THE JOURNAL OF ECONOMIC SCIENCES: THEORY AND PRACTICE, V.72, # 2, 2015, pp. 4-23

FACTOR-AUGMENTED J-CURVE

Mahammad R. Jamilov
Ph.D., Azerbaijan State University of Economics (UNEC)

Rustam M. Jamilov
Ph.D., London Business School. Corresponding author. We are grateful to Mohsen Bahmani-Oskooee for providing the trade balance data.

Received 16 July 2015; accepted 16 December 2015;

Abstract

We introduce the notion of the factor-augmented J-curve which substantially improves the presentation of and the intuition behind industrial J-curve analysis. Explorative factor analysis is performed on a large number of bilateral industry-level trade balances, and a small number of common factors is extracted. An Auto-Regressive Distributed (ARDL) model is then estimated for the bilateral exchange rate and the scores of the extracted factors. The new strategy is tested on a dataset of US-China bilateral trade over the 1981-2006 period. Factor analysis reduces the parameter dimension from 59 industries to 9 composite factors, to which we arbitrarily assign intuitive labels. Estimation of the trade balance model via ARDL reveals that for 3 factors, namely Total Trade, Heavy Metals and Organic Chemical Industries, and Agriculture and Non-Organic Chemical Industries, the trade balance improves in the long run following a depreciation in the exchange rate. Evidence for the presence of the J-curve effect in the short run is also found. According to the CUSUM and CUSUMSQ tests for parameter stability our results are stable and policy implications are robust. This analysis carries policy implications and is replicable for any bilateral trade dataset.

Keywords: J-curve; Marshall-Lerner Condition; Factor Analysis; ARDL Regression
JEL Codes: C38, F14, F31

Introduction

The methodological journey of the J-curve stream of literature has been long and extensive. The nexus between trade balance performance and exchange rate management has remained a focal point of interest for empirical trade scholars during the past three decades. The theoretical foundations originate in Magee (1973) and Dornbusch and Krugman (1976), who postulated that a cheaper currency should carry a positive net impact on the balance of trade. The empirical complexity arises in the dynamic of simultaneous reactions of both exports and imports to an exogenous currency devaluation shock. It is generally expected that in the short run a devalued currency will be more flexible and trigger a decline in the value of exports and a rise in imports, due to the so-called "price effect". However, in the long run the selling power of exporters (because of the cheaper currency) increases, exportation expands, and eventually overpowers the rise in imports via the "quantity effect". If the volume effect dominates the price effect, or in other words – the long-run elasticity of the trade balance in response to the exchange rate shock is larger than unity – then we observe the so-called Marshall-Lerner condition. If plotted over time, the dynamic of the balance of trade will resemble the letter "J", leading to the now famous J-curve effect.

Bahmani-Oskooee (1985) provides a pioneering empirical investigation of the J-curve phenomenon using aggregated data [Some other examples of the aggregated approach include Narayan (2004), Halicioglu (2007), and Hsing (2008)]. The presumably infective aggregation bias, present in all aggregated approaches to the question, is solved in Rose and Yellen (1989), who proposed to treat the matter with disaggregated, country-specific bilateral trade balance data [Some of the papers belonging to the bilateral approach are Bahmani-Oskooee and Brooks (1999), Bahmani-Oskooee et al. (2006), Halicioglu (2008), Bahmani-Oskooee and Kutan (2009), Perera (2011), and Jamilov (2013)] . Starting from Ardalani and Bahmani-Oskooee (2007), however, literature has glided towards *further* disaggregation, now to the level of industry-specific balance of trade parameters [The industrial approach includes such titles as Bahmani-Oskooee and Wang (2008), Bahmani-Oskooee and Hajilee (2009), Bahmani-Oskooee and Hegerty (2009), Bahmani-Oskooee and Mitra (2009), Soleymani and Saboori (2012), Bahmani-Oskooee et al. (2013)]. Despite the plethora of empirical attacks at the J-curve question, results are still substantially heterogeneous across regions, time periods, and individual industries. A more thorough review of the J-curve literature is provided by Bahmani-Oskooee and Ratha (2004).

In spite of some mechanical precision of working with highly disaggregated data series, the industry-level J-curve studies are still not entirely intuitive, are often very spacious, and the results are rarely illustrative for policy purposes. First, contemporary industry-level studies fail to explicitly account for mutual commonality of the industries examined, neglecting the confounding factor of mutual dependency and interconnectedness. In reality, however, it is very easy to see how such industries as, for example, "Metal plates", "Aluminum" and "Heavy Construction Materials" should possess some underlying common factor. It is possible that a single currency shock could carry a direct effect on the invisible *common factor*, which in turn indirectly initiates a subsequent chain reaction on the industries themselves.

Second, final results and baseline conclusions in most industry-level studies lack economic intuition and concrete policy relevance. Most papers conclude their respective analyses by claiming that, for example, 150 out of the 400 examined industries fulfill the M-L criteria in the long run or follow the J-curve pattern in the short run. However, the natural practical question to ask is: so what? Should the quantity 150 be considered as a positive or negative outcome? Does there exist some optimal ratio of criteria-fulfilling industries for a given economy? It is challenging to answer these follow-up questions if the number of industries gets sufficiently large, which is often the case in bilateral J-curve studies on large industrialized economies. It is even more challenging to convey a concise policy-relevant message when the referenced block of results counts hundreds of coefficient parameters, spacious and unfriendly for the most meticulous academic economists, let alone hasty and occupied policy-makers.

The answer to all of the issues raised and discussed above is the factor-augmented approach to J-curve estimation (FA-J). First, the FA-J method allows us to extract a small number of common factors from a large volume of industries, thus explicitly accounting for industrial commonalities and cross-correlation. Second, the large number of initial industries gets reduced to a more comprehensible number of common factors (in this paper, the reduction procedure transforms 59 industries into 9 factors). Third, intuition and policy-friendliness is greatly enhanced since authors can arbitrarily label the resulting 9 factors based on the observed factor loadings (the measure which shows how much each industry gets explained by at least one of the 9 factors). Finally, the test for the J-curve effect (positive long-run elasticity of the balance of trade, to be more precise), is a simple regression of the bilateral exchange rate on the obtained common factors. If the coefficient of impact is positive and significant, then the exchange rate devaluation will improve the bilateral balance of trade for this *particular* factor. If necessary, we return to the table with factor loadings and look at the industries which are most affected by our factor of interest.

Overall, we believe that this paper can at the very least provide a useful methodological alternative for policy-targeted empirical studies of the J-curve effect.

On the upper side, this study can open up a new stream of literature in this field, with a methodological framework to be followed and expanded upon in future studies. The remaining of this paper is structured as follows: Section 2 lays out the empirical strategy and describes the dataset. Section 3 reports the estimation results. Finally, Section 4 concludes.

1. Methodology and Data

Our empirical strategy consists of two fundamental components. First, we employ the rather conventional existing techniques of exploratory factor analysis [There are many good references on the general mechanics of factor analysis. Consult, for example, Vincent (1971) and Jae-on and Mueller (1978) for an excellent treatment of the subject. Hamilton (2006) is recommended for practical implementations on STATA]. Consider a generic function $Y = f(F_k(p))$, where F_k are unobserved random variables and p is a set of observable random variables x_p with means μ_p. Applying the generic formula to our study, the dependent variable becomes the bilateral exchange rate, p – the industry-specific trade balance volumes, and F_k – the unobserved common factors. The relationship between Y and p is indirect, with the factor matrix being the intermediary step. Our dimension reduction technique (factor analysis) will reduce the matrix p to F, thus bridging the association gap.

Further, suppose that for some unknown parameters a_{ij} and the unobserved variables F_j, with $i \in 1, \dots p$ and $j \in 1, \dots k$, and for every $k < p$, we impose:

$$x_i - \mu_i = a_{i1}F_1 + \cdots + a_{ik}F_k + \varepsilon_i \qquad (1)$$

Where ε_i are the error terms with zero mean, $E(\varepsilon) = 0$, and finite but heteroskedastic variance. The variance of ε_i is set at σ_i and is defined as:

$$\sigma(\varepsilon_i) = D_{i,j}(\sigma_1, \dots, \sigma_p) = \sigma \qquad (2)$$

Where $D_{i,j}$ is a diagonal matrix with all entries outside the main diagonal

$$x - \mu = A * F + \varepsilon \qquad (3)$$

Where capital A is the matrix of the of the unobserved coefficients a_{ij}.

Now, we assume that we have n observations so that the dimensions of the matrix components can be represented as x_{p*n}, A_{p*k}, and F_{n*k}. Matrix A is static across all cases, while columns x and F are observation-specific. We impose three binding assumptions on the behavior of the parameter F in (3). First, the factorial zero-conditional mean rule, i.e. $cov(F, \varepsilon) = 0$. Second, the static zero mean assumption: $E(F) = 0$. Finally, zero correlation across the factor parameters F_k: $cov(F) = I$. Under the established constraints on F, component A is the factor loading matrix while the solution to (3) is the dimension-reduced factor.

The factor analysis procedure will produce a set of result tables, from which the primary ones we will now briefly discuss one by one. First, the communalities matrix, which will not be reported to preserve space, produces the coefficients of across-industrial correlation. It is believed that any post-extraction communality coefficient of above 0.8 can be considered as solid and sufficient. The so-called Kaiser method of sampling adequacy will also be presented as part of our factor analysis exploration stage. The adequacy test shows if our sample is suitable for the factor analysis approach in the first place. Any Kaiser adequacy coefficient of above 0.7 indicates a positive response.

Following the preliminary assessment, the principal components method with correlation matrices is chosen as the method of factor extraction. We extract only the factors with an eigenvalue greater than unity, which is a standard rule in literature. This shows that the percentage of variation in our parameters is better explained *after* the factor is introduced; if the eigenvalue is smaller than unity then the model is better off without dimension reduction. The maximum number of iterations is set at 1000, after which the procedure selects the optimal quantity of common factors (in our case, for example, 9 underlying factors were established). In theory, it is possible to parsimoniously select the number of factors by the author himself and force the procedure to load the observables on the imposed quantity of unobservable factors. However, we leave such experimentations for future research and resort to the rule-based selection procedure for now.

After obtaining the first baseline results, it is recommended to perform a rotation on the parameter matrix. We rotate the factor solution with the *oblique varimax* rotation method with Kaiser normalization. Matrix rotations straighten and improve factor loadings for interpretation purposes as well as for more precise arbitrary labeling. Oblique rotation is designed specifically for potentially cross-correlated variables, which is indeed the case in our model (under our assumption that industries are interconnected). Again, 1000 rounds of iterations was chosen as the maximum for rotation convergence. The rotation matrix will report the important values of factor loadings of each industry on each of the previously extracted factors. We will suppress small factor score coefficients of below 0.1 in both the baseline and the rotated matrices. This allows us to focus our vision on the bigger coefficients, which correspond to better loadings on our extracted factors. Coefficient suppression is a rather common procedure in factor analysis literature. Finally, we save the rotated score matrix as a group of 9 separated series (in our case, it is the “factorial trade balances”).

The second stage of our estimation strategy employs the Auto-Regressive Distributed Lag model approach to cointegration, which is best described in Pesaran et al. (2001). The ARDL methodology is beneficial on several levels and primarily because it allows us to estimate both the short-run effects and the long-run cointegrating equation estimates of a given model. In addition, this method solves the problem of variable endogeneity and the inability to test hypotheses on the estimated coefficient. Narayan (2005) claims that the performance of the ARDL-based bounds testing approach in small samples is superior to that of multivariate cointegration, a claim which is particularly useful for our case due to our small sample sizes. Moreover, ARDL regressions do not require the variables in the model to be non-stationary in level forms; ARDL works regardless of whether there exists a unit root in the regressors or not. However, we will still perform and present results from the Augmented Dickey-Fuller test (Dickey and Fuller, 1979; 1981). It is important to ensure that variables are stationary at least in first differences, since I(2) processes will not work with the ARDL framework.

We can now set up a very simple single-equation trade balance model in its ARDL form:

$$TB_{F,t} = \alpha_0 + \sum_{j=1}^{m} \alpha_{1F} \Delta \ln TB_{F,t-j} + \sum_{j=0}^{m} \alpha_{2F} \Delta \ln EXR_{t-j} + \alpha_3 TB_{F,t-1} + \alpha_8 \ln EXR_{F,t-1} + \nu_t \quad (4)$$

Where TB, EXR stand for the trade balance and the bilateral exchange rate parameters, respectively. Trade balance is defined as the ratio of exports to imports; the exchange rate is the ln-transformed USD/YUAN bilateral exchange rate. α_0, α_{2i} are the constant and the elasticity estimates, respectively. ν_t is the stochastic component. Small-cased F, t, m refer to the factor, time, and lag-length indexes, respectively. Essentially, we regress each of the 9 factorial trade balances on the exchange rate variable, thus running 9 distinct ARDL regressions. A positive coefficient α_{2F} signals an improvement of the trade balance in response to devaluation for a particular factor, confirming the Marshall-Lerner hypothesis.

We can proceed with testing for long-run cointegration. The bounds testing approach presented in Pesaran et al. (2001) achieves this by presenting an F-statistic which tests the null hypothesis of no cointegration (H_0: $\alpha_5=\alpha_6= \alpha_7= \alpha_8=0$) against the alternative hypothesis (H_1: $\alpha_5\neq0$, $\alpha_6\neq0$, $\alpha_7\neq0$, $\alpha_8\neq0$). For every significance level there are two sets of critical values. If the F-statistic exceeds the upper-bound critical value, then the null hypothesis is rejected. If the F-statistic is below the lower-bound, then the null is accepted and we have no cointegration. Finally, if the F-statistic is between the two bounds then the test has no conclusive result. There is another way of testing for cointegration, which is looking at the error correction term in the ARDL's short-run representation via an error correction model (Kremers et al., 1992). If the error correction term is statistically significant and negative, it implies that the variables are quick on approaching their long-run stabilizing conditions.

The general form of the error correction model, which we need in order to review the short-run dynamics of the balance of trade model, is presented below:

$$TB_{F,t} = \alpha_0 + \sum_{j=1}^{m} \alpha_{1i} \Delta TB_{F,t-j} + \sum_{j=0}^{m} \alpha_{2i} \Delta \ln EXR_{t-j} + \lambda EC_{t-1} + u_t \qquad (5)$$

where λ is the coefficient of the speed of adjustment to long-run equilibrium and EC is the residuals obtained from the estimation of (4). We will therefore be able to simultaneously check on the long-run and the short-run behavior of our model. Should the lagged parameters $\Delta \ln EXR_{t-j}$ be negative and statistically significant, then we can argue for the fulfillment of the J-curve condition. In the end, after performing the tests for cointegration, presenting the long-run and the short-estimates of our factor-augmented trade balance model, we will present the stability checks of Brown et al. (1975), which are mostly known as cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests of the recursive regression residuals. Stability of the regression coefficients is proven if the plot of the statistics falls within the 5% significance bounds. Evidence of robustness of our parameters will provide more relevance to our implications and conclusions.

The balance of trade dataset has been obtained from Mohsen Bahmani-Oskooee upon request. The exchange rate is taken from IMF's International and Financial Statistics. This paper will analyze bilateral industry-level trade balances between United States and China for the 1981-2006 period. All variables are in annual frequency. Here, "China" includes within itself the mainland China as well as Honk Kong, Taiwan, and Vietnam. 59 industries in total are analyzed. The sample has been cleaned from all missing variables, thus enabling the principle components procedure. The U.S. is taken as the "home country", and trade balance is defined as the ratio of exports from U.S. to China to Chinese imports to the U.S. We take the logarithmic transform of the exports/imports ratio for interpretation purposes. The bilateral exchange rate is in the USD/YUAN form. Under such specification, an increase in the variable constitutes an exogenous devaluation of the Dollar with respect to the Renminbi and should, in theory, be positively correlated with the trade balance improvement. The dataset was cleaned from missing values, which would otherwise deem the principal components-based factor analysis procedure impossible. If any missing values still remained in the reduced 1981-2006 period for 59 industries, we substituted them with the across-period series average, which is a normal procedure in statistical economics.

2. Empirical Results

We now begin to report our empirical results from the factor analysis stage. Table 1 presents the measurements of sampling adequacy as part of the required preliminary sample assessment. The total sample's Kaiser MSA is 0.71, which is above the traditionally accepted threshold of 0.7. This suggests that our sample of 59 industries fits into the factor analysis frame with a sufficient potential for discovering the underlying common factors. We can now proceed to the determination of the optimal quantity of the factors.

Table 2 presents the composition of the parameter variance explained by each of the 59 industrial components in our sample. Note that based on the selection rule of eigenvalues being strictly larger than unity, the optimal number of common factors is 9. Together, these 9 factors are able to explain up to 92% of the cumulative variation in our sample variables. In order to even out the explanatory power differential between the first factor, which accounts for 52% of the explained variance, and the remaining factors, we rotate our industry matrix using the oblique varimax method and obtain the rotated sums of the squared loadings. We highlight that the total variance explained by the 9 factors remains unchanged, but the first factor's role has declined by 10%, thus raising the relevance of the other factors. Which is precisely what we wanted. We now investigate each industry's loading score on each of the 9 extracted factors in order to deduce their most intuitive labeling.

We will only report the factor loading estimates for the *rotated* matrix case, since this is more correct both for the technical and the intuitive reasons outlined earlier in the paper. Table 3 reports the rotated matrix's factor scores for each industry. Under the oblique varimax rotation and the principal components method of extraction, matrix rotation convergence was achieved after only 28 iterations. We first note that factor belongingness is not restrictive, meaning that certain industries can load on more than just one factor with equal degrees of score strength. We can also clearly notice that the first factor is loaded on by almost all industries, whereas factor 9 is the least responsive. Intermediary factors are all moderately influential. We are sticking to the eigenvalue selection rule and will not act by discretion and drop any of the least powerful factors, although such decision would have been justified.

Based on the factor score matrix we will now assign arbitrary factor-specific labels and thus complete the dimension reduction procedure (Table 4). Given the universal loading of basically every industry on factor 1, we label it simply as the "All Industries" factor. Careful scrutiny of the rotated factor scores have led us to assign the following names to the remaining 8 factors: "Non-Heavy Industries", "Communication and Utilities", "Textiles and Light Equipment", "Machinery, Vehicles, and Related Tools", "Heavy Metals and Inorganic Chemicals", "Storage and Infrastructure", "Agriculture and Organic Chemicals", and "Mineral and Quarrying Goods". We emphasize that in no way are our labels final and undisputable. It may well be that an attentive reader or future studies would detect an even better and more intuitive labeling strategy. However, this is the best we can offer, and we believe that the labels are broad and yet specific enough for implications and conclusions. We therefore save our extracted 9 factors as separate series and use them for the purpose of our balance of trade regression.

We continue the representation of results with the second and final phase of our empirical strategy: an ARDL analysis of the effect of exchange rate shocks on the common factors. Although the method does not require it, we still report the unit root test results in Table 5. Some of the variables possess a unit root, while all of the variables are stationary in first-differences. In general, this is not existential for the purposes of ARDL modeling, as explained earlier in the paper. Nevertheless, this would have produced a spurious regression problem had we resorted to simple OLS techniques. We now run 9 ARDL regressions using the factorial balance of trade parameters as our dependents and the exchange rate as the main covariate.

Table 6 presents the preliminaries for the bounds-testing procedure. The F-statistic is statistically significant for 6 of the 9 cases, suggesting that in for those regressions long-run cointegration is achieved. For the case of the final factor – Mineral and Quarrying Goods – the F-stat is insignificant but the error correction term is both negative and significant. We can therefore conclude that cointegration is established for this 7th factor as well. The average value of the error correction term is 0.7, suggesting that, on average, an exchange rate shock gets transmitted to the exports-imports relationship within 8 months. In other words, less than one calendar year is required for a devaluation to affect the balance of trade dynamic. The high, considering our small sample size and one single covariate, coefficients of determination – R-squared – simply imply that exchange rate works well as an explanatory variably of the total variation in egression outcomes. The lag order has been chosen according to the Schwarz-Bayesian criterion (SBC). In rare cases when the SBC suggested zero lags for the exchange rate, we forced one lag for reasons of short-run analysis.

Table 7 reports the main results of this paper. Three of the nine factors suggest the fulfillment of the Marshall-Lerner condition: the long-run elasticity of the exports-imports ratio in response to an exchange rate shock is positive and significant. For other factors, the impact is not significant at acceptable levels. Estimates of the lagged exchange rate variable are negative for almost all cases, and statistically significant for the 3 factors for which the Marshall-Lerner condition holds. This points at the presence of the J-curve effect: the collapse of the trade balance ratio in the short run due to the price effect and the volume-driven expansion in the long-run. All in all, negative values for the lagged exchange rate estimate and positive long-run elasticity estimates for factors 1, 6, and 8 suggest that both the M-L condition and the J-curve effect hold true for “All Industries”, “Heavy Metals and Inorganic Chemicals”, “Agriculture and Organic Chemicals” factors.

Note that the M-L and the J-curve hypotheses are supported for the trade sector as a whole since the factor “All Industries”, representing all 59 industries in the sample, improves following a dollar depreciation. As far as disaggregated factors are concerned, our results suggest that an exchange rate devaluation would trigger an improvement in the balance of trade for such spheres as heavy metals, organic and inorganic chemicals, and the agricultural industries. These sectors are composites, i.e. consisting of a number of interconnected smaller industries. The interested reader can return to Table 3 to revise which industry loads stronger on Factors 6 and 8. For policy purposes, it is enough to refer to the two composite factors to convey a clear and concise message on which sectors of the domestic economy would most positively respond to a potential exchange rate devaluation.

We complete the representation of results with the CUSUM and CUSUMSQ tests for parameter stability in Figures 1 and 2. To preserve space, we report the illustrations for the case of Factor 6 ("Heavy Metals and Inorganic Chemicals)" only. Remaining graphs are available upon request. Note that policy implications for this particular factor are even stronger, since the short-run (J-curve) and long-run dynamic (M-L condition) are found to be recursively stable.

3. Conclusion and Advice for Future Research

This paper has introduced an innovative way on how to empirically investigate the J-curve hypothesis and the Marshall-Lerner condition. Exploratory factor analysis has been employed for the first time in this stream literature, and the posterior regression analysis establishes the trade balance-exchange rate nexus. We have applied the procedure to the bilateral industry-level trade between the United States and China. We have successfully compressed a large dataset of 59 industries into just 9 composite common factors. All assessment tests pass the necessary requirements. ARDL regressions reveal that for 3 of the 9 factors an exchange rate devaluation triggers a positive long-run response in the factorial balance of trade. Moreover, the J-curve effect is observed in the short run. The superiority of this paper's approach is that final results carry intuitive and clear policy implications, are not excessively spacious, and account for any underlying across-industry commonalities.

Future studies have great room for maneuvering and improvement on this paper's methodology. First, a factor-augmented approach could be applied to a variety of regions and time periods, in order to improve interpretation of the existing industry-level studies. Second, this paper has focused primarily on the eigenvalue-based rule of factor extraction. Future attempts can experiment with confirmative factor analysis, i.e. imposing a concrete amount of factors. Third, the factor-augmented approach is useful for testing the workability of an existing hypothesis. For example, we theorize that there exist only 4 major clusters of industries which differ in terms of factor intensiveness: labor, capital, technology, and land oriented sectors. In the factor analysis stage we order the procedure to extract 4 common factors out of the set of N industries, and then examine the factor-specific loadings of each industry. If we observe that the industries which are supposedly labor-intensive (such as textile or clothing manufacturing, for example) do indeed load highly on one of the factors, and if a similar situation holds with the remaining factors, then we can argue that the theory is not only positive but also normative. Finally, while this paper's main contribution is in the introduction of the *factor analysis* approach, future studies should enhance the empirical strategy with further state-of-the-art regressions, such as the Dynamic OLS (DOLS), Two-State Least-Squares (2SLS), Cointegrated time-series, Vector Autoregressions (VAR), etc. The new frontier is there for the taking.

References

[1] Ardalani, Z., Bahmani-Oskooee, M. (2007), "Is there a J-Curve at the Industry Level?" *Economics Bulletin*, Vol. 6, No. 26 pp. 1-12.

[2] Bahmani-Oskooee, M, (1985). "Devaluation and the J-Curve: Some Evidence from LDCs," *The Review of Economics and Statistics*, 67(3), 500-504.

[3] Bahmani-Oskooee, M. and Brooks T. J. (1999), "Bilateral J–Curve between US and her Trading Partners," *Weltwirtschaftliches Archiv* 135: 156–165.

[4] Bahmani-Oskooee, M., Ratha, M. (2004), "The J-curve dynamics of US bilateral trade," *Journal of Economics and Finance* 28, 32–38

[5] Bahmani-Oskooee, M., Economidou, C., and Goswami, G. G. (2006), "Bilateral J-curve between the UK vis-à-vis her major trading partners," *Applied Economics* 38, 879-888.

[6] Bahmani-Oskooee, M and Kutan, A. M. (2009), "The J-curve in the Emerging Economies of Eastern Europe," *Applied Economics* 41, pp. 2523-2532.

[7] Bahmani-Oskooee, M. and Wang, Y. (2008), "The J-curve: Evidence from Commodity Trade between US and China," *Applied Economics*, 40: 2735-2747.

[8] Bahmani-Oskooee, M. and Hajilee, M. (2009), "The J-curve at Industry Level: Evidence from Sweden-US Trade," *Economic Systems*, 33: 83-92.

[9] Bahmani-Oskooee, M. and Hegerty, S.W. (2009), "The Japanese-US Trade Balance and the yen: Evidence from Industry Data," *Japan and World Economy*, 21: 161-171.

[10] Bahmani-Oskooee, M., Mitra, R. (2009), "The J-Curve at the industry level: evidence from U.S.-India trade ", *Economics Bulletin*, Vol. 29 no.2 pp. 1520-1529.

[11] Bahmani-Oskooee, M., Huseynov, S., Jamilov R. (2013), “Is there a J-Curve for Azerbaijan? New Evidence from Industry-Level Data,” Unpublished Monograph.

[12] Brown, R. L., Durbin, J. and Evans, J.M. (1975) Techniques for testing the constancy of regression relations over time, *Journal of the Royal Statistical Society*, 37, 149-163

[13] Dickey, D.A., Bell, W.R., Miller, R.B., (1986). “Unit Roots in time series models: tests and implications”, *American Statistician* 40, 12-26.

[14] Dornbusch, R., Krugman, P. (1976), “Flexible Exchange Rates in the Short Run,” *Brookings Papers of Economic Act*ivity 3, 537-584.

[15] Hamilton, L., “Statistics with STATA”, Thomson Books Publishing.

[16 Halicioglu, F. (2007), “The J-curve Dynamics of Turkish Bilateral Trade: A Cointegration Approach”, *Journal of Economic Studies* 34, 103-119.

[17] Halicioglu, F. (2008) “The Bilateral J-curve: Turkey versus her 13 Trading Partners,” *Journal of Asian Economics* 19, 236-243.

[18] Hsing, Y. (2008), “A Study of the J-curve for Seven Selected Latin American Countries”, *Global Economy Journal*, 8: Article 6.

[19] Jae-on, K., Mueller, C.W. (1978), |Factor Analysis. Statistical Methods and Practical Issues”, Sage Publications.

[20] Jamilov, R., (2013), “J-curve Dynamics and the Marshall-Lerner Condition: Evidence from Azerbaijan”, *Transition Studies Review* 19, 313-323.

[21] Kremers, J. J. M., Ericson, N. R. and Dolado, J. J. (1992) “The power of cointegration tests,” *Oxford Bulletin of Economics and Statistics*, 54, 325-348.

[22] Magee, S. P. (1973) Currency contracts, pass through, and devaluation, *Brookings Papers of Economic Activity*, 1, 303-325.

[23] Narayan, P. K. (2004) “New Zealand’s Trade Balance: Evidence from the J-curve and Granger Causality,” *Applied Economics Letters* 11, 351-354.

[24] Perera, W. (2011) “Bilateral J-curve between Sri Lanka and its major trading partners”, Central Bank of Sri Lanka Staff Studies, North America, 39.

[25] Pesaran, M. H., Shin, Y. and Smith, R. J. (2001), “Bounds Testing Approaches to the Analysis of Level Relationship,” *Journal of Applied Econometrics*, 16: 289–326.

[26] Rose, A.K., Yellen, J.L. (1989) “Is there a J-curve?” *Journal of Monetary Economics* 24, 53–68.

[27] Soleymani, A., Saboori B. (2012), “The J-curve: Evidence from Commodity Trade Between Malaysia and Japan”, *International Journal of Applied Economics and Finance* 6 (2): 64-73.

[28] Vincent, J. (1971), “Factor Analysis in International Relations. Interpretation, Problem Areas and Application”, University of Florida Press, Gainsville.

Table 1: Sample Adequacy Testing

	MSA		MSA
Alcoholic beverages	0.84	**Telecommunications apparatus**	0.62
Household equipment	0.56	**Machines for special industries**	0.82
Manufactures of metal	0.67	**Clothing except fur clothing**	0.38
Textile and leather machinery	0.81	**Tubes ,pipes and fittings of iron**	0.81
Furniture	0.74	**Metalworking machinery**	0.69
Musical instruments	0.57	**Iron and steel scrap**	0.75
Articles of paper & paperboard	0.83	**Synthetic goods**	0.86
Domestic electrical equipment	0.77	**Leather**	0.57
Other inorganic chemicals	0.64	**Equipment for electricity**	0.71
Sanitary, plumbing, heating	0.81	**Other electrical machinery**	0.74
Glass	0.83	**Printed matter**	0.76
Articles of artificial plastic mate	0.90	**Office machines**	0.71
Paper and paperboard	0.63	**Petroleum products**	0.72
Agricultural machinery	0.41	**Chemical materials and products**	0.46
Manufactured articles	0.62	**Plastic materials**	0.81
Veneers, plywood boards	0.74	**Pulp & waste paper**	0.79
Power generating machinery	0.68	**Inorg. chemicals**	0.42
Articles of rubber	0.76	**Wood manufactures**	0.81
Electric power machinery	0.76	**Organic chemicals**	0.78
Soaps, cleansing polishing tools	0.66	**Pigments, paints, varnishes**	0.62
Aircraft	0.71	**Ships and boats**	0.86
Watches and clocks	0.65	**Hand Tools**	0.69
Crude vegetable materials	0.41	**Aluminium**	0.71
Pharmaceutical products	0.79	**Clay and refractory construction**	0.89
Special textile fabrics and related	0.44	**Universals, plates of iron**	0.82
Nails, screws, nuts, bolts	0.76	**Copper**	0.88
Developed cinematographic film	0.50	**Metal containers for storage**	0.79
Scientific, medical, optical tools	0.44	**Finished structural parts**	0.48
Machinery and appliances	0.21	**Road motor vehicles**	0.76
		Mineral manufacturing	0.70
Kaiser's MSA	0.7137		

Note: MSA stands for Measurement of Sampling Adequacy. Kaiser’s total sample MSA of above 0.7 passes the test of sample appropriateness.

Table 2: Total Variance

Component	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	30.48	51.67	51.67	24.30	41.19	41.19
2	9.09	15.41	67.09	8.89	15.06	56.25
3	3.90	6.61	73.70	8.12	13.76	70.02
4	3.40	5.76	79.47	3.34	5.66	75.69
5	2.25	3.82	83.29	2.77	4.69	80.39
6	1.94	3.29	86.58	2.35	3.99	84.38
7	1.30	2.21	88.80	1.75	2.97	87.35
8	1.22	2.07	90.87	1.73	2.93	90.28
9	1.15	1.95	92.82	1.49	2.53	92.82
10	.70	1.19	94.01			
11	.64	1.10	95.11			
12	.48	.82	95.94			
13	.45	.77	96.72			
14	.41	.70	97.42			
15	.29	.50	97.92			
16	.27	.46	98.39			
17	.24	.41	98.80			
18	.19	.32	99.13			
19	.13	.22	99.36			
20	.12	.21	99.57			
21	.08	.15	99.72			
22	.06	.10	99.82			
23	.05	.08	99.91			
24	.03	.05	99.97			
25	.01	.02	100.00			
26	1.287E-	2.182E-15	100.00			
…	1.087E-	1.842E-15	100.00			
59	-	-2.325E-15	100.00			

Note: Extraction method is Principal Component Analysis. Number of factors is determined by the Kaiser method. The extracted 9 factors explain up to 93% of the total variation of the industry values.

Table 3: Rotated Component Matrix

	Component								
Industry	1	2	3	4	5	6	7	8	9
Alcoholic beverages	.928	.115	-.231						
Household equipment	.921	-.107		.116					
Manufactures of metal	.918	.280							
Textile and leather machinery	-.906		-.327		.119				
Furniture	.900	.221	.175	.250				.138	
Musical instruments	.898	.325							.138
Articles of paper & paperboard	.897	.347			-.131			.170	
Domestic electrical equipment	.890	.229				.293			
Other inorganic chemicals	-.873			.220		.114	.214	.200	
Sanitary, plumbing, heating	.868	.150	.269	.106				.195	.235
Glass	.867	.375	-.192					.186	
Articles of artificial plastic mate	.861	.259	-.160	.113	-.198		.110	.159	.132
Paper and paperboard	-.854	-.467		-101					
Agricultural machinery	-.835	-.281	-.133			-105		-.292	.185
Manufactured articles	.807	.370		.241	-.113			.199	
Veneers, plywood boards	.804	.545						.140	
Power generating machinery	-.798		-.352	-291	.211				
Articles of rubber	.777	.337	.148	.428		.137			
Electric power machinery	.771	.548		.169			.180		
Soaps, cleansing polishing tools	.753	.405		.406	-.266				
Aircraft	-.746		-.396	-381	.165	.119			
Watches and clocks	.743	-.163	.411	-126			.176	-.164	
Crude vegetable materials	.741	.346	.409		-.115			.237	.124
Pharmaceutical products	.730	.424	.116		-.195		.165	.301	
Special textile fabrics	.730	.386		.320	.118	.157			
Nails, screws, nuts, bolts	.727	.338	.250	.225	-.150	.233		.212	-.267
Developed cinematographic film	-.712	-.378	.439		.102			-.145	
Scientific, medical, optical tools	.696	.631	.236	.182					

Machinery and appliances	.668	.657	-.118	.216		.101	.153		
Telecommunications apparatus	.653	.522	-.453						.175
Machines for special industries	-.637		.154	-178	.347		-241	-.468	.259
Clothing except fur clothing	.612	.575	-.319	.223	-.168		.230	.101	
Tubes ,pipes and fittings of iron	.595	.427			-.135	.525			
Metalworking machinery	.224	.919							
Iron and steel scrap	.349	.844	.169	.231		-170			.127
Synthetic goods	-.532	-.695	.241	.209	.223			-.133	.101
Leather	-.597	-.618	.325	-245		-105		-.220	
Equipment for electricity	.273	.568	-.520	-.446		.126			.122
Other electrical machinery			.974						
Printed matter		-.165	.922	-199			.173		
Office machines	.199	.115	.903	.173	-.127		.147		
Petroleum products		.304	-.703	.287		-120			-.380
Chemical materials	.410	-.485	.671	.189		.138	-209	.101	
Plastic materials	.225	-.240	.648	.544	-.154				.180
Pulp & waste paper	-.494	-.479	-.645		.115	.156	-113		
Inorg. chemicals	.339	.278	.606			.346	-208	.421	
Wood manufactures	.459	.556	-.603			-135			.238
Organic chemicals	.240	.287		.780		.268		.192	
Pigments, paints, varnishes	.523	.381	-.307	.605					
Ships and boats	-.283	-.131	-.257	.225	.814				
Hand Tools	.237		.519	-105	.715			-.269	
Aluminium			-.397	-400	.666		-407		
Clay and construction	.392	.394	-.189	.143	-.550	.478			
Universals, plates of iron	-.330	-.149	.180			.798	.162	.143	
Copper	.346	-.100	-.194	.198	-.266	.706		-.101	-.355
Metal containers for storage	.518				-.119	.176	.730	.119	.224
Finished structural parts	.332	-.173	-.348	-136	.122	-102	-657		.318
Road motor vehicles	-.585			-148	.262		-224	-.648	
Mineral manufacturing	.178	.556				-103			.702

Note: Extraction method is Principal Components Analysis. Rotation choice is oblique varimax with Kaiser normalization. Matrix rotation convergence achieved in 28 iterations. Factor loadings of below 0.1 have been suppressed.

Table 4: Factor Labeling

Factor	Factor Label	Cumulative Variance Explained, %
1	All Industries	51.67
2	Non-Heavy Industries	67.09
3	Communication and Utilities	73.70
4	Textiles and Light Equipment	79.47
5	Machinery, Vehicles, and Related Tools	83.29
6	Heavy Metals and Inorganic Chemicals	86.58
7	Storage and Infrastructure	88.80
8	Agriculture and Organic Chemicals	90.87
9	Mineral and Quarrying Goods	92.82

Note: Factor labels are put arbitrarily, based on the authors' analysis of the rotated component matrix.

Table 5: Unit Root Test Results

	Level		First-Differences	
	t-stat	P-value	t-stat	P-value
Exchange Rate	-1.97	0.59	-2.05	0.07*
All Industries	-2.65	0.26	-2.91	0.06*
Non-Heavy Industries	-5.23	0.00**	-3.95	0.01
Communication and Utilities	-0.67	0.96	-2.52	0.02**
Textiles and Light Equipment	-2.61	0.28	-7.86	0.00**
Machinery, Vehicles, and Related Tools	-3.59	0.05	-3.93	0.01**
Heavy Metals and Inorganic Chemicals	-4.20	0.02**	-6.19	0.00
Storage and Infrastructure	-4.38	0.01**	-5.42	0.00
Agriculture and Organic Chemicals	-3.56	0.06	-5.19	0.00**
Mineral and Quarrying Goods	-2.66	0.26	-3.66	0.01**

Note: Regressions in Level form include the Time Trend and the Intercept. Regressions in First-Differences include the Intercept only. 1 lag has been chosen in all cases. *,**- indicates rejection of the null hypothesis of unit root at the 10% and 5% levels, respectively.

Table 6: ARDL Cointegration Testing

	F-Stat	ECT	R-squared	Lag Order
All Industries	9.73**	-0.51**	0.54	1.2
Non-Heavy Industries	5.63*	-0.57**	0.36	1,0
Communication and Utilities	3.39	0.02	0.25	1,0
Textiles and Light Equipment	8.80**	-0.60**	0.48	1,0
Machinery, Vehicles, and Related Tools	14.85**	-1.76**	0.78	3,0
Heavy Metals and Inorganic Chemicals	9.05**	-0.81**	0.58	1,1
Storage and Infrastructure	7.73**	-0.90	0.46	1,1
Agriculture and Organic Chemicals	4.72	-0.59	0.31	1,0

Mineral and Quarrying Goods	3.96	-0.54**	0.29	1,0

Note: F-stat is the F-statistic for the bounds-test of cointegration. ECT is the error correction term. R-squared is the coefficient of determination from the error correction regression. Lag order is the optimal lag length according to the Schwarz-Bayesian criterion. *,**- indicate statistical significance at the 5% and 1% level, respectively.

Table 7: ARDL Regression Estimates

Factors	Estimate	Constant	D(EXR)
All Industries	**2.18**	**-3.58**	**-1.23**
Non-Heavy Industries	-0.30	0.87	-0.17
Communication and Utilities	-3.19	6.46	0.55
Textiles and Light Equipment	-0.77	1.59	-0.46
Machinery, Vehicles, and Related Tools	-0.17	0.28	-0.30
Heavy Metals and Inorganic Chemicals	0.13	0.43	**-3.96**
Storage and Infrastructure	0.34	-0.68	1.14
Agriculture and Organic Chemicals	0.44	-0.77	**-0.25**
Mineral and Quarrying Goods	-0.59	1.15	-0.32

Note: Dependent variable is factor-specific trade balances. Independent variable is the ln-transformed US/YUAN bilateral exchange rate. Estimates in column 2 refer to the long-run elasticity of the factorial balance of trade parameters in response to a 1% shock in the exchange rate. D(EXR) is the lagged exchange rate variable indicating the short-run dynamics.

Figure 1: CUSUM Test for Heavy Metals and Inorganic Chemicals

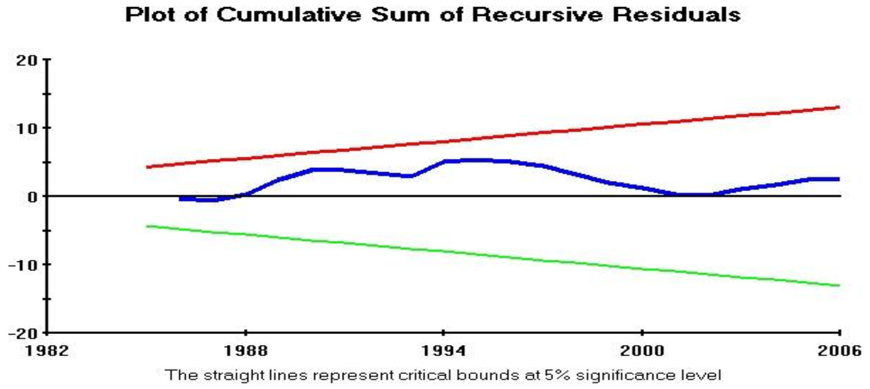

Figure 2: CUSUMSQ Test for Heavy Metals and Inorganic Chemicals