Inventory Levels Effect on Comparative Advantage in the Chemical Market Pulp Industry

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Spring, 2001
Abstract:

The competitive benefits of inventory management strategies, such as Just in Time (JIT) production, are routinely heralded. This paper attempts to analyze the effects of JIT production on comparative advantage in the international trade of pulp. Using ending inventories as a percent of total production, and the standard deviation of monthly inventory levels, as proxies for JIT, I find mixed results of their impact on international trade. A relatively large ending inventory, a compared to production, has a statistically significant negative impact on comparative advantage. However, the variation in monthly inventories does not appear to significantly impact comparative advantage. The apparent incongruence in my results should not detract from the importance of my findings, that inventory management techniques do affect comparative advantage.

Received by: Bruce Blonigen

Date: 6/4/01
Introduction:

Beginning in the mid-80's many Asian countries began using the "Just in Time" (JIT) production technique in many of their manufacturing facilities. One goal of JIT production is to minimize the capital resources invested in holding inventories. These inventories can include both inputs or finished goods, and possibly both. My analysis focuses on the benefits derived from reducing the level of finished good inventories. A second goal of JIT production is hold relatively small amounts of the factors of production in inventory. That is, schedule input deliveries so that they are moved from the truck directly to the production line. Using this method of JIT, the inventories in focus are in the beginning, rather than the end, of the production cycle. Either focus of JIT production has several key benefits. First, resources that are not tied up storing inventories can be invested elsewhere. Second, the risks of losses to inventory either through "shrinkage" (i.e. theft), aging or damage are diminished. Lastly, in order to utilize JIT production a reduction in defects must occur because without inventories a producer is unable to make returns without affecting production schedules. This increase in the product quality, if properly leveraged, is a competitive advantage. For instance in the pulp and paper industry the amount of "cull", the industry term for product that doesn't meet quality standards and must be re-pulped, has a huge impact on production costs.

Do these benefits increase one's comparative advantage, and, hence lead to increased net exports? The forest products industry within the United States has yet to broadly adopt JIT production techniques. Typically they produce as much as possible, regardless of sales, amassing large inventories when during economic downturns. This style of production is due, in part, by the perception that the immense capital investments made on equipment can be most efficiently recouped by spreading out the investment costs across the greatest amount of
production, lowering the amount of fixed costs per unit. However, it appears as if this style of 
production focuses on the “sunk” costs of production, rather than the increase in variable costs 
due to storage and handling of excess inventories. However, it should be noted that in the pulp 
industry some inventory is necessary to maintain operations during scheduled maintenance. I 
would like to determine if the current practices of the forest products industry within the United 
States are placing them at a competitive disadvantage in the global marketplace.

**Literature Review:**

According to Little (1992), inventory management systems, an example being JIT, have 
an unambiguously positive effect on the U.S. economy. However, she notes the U.S. started 
using lean production, and other methods to reduce the inventory to sales ratio, in reaction to 
reductions in international competitiveness. This reduction was caused by the dollar’s 
appreciation during the 1980’s, as well as inventory management techniques being adopted in 
Asian countries, such as Japan. Furthermore, Little discusses the extent to which different 
industries in manufacturing have adopted JIT, noting that the paper and allied products industry 
is one of the industries with the least integration of inventory management plans. Also, she 
showed that the benefits of lean production have yet to outweigh the costs associated with 
learning a new production technique in many U.S. industries. This indicates that the U.S. pulp 
and paper industry may have lost some of the comparative advantage it possessed. Wolf (1997) 
explains one reason for trade specialization is the “technology gap”. This theory indicates that 
the technology gaps between countries will be a major reason for trade flows and direction of 
flows. If true, it would reinforce my hypothesis that countries utilizing JIT production 
techniques have a comparative advantage over those who don’t. Furthermore, Posner (1961) 
originally postulated that technology would induce trade flows during the time it takes for other
countries to obtain or mimic the technology. Although not specifically defined as a technology in Wolf's paper I believe that different styles of production, including JIT, would have a similar impact. Lastly, Oman (1999) writes about the flexible “post-Taylorism” production techniques that have evolved and spurred greater regional and global competition. Taylorism was the style of scientific management that increased global productivity and pushed global competition higher between the 1950’s and 1960’s. Unfortunately, scientific management built serious rigidities into the production cycle, which Oman argues were a major cause of slowing production and stagflation of the 1970’s. As this occurred capital began accelerating its flight to low-wage non-OECD countries, particularly in Asia. The acceleration of the flight of capital continued until the 1980’s, when it began decelerating as OECD countries began to adopt more flexible production techniques. Oman also notes that the increases in production due to flexible production techniques found in OECD far exceed those used by Taylorist firms. This would indicate that countries in which JIT production is common (JIT being a form of flexible production) might have a comparative advantage over countries that use a more rigid style of production.

Theory:

Most empirical tests of trade patterns derive from the traditional H-O model, which doesn’t account for technological differences. To demonstrate the traditional H-O model’s, without an adjustment for technology, inefficiency in determining trade flows I ran the following regression.

Net Exports = f(Labor, Capital, Forest)

**Net Exports** = Total annual net exports of chemical wood pulp, all grades (SITC 2516-18), in thousands of U.S. dollars during 1997.


Forest = Total forested area in thousands of square kilometers in 1990\(^1\) as published on the World Bank's website.

The results of traditional H-O model are as follows:

<table>
<thead>
<tr>
<th>Dependent Variable and Empirical Model</th>
<th>Heckscher - Ohlin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regressors</td>
<td>Net Exports</td>
</tr>
<tr>
<td>----------------------------------------</td>
<td>-------------------</td>
</tr>
<tr>
<td>LABOR</td>
<td>-222961</td>
</tr>
<tr>
<td></td>
<td>(132399)</td>
</tr>
<tr>
<td>CAPITAL</td>
<td>252577.8*</td>
</tr>
<tr>
<td></td>
<td>(108168.3)</td>
</tr>
<tr>
<td>FOREST</td>
<td>148538.1*</td>
</tr>
<tr>
<td></td>
<td>(59622.24)</td>
</tr>
<tr>
<td>C</td>
<td>343188.5</td>
</tr>
<tr>
<td></td>
<td>(662027.3)</td>
</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.279502</td>
</tr>
<tr>
<td>F-statistic</td>
<td>5.043085</td>
</tr>
<tr>
<td>Sample Size</td>
<td>43</td>
</tr>
</tbody>
</table>

Although the F-statistic is significant at a 1% level of confidence the low adjusted r-squared indicates this model has little explanatory power. On the following page of is a graph of the residuals against the actual results. The graph also supports the conjecture that H-O model doesn't consistently predict trade patterns with great deal of accuracy.

\(^1\) Due to data limitations I was unable to gather more recent data. However, assuming that the local timber industry practices reforestation, as in many parts of the world, the variation between the data used and current data should be immaterial.
Furthermore, others have also shown the inaccuracy of the traditional H-O model in predicting trade flows. Trefler (1995) demonstrates how the H-O model should be rejected for a model that allows for technological or other differences, other than factor endowments, between countries. He states that the high failure rate of the H-O model in predicting trade flows in the factor service industry is evidence of its shortcomings. He goes on to say that other economic models that perform equally poor are typically rejected and in search of a better model.

However, Leamer (1984) counters the argument that technology isn’t included within the H-O model. He states that technological differences are, at least in part, accounted for within the various levels of factor endowments. For instance, if the labor endowment were disaggregated to identify various levels of education it would implicitly describe the level of productivities.

After concluding my literature review and the brief empirical survey, I believe that adjusting the standard H-O model to account for the use of JIT production is a theoretically sound modification. Using two variations of the H-O model I can effectively determine if accounting for inventory levels increases the explanatory power H-O model in determining comparative advantage. I will also be able to independently test the significance of the relative
inventory levels on international trade. Below are descriptions of the relative variables under the H-O model of comparative advantage in the chemical pulp industry.

\[ Y = f (I, K, L, F) \]

\[ Y = \text{Due to data limitations I was unable to gather import data, on a monthly basis, for chemical pulp. As such, I was unable to calculate net exports. I am satisfied that total exports, in 000's of tons, is a justifiable proxy for comparative advantage. However, I do recognize that the data limitations may cause specification problems within the H-O model.} \]

\[ I = \text{A proxy variable for JIT production. I am using total month end inventories divided by total monthly production. I expect negative relationship between the amounts of inventory carried, as a percent of production, and a nation's comparative advantage and, hence, exports, because of the opportunity cost of holding large amounts of inventory.} \]

\[ K = \text{The total value of gross capital formation, given in billions of U.S dollars. The H-O model assumes that the level factor endowments cause an increase in comparative advantage. As such, I predict a positive relationship between the level of gross capital flows and the percent of world exports.} \]

\[ L = \text{Total employment, given in thousands, in the manufacturing industry. The H-O model assumes that the level factor endowments cause an increase in comparative advantage. As such, I predict a positive relationship between the number of people employed and the percent of world exports.} \]

\[ F = \text{The total area of forest available for harvest. Because timber is the primary resource used in the production of pulp a large area of available timber means reduced production costs and an increased comparative advantage. The production costs would be reduced because a} \]
country with a large amount of timber (e.g. United States) will not have as high transportation costs as a country that imports logs to produce the pulp (e.g. Japan).

Data

I encountered great difficulty in collecting inventory data, which limited the countries I selected for my sample. The inventory, production, and export data was gathered from tables published by the Market Pulp Producers Association (MPPA). It can be assumed that the countries selected by the MPPA are “players” in the chemical pulp industry, thereby possessing a comparative advantage in relation to the rest of the world. This constraint on my sample may cause sample selection bias. The data used was report on a monthly basis from October 1995 – Oct 1998. The gross capital formation data was calculated from gross capital formation as a percent of GDP, gathered from the International Financial Statistics Yearbook (2000), multiplied by total GDP in U.S. dollars. The employment data was gathered from the Yearbook of Labour Statistics (2000). Both the gross capital formation data and employment statistics were reported on an annual basis. In order to utilize this information I evenly distributed the monthly portion of the annual change. The redundancy in the capital and labor statistics may cause my model to lose some descriptive power, over emphasizing the importance of capital and labor. To counter this effect I will run secondary regressions across the three years on an annual basis. In the secondary regression I will use the standard deviation of my JIT variable. This is consistent with my original hypothesis because countries using JIT production will have inventory management systems that will allow them to adjust to rapid changes in demand. This adaptability should correlate with smaller variations in monthly inventory levels.
Empirical Model

H-O Model – monthly basis

1) \( Y = \beta_0 + \beta_1 \ln(L) + \beta_2 \ln(K) + \beta_3 \ln(F) + \varepsilon \)
2) \( Y = \beta_0 + \beta_1 \ln(L) + \beta_2 \ln(K) + \beta_3 \ln(F) - \beta_4 (I) + \varepsilon \)

Secondary Regressions – annual basis

3) \( Y = \beta_0 + \beta_1 \ln(L) + \beta_2 \ln(K) + \beta_3 \ln(F) + \varepsilon \)
4) \( Y = \beta_0 + \beta_1 \ln(L) + \beta_2 \ln(K) + \beta_3 \ln(F) - \beta_4 \mathrm{StdDev}(I) + \varepsilon \)

Empirical Results

\[
\begin{array}{lll}
\text{Dependent Variable and Empirical Model} & \text{Heckscher-Ohlin} & \text{Exports Chemical Pulp} \\
\hline
\text{Regressors} & \text{Model 1} & \text{Model 2} \\
\text{LABOR} & -11.10072^* & -9.34056 \\
& (5.090998) & (5.571997) \\
\text{CAPITAL} & -10.02065^* & -15.4213^* \\
& (5.081976) & (5.062551) \\
\text{FOREST} & 91.40753^* & 87.00781^* \\
& (7.041779) & (7.036944) \\
\text{JIT} & & -27.16314^* \\
& & (7.216816) \\
\text{C} & -844.3852 & -807.75552 \\
& (65.73784) & (65.71786) \\
\hline
\text{Adjusted R-squared} & 0.534714 & 0.543386 \\
\text{F-statistic} & 168.552 & 130.6062 \\
\text{Sample Size} & 444 & 444 \\
\end{array}
\]

The following two-sided hypothesis tests were created under my assumptions for the theoretical model.

Labor: \( H_0: \beta_1 = 0; \ Ha: \beta_1 \neq 0 \)  
Capital: \( H_0: \beta_2 = 0; \ Ha: \beta_2 \neq 0 \)  
Forest: \( H_0: \beta_3 = 0; \ Ha: \beta_3 \neq 0 \)  
JIT: \( H_0: \beta_4 = 0; \ Ha: \beta_4 \neq 0 \)  

The critical value of \( t \), for a two-sided test, with 95% probability and degrees of freedom of 440 is approximately 1.96. The results of my hypothesis tests for models one and two are as follows.
Model 1:
Labor: $|t - \text{labor}| > t\text{-critical}; \text{ reject the null}$
Capital: $|t - \text{capital}| > t\text{-critical}; \text{ reject the null}$
Forest: $|t - \text{forest}| > t\text{-critical}; \text{ reject the null}$

Model 2:
Labor: $|t - \text{labor}| < t\text{-critical}; \text{ can't reject the null}$
Capital: $|t - \text{capital}| > t\text{-critical}; \text{ reject the null}$
Forest: $|t - \text{forest}| > t\text{-critical}; \text{ reject the null}$
JIT: $|t - \text{JIT}| > t\text{-critical}; \text{ reject the null}$

### Dependent Variable and Empirical Model

<table>
<thead>
<tr>
<th>Regressors</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>LABOR</td>
<td>-4.276472</td>
<td>4.523027</td>
</tr>
<tr>
<td></td>
<td>(16.28015)</td>
<td>(15.30382)</td>
</tr>
<tr>
<td>CAPITAL</td>
<td>-10.09131</td>
<td>-20.08225</td>
</tr>
<tr>
<td></td>
<td>(16.75018)</td>
<td>(16.05985)</td>
</tr>
<tr>
<td>FOREST</td>
<td>79.29799*</td>
<td>79.36734*</td>
</tr>
<tr>
<td></td>
<td>(25.09803)</td>
<td>(23.49827)</td>
</tr>
<tr>
<td>JIT</td>
<td></td>
<td>-182.8745</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-112.5024</td>
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<tr>
<td>C</td>
<td>-753.1818</td>
<td>-725.3366</td>
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<tr>
<td></td>
<td>(227.0018)</td>
<td>(208.4998)</td>
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<tr>
<td>Adjusted R-squared</td>
<td>0.524718</td>
<td>0.556492</td>
</tr>
<tr>
<td>F-statistic</td>
<td>11.77</td>
<td>9.724311</td>
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<tr>
<td>Sample Size</td>
<td>36</td>
<td>36</td>
</tr>
</tbody>
</table>

The following are the results of the two-sided t-tests using my previous assumptions.

The critical value of $t$ with 95% probability and 32 degrees of freedom is approximately 2.042.

Model 3:
Labor: $|t - \text{labor}| < t\text{-critical}; \text{ can't reject null}$
Capital: $|t - \text{capital}| < t\text{-critical}; \text{ can't reject null}$
Forest: $|t - \text{forest}| > t\text{-critical}; \text{ reject null}$

Model 4:
Labor: $|t - \text{labor}| < t\text{-critical}; \text{ can't reject null}$
Capital: $|t - \text{capital}| < t\text{-critical}; \text{ can't reject null}$
Forest: $|t - \text{forest}| > t\text{-critical}; \text{ reject null}$
JIT: $|t - \text{JIT}| < t\text{-critical}, \text{ can't reject null}$
In model 2, I was able to reject the null regarding JIT production. This indicates that relatively high levels of inventory adversely affect comparative advantage. However, in model 4, which focused on monthly inventory variation, I was unable to reject the null regarding JIT. My results indicate that the relative levels of inventory are important in determining comparative advantage while the variation in inventories does not appear to significantly impact trade. The addition of JIT to my both series of equations improved my adjusted r-squared while decreasing the f-statistic. Furthermore, The significant increase in the f-stat and adjusted r-squared is also evidence of the traditional H-O inadequacy in prediction trade flows.

Conclusion

It appears that JIT, and other inventory management techniques, do affect an industry’s comparative advantage in the global marketplace. The carrying costs associated with continually carrying a relatively high level of inventory could be a source of this advantage. Although, the smaller expected variations in monthly inventories associated with JIT production do not conclusively affect comparative advantage. This implies the benefits associated with JIT production stem from lower levels of inventory rather than decreased variation in inventory levels. As the more countries engage in free trade it is important for the U.S., and other countries, to fully understand how to maximize their comparative advantage. Under the H-O model countries can do nothing to change their relative advantage. It has been shown that various management techniques, such as JIT, affect trade patterns and that countries which readily pursue these tactics may be better able to improve their relative place in the global market place.
Works Cited

Leamer, Edward E. “Sources of International Comparative Advantage” Cambridge, MA, MIT, 1984


Wolf, Edward N. “Productivity growth and shifting comparative advantage on industry level” Technology and International Trade (1997) 1-20
Dependent Variable: NEXPORTS
Method: Least Squares
Date: 05/22/01  Time: 18:02
Sample: 1 43
Included observations: 43

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<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
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<td>LOG(LABOR)</td>
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<td>343188.5</td>
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<td>0.518390</td>
<td>0.6071</td>
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</table>

R-squared: 0.279502  Mean dependent var: 203197.8
Adjusted R-squared: 0.224079  S.D. dependent var: 981516.9
S.E. of regression: 864582.4  Akaike info criterion: 30.26629
Sum squared resid: 2.92E+13  Schwarz criterion: 30.43012
Log likelihood: -646.7252  F-statistic: 5.043085
Durbin-Watson stat: 1.680598  Prob(F-statistic): 0.004763
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<th>Std. Error</th>
<th>t-Statistic</th>
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<td>-844.3852</td>
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</table>

R-squared          | 0.534714    | Mean dependent var | 159.0068 |
Adjusted R-squared | 0.531542    | S.D. dependent var | 181.1900 |
S.E. of regression | 124.0136    | Akaike info criterion | 12.48763 |
Sum squared resid  | 6766929.    | Schwarz criterion  | 12.52453 |
Log likelihood     | -2768.254   | F-statistic       | 168.5520 |
Durbin-Watson stat | 0.135644    | Prob(F-statistic) | 0.000000 |
Dependent Variable: EXPORTS
Method: Least Squares
Date: 05/22/01   Time: 18:12
Sample: 1444
Included observations: 444
White Heteroskedasticity-Consistent Standard Errors & Covariance

<table>
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<tbody>
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R-squared 0.543386  Mean dependent var 159.0068
Adjusted R-squared 0.539226  S.D. dependent var 181.1900
S.E. of regression 122.9924  Akaike info criterion 12.47332
Sum squared resid 6640813  Schwarz criterion 12.51944
Log likelihood -2764.077  F-statistic 130.6062
Durbin-Watson stat 0.136808  Prob(F-statistic) 0.000000
Dependent Variable: EXPORTS
Method: Least Squares
Date: 05/23/01   Time: 20:08
Sample: 1 36
Included observations: 36
White Heteroskedasticity-Consistent Standard Errors & Covariance

<table>
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<tr>
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R-squared 0.524718  Mean dependent var 145.5237
Adjusted R-squared 0.480161  S.D. dependent var 160.6580
S.E. of regression 115.8342  Akaike info criterion 12.44664
Sum squared resid 429362.0  Schwarz criterion 12.62258
Log likelihood -220.0394  F-statistic 11.77617
Durbin-Watson stat 1.300559  Prob(F-statistic) 0.000023
Dependent Variable: EXPORTS  
Method: Least Squares  
Date: 05/23/01  Time: 20:09  
Sample: 1 36  
Included observations: 36  
White Heteroskedasticity-Consistent Standard Errors & Covariance

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
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R-squared: 0.556492  
Adjusted R-squared: 0.499265  
S.E. of regression: 113.6858  
Sum squared resid: 400658.4  
Log likelihood: -218.7940  
Durbin-Watson stat: 1.400597

Mean dependent var: 145.5237  
S.D. dependent var: 160.6580  
Akaike info criterion: 12.43300  
Schwarz criterion: 12.65293  
F-statistic: 9.724311  
Prob(F-statistic): 0.000032