technique partials the cross section fixed effect from the data by applying a mean deviation transform to each variable, when the mean is calculated at the cross-section unit level. However, this approach does not eliminate the "dynamic panel bias." According to Bond (2002) the lagged dependent variable under the WG estimator becomes $y^*_{it-1} = y_{it-1} - \frac{1}{T-1}(y_{i2} + ... + y_{iT})$ while the error term becomes $v^*_{it} = v_{it} - \frac{1}{T-1}(v_{i2} + ... + v_{iT})$. The problem is that the y_{it-1} term in y^*_{it-1} correlates negatively with $-\frac{1}{T-1}v_{it-1}$ in v^*_{it}. Hence, the coefficient on the lagged dependent variable will be biased downwards. Finally, in the case of conditional convergence studies, the problem of potential endogeneity of other variables such as savings/investment rate is also neglected.

The panel data analysis by using both cross sectional and time series variability is well equipped to deal with the above problems. One of such methods is the DIFF-GMM. As suggested by Arellano and Bond (1991), the endogeneity problem of the lagged dependent variable can be corrected by first differencing the data and under the assumption of serially uncorrelated level residuals, the second and third untransformed lags are used as instruments.[10] This implies the following moment condition $E(y_{it}\Delta\mu_{it}) = 0$ for all *t =3,….T.* At the same time differencing the data addresses the problem of unobserved fixed effect. Applying the transformation to equation (9) gives:[11]

$$\Delta y_{it} = \gamma\Delta y_{it-1} + \sum_{j=2}^{3}\beta_j \Delta x^j_{it} + \Delta v_{it}. \tag{10}$$

Though the fixed effect is expunged, and the endogeneity problem is solved by first differencing the data, Blundell and Bond (1998) demonstrate that if y is persistent (close to random walk) then DIFF-GMM performs poorly because past levels convey little information about future changes. Hence, untransformed lags are weak instruments for transformed variables. This is referred to as the "weak instrument problem" of the DIFF-GMM estimator.[12]

The SYS-GMM developed by Blundell and Bond (1998) addresses the weak instrument problem of DIFF-GMM.[13] The approach comprises of two equations. The first is the usual DIFF-GMM which uses lagged levels as instruments for equations in first differences. In the second equation, instead of differencing the data to expunge the fixed effect, it takes the first difference of the variables to make them exogenous to the fixed effect and use them as instruments in the level equation. This amounts to adding another moment condition, $[E(\Delta w_{it}\mu_i) = 0]$, for all *i* and *t*, where Δw_{it} is the instrument and μ_i is the fixed effect. By exploring more moment conditions, the SYS-GMM estimator is more efficient asymptotically and in finite sample properties than the DIFF-GMM estimator that uses only a subset of linear moment conditions. The efficiency gain from imposing the level moment condition comes with some potential problems with the SYS-GMM estimator. There is the need for additional assumptions, which if not satisfied will lead to bias in the estimates. For instance, if the unit specific effects are correlated, then some of the level moments conditions will not be valid and the SYS-GMM estimates will be inconsistent. It is, therefore, important to conduct a specification test to justify the use of additional level moment conditions. This can be evaluated by the Sargan-difference test for instruments validity. To evaluate the finite sample performance of both the DIFF-GMM and SYS-GMM estimators, we used the OLS and the WG estimators to establish an upper and lower bound for the autoregressive parameter (y_{it-1}).

All the data used for the study were obtained from the online database of Statistics Canada: CANSIMM II. The period of analysis is from 1982 to 2006. Since we want to determine the effects of federal fiscal transfers on provincial income convergence, we used annual data on per capita real personal income, with and without government transfers for all the ten provinces. If the convergence rate for the per capita real personal income with government transfers is greater than that of the per capita real income without government transfers, then the federal-provincial transfers have helped reduce the extent of provincial income disparities in Canada. Other variables for which we collected data are: real investment, labour force growth

[10] Another form of transformation known as "forward orthogonal deviation" or "orthogonal deviation" is commonly used.

[11] We are assuming that the predetermined variables x_i may not be strictly exogenous.

[12] Blundell and Bond (1998) used Monte Carlo simulation to demonstrate that the weak instrument problem can result in large finite-sample biases when using DIFF-GMM estimator to estimate autoregressive models with relatively short panels.

[13] Blundell and Bond (1998) have also demonstrated that under a random effect model, the DIFF-GMM estimator can suffer from serious efficiency losses. This is because there are potential informative moment conditions that are ignored in the DIFF-GMM approach.

for working age population (between 15 and 65 years). To render our results comparable with other studies using Canadian data, we defined all our variables as relative to the Canadian average.[14] By adopting this approach, our results are less likely to be influenced by business cycle fluctuation.

4 EMPIRICAL INVESTIGATION AND RESULTS

The regression results for the test of the effect of the federal government transfer systems on income convergence in Canada are reported in Tables 1 and 2 below. As discussed in the previous section, the OLS level estimators by omitting the unobserved unit specific effects in a dynamic panel data model, yield estimates that are biased upwards and inconsistent due to the positive correlation between the lagged dependent variable (y_{it-1}) and the fixed effects (μ_i). On the other hand, the WG estimator produces a downward bias with the extent of attenuation increasing when exogenous variables are added to the model. In this section, we use the OLS and the WG estimators to establish the upper-lower bound for the coefficient of the lagged dependent variable. A good estimate of the true parameter should therefore fall within the range established by these two estimators. Hence, we use the estimates from the OLS and WG estimators to judge the unbiasedness of the DIFF-GMM and SYS-GMM estimators.

Table 1: *Panel test for conditional convergence of PIT*

	(1) OLS	(2) WG	(3) DIFF-GMM	(4) SYS-GMM
ln (y_{t-1})	0.9813***	0.9132***	0.9105***	0.9657***
	(0.0124)	(0.1251)	(0.0128)	(0.1285)
ln $(n+g+\delta)$	0.0084	-0.0071	0.0125	0.0094
	(0.0113)	(0.0174)	(0.0144)	(0.1441)
ln(I/GDP)	0.0062	0.0034	0.0531	0.0168**
	(0.0086)	(0.0167)	(0.1153)	(0.0123)
Constant	-0.1673	-0.0223	NA	-0.0096
	(0.0203)	(0.0303)		(0.0260)
Sargan Test (P-value)			0.017	0.235
$g_{\min}$			8.16	14.73
No. of Observations	240	240	210	220

Notes: Standard errors in parentheses. All reported standard errors are corrected for heteroscedasticity. The parameter estimates and the standard errors reported from the GMM are one-step estimators. The figure reported for the Sargan test is the *p* value of the null hypothesis of valid instruments. ***, **, * denote significance at 1, 5, and 10 percent respectively. The $g_{\min}$ is calculated using 3 instruments for the DIFF-GMM and 6 instruments for the SYS-GMM. The desired maximum bias of the IV estimator relative to OLS is 10%.

Column 1 and 2 of the tables report the results of the OLS and WG estimators respectively. The third and fourth columns report the parameter estimates using the DIFF-GMM and SYS-GMM estimators respectively. Table 1 reports results from personal income less government transfers (PIT). The estimated coefficients for y_{it-1} for all four estimation methods are very significant. The implied speed of convergence from the OLS result is 1.87 percent which is significantly lower than the 8.68

[14] Specifically, the provincial economic variables Q_{it} (like y_{it}, x_{it}) are measured as the logarithmic deviation from the cross-sectional mean at time *t*.

$$Q_{it} = \log\left(Q_{it} \middle/ \sum_{i=1}^{N} \frac{1}{N} Q_{it} \right).$$

percent speed of convergence implied by the WG estimation[15]. The result for the OLS is similar to what other studies using the OLS technique have obtained for Canada. The parameter estimate of the y_{it-1} for the DIFF-GMM estimator, though significant, falls out of the upper and lower bound (0.9813-0.9132) established by the OLS and the WG estimators. Its implied convergence rate is 9 percent[16]. As discussed earlier, this weak performance of the DIFF-GMM estimator is likely due to the weakness of the instrument set. The Stock and Yogo (2001) test procedure for weak instruments was conducted. The displayed statistics of 8.16 is less than the critical value of 9.8 at the 5% significance level, indicating that the instruments for the lagged dependent variable for the DIFF-GMM estimator are weak. We then conducted the Sargan test of instrument validity. The *p*-value suggests that the instrumental variables used in the DIFF-GMM estimator are not valid. Hence, the estimator suffers from the weak instrument problem. The coefficient estimate of (y_{it-1}) for the SYS-GMM estimator (0.9657) is significant and falls between the upper and lower bound (0.9813-0.9132). Therefore, the estimator is likely to be unbiased. The Sargan test (p-value= 0.235) suggests that the instrumental variables used in the SYS-GMM are valid. Hence, the rate of convergence of personal income less government transfers is 3.43, which is significantly larger than the one obtained from the OLS estimation technique (1.87). With the exception of the results for the SYS-GMM where the coefficient for the (I/GDP) is significant, the coefficients on the conditional variables $((n+g+\delta), I/GDP)$ in all other equations are mostly not significant and carried the wrong signs.

Table 2: *Panel test for conditional convergence of PI*

	(1)	(2)	(3)	(4)
	OLS	WG	DIFF-GMM	SYS-GMM
ln (y_{t-1})	0.9780***	0.9074***	0.8924***	0.9552***
	(0.01251)	(0.0309)	(0.2859)	(0.1425)
ln $(n+g+\delta)$	0.0084	0.0013	-0.1752	0.0093
	(0.0113)	(0.0145)	(0.1788)	(0.1190)
ln(I/GDP)	0.0063	0.0035	0.0419	0.0246**
	(0.0811)	(0.1394)	(0.0321)	(0.0121)
Constant	-0.1673	-0.1064	NA	-0..1821
	(0.2037)	(0.0257)		(0.2147)
Sargan Test				
(P-value)			0.026	0.426
$g_{\min}$			7.69	14.33
No. of Observations	240	240	210	220

Notes: Standard errors in parentheses. All reported standard errors are corrected for heteroscedasticity. The parameter estimates and the standard errors reported from the GMM are one-step estimators. The figure reported for the Sargan test is the *p* value of the null hypothesis of valid instruments. ***, **, * denote significance at 1, 5, and 10 percent respectively. The $g_{\min}$ is calculated using 3 instruments for the DIFF-GMM and 6 instruments for the SYS-GMM. The desired maximum bias of the IV estimator relative to OLS is 10%.

Table 2 reports the results for per capita personal income (PI). The pattern of the parameter estimates is similar to those in table 1. The convergence parameter for the DIFF-GMM estimator (0.8924) falls out of the upper-lower bound (0.9780-0.9074) established by the OLS and the WG estimators. The weak instruments and the Sargan tests indicate that the instruments used in the DIFF-GMM are weak and the moment conditions are not valid. The SYS-GMM estimate (0.9552) falls within the bound, and according to the Sargan test, the instruments used are valid. The implied convergence rate for the estimator is 4.48 percent which is greater than the 3.43 we obtained for the results for the per capita personal income less government transfers (PIT). This implies that the federal-provincial fiscal transfers have helped reduce the extent of provincial income disparities.

[15] The speed of convergence is calculated as 1- γ (the parameter of the lagged dependent variable).

[16] It is important to note that these numbers are themselves point estimates with associated confidence intervals.

Again, with the exception of the results for the SYS-GMM where the coefficient for the (I/GDP) is significant, the coefficients on the conditional variables $((n+g+\delta), I/GDP)$ in all other equations are mostly not significant and carried the wrong signs.

5 CONCLUSION

The issue of provincial income disparity in Canada is a complex one that has its root in the distribution of natural resources and industrial activities in the country. To address the issue, the federal government has implemented several policies the most significant of it is the Constitution Act of 1982, Section 36 which spells out federal responsibilities in the area of provincial disparities and equalization. As a result, the federal and provincial governments have embarked on a comprehensive fiscal transfer program particularly aimed at bridging the gap between the poor and rich provinces. This policy shift has generated a lot of empirical research which have focused on the evaluation its impact on income disparities in Canada. These researches have generally used the OLS estimation technique which ignores the unobserved unit specific effects in a dynamic panel data model. It is also a well known fact in the convergence literature that the lagged dependent variable (y_{it-1}) is endogenous to the fixed effect μ_i . Hence, OLS estimation without the fixed effect gives rise to dynamic panel bias (endogeneity problem). This paper extends the analysis of previous studies on provincial income convergence in Canada by using a new methodology which allows us to correct for endogeneity of right hand side variables and incorporate, albeit implicitly, provincial fixed effects.

The central conclusions of the paper are as follows. First, using results from an application of OLS and WG estimators, the SYS-GMM estimator is shown to be the preferred estimation method, in terms of providing consistent and more efficient estimates of the convergence parameter. Second, the current rate of convergence of per capita personal income is 4.48 percent per year. This is considerably higher than the range of 1.8 to 2.4 percent per year that previous studies using least square estimators have reported. The result is also consistent with the claim by Islam (1995) that the speed of convergence parameter based upon panel data studies has in general been considerably higher than the average of 2 percent reported by the cross sectional studies. Third, the equalization program, which is part of the overall federal fiscal transfers, has reduced income disparities among Canadian provinces. This implies that the transfers have succeeded in making poorer provinces catch up with the richer ones as earlier studies such Coulombe and Lee (1995) and Coulombe (1996) have already demonstrated.

From a policy point of view, this paper has highlighted the relative importance of interprovincial fiscal redistribution in the issue of income disparities among Canadian provinces. The methodology used and the results reported have provided a sound basis for further research. In the empirical application of the GMM estimators, we assumed that technological progress is homogeneous among Canadian provinces. This is an empirical issue that needs to be tested explicitly. It is also important to mention a potential weakness of this paper. According to Blundell and Bond (1998), the SYS-GMM estimator yields better results when the cross sectional dimension of the panel data is large and the time series dimension is small. In our dataset we have large time series and small cross section unit.

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