The Role of the Economy Structure in the U.S. - China Bilateral Trade Deficit

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Abstract

This study investigates the effect of the economy structure on the U.S. - China bilateral trade deficit as alternative to the influence of the exchange rate fluctuation. The revealed comparative advantage indices are proposed as the measure of the relative structural differences between two countries due to factor endowments and technology. A Bayesian Stochastic Search Variable Selection method is applied to the U.S. - China annual trade data for 57 commodity groups at the SITC 2-digit industry aggregation level to obtain empirical variable inclusion probabilities. Based on the data, we found no conclusive evidence against the hypothesis of the short-run effect of either of the explanatory factors, while the long-run influence is revealed to be insignificant in most of the cases.

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Introduction

Bilateral trade volume between the United States and China increased significantly over past two decades, from \$20.03 billion in 1990 to approximately \$365.87 billion in 2009 according to the International Trade Administration of the U.S. Department of Commerce (http://tse.export.gov). However, the trade balance between two countries deteriorated dramatically during the same period to yield bilateral trade deficit of \$226.88 billion in 2009 (\$10.42 billion in 1990). This accounts for approximately 45% of the total U.S. trade deficit in 2009 as compared to the 25% in 2004 and 10% in 1990. The current discussion on the causes of such an imbalance is focused on China's exchange rate policy (e.g. Soofi 2009, Marquez and Schindler 2009, Thorbecke and Smith 2010) as it is often argued that the undervaluation of the renminbi (RMB) makes Chinese goods significantly less expensive thus effectively increasing the U.S. imports from China and as a result - the existing trade deficit. Empirical studies estimated the effect of U.S. - China exchange rate changes on the trade balance to be ambiguous. Some studies found it significant (e.g. Koo and Zhuang 2007, Bahmani-Oskooee and Wang 2007, Baak 2008, Chiu, Lee and Sun 2010) while others estimated the effect to be modest or negligible (Cho and Koo 2004, Groenewold and He 2007) with more accurate results obtained at the disaggregate level of analysis. However, recently the Chinese government argued that the trade deficit is not caused by the exchange rate regime but is rather determined by the structure of economy of the United States and China. The objective of this study is to examine the effect of the exchange rate on the U.S. - China bilateral trade accounting for the historical production patterns. We argue that the difference between the structure of the industries of both countries defined by the differences in factor endowments, production costs and technologies has the major influence on the observed bilateral trade patterns and the existing trade balance. In this case appreciation of the foreign currency will not necessary reduce the level of home country imports for the products that are cannot be competitively produced by the domestic companies and has to be imported (such as the labor intensive goods in the U.S. - China case) thus increasing the value of the trade deficit instead of improving the trade balance.

Model

We use the modified form of the standard bilateral trade balance equation (e.g. Bahmani-Oskooee and Brooks 1999) to formulate the ADL version of the model as

$$\begin{aligned} \ln TB_{it} = \mu &+ \sum_{j=0}^{p} \alpha_j \ln TB_{it-j} + \sum_{j=0}^{q} \beta_{1j} \ln GDP_{t-j} + \sum_{j=0}^{q} \beta_{2j} \ln RER_{t-j} \\ &+ \sum_{j=0}^{q} \beta_{3j} \ln RCA_{it-j} + \varepsilon_{it} \quad \varepsilon_i \sim N(0, \sigma^2 I_{T-p}) \end{aligned} \tag{1}$$

where $\ln TB_{it} = \ln X_{it} - \ln M_{it}$ is the logarithm of the bilateral trade balance in commodity i at time t and X_{it} and M_{it} are value of corresponding export and import. $\ln GDP_t$ represents the logarithm of the ratio of the real gross domestic products of the U.S. and China at time t. $\ln RER_t = \ln(CPI_t^{us} ER_t / CPI_t^{chn})$ is the real exchange rate of Chinese Yuan to the U.S. dollar at time t. ER_t stands for the nominal exchange rate, while CPI_t^{us} and CPI_t^{chn} are consumer price indices for the U.S. and China, respectively. Finally, $\ln RCA_{it} = \ln RCA_{it}^{us} - \ln RCA_{it}^{chn}$ denotes the logarithm of ratio of the U.S. and China the revealed comparative advantage in commodity i at time t. Based on Balassa's (1965) work the Revealed Comparative Advantage measure for country j and product i at time t used in this study is constructed as

$$RCA_{it}^{j} = \frac{X_{it}^{j} / X_t^{j}}{X_{it}^{w} / X_t^{w}} \tag{2}$$

where X_{it}^{j} and X_{it}^{w} are the value of the country j and world export of the commodity i at time t, respectively. Similarly, X_t^{j} and X_t^{w} denote the value of the country j and world total exports at time t. A higher RCA value corresponds to a higher share of the exports of the good for the selected country relative to the share of total world exports of the same good. Thus RCA "reveals" the comparative advantage the country has in that product. We use the RCA index as the measure of the country's unobserved industry level advantage in factor endowment including the openness to export.

A slightly modified version of (1) is often more convenient to work with,

$$\begin{aligned}\triangle \ln TB_{it} = \mu + \sum_{j=1}^{p} \eta_j \triangle \ln TB_{it-p} + \sum_{j=1}^{q} \gamma_{1j} \triangle \ln GDP_{t-j} + \sum_{j=1}^{q} \gamma_{2j} \triangle \ln RER_{t-j} \\ + \sum_{j=1}^{q} \gamma_{3j} \triangle \ln RCA_{it-j} + \lambda_1 \ln TB_{it-1} + \lambda_2 \ln GDP_t \\ + \lambda_3 \ln RER_t + \lambda_4 \ln RCA_{it} + \varepsilon_{it} \quad \varepsilon_i \sim N(0, \sigma^2 I_{T-p}) \end{aligned} \tag{3}$$

where the coefficients of the original model can be computed using the set of linear relations assumed by the transformation from (1) to (3) (see, e.g. Pesaran, Shin and Smith (1999), Eq.(1) - (3)). It is conventionally assumed that the effect of the GDP is positive since a higher domestic real income may increase imports and decrease exports to compensate for a higher domestic consumption. Therefore it is expected that the U.S. - China bilateral trade balance will improve with the growth of the real GDP of China and decrease in the U.S. income. The trade theory suggest that a real depreciation of the Chinese Yuan will lead to an increase in Chinese imports and decrease in its exports thus deteriorating the U.S. - China bilateral trade deficit, holding everything else constant. On a contrary, an increase in the difference between the U.S. and China comparative advantage in a given industry is expected to increase the production of its good in by a more competitive country improving the U.S. - China trade balance. Hence the assumed effect of RER and RCA on the trade balance value is negative and positive, respectively.

Estimation

Let X be a $T-p \times k$ design matrix that contains the set of all possible explanatory variables and y be a $T-p \times 1$ response vector. Denote $\theta = \{\mu, \gamma, \lambda\}'$ to be a $k \times 1$ complete vector of regression coefficients. The general form of (3) assumes a large number of potentially important explanatory variables $(1 + 4(p+1))$ relative to the effective size of the data available which is limited to $T-p$ observations. In this case we are interested in finding the most parsimonious specification of (3) without imposing unnecessary restrictions. To achieve this goal a popular approach to Bayesian regression analysis known as the stochastic search variable selection (SSVS) introduced in George and McCulloch (1993) can be used. An application of SSVS technique to a ADL models can be found for example in So, Chen and Liu (2006). The SVSS method suggests using the prior distribution for every element of θ that is based on the finite mixture of two zero-mean normal densities as

$$\theta_i \sim (1-\delta_i)N(0, \tau_1^2) + \delta_i N(0, \tau_2^2) \quad i = 1, \ldots, k \tag{4}$$

where τ_1^2 and τ_2^2 are known variances that are set to have a very small and a very large value, respectively. The first component of the mixture is an informative distribution that provides strong prior evidence that the corresponding regressor should be excluded from the model. Conversely, the second component contains a vague prior information as for the explanatory power of the given variable implying that such a variable could be useful since only a small portion of the density is allocated around $\theta_i = 0$. Mixture component indicators δ_i are Bernoulli distributed binary random variables, such that

$$\delta_i \sim Be(1, p_i) \quad i = 1, \ldots, k \tag{5}$$

where $0 \leq p_i \leq 1$ is a prior probability of $\delta_i = 1$. The value of $\delta_i = 0$ indicates that the coefficient θ_i is a member of the first mixture component and thus, intuitively, can be interpreted as the strong evidence that the corresponding explanatory variable should be excluded from the set of predictors *a posteriori*. The inverted gamma prior distribution is assumed for σ^2, so that

$$\sigma^2 \sim IG(a, b) \tag{6}$$

We fit the model using a Gibbs sampler with data augmentation where the posterior simulations are being conducted by iteratively drawing according to Steps 1 – 3 below.

Step 1: $\theta|\delta, \sigma^2, y$

Given the choice of prior distributions the posterior distribution of θ is obtained conditionally on the values of component indicators δ using the traditional Bayesian protocol for normal linear regression models,

$$\theta \sim MVN(Dd, D) \tag{7}$$

where $D = (X'X/\sigma^2 + V^{-1}(\delta))^{-1}$ and $d = X'y/\sigma^2$. The prior covariance matrix $V(\delta)$ is constructed as the $k \times k$ diagonal matrix with $\delta\tau_1 + (1-\delta)\tau_2$ being its (i, i) element.

Step 2: $\sigma^2|\theta, \delta, y$

The posterior density of σ_j^2 is defined as

$$\sigma^2 \sim IG\left(\frac{T-p}{2}+a, \left[b+\frac{1}{2}(y-X\theta)'(y-X\theta)\right]^{-1}\right) \tag{8}$$

where $T-p$ denotes the number of time periods effectively used.

Step 3: $\delta|\theta, \sigma^2, y$

The posterior distribution of mixture component indicators δ is Bernoulli, such that

$$\delta_i \sim B\left(1, \frac{p_i\phi(\theta_i|0,\tau_1)}{p_i\phi(\theta_i|0,\tau_1)+(1-p_i)\phi(\theta_i|0,\tau_2)}\right) \tag{9}$$

Data

The study uses annual data from 1984 to 2007 for 57 commodity groups at SITC 2 digit aggregation. Industries in groups 3 and 4 are aggregated and labeled 30 and 40 respectively to provide balanced series. U.S. - China import/export and the trade data required for calculating RCA are obtained from UN COMTRADE database and TSE administration. RCA's are robustified by removing U.S. - China bilateral trade flow values to alleviate the endogeneity problem. Consumer price indices, real GDP (in constant $2000) and nominal exchange rate are taken from the World Bank country data statistics.

Preliminary Results and Conclusions

A general $p = 1, q = 1$ model were considered. A series of 200,000 draws were generated for each industry case to guarantee that the sampler visited every possible model specification non-trivial number of times. We discarded the first 10,000 draws as burn-in. The posterior probability of variable inclusion are reported in Table 1 and Table 2. It can be observed that for the most industry cases there is considerable evidence against using the levels of the explanatory variables in the regression model. The differenced data series often contain a reasonable amount of information. However, in many cases the posterior information provided by the SSVS algorithm is not conclusive as the estimated probabilities of inclusion lay within the indifference interval of $0.4 - 0.6$. Therefore based on the data available the influence of both short-run income, exchange rate and economy structure as represented by the revealed comparative advantage indices on the commodity level trade balance should be considered a valid argument. Generally a longer data series are required to facilitate the decision process and provide the stronger evidence towards either of the hypotheses of interest. Alternatively, a flexible hierarchical methods for heterogeneous panel models can be applied to increase the effective sample size. The results of the SSVS estimation can further be used to select a most likely parsimonious model based on the researchers choice of the desirable probability of inclusion or can be directly applied in a Bayesian model averaging fashion when considering the more robust model specification.

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Table 1: Posterior probability of inclusion for SITC $1-58$

$SITC$	TB_{t-1}	GDP_t	$\triangle GDP_t$	RER_t	$\triangle RER_t$	RCA_t	$\triangle RCA_t$
1	0.526	0.149	0.541	0.150	0.470	0.480	0.257
2	0.319	0.331	0.559	0.356	0.499	0.164	0.248
3	0.044	0.103	0.420	0.053	0.506	0.176	0.332
4	0.091	0.096	0.504	0.115	0.486	0.125	0.935
5	0.075	0.067	0.444	0.050	0.341	0.106	0.291
6	0.649	0.566	0.468	0.317	0.472	0.320	0.275
7	0.593	0.374	0.516	0.122	0.307	0.415	0.231
8	0.963	0.845	0.420	0.348	0.514	0.153	0.653
9	0.843	0.061	0.474	0.133	0.414	0.121	0.243
11	0.126	0.101	0.440	0.160	0.820	0.194	0.349
12	0.420	0.106	0.450	0.111	0.472	0.126	0.510
21	0.426	0.188	0.417	0.229	0.587	0.439	0.378
22	0.968	0.197	0.539	0.228	0.368	0.920	0.339
23	0.393	0.313	0.478	0.140	0.700	0.067	0.107
24	0.063	0.055	0.722	0.065	0.359	0.099	0.390
25	0.845	0.262	0.389	0.818	0.561	0.222	0.233
26	0.147	0.042	0.343	0.129	0.450	0.075	0.587
27	0.082	0.074	0.412	0.066	0.320	0.182	0.277
28	0.033	0.041	0.516	0.075	0.381	0.106	0.513
29	0.045	0.032	0.416	0.027	0.241	0.050	0.208
30	0.252	0.098	0.591	0.048	0.499	0.134	0.456
40	0.282	0.139	0.496	0.178	0.547	0.155	0.240
51	0.070	0.022	0.317	0.039	0.218	0.049	0.587
52	0.070	0.039	0.427	0.041	0.330	0.140	0.225
53	0.171	0.029	0.336	0.033	0.325	0.064	0.247
54	0.101	0.064	0.405	0.043	0.375	0.034	0.217
55	0.225	0.047	0.504	0.045	0.264	0.043	0.293
56	0.131	0.149	0.490	0.128	0.420	0.141	0.213
57	0.319	0.330	0.375	0.085	0.340	0.101	0.409
58	0.053	0.051	0.356	0.067	0.300	0.101	0.254

Table 2: Posterior probability of inclusion for SITC $59-89$

$SITC$	TB_{t-1}	GDP_t	$\triangle GDP_t$	RER_t	$\triangle RER_t$	RCA_t	$\triangle RCA_t$
59	0.075	0.028	0.261	0.022	0.708	0.028	0.145
61	0.088	0.071	0.403	0.085	0.290	0.098	0.551
62	0.027	0.029	0.447	0.032	0.204	0.083	0.126
63	0.042	0.040	0.435	0.048	0.457	0.172	0.403
64	0.050	0.040	0.704	0.051	0.214	0.055	0.219
65	0.057	0.028	0.374	0.064	0.196	0.034	0.299
66	0.410	0.059	0.312	0.416	0.225	0.150	0.407
67	0.282	0.182	0.523	0.224	0.811	0.228	0.228
68	0.284	0.070	0.357	0.045	0.643	0.174	0.234
69	0.024	0.036	0.406	0.046	0.516	0.434	0.574
71	0.048	0.050	0.441	0.070	0.297	0.053	0.205
72	0.045	0.061	0.409	0.054	0.272	0.055	0.375
73	0.049	0.034	0.373	0.051	0.325	0.048	0.464
74	0.048	0.027	0.380	0.028	0.316	0.027	0.676
75	0.024	0.147	0.540	0.087	0.324	0.144	0.455
76	0.077	0.034	0.331	0.055	0.262	0.145	0.656
77	0.122	0.065	0.481	0.050	0.403	0.231	0.702
78	0.204	0.107	0.408	0.127	0.325	0.092	0.246
79	0.083	0.079	0.421	0.047	0.364	0.037	0.148
81	0.043	0.079	0.456	0.063	0.206	0.089	0.342
82	0.021	0.026	0.366	0.027	0.203	0.096	0.176
83	0.607	0.324	0.446	0.089	0.426	0.537	0.552
84	0.458	0.223	0.479	0.603	0.304	0.129	0.468
85	0.374	0.405	0.393	0.379	0.626	0.235	0.495
87	0.106	0.061	0.409	0.058	0.227	0.065	0.545
88	0.233	0.040	0.332	0.058	0.291	0.281	0.699
89	0.020	0.024	0.237	0.031	0.265	0.065	0.293