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MODELGRUPPEN

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Alternative Estimations of Manufactured Exports: mean-group, pooled mean-group and GMM estimators

Resumé:

The paper DSI30414 presented a panel estimation of manufactured exports using the new export market data described in DSI10513. This paper presents additional estimates using different techniques of estimation: mean-group, pooled mean-group and GMM. The paper also presents estimates using wage rates as instruments for price indices. The estimated long-term price elasticities are within the range -1.2 and -1.7, which is similar to the conclusion in DSI30414.

DSI

Keywords: Price elasticity, Mean-group, Pooled mean-group, GMM

1. Introduction

The size of the foreign trade price elasticities in ADAM have always been subjected to a debate. The elasticity estimates can vary depending on the theoretical model and method of estimation used. Sisay (2014) presented a panel estimation of manufactured exports based on the new export market data described in Sisay (2012, 2013). The panel estimates were not found to be significantly different from the elasticity estimates in ADAM. Currently, the price elasticity estimates for imports are in the vicinity of -1 and for exports -2. The panel estimation contributed to the elasticity debate, reassuring the long held estimates in the model-group. This paper investigates possible shortcomings that can arise in earlier estimates and provides alternative estimations using the same dataset. Hence, this is also a contribution toward the elasticity debate.

Panel models based on the traditional random or fixed effect techniques generally focus on small T and large N panels and assume homogeneity of slop coefficients, which can be inappropriate. As the time dimension of dynamic panels increase, concern about non-stationarity also increases. The traditional methods give no consideration to cointegration issues in dynamic models, cf. Pesaran, Shin, and Smith (1997, 1999), Woodridge (2002), and Im, Pesaran and Shin (2003). In this paper we apply two techniques proposed by Pesaran, Shin and Smith (1997, 1999) to estimate non-stationary dynamic panels in which the parameters are heterogeneous across units. The techniques are called mean-group (MG) and pooled mean-group (PMG) estimators. The former estimates N time-series equations and averages the coefficients and the later applies a combination of pooling and averaging of coefficients.

One of the basic assumptions in OLS is orthogonality between the explanatory variables and the error term. This is rather a very restrictive assumption and the primary motivation for using panel data is to solve the omitted variables problem. Random and fixed effect models explicitly model unobserved effects to insure orthogonality between the regressors and the error term. However, if one is considering dynamic panel data models, the orthogonality condition will not be fulfilled. That is, even after we remove unobserved effects through differencing or demeaning, there will be correlation between the lagged dependent variable and the error term as the latter enter every value of the dependent variable by assumption. This problem can be mitigated through instrumental variable estimation techniques. This paper applies the Generalized Method of Moment (GMM) estimation developed by Arellano and Bond (1991) [1] to deal with the endogeneity problem in dynamic panel models. GMM basically uses internal instruments, we also present estimations using external instruments, namely wage rates as instruments for prices. The following section provides a brief description of the alternative estimation techniques, section 3 presents the estimation results and section 4 concludes.

[1] The GMM technique is in fact the work of Holtz-Eakin, Newey and Rosen (1988), Arellano and Bond (1991) popularized it.

2. Econometric framework

Exports and imports in ADAM are modelled using the Armington (1969) approach. The long-term relation for exports is given as

$$fE_{it} = \mu_i + \theta_i \cdot fEe_{it} + \beta_i \cdot \frac{pe_{it}}{pee_{it}} + u_{it} \qquad (1)$$
$$t = 1,2,\dots,T \;\&\; i = 1,2,\dots,N$$

Where fE_{it} and pe_{it} are the log of volumes and prices of Danish exports to partner i at time t, respectively; fEe_{it} and pee_{it} are the log of volumes and prices of imports of partner i at time t, respectively; θ_i and β_i are the long term demand and price elasticities, respectively; μ_i is the constant term and u_{it} is the error term. The Armington approach imposes the restriction $\theta_i = 1$, so that it is a model of market share as a function of relative prices. If the variables are integrated order of one, *I(1)*, and cointegrated, then the error term u_{it} will be *I(0)* for all partners i.

To capture dynamics equation (1) can be written in autoregressive distributed lag (ARDL) form. If we assume a lag length of 1, the dynamic panel specification can be written as

$$\begin{aligned} fE_{it} = {} & \mu_i + \alpha_i \cdot fE_{it-1} + \theta_{1i} \cdot fEe_{it} + \theta_{2i} \cdot fEe_{it-1} \\ & + \beta_{1i} \cdot \frac{pe_{it}}{pee_{it}} + \beta_{2i} \cdot \frac{pe_{it-1}}{pee_{it-1}} + u_{it} \end{aligned} \qquad (2)$$

Equation (2) can also be written in error correction form as

$$\begin{aligned} \Delta fE_{it} = {} & \theta_{1i} \cdot \Delta fEe_{it} + \beta_{1i} \cdot \Delta \frac{pe_t}{pee_{it}} \\ & + \gamma_i \cdot \left[fE_{it-1} - \theta_i \cdot fE_{it-1} - \beta_i \cdot \frac{pe_{t-1}}{pee_{it-1}} - k_i \right] + u_{it} \end{aligned} \qquad (3)$$

Where $\gamma_i = -(1-\alpha_i)$, $\theta_i = (\frac{\theta_{1i}+\theta_{2i}}{(1-\alpha_i)})$, $\beta_i = (\frac{\beta_{1i}+\beta_{2i}}{(1-\alpha_i)})$, and $k_i = (\frac{\mu_i}{(1-\alpha_i)})$. The error correction coefficient γ is expected to be negative, in which case there is a long-term relation between the variables. If the coefficient is rather zero, there is no evidence of long-term relationship.

In Sisay (2014), equation (3) is estimated using the fixed-effect and random-effect approaches. The former allows only the intercepts to differ across countries and the latter assumes a common intercept and slop coefficient. If the slop coefficients differ in reality, the parameter estimates can be inconsistent. Pesaran and Smith (1995) propose fitting separate regression for each country and calculate a simple arithmetic average of the coefficients. This is the mean group (MG) estimator. Pesaran, Shin and Smith (1997, 1999) propose an alternative estimator that combines both pooling and averaging. This is the pooled mean-group (PMG) estimator. The PMG estimator constrains the long-term coefficients to be the same across countries and allows only the short-term coefficients to vary. The technique applies the maximum likelihood estimator as equation (3) is non-linear in parameters.

The presence of lagged dependent variable in equation (2) and (3) creates endogeneity problem, and the MG and PMG estimates could be misleading. For example, time invariant unobserved effects that are included in the error term will be correlated with the lagged dependent variable leading to a dynamic panel bias. In addition, endogeneity can also arise due to measurement error in splitting value of exports into price and quantity. Under such circumstances, Arellano and Bond's (1991) GMM technique for dynamic panels comes in handy, for a pedagogical presentation of GMM, see Roodman (2009). GMM is a form of instrumental variable estimation that is applied to deal with endogeneity problems. GMM uses lags of the variables as instruments, hence the instruments are internal. The technique can also accommodate external instruments. GMM has two variants. The first one starts by transforming the variables (such as differencing) to get rid of unobserved effects and applies GMM to the transformed variables. This is called difference GMM. The other approach assumes that the first differences of the instrument variables are uncorrelated with the unobserved individual effects, and builds a system of two equations (the original and transformed equations). This is called system GMM. The following section reports the different estimation results.

3. Estimation result[2]

a. Mean-group and pooled mean-group estimators

Table 1 reports the MG and PMG estimation results for equation (3), see Sisay (2012, 2013) for a description of the dataset. The sample covers the period 1976-2012 and 20 partner countries. The MG estimates are the un-weighted mean of the individual regressions on each country. The PMG estimator estimates a common long run coefficients and different short run coefficients, below the average short-run parameters are reported, see appendix for detailed output.

Table 1. MG and PMG estimation result, manufactured exports[3]

Variable	Coeff.	MG	PMG
Dlog(fE)			
Dlog(fEe)	θ_1	0.591	0.600
		[0.038]	[0.039]
Dlog(pe/pee)	β_1	-0.649	-0.633
		[0.049]	[0.048]
log(fE$_{-1}$/$\widehat{fE}_{-1}$)	γ	0.260	0.228
		[0.039]	[0.036]
log(pe$_{-1}$/pee$_{-1}$)	β	-1.712	-1.165
		[0.273]	[0.074]
	k	-0.002	-0.002
		[0.010]	[0.008]

Standard errors are given in square brackets.
The sample covers the period T=1976-2012 and countries N = 18. Austria and Switzerland are excluded due to outliers.
Note: $\log(\widehat{fE}) = \log(fEe) - \beta \cdot \log\left(\frac{pe}{pee}\right), \theta = 1$
Hausman test - H_o :pmg vs H_1:mg, Chisq(1) = 4.10, p-value = [0.043]

[2] All estimations in this paper are carried out in STATA.
[3] German imports are corrected to account for the re-unification of Germany, see AMB120797.

The MG long run price elasticity estimate is larger than the PMG estimate, the adjustment coefficient is also marginally higher in the former. The PMG estimator by pooling across countries provides efficient and consistent estimates (Blackburne III and Frank, 2007). If, however, slop homogeneity is rejected, the PMG estimates will be inconsistent. The MG estimates are consistent in either case. The Hausman test rejects the null hypothesis that the PMG estimator is efficient with a significance level of 5 percent, but not at 1 percent. Hence, the argument for MG estimator is not that strong. The MG long-run price elasticity is not different from the values reported in Sisay (2014). We now turn to GMM estimation results.

b. GMM

It is convenient to work with equation (2) for GMM estimation, the parameters in (3) can be easily calculated afterwards.[4] Column 1 in table 2 presents a simple OLS regression of (2). The problem is that fE_{it-1} is correlated with the fixed effects in the error term and creates a dynamic panel bias (Roodman 2009). And the correlation is positive, which biases the coefficient estimate upward. This is equivalent to a downward bias in the error correction coefficient in (3).

The individual fixed effects can be removed by differencing (2), which gives the name difference GMM, written as

$$\begin{aligned} \Delta fE_{it} &= \alpha_i \cdot \Delta fE_{it-1} + \theta_{1i} \cdot \Delta fEe_{it} + \theta_{2i} \cdot \Delta fEe_{it-1} \\ &\quad + \beta_{1i} \cdot \Delta \frac{pe_{it}}{pee_{it}} + \beta_{2i} \cdot \Delta \frac{pe_{it-1}}{pee_{it-1}} + \Delta u_{it} \end{aligned} \tag{4}$$

Differencing removes the fixed effects, however, the lagged dependent variable is still potentially endogenous, because fE_{it-1} in ΔfE_{it-1} is correlated with u_{it-1} in Δu_{it}. The price term can also be endogenous as it can be related with u_{it-1}. Difference GMM uses longer lags of the regressors as instruments that are orthogonal to the error term. The assumption is that external instruments are not available in the outset, and GMM draws instruments from within the dataset. For instance ΔfE_{it-2} can be used as instrument for ΔfE_{it-1}, because the former is mathematically related to the latter but not to the error term Δu_{it}.

Column 2 to 5 in table 2 reports the GMM estimates with the assumption that only fE_{it-1} is endogenous. All coefficients are significantly estimated except the constant term. The long-term GMM price elasticity estimates are within the range reported in Sisay (2014), namely between -1.4 and -1.6. The difference GMM estimates produce the highest error correction coefficients. Table 3 reports the GMM estimates when both the lagged dependent variable and relative prices are assumed to be endogenous. Here the long-term price elasticities fall marginally, the remaining changes are negligible. Arellano and Bond (1991) based on Monte Carlo simulations conclude that the difference

[4]The Armington restriction of unitary long-term demand elasticity, $\theta = 1$, can be tested in equation (2) as $H_0\colon \alpha + \theta_1 + \theta_2 = 1$. This was not rejected in table 2 and 3, which facilitated the transformation between equation (2) and (3).

GMM exhibits the least bias and variance in the class of estimators. The difference GMM long-term prices elasticity estimates in table 2 and 3 are the highest.

Table 2. GMM estimation result, manufactured exports, lagged dependent variable as endogenous

Variable	Coeff	OLS	One-step system GMM	Two-step system GMM	One-step difference GMM	Two-step difference GMM
Log(fE)						
$\log(fE_{-1})$	α	0.875	0.872	0.830	0.758	0.750
		[0.016]	[0.016]	[0.057]	[0.023]	[0.031]
log(fEe)	θ_1	0.594	0.593	0.615	0.611	0.601
		[0.045]	[0.045]	[0.031]	[0.044]	[0.041]
$\log(fEe_{-1})$	θ_2	-0.474	-0.470	-0.453	-0.368	-0.358
		[0.046]	[0.046]	[0.045]	[0.048]	[0.042]
log(pe/pee)	β_1	-0.566	-0.572	-0.545	-0.583	-0.607
		[0.066]	[0.066]	[0.053]	[0.065]	[0.056]
$\log(pe_{-1}/pee_{-1})$	β_2	0.381	0.377	0.343	0.245	0.246
		[0.066]	[0.066]	[0.076]	[0.067]	[0.072]
	μ	0.004	0.004	0.005	-	-
		[0.006]	[0.006]	[0.002]		
	γ	0.125	0.128	0.170	0.242	0.250
	β	-1.480	-1.523	-1.188	-1.400	-1.444

Table 3. GMM estimation result, manufactured exports, lagged dependent variable and relative prices as endogenous

Variable	Coeff	One-step system GMM	Two-step system GMM	One-step difference GMM	Two-step difference GMM
Log(fE)					
$\log(fE_{-1})$	α	0.875	0.832	0.784	0.730
		[0.016]	[0.057]	[0.022]	[0.064]
log(fEe)	θ_1	0.592	0.615	0.612	0.635
		[0.045]	[0.031]	[0.044]	[0.043]
$\log(fEe_{-1})$	θ_2	-0.473	-0.456	-0.399	-0.379
		[0.046]	[0.045]	[0.047]	[0.070]
log(pe/pee)	β_1	-0.566	-0.540	-0.570	-0.621
		[0.066]	[0.053]	[0.064]	[0.076]
$\log(pe_{-1}/pee_{-1})$	β_2	0.381	0.346	0.274	0.250
		[0.065]	[0.076]	[0.066]	[0.043]
	μ	0.004	0.004	-	-
		[0.006]	[0.002]		
	γ	0.125	0.168	0.216	0.27
	β	-1.480	-1.155	-1.370	-1.374

c. Random effect (RE) and fixed effect (FE) estimators

This section briefly repeats the RE and FE estimations from DSI30414 by using wage rates as instruments for price indices. Data for partner countries' industrial wage rate is obtained from the OECD statistics. Table 4 reports the estimation result for equation (3).

Table 4. RE and FE IV regression, manufactured exports, wages as instruments for prices

Variable	Coeff.	RE	FE
Dlog(fE)			
Dlog(fEe)	θ_1	0.625	0.626
		[0.045]	[0.045]
Dlog(pe/pee)	β_1	-0.611	-0.611
		[0.087]	[0.089]
log($fE_{-1}/\widehat{fE}_{-1}$)	γ	0.226	0.227
		[0.036]	[0.036]
log(pe_{-1}/pee_{-1})	β	-1.425	-1.422
		[0.070]	[0.070]
	k	-0.006	-0.002
		[0.092]	[0.008]

Standard errors are given in square brackets.
The sample covers the period T=1976-2012 and countries N = 20.
Note: $\log(\widehat{fE}) = \log(fEe) - \beta \cdot \log\left(\frac{pe}{pee}\right), \theta = 1$
Instrumented: Dlog(pe/pee), Log(pe_{-1}/pee_{-1})

The estimated long-term price elasticities and adjustment terms are similar with the estimates in DSI30414. Instrumenting with wages does not seem to change the parameter estimates significantly.

4. Conclusion

The paper presented alternative estimations of manufactured exports using a panel dataset. This is a continuation of earlier work with panel data in Sisay (2014). The paper uses the mean-group, pooled mean-group and GMM techniques. Instrumenting prices with wage rates is also attempted. The elasticity estimates in this paper are not found to be significantly different from earlier estimates. The long-term price elasticity estimates are found to be within the range -1.2 and -1.7, which is similar to the fixed effect and random effect estimates in Sisay (2014).

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Appendix

Appendix I. Detailed output from PMG estimation, manufactured exports, equation (3)

	Coeff.	SE	z	p>z	[95% Conf. Interval]	
β	-1,165	0,075	-15,600	0,000	-1,311	-1,018
			AUS			
γ	-0,393	0,118	-3,330	0,001	-0,625	-0,162
θ_1	0,638	0,235	2,720	0,007	0,178	1,098
β_1	-0,560	0,207	-2,700	0,007	-0,967	-0,154
k	-0,091	0,048	-1,910	0,057	-0,184	0,003
			BEL			
γ	-0,130	0,053	-2,440	0,015	-0,234	-0,026
θ_1	0,513	0,187	2,740	0,006	0,146	0,880
β_1	-0,894	0,307	-2,910	0,004	-1,496	-0,292
k	0,008	0,016	0,520	0,603	-0,022	0,039
			CAN			
γ	-0,202	0,081	-2,490	0,013	-0,360	-0,043
θ_1	0,476	0,321	1,480	0,138	-0,153	1,106
β_1	-0,489	0,210	-2,320	0,020	-0,901	-0,077
k	-0,016	0,030	-0,540	0,587	-0,076	0,043
			DEU			
γ	0,044	0,055	0,810	0,418	-0,063	0,151
θ_1	0,383	0,116	3,310	0,001	0,156	0,609
β_1	-1,105	0,261	-4,240	0,000	-1,616	-0,594
k	0,024	0,013	1,810	0,071	-0,002	0,050
			ESP			
γ	-0,205	0,083	-2,470	0,014	-0,368	-0,042
θ_1	0,670	0,110	6,070	0,000	0,454	0,886
β_1	-0,651	0,259	-2,520	0,012	-1,158	-0,145
k	-0,015	0,022	-0,650	0,515	-0,058	0,029
			FIN			
γ	-0,191	0,065	-2,950	0,003	-0,317	-0,064
θ_1	0,719	0,069	10,430	0,000	0,584	0,854
β_1	-0,747	0,183	-4,080	0,000	-1,105	-0,388
k	0,026	0,008	3,280	0,001	0,011	0,042
			FRA			
γ	-0,138	0,061	-2,260	0,024	-0,258	-0,018
θ_1	0,742	0,108	6,860	0,000	0,530	0,955
β_1	-0,558	0,225	-2,470	0,013	-1,000	-0,116
k	-0,009	0,013	-0,720	0,471	-0,035	0,016
			GBR			
γ	-0,260	0,079	-3,300	0,001	-0,414	-0,105
θ_1	0,842	0,166	5,070	0,000	0,516	1,168
β_1	-0,684	0,167	-4,080	0,000	-1,012	-0,355
k	0,001	0,013	0,070	0,947	-0,026	0,027
			IRL			

γ	-0,174	0,083	-2,090	0,036	-0,336	-0,011
θ_1	0,607	0,254	2,380	0,017	0,108	1,105
β_1	-0,833	0,358	-2,330	0,020	-1,533	-0,132
k	-0,049	0,036	-1,350	0,176	-0,121	0,022
			ISL			
γ	-0,384	0,091	-4,230	0,000	-0,561	-0,206
θ_1	0,695	0,089	7,800	0,000	0,520	0,870
β_1	-0,817	0,180	-4,530	0,000	-1,170	-0,463
k	0,112	0,027	4,200	0,000	0,059	0,164
			ITA			
γ	-0,486	0,109	-4,480	0,000	-0,699	-0,274
θ_1	0,682	0,088	7,750	0,000	0,510	0,854
β_1	-0,365	0,173	-2,110	0,035	-0,705	-0,025
k	-0,043	0,017	-2,550	0,011	-0,076	-0,010
			JPN			
γ	-0,180	0,103	-1,740	0,081	-0,383	0,022
θ_1	0,572	0,159	3,590	0,000	0,259	0,884
β_1	-0,329	0,156	-2,110	0,035	-0,634	-0,024
k	0,033	0,019	1,750	0,080	-0,004	0,069
			NLD			
γ	-0,202	0,064	-3,180	0,001	-0,327	-0,078
θ_1	0,414	0,165	2,510	0,012	0,090	0,737
β_1	-0,706	0,198	-3,570	0,000	-1,093	-0,318
k	0,028	0,013	2,240	0,025	0,004	0,053
			NOR			
γ	-0,140	0,049	-2,850	0,004	-0,236	-0,044
θ_1	0,352	0,094	3,750	0,000	0,168	0,536
β_1	-0,507	0,166	-3,050	0,002	-0,834	-0,181
k	0,026	0,009	3,000	0,003	0,009	0,043
			NZL			
γ	-0,541	0,152	-3,570	0,000	-0,838	-0,244
θ_1	0,275	0,518	0,530	0,595	-0,741	1,291
β_1	-0,498	0,529	-0,940	0,347	-1,534	0,539
k	0,013	0,052	0,250	0,806	-0,089	0,115
			PRT			
γ	0,016	0,062	0,260	0,794	-0,106	0,139
θ_1	0,861	0,169	5,080	0,000	0,529	1,193
β_1	-0,346	0,368	-0,940	0,347	-1,066	0,375
k	-0,023	0,021	-1,130	0,258	-0,064	0,017
			SWE			
γ	-0,276	0,079	-3,510	0,000	-0,430	-0,122
θ_1	0,659	0,067	9,880	0,000	0,528	0,790
β_1	-0,634	0,135	-4,680	0,000	-0,899	-0,369
k	0,007	0,007	0,940	0,348	-0,007	0,021
			USA			
γ	-0,257	0,092	-2,810	0,005	-0,437	-0,078

θ_1	0,693	0,226	3,070	0,002	0,250	1,135
β_1	-0,678	0,170	-3,980	0,000	-1,012	-0,344
k	0,012	0,023	0,520	0,601	-0,033	0,058