A GMM Study of the Effect of NAFTA on Quebec Manufacturing Industries*

Wanling Huang†

July 2010, PhD Job Market Paper II

Abstract

Using Generalized Method of Moments (GMM), this paper examines the effect of the North American Free Trade Agreement (NAFTA) on earnings of the Quebec manufacturing industries. It calculates Canadian tariff rates over the period 1991-2007 for manufacturing industries classified using the North American Industry Classification System (NAICS) and analyzes the effect of Canadian tariff concessions granted to the United States and Mexico. The system GMM method is used to estimate a two-way dynamic panel data model. In order for the system GMM estimator to have best possible properties, it proposes a simulation-based moment selection procedure, uses the procedure to select instruments, and shows that the system GMM estimator is not worse than the bootstrap-based bias-corrected least-squares dummy variable (LSDVb) estimator (Everaert and Pozzi, 2007) if moments are properly chosen. In other words, we use simulations to choose instruments so that the finite sample properties of the GMM are optimized, then we compare this "optimal" GMM estimator with the "best" non-GMM alternative. Finally, using this "optimal" GMM estimator, we find that the Canadian tariff concessions' effect on Quebec manufacturing earnings is statistically significant but economically very small.

JEL Classification: F13, F14, F15, F16

Keywords: Free trade, NAFTA, GMM, Dynamic panel data model, Moment selection

*I would like to thank my supervisor Prof. Artem Prokhorov for many helpful discussions and important suggestions. We would like to thank Prof. Jeffrey M. Wooldridge for the very illuminating discussion in May, 2009. The FQRSC Doctoral Scholarship is highly appreciated. We thank the World Bank for the financial contribution which makes it possible for us to use WITS and access UNCTAD-TRAINS database. We thank Rajiv Johal and Alex Guindon for their helpful guidance in obtaining the original data.

†Department of Economics, Concordia University, 1455 de Maisonneuve Blvd W, Montreal, QC, H3G1M8, Canada, email: whuang@live.concordia.ca; School of Finance and Economics, Jiangsu University, Zhenjiang city, Jiangsu 212013, China, email: wanlinghuang@ujs.edu.cn.

1 Introduction

As argued in a recent article (Postrel, 2005) in The New York Times, "Economists argue for free trade. They have two centuries of theory and experience to back them up. And they have recent empirical studies of how the liberalization of trade has increased productivity in less-developed countries like Chile and India. But still, free trade is a tough sell." Trefler (2004) argues that one reason for this is that there is not enough research on how free trade affects industrialized countries like the United States and Canada. There are a few articles addressing this question (see e.g., Romalis (2007) and references therein), but these are very rare. For research on Canada specifically, see the references listed by Trefler (2004).

In Canada, more than a half of the population live in the central area, which is made up of Ontario and Quebec. This area is the industrial and manufacturing heartland of Canada and produces more than three-quarters of all Canadian manufactured goods (*A Look at Canada*, 2007 edition). The manufacturing production of Quebec accounts for about 35% of that share (Table 304-0015, Statistics Canada). It is therefore not surprising that this paper focuses on the effect of the North American Free Trade Agreement (NAFTA) on Quebec manufacturing industries.

Implemented in 1994, NAFTA called for gradual reduction of tariffs among Canada, Mexico and the United States. With about one-third of the world's total GDP, NAFTA has become the world's largest free trade area, significantly larger than the European Union. Before NAFTA, there are other two major events in the history of trade liberalization among the three member countries. One is that Mexico jointed GATT in 1985, and the other is that the Canada-U.S. Free Trade Agreement (CUSFTA) came into effect in 1989. Gaston and Trefler (1997), Beaulieu (2000), and Trefler (2004) analyze the effect of tariff reductions on earnings of the Canadian industries. The data used in these articles are from 1996 and earlier, so their focus is mainly on the effect of CUSFTA. Our data cover a wider period of 1991-2007, which is far enough from CUSFTA and long enough to include the effect of NAFTA.

According to Foreign Affairs and International Trade Canada (FAITC), "NAFTA has contributed to raising standards of living" (FAITC, 2001). This paper seeks to evaluate this statement quantitatively by looking at earnings of the Quebec manufacturing industries before and after introduction of NAFTA. Specifically, the question we ask in this paper is: what is the tariff reductions effect of NAFTA on Quebec manufacturing earnings?

The remainder of the paper is organized as follows. In Section 2, we discuss the econometric model and estimation method. Specifically, the system GMM (Arellano and Bover, 1995; Blundell and Bond, 1998) is used to estimate a two-way dynamic panel data model. Our sample is small, so in order for the system GMM estimator to have desirable properties, we need to decide which instruments to use. Thus, a simulation-based moment selection procedure is proposed in Section 3. Based on this procedure, the system GMM estimator is compared with the bootstrap-based bias-corrected least-squares dummy variable (LSDVb) estimator (Everaert and Pozzi, 2007), which is also described in Section 3. Estimation results are presented and analyzed in Section 4. Some brief conclusions are given in Section 5.

2 Econometric Model and Estimation Method

The main purpose of the paper is to estimate the effect of Canadian tariff reductions on Quebec manufacturing earnings. It is well-known that earnings data usually display strong autocorrelation. The autocorrelation among Quebec manufacturing earnings data is presented in Table 1. The strong autocorrelations suggest that the appropriate econometric model for Quebec manufacturing earnings should be a dynamic one.

An alternative approach that accounts for strong autocorrelations is known as long double differencing. Long double differencing is essentially a difference-in-difference approach that compares changes in the dependent variable at two distant points in time, one before FTA and one after. Trefler (2004, p. 874) argues that every previous FTA study used annual data without any correction for autocorrelation. He cites Gaston and Trefler (1997), Head and Ries (1999a,b), Beaulieu (2000) and Clausing (2001). He then adopts long double-differencing models to avoid the dynamic panel estimation problems. From the perspective of

Table 1: Autocorrelation Among Quebec Manufacturing Earnings : 1991-2007

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
1991	1	.98	.96	0.95	0.96	0.95	0.93	0.91	0.87	0.87	0.86	0.84	0.81	0.74	0.71	0.70	0.70
1992	0.98	1	0.97	0.96	0.96	0.95	0.93	0.91	0.89	0.89	0.87	0.86	0.83	0.77	0.73	0.72	0.72
1993	0.96	0.97	1	0.99	0.98	0.97	0.95	0.92	0.91	0.90	0.90	0.89	0.86	0.81	0.78	0.77	0.75
1994	0.95	0.96	0.99	1	0.98	0.96	0.96	0.94	0.92	0.91	0.90	0.88	0.85	0.81	0.78	0.76	0.74
1995	0.96	0.96	0.98	0.98	1	0.98	0.96	0.93	0.92	0.92	0.91	0.89	0.86	0.82	0.78	0.76	0.75
1996	0.95	0.95	0.97	0.96	0.98	1	0.97	0.94	0.92	0.92	0.91	0.90	0.88	0.84	0.80	0.78	0.75
1997	0.93	0.93	0.95	0.96	0.96	0.97	1	0.97	0.94	0.94	0.93	0.92	0.91	0.85	0.82	0.81	0.78
1998	0.91	0.91	0.92	0.94	0.93	0.94	0.97	1	0.98	0.97	0.96	0.95	0.93	0.87	0.84	0.82	0.80
1999	0.87	0.89	0.91	0.92	0.92	0.92	0.94	0.98	1	0.99	0.98	0.96	0.95	0.90	0.87	0.85	0.82
2000	0.87	0.89	0.90	0.91	0.92	0.92	0.94	0.97	0.99	1	0.99	0.97	0.96	0.92	0.89	0.87	0.84
2001	0.86	0.87	0.90	0.90	0.91	0.91	0.93	0.96	0.98	0.99	1	0.99	0.98	0.93	0.90	0.88	0.86
2002	0.84	0.86	0.89	0.88	0.89	0.90	0.92	0.95	0.96	0.97	0.99	1	0.98	0.94	0.91	0.89	0.86
2003	0.81	0.83	0.86	0.85	0.86	0.88	0.91	0.93	0.95	0.96	0.98	0.98	1	0.97	0.93	0.92	0.88
2004	0.74	0.77	0.81	0.81	0.82	0.84	0.85	0.87	0.90	0.92	0.93	0.94	0.97	1	0.98	0.95	0.91
2005	0.71	0.73	0.78	0.78	0.78	0.80	0.82	0.84	0.87	0.89	0.90	0.91	0.93	0.98	1	0.98	0.94
2006	0.70	0.72	0.77	0.76	0.76	0.78	0.81	0.82	0.85	0.87	0.88	0.89	0.92	0.95	0.98	1	0.96
2007	0.70	0.72	0.75	0.74	0.75	0.75	0.78	0.80	0.82	0.84	0.86	0.86	0.88	0.91	0.94	0.96	1

interpretation, a dynamic panel data model is more appropriate for the present paper than a long double-differencing one. As Baltagi (2005) points out, "many economic relationships are dynamic in nature and one of the advantages of panel data is that they allow the researcher to better understand the dynamics of adjustment."

Using a panel of 71 Quebec manufacturing industries over the period 1991-2007, we estimate a typical two-way dynamic panel data model. A list of these industries is provided in Table A in the Appendix. Holtz-Eakin (1988) finds evidence in the Panel Study of Income Dynamics (PSID) data that the wage dynamics follows an AR(2) model. We initially included two lags of the dependent variable as regressors, but regressions using the present data always show that the second lag is insignificant. This is not surprising because large high-order autocorrelation in the dependent variable does not imply the same order AR model.

Let i index industries ($i = 1, 2, \cdots, N; N = 71$) and t index years ($t = 1, 2, \cdots, T; T = 17$), then the model can be specified as:

$$\ln y_{it} = \alpha \ln y_{i(t-1)} + \beta'(L)x_{it} + \lambda_t + u_{it}, \qquad |\alpha| < 1, \tag{2.1}$$

where

$$u_{it} = \eta_i + v_{it}.$$

The first-differenced transformation of (2.1) can be written as:

$$\Delta \ln y_{it} = \alpha \Delta \ln y_{i(t-1)} + \beta'(L)\Delta x_{it} + \Delta\lambda_t + \Delta v_{it}. \tag{2.2}$$

Here y_{it} is CPI-adjusted Quebec manufacturing earnings; x_{it} is a vector containing a set of explanatory variables which include τ_{it}^{us}, the effective tariffs[1] imposed by Canada on imports from the United States, and τ_{it}^{mex}, the effective tariffs for imports from Mexico; $\beta'(L)$ is a vector of polynomials in the lag operator; λ_t is a time effect; and η_i is an industry-specific effect. Detailed data description is provided in the Appendix. In order to be assured of capturing a sufficiently long effect of the tariffs, the maximum number of lags in x_{it} is initially

[1] In calculating tariffs, both non-zero and zero imports are considered. See the Appendix for details.

set at four. In subsequent notation, q and k denote the maximum number of lags in x_{it} and the dimension of x_{it} respectively; then $q = 4$ and $k = 2$. A panel unit root test using the cross-sectionally augmented ADF (CADF) statistic proposed by Pesaran (2007) shows that, augmented by one lag, the P-value of the test statistic is 0.001. This verifies that $|\alpha| < 1$ is satisfied.

The main reason for including a time effect λ_t is to remove the business cycle effect illustrated in Figure 1. Since N here is considered large and T is small, the time effects can be treated as unknown period specific parameters to be estimated, and a full set of time dummies is included for estimation (see also Arellano, 2003, p. 61 and Dahlberg and Johansson, 2000, p. 403). Alternatively, one might consider including a generated regressor in the differenced model to control for the business cycle. For example, Trefler (2004) runs a differenced time-series regression for each i to obtain the business cycle control variable. Note that this cannot be done for equations in levels, because of possible trends and unit root problems in time-series regression. However, this method has additional complications. First, the estimates of the standard deviation are wrong unless the nuisance parameters do not enter into the moment functions of interest (see, e.g., Pagan, 1984; Prokhorov and Schmidt, 2009), so an adjustment is usually needed (see, e.g., Wooldridge, 2002). Secondly, since N is large, regressions with specification tests for each i are time-consuming. Thirdly, in the regressions for each i, sample sizes are not large and some corrections may be necessary to avoid invalid inference.

The v_{it} in (2.1) is assumed to have finite moments and in particular $\mathbb{E}(v_{it}) = \mathbb{E}(v_{it}|y_{i(t-1)}, \lambda_t, \eta_i) = 0$ for all t. This assumption implies that v is serially uncorrelated but not necessarily independent over time. The OLS estimator from the first-difference specification is not consistent since $\Delta v_{it} = v_{it} - v_{i(t-1)}$ and $\Delta y_{i(t-1)} = y_{i(t-1)} - y_{i(t-2)}$ are correlated. However, $v_{it} - v_{i(t-1)}$ is uncorrelated with $y_{i(t-s)}$ for $s \geq 2$ and the differenced equation can be estimated consistently by GMM using $y_{i(t-s)}(s \geq 2)$ as instruments. It is obvious that an estimator that uses lags as instruments under the assumption of white noise errors would lose its consistency

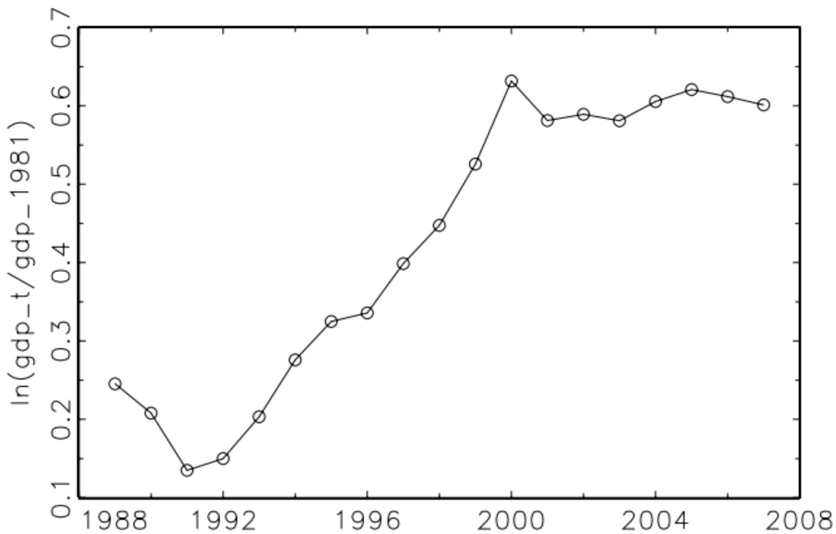

Figure 1: Real Canadian Manufacturing GDP

if in fact the errors in the levels equation were serially correlated. In other words, the validity of the instrumental variables hinges heavily upon lack of serial correlation in the errors. The first-order serial correlation in the first-difference errors need not be zero, but the second-order serial correlation has to be zero. Therefore, equivalently we can say that the consistency of the GMM estimators depends on the assumption $\mathbb{E}(\Delta v_{it} \Delta v_{i(t-2)}) = 0$ (Arellano and Bond, 1991, p. 281), which is exactly the null hypothesis of the Arellano-Bond specification test. Arellano and Bond (1991) show that asymptotically this test statistic has a standard normal distribution.

Note that we do not impose any restrictions on x_{it}. Let Z_i^+ denote the matrix of instruments used in estimation. Then (Blundell and Bond, 1998, p. 126),

$$Z_i^+ = \begin{bmatrix} Z_i & 0 & 0 & \cdots & 0 \\ 0 & \Delta y_{i2} & 0 & \cdots & 0 \\ 0 & 0 & \Delta y_{i3} & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & \Delta y_{i(T-1)} \end{bmatrix}, \tag{2.3}$$

where Z_i is a matrix of instruments for the differenced equation (Arellano and Bond, 1991) and Δy_{is} $(s = 2, \cdots, T-1)$ are the instruments for the levels equation (Arellano and Bover, 1995; Blundell and Bond, 1998). The form of Z_i depends on whether x_{it} is strictly exogenous, predetermined or endogenous. If x_{it} is strictly exogenous, i.e. $\mathbb{E}(x_{it}v_{is}) = 0$ for all t and s, all the $x's$ are valid instruments and Z_i has the form:

$$Z_i = \begin{bmatrix} y_{i1} & x'_{i1} & \cdots & x'_{iT} & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & y_{i1} & y_{i2} & x'_{i1} & \cdots & x'_{iT} & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & \cdots & y_{i1} & \cdots & y_{i(T-2)} & x'_{i1} & \cdots & x'_{iT} \end{bmatrix}.$$

So Z_i is a $(T-2) \times (T-2)[(T-1) + 2kT]/2$ matrix. If x_{it} is not strictly exogenous, things would be a little more complicated. Consider a simple situation where no lags of x_{it} are included. Due to a possible feedback from lags of the dependent variable to the current values of x, v_{it} can be correlated with future values of x and x_{it} is not strictly exogenous but only predetermined in the sense that $\mathbb{E}(x_{it}v_{is}) \neq 0$ for $s < t$ and zero otherwise. Then only $x_{i1}, \cdots, x_{i(s-1)}$ are valid instruments in the differenced equation for period s so that Z_i has the form:

$$Z_i = \begin{bmatrix} y_{i1} & x'_{i1} & x'_{i2} & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & y_{i1} & y_{i2} & x'_{i1} & x'_{i2} & x'_{i3} & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & y_{i1} & \cdots & y_{i(T-2)} & x'_{i1} & \cdots & x'_{i(T-1)} \end{bmatrix},$$

which is a $(T-2) \times (T-2)[(T-1) + k(T+1)]/2$ matrix. If, further, x_{it} is endogenous instead of just predetermined, then we lose one instrument for each regressor in x for each period. That is, only $x_{i1}, \cdots, x_{i(s-2)}$ are valid instruments in the differenced equation for period s so that Z_i has the form:

$$Z_i = \begin{bmatrix} y_{i1} & x'_{i1} & 0 & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ 0 & 0 & y_{i1} & y_{i2} & x'_{i1} & x'_{i2} & \cdots & 0 & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & \cdots & y_{i1} & \cdots & y_{i(T-2)} & x'_{i1} & \cdots & x'_{i(T-2)} \end{bmatrix},$$

which is a $(T-2) \times (T-2)(T-1)(1+k)/2$ matrix. Now it is pretty easy to consider the situation that q lags of x_{it} are also included in the model specification, in which case we lose q instruments for every regressor in x for each period as compared with the no lags case.

An estimator using only elements in Z_i as instruments is known as the differenced GMM estimator in the literature, while an estimator using both Z_i and Δy_{is} as instruments is known as the system GMM estimator. Simulations by Blundell et al. (2000) show that the system GMM estimator has much better finite sample properties than the differenced GMM estimator: it not only greatly improves the precision but also greatly reduces the finite sample bias.[2] Therefore, we use the system GMM estimator. The sample moments, on which the system GMM estimator is based, can be expressed as $N^{-1} \sum_{i=1}^{N} Z_i^{+\prime} v_i^{+}$, where

$$v_i^{+} = \begin{bmatrix} \Delta v_{i3} \\ \vdots \\ \Delta v_{iT} \\ u_{i3} \\ \vdots \\ u_{iT} \end{bmatrix}_{2(T-2)\times 1} . \tag{2.4}$$

With the advent of the system GMM estimator, the imprecision of the GMM estimator is not so severe anymore, but an important decision still has to be made while using this estimation method: which instruments should be used? Perhaps the best estimator so far for dynamic panel data models is the LSDVb estimator[3] proposed by Everaert and Pozzi (2007). The bootstrap is a very effective method in bias correction for non-GMM estimators, as shown by Everaert and Pozzi (2007), but it might not be appropriate for GMM estimators due to weak instruments. However, if moments are properly selected, the system GMM estimator

[2]Interested readers may refer to Hayakawa (2007) for an analysis of why the system GMM estimator is less biased than the differenced GMM estimator even though the former uses more instruments.

[3]LSDVb is a bias-corrected version for the least-squares dummy variable estimator based on an iterative bootstrap procedure.

might not be a bad choice. In the next section, we propose a simulation-based moment selection procedure and discuss this issue in detail. We later show that the system GMM estimator is not worse than the LSDVb estimator.

3 Simulation-Based Moment Selection

It has been seen in Section 2 that the number of moment conditions is of order T^3, which can be very large even if T is only moderately large. Simulations by Ziliak (1997) indicate that the bias/efficiency trade-off exists for GMM as the number of moment conditions increases, and that the downward bias in GMM is quite severe as the number of moment conditions expands, outweighing the gains in efficiency. Bun and Kiviet (2006) derive the second-order bias of the system GMM estimator and examine how the order of magnitude of bias changes when a different set of instruments is used. Andrews and Lu (2001) and Han and Phillips (2006) address the problem of GMM with many moment conditions asymptotically, and Newey and Windmeijer (2009) give a new variance estimator for generalized empirical likelihood (GEL) in this aspect. Okui (2009) derives an approximation of the mean square error (MSE) and proposes a procedure for choosing the number of instruments for the differenced GMM estimator. Doran and Schmidt (2006) use principal components of the weighting matrix to effectively drop some of the moment conditions and improve finite sample properties of GMM estimators. In this section, we consider a moment selection approach for the system GMM estimator, based on real-life data simulations. Simulation using real-life data is not new (see, e.g., Dahlberg and Johansson, 2000), but this kind of simulation for moment selection has not been studied yet. Dahlberg and Johansson (2000) use real-life data in Monte Carlo experiments to verify that testing against bootstrap critical values is superior to testing against asymptotic critical values. We use a similar method to select moments for the purpose of obtaining a better system GMM estimator.

3.1 Motivation

Assume x_{it} is strictly exogenous. We exploit the exogeneity of Δx_{it} and $\Delta\lambda_t$ in the differenced equation (2.2) and the instruments $\Delta y_{i(t-1)}$ for the levels equation (2.1). Then, adding a different number of lags of the dependent variable as additional instruments for equation (2.2) would have different regression results, see Table 2. In column (a'), only one lagged dependent variable $y_{i(t-2)}$ is used as an additional instrument. Eliminating insignificant regressors, we obtain results in (a). Similarly, if two lags $(y_{i(t-2)}, y_{i(t-3)})$ or three lags $(y_{i(t-2)}, y_{i(t-3)}, y_{i(t-4)})$ are used as additional instruments, (b) and (c) are eventually obtained respectively. For each regression in Table 2, the standard error is corrected based on Windmeijer (2005). Both the Arellano-Bond test and the Wald test verify that the model specification for each regression in Table 2 is correct[4].

The results in Table 2 show that as more lags of the dependent variable are added as instruments, the coefficient estimate of the lagged dependent variable becomes smaller, from .9697 to .9526, and the magnitude and significance of the estimates for other regressors are different. When all lags (from $y_{i(t-2)}$ to y_{i1}) of the dependent variable are added, the coefficient estimate of the lagged dependent variable is as small as .7111[5], which has not been reported in Table 2. A practical question is which regression should be used, i.e., how many instruments to employ.

A reasonable answer to the question is to choose the regression with the smallest MSE, but the MSE cannot be computed because the true values of the coefficients are unknown. Therefore, we assume that earnings are a function of tariffs and perform simulations.

[4]The null hypothesis of the Arellano-Bond test is discussed in the main text. The Wald test for model specification tests the joint significance of the independent variables, but it is not shown in the table to save space.

[5]This suggests that for some classic examples in the literature of dynamic panel data models, if fewer instruments are used, the estimate of the lagged dependent variable may approach one.

Table 2: GMM Estimation Using Different Instruments

Independent variables[a]	(a')	(a)	(b)	(c)
$\ln earnings_{i(t-1)}$	.9676 (.0414)	.9697 (.0394)	.9614 (.0381)	.9526 (.0377)
τ_{it}^{us}	.0274 (.0050)	.0293 (.0053)	.0268 (.0058)	.0257 (.0085)
$\tau_{i(t-1)}^{us}$	.0057 (.0078)	—	—	—
$\tau_{i(t-2)}^{us}$	.0130 (.0069)	.0117 (.0039)	.0128 (.0048)	—
$\tau_{i(t-3)}^{us}$	-.0110 (.0075)	—	—	—
$\tau_{i(t-4)}^{us}$	-.0234 (.0075)	-.0267 (.0057)	-.0288 (.0069)	-.0359 (.0116)
τ_{it}^{mex}	-.0292 (.0235)	—	-.0449 (.0194)	—
$\tau_{i(t-1)}^{mex}$	.0079 (.0171)	.0283 (.0110)	—	—
$\tau_{i(t-2)}^{mex}$	-.0087 (.0223)	—	—	—
$\tau_{i(t-3)}^{mex}$	-.0040 (.0260)	—	—	—
$\tau_{i(t-4)}^{mex}$	-.0038 (.0376)	—	—	—
Arellano-Bond test	-1.147	-1.1771	-1.1252	-1.1387
No. of observations	923	923	923	923

[a] Dependent variable is $\ln(earnings)_{it}$.

Notes:

(i) Windmeijer WC-robust estimators for standard errors are reported in parentheses;

(ii) The GMM estimates reported are all two step;

(iii) Time dummies are not shown here to save space;

(iv) The Arellano-Bond test reports the test for second-order serial correlation in the first-differenced residuals.

3.2 Experimental Design

Suppose earnings are a function of last year's earnings, tariffs (possibly at some lags) imposed by Canada on imports from the United States and tariffs for imports from Mexico. A time effect (λ_t), an individual fixed effect (η_i) and a white noise error term (v_{it}) are also included in the function. The basic idea for simulations is: take a set of coefficient estimates from Table 2 as the true parameter values and use the real data on regressors to generate values on the dependent variable, then run regressions using different instruments and calculate the MSE for each regression. Since there are multiple regressors in the model, we use the sum over the MSE calculated for the coefficient estimate on each regressor, denoted by sumMSE, as a criterion. This process is repeated many times. Note that every time, the number of instruments for the minimum sumMSE regression might not be the same. We choose the number of instruments for which sumMSE is minimized most frequently.

Three Monte Carlo experiments are conducted. The data generating process (DGP) of the three experiments are represented by equations (3.1), (3.2) and (3.3):

$$\hat{\ln} y_{i1} = \ln y_{i1},$$

$$\hat{\ln} y_{it} = \alpha \hat{\ln} y_{i(t-1)} + \beta_{10}\tau_{it}^{us} + \beta_{12}\tau_{i(t-2)}^{us} + \beta_{14}\tau_{i(t-4)}^{us} + \beta_{21}\tau_{i(t-1)}^{mex} + \lambda_t + \hat{\eta}_i^a + v_{it}, \tag{3.1}$$

$$\hat{\ln} y_{it} = \alpha \hat{\ln} y_{i(t-1)} + \beta_{10}\tau_{it}^{us} + \beta_{12}\tau_{i(t-2)}^{us} + \beta_{14}\tau_{i(t-4)}^{us} + \beta_{20}\tau_{it}^{mex} + \lambda_t + \hat{\eta}_i^b + v_{it}, \tag{3.2}$$

$$\hat{\ln} y_{it} = \alpha \hat{\ln} y_{i(t-1)} + \beta_{10}\tau_{it}^{us} + \beta_{14}\tau_{i(t-4)}^{us} + \lambda_t + \hat{\eta}_i^c + v_{it}, \tag{3.3}$$

$$|\alpha| < 1, \quad t = 2, \cdots, T$$

where $\hat{\eta}_i^a$, $\hat{\eta}_i^b$ and $\hat{\eta}_i^c$ are estimated from real-life data:

$$\hat{\eta}_i^a = \frac{1}{T-4}\sum_{t=5}^{T}(\ln y_{it} - \alpha \ln y_{i(t-1)} - \beta_{10}\tau_{it}^{us} - \beta_{12}\tau_{i(t-2)}^{us} - \beta_{14}\tau_{i(t-4)}^{us} - \beta_{21}\tau_{i(t-1)}^{mex} - \lambda_t),$$

$$\hat{\eta}_i^b = \frac{1}{T-4}\sum_{t=5}^{T}(\ln y_{it} - \alpha \ln y_{i(t-1)} - \beta_{10}\tau_{it}^{us} - \beta_{12}\tau_{i(t-2)}^{us} - \beta_{14}\tau_{i(t-4)}^{us} - \beta_{20}\tau_{it}^{mex} - \lambda_t),$$

$$\hat{\eta}_i^c = \frac{1}{T-4}\sum_{t=5}^{T}(\ln y_{it} - \alpha \ln y_{i(t-1)} - \beta_{10}\tau_{it}^{us} - \beta_{14}\tau_{i(t-4)}^{us} - \lambda_t).$$

Here $\ln y_{it}$, τ_{it}^{us}, τ_{it}^{mex} and λ_t are real-life data for Quebec manufacturing industries, and $\hat{\ln y_{it}}$ denotes generated data. There are 71 cross-sections denoted by i and 17 time periods denoted by t. The parameter values for equations (3.1), (3.2) and (3.3) are taken from columns (a), (b) and (c) of Table 2 respectively.

For each of the three experiments, the number of replications is set to be 100: 110 samples are produced from each of the equations (3.1), (3.2) and (3.3) and the first ten samples are discarded. For each sample in each experiment, regressions using different lags of the dependent variable as additional instruments are run. Finally, sumMSE for each regression is calculated and the regression with the smallest sumMSE for each sample is found. This "optimal" regression is denoted as GMMsj, where j is the number of lags of the dependent variable that are used as additional instruments.

3.3 Simulation Results

The results from the three experiments are displayed in Table 3. In Experiment I, 74 out of 100 samples (74%) have the smallest sumMSE occuring at GMMs1, i.e., using only one lagged dependent variable $y_{i(t-2)}$ as an additional instrument[6] for each period. In Experiments II and III, the occurrence increases to 81% and 85% respectively. For all three experiments, the smallest sumMSE never occurs at $j > 4$. The simulation results suggest that using lags more than four as additional instruments would never be justified in terms of sumMSE, and the system GMM using only one lagged dependent variable $y_{i(t-2)}$ as an additional instrument is statistically the best choice. In other words, adding moments beyond GMMs1 increases bias too much to make efficiency impovement useful. Therefore, the system GMM using only one lagged dependent variable $y_{i(t-2)}$ as an additional instrument for each period is appropriate for our application.

[6]in addition to $\Delta y_{i(t-1)}$.

Table 3: Occurrence of Regression with Smallest sumMSE at GMMsj : Estimation

Experiment[a]:	I	II	III
GMMs1	74%	81%	85%
GMMs2	17%	14%	11%
GMMs3	7%	3%	2%
GMMs4	2%	2%	2%
Total:	100%	100%	100%

[a]Experiment I, II and III: true values of coefficients are from (a), (b) and (c) in Table 2 respectively.

3.4 System GMM vs LSDVb

Although the simulation-based moment selection procedure above is presented for the special case of Quebec manufacturing industries, its basic idea applies to any kind of empirical analysis. Obviously, it also applies to simulations with known true parameter values. Take Table 2 of Everaert and Pozzi (2007) as an example[7]. In it, the authors report bias, standard deviation and root MSE in estimating γ and β[8]. Their results suggest that the system GMM may perform worse than LSDVb. We want to find out why in some cases the system GMM estimator performs worse than LSDVb and in other cases better.

We are interested in cases with $N > T$. Specifically, we compare GMMs3 (estimated with instrument set $\{y_{i(t-2)}, y_{i(t-3)}, y_{i(t-4)}, x_{i(t-1)}, x_{it}, x_{i(t+1)}\}$ for each period) with LSDVb for five cases: (i) $T = 5$, $N = 20$; (ii) $T = 10$, $N = 20$; (iii) $T = 5$, $N = 100$; (iv) $T = 10$, $N = 100$; (v) $T = 5$, $N = 500$. The relative results of Everaert and Pozzi (2007) are reprinted in Table 4, from which we can say that, based on the sumMSE, the system GMM performs worse than LSDVb in cases (i), (ii) and (iv), but better in cases (iii) and (v). Table 5 reports the frequency of the smallest sumMSE regression occuring at GMMsj ($j = 1, \cdots, 8$) for each case. Our attention at this point is focused on GMMs3, which uses three lags of the dependent

[7]We thank Gerdie Everaert and Lorenzo Pozzi for their code.

[8]γ and β are the coefficients in their model $y_{it} = \gamma y_{i(t-1)} + \beta x_{it} + \eta_i + \varepsilon_{it}$.

variable as additional instruments. This is the number of instruments at which the relative frequency of minimum sumMSE is largest for cases (i) (60%), (iii) (67%) and (v) (65%). For cases (ii) and (iv), the frequency is 16% and 10% respectively.

Table 4: Part of Table 2 on p. 1171, Everaert and Pozzi (2007)

T	N		Bias γ	Std γ	Rmse γ	Bias β	Std β	Rmse β
5	20	LSDVb	-0.143	0.154	0.210	-0.016	0.183	0.184
		GMMs3	-0.139	0.182	0.229	0.004	0.203	0.203
10	20	LSDVb	-0.036	0.085	0.093	-0.004	0.099	0.099
		stacked GMMs3	-0.042	0.116	0.123	0.008	0.125	0.126
5	100	LSDVb	-0.132	0.073	0.151	-0.011	0.076	0.077
		GMMs3	-0.030	0.099	0.104	-0.000	0.092	0.092
10	100	LSDVb	-0.037	0.038	0.053	-0.003	0.045	0.045
		GMMs3	-0.024	0.053	0.058	-0.001	0.059	0.059
5	500	LSDVb	-0.126	0.030	0.130	-0.010	0.035	0.036
		GMMs3	-0.003	0.037	0.037	-0.000	0.039	0.039

In cases (iii) and (v) where sample sizes are not very small, the properties of the system GMM estimator are not worse than LSDVb: the root MSE of γ is much smaller though that of β is slightly larger. In case (i) where the sample size is small, the bias of the system GMM is much smaller as compared with any bias-corrected estimators in the original table of Everaert and Pozzi (2007), but the bias is not small enough to offset the large standard deviation. If the sample size is not so small, say $N = 50$, which is a sample size often encountered in empirical applications, we run the regression using Gerdie Everaert and Lorenzo Pozzi's code and find that the root MSE of γ of the system GMM is better than LSDVb but that of β is worse than LSDVb.

In cases (ii) and (iv), however, the relative frequency of minimum sumMSE regression occuring at GMMs3 is low (16% and 10% respectively), and the system GMM performs worse than LSDVb. As shown in Table 5, in both cases, the relative frequency is not higher than 50% for any GMMsj.

Table 5: Occurrence of Regression with Smallest sumMSE at GMMsj : Discussion

Case:	(i)	(ii)	(iii)	(iv)	(v)
GMMs1	16%	20%	10%	5%	7%
GMMs2	24%	24%	23%	10%	28%
GMMs3	60%	16%	67%	10%	65%
GMMs4	—	9%	—	10%	—
GMMs5	—	8%	—	10%	—
GMMs6	—	9%	—	18%	—
GMMs7	—	4%	—	15%	—
GMMs8	—	10%	—	22%	—
Total:	100%	100%	100%	100%	100%

4 Estimation Results

As suggested in Section 3, system GMM using one lagged dependent variable $y_{i(t-2)}$ as an additional instrument for each period seems to be appropriate in our setting. This means that the results in column (a) of Table 2, which are concisely reprinted in Table 6, are what we are looking for in this paper.

Four cross-sections are lost in constructing lags and taking first differences, so that the number of useable observations is 923. τ_{it}^{us} and τ_{it}^{mex} are assumed to be strictly exogenous, and the Arellano and Bond test does not provide evidence to suggest that the assumption of serially uncorrelated errors is inappropriate. In general, when a tariff is lower, more foreign products would come in and the demand for domestic goods would decrease, thus decreasing earnings. The results show that a one percentage point reduction in the current tariffs on imports from the U.S. decreases Quebec manufacturing earnings by about 0.0293%[9], one percentage point reduction in tariffs two periods earlier on imports from the U.S. decreases Quebec manufacturing earnings by about 0.0117%, one percentage point reduction in tariffs one period earlier on imports from Mexico decreases Quebec manufacturing earnings by about 0.0283%, but one percentage point reduction in tariffs four periods earlier on imports from the U.S. *increases* Quebec manufacturing earnings by about 0.0267%. One possible explanation for the *increasing* effect is the long term stable demand for domestic products because of their high competitiveness. In order to see how the effect of tariff reductions changes when exports are controlled for, Canadian exports to the U.S. and Mexico are included in the specifcation in column (d). It turns out that controlling for exports does not change the results much, and the coefficient estimates of exports are insignificant. Finally, if we define the "long-run" effect of NAFTA on earnings as the effect by one percentage point tariff reduction in each of the current year and previous four years, then our results show that the long-run effect of Canadian tariff reductions for U.S. and Mexico imports is about 0.0143% and 0.0283% respectively.

The effect of NAFTA tariff reductions on Quebec manufacturing earnings, whether it is positive or negative, is statistically significant but economically very small. In analyzing the effect of CUSFTA tariff reductions on Canadian manufacturing earnings, Gaston and Trefler (1997) and Beaulieu (2000) find no statistically significant effect, and Trefler (2004) finds slight earnings gains. Trefler (2004) says a 3% rise in earnings spread over eight years will buy you more than a cup of coffee but not at Starbucks. Our results indicate a reduction of earnings of even smaller magnitude.

[9] Note that the tariffs data for regression is in percentage, but the regression results should be interpreted as the effect of each *percentage point* change in tariffs. The reason for this is that tariffs are changed gradually in reality, rather than one (i.e., 100%) at a time.

Table 6: GMM Estimation for Quebec Manufacturing Earnings : 1991-2007

Independent variables[a]	(a)	(d)
$\ln earnings_{i(t-1)}$	.9697 (.0394)	.9869 (.0425)
τ_{it}^{us}	.0293 (.0053)	.0297 (.0057)
$\tau_{i(t-2)}^{us}$	.0117 (.0039)	.0098 (.0047)
$\tau_{i(t-4)}^{us}$	-.0267 (.0057)	-.0275 (.0058)
$\tau_{i(t-1)}^{mex}$	.0283 (.0110)	.0289 (.0126)
exp_{it}^{us}	—	-4.91e-06 (4.79e-06)
exp_{it}^{mex}	—	-.0003 (.0004)
Arellano-Bond test	-1.1771	-1.1932
No. of observations	923	923

[a]Dependent variable is $\ln(earnings)_{it}$. *Notes*: (i) - (iv) are the same as in Table 2.

5 Concluding Remarks

Using data over the period 1991-2007, this paper presents an empirical analysis of the effect of NAFTA tariff reductions on earnings for 71 Quebec manufacturing industries. It chooses the system GMM method to estimate a two-way dynamic panel data model. In order for the system GMM estimator to have best possible properties, it proposes a simulation-based moment selection procedure, uses the procedure to select instruments, and shows that the system GMM estimator is not worse than the LSDVb estimator —the best non-GMM alternative. In other words, we use simulations to choose instruments so that the finite sample properties of GMM are optimized, then we compare this "optimal" GMM estimator with the "best" non-GMM alternative.

It is found that one percentage point reductions in the current tariffs on imports from the U.S., in tariffs two periods earlier on imports from the U.S., and in tariffs one period earlier on imports from Mexico decrease Quebec manufacturing earnings by about 0.0293%, 0.0117%, and 0.0283% respectively, but one percentage point reduction in tariffs four periods earlier on imports from the U.S. increases Quebec manufacturing earnings by about 0.0267%.

No matter the effect is positive or negative, it is statistically significant but economically very small.

As mentioned earlier, NAFTA has become the world's largest free trade area, and Ontario and Quebec are the industrial and manufacturing centers of Canada. It is meaningful to compare the effect of NAFTA on Quebec manufacturing industries and that on Ontario's, which would be the next step of research. In addition, we found that if moments are properly selected, using system GMM method in some classic empirical examples in the dynamic panel data model literature may result in a very large estimate for the coefficient of the lagged dependent variable, which suggests that there may exist panel unit root. Existing panel unit root test methods verify that panel unit root does exist in the datasets of these examples. There are certainly a lot more to do in the future for dynamic panel data models.

A Data Description

The 71 Quebec manufacturing industries, listed in Table A, are selected from the 4-digit manufacturing industries classified using the North American Industry Classification System (NAICS). The selection is based on the data availability of the variables used in the present paper. The earnings data are average weekly earnings (Table 281-0027, Statistics Canada) adjusted by consumer price index (CPI) (Table 326-0021, Statistics Canada). The exports data are from Industry Canada, in 1,000,000 Canadian dollars and adjusted by CPI. The tariffs data are calculated according to both the tariff schedules from the UNCTAD-TRAINS database and the actual import duty raw data from the DLI database of Statistics Canada[10]. In calculation of the manufacturing tariff rates, the Concordance between the Customs Tariff of Canada (CT) and the 2002 NAICS is used, with the Concordance between NAICS Canada 2007 and NAICS Canada 2002 as a reference.

In studying the effect of free trade agreement, Trefler (2004, p. 888) considers tariffs of only non-zero imports, and Romalis (2007, p. 424) takes into account tariffs of both non-zero

[10]The results or views expressed are those of the authors.

and zero imports. There might be two reasons that cause a product not to be imported from a foreign country: one is that this foreign country does not have comparative advantage, and the other is that the tariff is too high. By investigating both the tariff schedules and actual import duties for Quebec manufacturing industries around the starting years of NAFTA, it is found that the latter cause should not be ignored. The tariffs data used in this paper are calculated using the following equation:

$$\tau_i = \frac{1}{2}\Big(\sum_{j\in J:\, m_j\neq 0} \tau_j m_j + \frac{1}{J_2}\sum_{j\in J:\, m_j=0} \tau_j\Big),$$

where i denotes an industry, j denotes an HS10 (for actual import duties) or HS8 (for tariff schedules) item feeding into industry i, J denotes the set of HS10 or HS8 items feeding into industry i, m_j denotes the share of industry i's imports accounted for by item j, J_2 denotes the set of items with zero imports, and τ denotes tariff rate. We divide all products in industry i into two parts: those with non-zero imports and those with zero imports. For the non-zero imports part, import-weighted average of tariffs over items is calculated; for the zero imports part, simple average of tariffs is calculated. Then, simple average over the resulting tariffs in the two parts is calculated to obtain the final tariffs data. The raw data for products with non-zero imports are from the DLI database of Statistics Canada, and the raw data for products with zero imports are from the UNCTAD-TRAINS database. At the time of calculation, the 2004 import duty raw data in the DLI database were partly missing, which were added later by Statistics Canada but some data are still not available, so we replace the 2004 tariffs data for the non-zero imports part using linear interpolation[11].

Table A: The 71 Quebec Manufacturing industries

NAICS	Industry Description
3111	Animal food manufacturing
3112	Grain and oilseed milling
3114	Fruit and vegetable preserving and specialty food manufacturing

continued on the next page

[11] Fukao et al. (2003) use a similar way for the missing tariffs data

Table A: The 71 Quebec Manufacturing industries (*continued*)

NAICS	Industry Description
3115	Dairy product manufacturing
3116	Meat product manufacturing
3118	Bakeries and tortilla manufacturing
3119	Other food manufacturing
3131	Fibre, yarn and thread mills
3132	Fabric mills
3133	Textile and fabric finishing and fabric coating
3141	Textile furnishings mills
3149	Other textile product mills
3151	Clothing knitting mills
3152	Cut and sew clothing manufacturing
3159	Clothing accessories and other clothing manufacturing
3161	Leather and hide tanning and finishing
3162	Footwear manufacturing
3169	Other leather and allied product manufacturing
3211	Sawmills and wood preservation
3212	Veneer, plywood and engineered wood product manufacturing
3219	Other wood product manufacturing
3221	Pulp, paper and paperboard mills
3222	Converted paper product manufacturing
3231	Printing and related support activities
3241	Petroleum and coal product manufacturing
3251	Basic chemical manufacturing
3252	Resin, synthetic rubber, and artificial and synthetic fibres and filaments manufacturing
3254	Pharmaceutical and medicine manufacturing
3255	Paint, coating and adhesive manufacturing
3256	Soap, cleaning compound and toilet preparation manufacturing
3259	Other chemical product manufacturing
3261	Plastic product manufacturing
3262	Rubber product manufacturing

continued on the next page

Table A: The 71 Quebec Manufacturing industries (*continued*)

NAICS	Industry Description
3271	Clay product and refractory manufacturing
3272	Glass and glass product manufacturing
3273	Cement and concrete product manufacturing
3279	Other non-metallic mineral product manufacturing
3311	Iron and steel mills and ferro-alloy manufacturing
3312	Steel product manufacturing from purchased steel
3313	Alumina and aluminum production and processing
3314	Non-ferrous metal (except aluminum) production and processing
3315	Foundries
3321	Forging and stamping
3322	Cutlery and hand tool manufacturing
3323	Architectural and structural metals manufacturing
3325	Hardware manufacturing
3326	Spring and wire product manufacturing
3327	Machine shops, turned product, and screw, nut and bolt manufacturing
3329	Other fabricated metal product manufacturing
3331	Agricultural, construction and mining machinery manufacturing
3332	Industrial machinery manufacturing
3333	Commercial and service industry machinery manufacturing
3334	Ventilation, heating, air-conditioning and commercial refrigeration equipment manufacturing
3335	Metalworking machinery manufacturing
3336	Engine, turbine and power transmission equipment manufacturing
3339	Other general-purpose machinery manufacturing
3342	Communications equipment manufacturing
3343	Audio and video equipment manufacturing
3344	Semiconductor and other electronic component manufacturing
3345	Navigational, measuring, medical and control instruments manufacturing
3346	Manufacturing and reproducing magnetic and optical media
3351	Electric lighting equipment manufacturing
3352	Household appliance manufacturing

continued on the next page

Table A: The 71 Quebec Manufacturing industries (*continued*)

NAICS	Industry Description
3353	Electrical equipment manufacturing
3359	Other electrical equipment and component manufacturing
3364	Aerospace product and parts manufacturing
3369	Other transportation equipment manufacturing
3371	Household and institutional furniture and kitchen cabinet manufacturing
3372	Office furniture (including fixtures) manufacturing
3391	Medical equipment and supplies manufacturing
3399	Other miscellaneous manufacturing

References

Andrews, D. W. K. and B. Lu (2001): "Consistent Model and Moment Selection Procedures for GMM Estimation with Application to Dynamic Panel Data Models," *Journal of Econometrics*, 101, 123–164.

Arellano, M. (2003): *Panel Data Econometrics*, Oxford ; New York : Oxford University Press.

Arellano, M. and S. Bond (1991): "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations," *The Review of Economic Studies*, 58, 277–297.

Arellano, M. and O. Bover (1995): "Another Look at the Instrumental Variable Estimation of Error-Components Models," *Journal of Econometrics*, 68, 29–51.

Baltagi, B. H. (2005): *Econometric Analysis of Panel Data*, Chichester ; Hoboken, NJ : J. Wiley & Sons, 3th ed.

Beaulieu, E. (2000): "The Canada-U.S. Free Trade Agreement and Labour Market Adjustment in Canada," *The Canadian Journal of Economics*, 33, 540–563.

Blundell, R. and S. Bond (1998): "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models," *Journal of Econometrics*, 87, 115–143.

Blundell, R., S. Bond, and F. Windmeijer (2000): "Estimation in Dynamic Panel Data Models: Improving on the Performance of the Standard GMM Estimator," in *Advances in Econometrics*, vol. 15, 53–91.

Bun, M. J. G. and J. F. Kiviet (2006): "The Effects of Dynamic Feedbacks on LS and MM Estimator Accuracy in Panel Data Models," *Journal of Econometrics*, 132, 409–444.

Clausing, K. A. (2001): "Trade Creation and Trade Diversion in the Canada - United States Free Trade Agreement," *The Canadian Journal of Economics*, 34, 677–696.

Dahlberg, M. and E. Johansson (2000): "An Examination of the Dynamic Behaviour of Local Governments Using GMM Bootstrapping Methods," *Journal of Applied Econometrics*, 15, 401–416.

Doran, H. E. and P. Schmidt (2006): "GMM Estimators with Improved Finite Sample Properties Using Principal Components of the Weighting Matrix, with an Application to the Dynamic Panel Data Model," *Journal of Econometrics*, 133, 387–409.

EVERAERT, G. AND L. POZZI (2007): "Bootstrap-Based Bias Correction for Dynamic Panels," *Journal of Economic Dynamics and Control*, 31, 1160–1184.

FAITC (2001): "NAFTA at Seven: Building on a North American Partnership," Foreign Affairs and International Trade Canada, http://www.international.gc.ca/trade–agreements–accords–commerciaux/agr–acc/nafta–alena/nafta_7.aspx?lang=en.

FUKAO, K., T. OKUBO, AND R. M. STERN (2003): "An Econometric Analysis of Trade Diversion Under NAFTA," *The North American Journal of Economics and Finance*, 14, 3–24.

GASTON, N. AND D. TREFLER (1997): "The Labour Market Consequences of the Canada-U.S. Free Trade Agreement," *The Canadian Journal of Economics*, 30, 18–41.

HAN, C. AND P. C. B. PHILLIPS (2006): "GMM with Many Moment Conditions," *Econometrica*, 74, 147–192.

HAYAKAWA, K. (2007): "Small Sample Bias Properties of the System GMM Estimator in Dynamic Panel Data Models," *Economics Letters*, 95, 32–38.

HEAD, K. AND J. RIES (1999a): "Can Small-Country Manufacturing Survive Trade Liberalization? Evidence from the Canada-U.S. Free Trade Agreement," Perspectives on North American Free Research Publication No. 1, Industry Canada.

——— (1999b): "Rationalization Effects of Tariff Reductions," *Journal of International Economics*, 47, 295–320.

HOLTZ-EAKIN, D. (1988): "Testing for Individual Effects in Autoregressive Models," *Journal of Econometrics*, 39, 297–307.

NEWEY, W. K. AND F. WINDMEIJER (2009): "Generalized Method of Moments With Many Weak Moment Conditions," *Econometrica*, 77, 687–719.

OKUI, R. (2009): "The Optimal Choice of Moments in Dynamic Panel Data Models," *Journal of Econometrics*, 151, 1–16.

PAGAN, A. (1984): "Econometric Issues in the Analysis of Regressions with Generated Regressors," *International Economic Review*, 25, 221–247.

PESARAN, M. H. (2007): "A Simple Panel Unit Root Test in the Presence of Cross-Section Dependence," *Journal of Applied Econometrics*, 22, 265–312.

Postrel, V. (2005): "Economic Scene: What Happened When Two Rich Countries Liberalized Trade? Pain, and then Gain." *The New York Times*, January 27.

Prokhorov, A. and P. Schmidt (2009): "GMM Redundancy Results for General Missing Data Problems," *Journal of Econometrics*, 151, 47–55.

Romalis, J. (2007): "NAFTA's and CUSFTA's Impact on International Trade," *Review of Economics and Statistics*, 89, 416–435.

Trefler, D. (2004): "The Long and Short of the Canada-U.S. Free Trade Agreement," *The American Economic Review*, 94, 870–895.

Windmeijer, F. (2005): "A Finite Sample Correction for the Variance of Linear Efficient Two-Step GMM Estimators," *Journal of Econometrics*, 126, 25–51.

Wooldridge, J. M. (2002): *Econometric Analysis of Cross Section and Panel Data*, Cambridge, Mass. : MIT Press.

Ziliak, J. P. (1997): "Efficient Estimation with Panel Data When Instruments Are Predetermined: An Empirical Comparison of Moment-Condition Estimators," *Journal of Business & Economic Statistics*, 15, 419–431.