Lebanon's PMI Exports Subindex as a Leading Indicator for Total Exports – An Empirical Investigation

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- **Introduction**

In this study, we aim to examine the relationship between new export orders (NEO) and total exports in the context of Lebanon. 'New export orders' is a subindex of the PMI that tracks foreign demand for both goods and services. Like the PMI, it is expressed as a diffusion index that ranges between 0 and 100. A reading above 50 indicates expansionary territory, whereby there is an increase in demand for Lebanese exports. Inversely, a reading below 50 indicates contraction, whereby there is a decrease in demand for Lebanese exports. Total exports include both goods and services exported from Lebanon. Both of these variables are generally considered to be correlated given a time lag, as the subindex is a leading indicator. We used a simple linear regression model with distributed lags to study the effect of the point change in NEO on the log change in total exports. Later, we built upon this model, combining several lagged terms and other variables for diagnostic reasons in order to assess the relationship more comprehensively.

- **Data Collection and Information**

The total exports data, comprising goods and services exports, was retrieved from Banque Du Liban (BDL) while the new export orders data (NEO) was retrieved from S&P Global and BlomInvest. The monthly sample data studied starts from June 2013 and ends at December 2025, hence a sample size of 151 months. However, considering we introduced time lags into our regression models, some of the models' sample sizes decrease to 149 months.

For total exports (TE), we used the log change in total exports, whereby:

$$\Delta \ln TE_t = \ln\left(\frac{TE_t}{TE_{t-1}}\right)$$

Since NEO data is expressed as a diffusion index, we used percentage point change:

$$\Delta NEO_t = NEO_t - NEO_{t-1}$$

When time lags are introduced, the formulas remain the same but only the 't' subscript changes corresponding to the lag.

We also introduced a dummy variable named "Variable LBP/USD" (denoted by VLU) which takes the value 0 if the exchange rate is stable/pegged and the value 1 if the exchange rate varies. In our sample data, the start of the 2019 banking crisis up to September 2023, VLU took a value of 1 and the remaining periods it was 0.

For further context, some of the technical and econometric concepts and definitions were excluded to avoid redundancy. If the reader wishes to explore the more technical aspect, we suggest reading our paper "The Relationship Between Lebanon PMI's Output Prices Subindex and CPI – A Quantitative Study" or any reliable source of their choice that clarifies these concepts.

Concepts/keywords include: Variance Inflation Factor, Durbin-Watson test, heteroskedasticity, biased coefficients, White test.

- ## Regression Models with 1 Independent Variable

We tested the log change in TE with the percentage point change of NEO at time t, t−1, and t−2, each individually.

Starting with time 't' we got the following results:

Regression Statistics	
Multiple R	0.3937
R Square	0.1550
Adjusted R Squa	0.1493
Standard Error	0.1405
Observations	151

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.539375296	0.539375296	27.3301633	5.70194E-07
Residual	149	2.940594176	0.019735531		
Total	150	3.479969471			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.00290664	0.011432521	-0.25424329	0.79965813	-0.02549745	0.019684171
NEO Change t	0.013633385	0.00260785	5.227825868	5.7019E-07	0.008480239	0.01878653

$$\Delta \widehat{ln\ TE_t} = \widehat{\beta_0} + \widehat{\beta_1} \Delta NEO_t$$

The coefficient of the change in NEO at the same month was significant at the 5% level with a p-value of 5.7×10^{-7}. At first glance, it seems counterintuitive; why is a subindex of the PMI, which is supposed to be a leading indicator, highly statistically significant within the same period? We first need to clarify the nature of the PMI and the way it is reported. The firms fill out the PMI surveys during the middle of the month and report any changes that happened from the last time they filled out the survey, which would be from the middle of the month prior. For example, if a firm filled out the survey on February 15, they are reporting all the changes that happened from January 15, which would be the last time they filled the survey. The PMI result itself is then released at the end of the month. Total exports, on the other hand, are reported based on the start to the end of the month. Therefore, some of the reported NEO results that are from the middle of the month prior are then realized as total exports in the month after, which is sort of like a 'semi-lag' effect.

Furthermore, the R-Squared was 15.5%, which means that the change in NEO explains 15.5% of the variability in the log change in total exports. This result is fairly acceptable, considering we have only 1 independent variable.

Moving on to time 't−1', we get the following output:

Regression Statistics	
Multiple R	0.1355
R Square	0.0184
Adjusted R Squar	0.0117
Standard Error	0.1517
Observations	150

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0.06367999	0.06367999	2.7684665	0.098254181
Residual	148	3.404281216	0.0230019		
Total	149	3.467961207			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-0.003415767	0.012383433	-0.275833568	0.7830607	-0.02788695	0.02105541
NEO Change t-1	0.004684569	0.002815464	1.663870944	0.0982542	-0.00087913	0.01024827

$$\Delta \widehat{ln\ TE_t} = \widehat{\beta_0} + \widehat{\beta_1} \Delta NEO_{t-1}$$

After introducing a 1-month lag, we got a p-value of 9.82%, which is statistically insignificant at the 5% level. This is quite odd given that a 1-month lookback horizon (or even slightly further given the 'semi-lag' we mentioned) is quite a reasonable timeline given the duration of ocean/sea freight required. Perhaps this could be due to omitted variable bias[1]. Furthermore, the R-Squared was 1.84%, which is horrendous. Let's observe what happens when we consider a period further than this such as t−2.

Regression Statistics	
Multiple R	0.1581
R Square	0.0250
Adjusted R Squar	0.0183
Standard Error	0.1509
Observations	149

ANOVA

	df	SS	MS	F	Significance F
Regression	1	0.08578684	0.08578684	3.766440259	0.054204324
Residual	147	3.348165534	0.022776636		
Total	148	3.433952373			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-0.001974	0.012363922	-0.159681677	0.873351034	-0.026408287	0.022459704
NEO Change t-2	-0.005437	0.002801646	-1.940731887	0.054204324	-0.01097395	9.94624E-05

[1] *Omitted variables bias (OVB) occurs when a statistical model leaves out a crucial factor that affects the outcome. That crucial variable should be correlated with another explanatory variable, which thus explains how leaving it out distorts metrics.*

$$\Delta \widehat{ln\ TE_t} = \widehat{b_0} + \widehat{b_1} \Delta NEO_{t-2}$$

The metrics here, at first glance, look a bit promising. The p-value is 5.42%, which is borderline insignificant at the 5% level. The R-Squared is 2.5%, which is still unfavorable but still better than the t−1 case. However, these numbers are still deceiving regardless; when we look at the coefficient, we observe a ***negative*** one! How can this be? If new exports orders 2 months ago increase by 1 point, then total exports this month are expected to decrease? Even when we observe the 95% confidence interval, the upper bound states a value of 9.96×10^{-5} or 0.0000996, which even then is barely bordering a pragmatic positive coefficient.

So far, the results have looked quite off:

1. At time t – despite the 'semi-lag' – the coefficient was highly significant and accounts for most of the variability relative to the other time lags. This is not really a problem though.
2. At time t−1, the coefficient was insignificant despite it being the most 'reasonable' duration between outgoing orders and the receiving of the shipment.
3. At time t−2, despite some higher potential in the p-value, the coefficient itself did not make any particular economic sense considering it was negative.

Let's now observe how the numbers change when we combine all 3 variables.

- **Combining the 3 Variables**

Regression Statistics	
Multiple R	0.465
R Square	0.216
Adjusted R Squar	0.200
Standard Error	0.136
Observations	149

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	0.741738001	0.247246	13.31642473	1.00071E-07
Residual	145	2.692214373	0.018566996		
Total	148	3.433952373			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.003723736	0.011166972	-0.333459765	0.739268969	-0.025794804	0.018347333
NEO Change t	0.015713348	0.002706909	5.804904126	3.90445E-08	0.010363252	0.021063445
NEO Change t-1	0.008402214	0.002768589	3.034836164	0.002853325	0.00293021	0.013874218
NEO Change t-2	-0.001876588	0.002666903	-0.703657991	0.482774192	-0.007147613	0.003394438

$$\Delta \widehat{\ln TE_t} = \widehat{\beta_0} + \widehat{\beta_1}\Delta NEO_t + \widehat{\beta_2}\Delta NEO_{t-1} + \widehat{\beta_3}\Delta NEO_{t-2}$$

After combining all 3 variables, we get much more promising results. NEO change at t remains highly significant, and now the change at t−1's p-value dropped from 9.82% to 0.2% making it significant at the 5% level. Perhaps we can analyze this in the sense that NEO change at t acted as a suppressor variable[2] for the change at t−1. It essentially already accounted for all the 'noise' (unrelated variance) and allowed the clean effect of NEO change at t−1 to emerge. This proves that the change at t−1 was suffering from omitted variable bias. Both coefficients remained positive, which backs up the empirical evidence and logic well. On the other hand, NEO change at t−2 had drastic changes. Previously, its p-value of 5.42% was bordering the significant threshold of 5%, so we speculated that perhaps with further modifications, the results could be improved. Now, its p-value shot up to 48.27% and its coefficient remained negative. Therefore, it no longer serves any practical purpose and we should omit it.

Furthermore, R-Squared now increased to 21.6%, which is better than that of NEO change at t individually, which was 15.5%.

Now let's observe the results after omitting NEO change at t−2.

[2] *A suppressor variable is a control or independent variable that increases the predictive power of another predictor by removing irrelevant "noise" or overlapping variance.*

Regression Statistics	
Multiple R	0.470
R Square	0.221
Adjusted R Squar	0.210
Standard Error	0.136
Observations	150

ANOVA

	df	SS	MS	F	Significance F
Regression	2	0.765263355	0.382631677	20.8113743	1.10068E-08
Residual	147	2.702697852	0.0183857		
Total	149	3.467961207			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-0.004059261	0.011071807	-0.366630406	0.71442191	-0.025939736	0.017821213
NEO Change t	0.016158376	0.002615762	6.177312334	6.0698E-09	0.010989021	0.021327731
NEO Change t-1	0.009052733	0.002614585	3.46239843	0.0007014	0.003885704	0.014219762

$$\Delta \widehat{\ln TE_t} = \widehat{\beta_0} + \widehat{\beta_1} \Delta NEO_t + \widehat{\beta_2} \Delta NEO_{t-1}$$

By omitting NEO change at t−2, the other coefficients remained positive and their p-values decreased even further. The R-Squared also increased from 21.6% to 22.1%, which may confuse some people. Adding a variable never decreases R-Squared, so why the increase when omitting one? The answer lies in the change in the sample size; in the model with all 3 variables, the sample size was 149 since NEO change at t−2 forced us to remove our 2nd starting data point. By omitting the variable, we were able to reinclude the previously lost data point which increased the sample size and consequently the R-Squared[3].

Having an independent variable and its lagged term slightly shifts the interpretations of the coefficients. Considering both coefficients were positive, this tells us that the NEO subindex has a prolonged multi-month effect, whereby orders take time to fulfill and this spreads the export effect over 60+ days. Combining both variables allowed us to avoid omitted variable bias and capture the full effect comprehensively. The fact that the coefficient of NEO change at t is higher than that of t−1 (1.61% > 0.9%) has more implications than a mere numerical difference. It implies that the effect of NEO last month on total exports is marginal, and then the month after reflects the full impact.

[3]*It is important to note that increasing the sample size does not inherently increase R-Squared, as that added sample point could be completely contrarian to the predicted model and actually decrease R-Squared. In our case, it happened to be correlated.*

We also ran a Durbin-Watson test (DWT) to test for serial autocorrelation[4] and got a result of 2.45. This figure is technically still within the acceptable range of ±0.5 from 2 but we decided to account for it either way by adding a 1-month lagged total exports as an independent variable, thus reaching our finalized regression model.

[4] *Serial autocorrelation occurs when the error terms (residuals) are correlated with each other across observations. This leads to overly optimistic p-values but leaves the coefficients unbiased. Adding a lagged dependent variable as a term generally fixes the problem and offers valid p-values but biases the coefficients. However, we don't care about the coefficients (besides the sign) as our goal is to merely observe if a relationship exists and not the impact itself, thus we only care about the p-values.*

- **The Final Model**

Regression Statistics	
Multiple R	0.5240
R Square	0.2746
Adjusted R Square	0.2597
Standard Error	0.1313
Observations	150

ANOVA

	df	SS	MS	F	Significance F
Regression	3	0.9521551	0.317385033	18.418834	3.44529E-10
Residual	146	2.515806107	0.017231549		
Total	149	3.467961207			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-0.00542471	0.010726678	-0.50572096	0.6138152	-0.02662433	0.015774918
TE Log Change t-1	-0.25780322	0.078280833	-3.29331221	0.0012423	-0.41251321	-0.10309324
NEO Change t	0.01621874	0.002532396	6.404505854	1.945E-09	0.011213855	0.021223634
NEO Change t-1	0.01257214	0.002747534	4.575791726	1.006E-05	0.007142067	0.018002222

$$\Delta \widehat{\ln TE_t} = \widehat{\beta_0} + \widehat{\beta_1}\Delta NEO_t + \widehat{\beta_2}\Delta NEO_{t-1} + \widehat{\beta_3}\Delta \ln TE_{t-1}$$

After adding the lagged log change in total exports, all coefficients are significant and the R-Squared increased to 27.46%. Our DWT now came out to 2.057, which is very close to the reference value of 2, meaning that we have successfully eliminated the issue of serial autocorrelation. In order to test for multicollinearity in our model, we conducted a Variance Inflation Factor (VIF) test and got the following results:

Regression Statistics	
Multiple R	0.4619
R Square	0.2134
Adjusted R Square	0.2027
Standard Error	3.9406
Observations	150

$$VIF_i = \frac{1}{1 - R_i^2}$$

$$VIF_i = \frac{1}{1 - 0.2134}$$

$$VIF_i = 1.271$$

After regressing all independent variables on one another across 3 models, the highest R-Squared observed was when NEO change at t−1 was regressed on NEO change at t and log change in total exports at t−1, which came out to 21.34%. The VIF result thus came out to 1.271, which is very good. For reference, a VIF of result less than 5 is generally considered acceptable, so our result that is close to 1 is near perfect. Therefore, this indicates that there is no worrying multicollinearity between our explanatory variables, and thus the R-Squared is not overinflated.

Moreover, we conducted a White test for heteroskedasticity to see if our p-values are overly optimistic. Given that the sample period included the 2019 banking crisis, it is important to check if the crisis had any effect on the volatility of the total exports. After regressing the squared residuals of the log change in total exports on our original explanatory variables, their squared terms, and their product terms, we get this result:

Regression Statistics	
Multiple R	0.2188
R Square	0.0479
Adjusted R Square	-0.0133
Standard Error	0.0257
Observations	150

The formula for the Langrage Multiplier (LM) statistic is given by:

$$LM = n \times R^2_{White}$$

$$LM = 150 \times 4.79\%$$

$$LM = 7.18$$

An LM statistic[5] of 7.18 implies a p-value of 61.8% thus it is insignificant at the 5% level, meaning that there is no evidence of heteroskedasticity in our model. This is a spectacular finding as it proves that our p-values are valid as they are and, on a macro level, the crisis did not have any significant effect on the change in total exports.

[5] *A Lagrange multiplier (LM) statistic follows an asymptotic (chi-squared) distribution.*

• Testing the Effect of VLU

Regression Statistics	
Multiple R	0.5251
R Square	0.2758
Adjusted R Square	0.2558
Standard Error	0.1316
Observations	150

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	0.956291643	0.239072911	13.8018044	1.45865E-09
Residual	145	2.511669564	0.017321859		
Total	149	3.467961207			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.0018269	0.013033345	-0.14017304	0.8887178	-0.0275868	0.023932956
TE Log Change t-1	-0.2589303	0.078519579	-3.29765255	0.00122639	-0.41412107	-0.10373952
VLU t	-0.0112625	0.023047003	-0.48867659	0.62580896	-0.056814	0.034288938
NEO Change t	0.0162238	0.002539044	6.389711335	2.1291E-09	0.011205441	0.021242077
NEO Change t-1	0.0125921	0.002755028	4.570595591	1.0329E-05	0.007146917	0.01803732

$$\Delta \widehat{ln\ TE_t} = \widehat{\beta_0} + \widehat{\beta_1}\Delta NEO_t + \widehat{\beta_2}\Delta NEO_{t-1} + \widehat{\beta_3}\Delta \ln TE_{t-1} + \widehat{\beta_4}\ VLU_t$$

We attempted to capture the effect of a varying exchange rate on the change in total exports by using our dummy variable VLU. Previously, we have used VLU as a proxy for a regime switch, which in our case was the 2019 crisis. Given that our White test's p-value was insignificant, we expect VLU to not have any significance either, which was proven in our above output. VLU had a p-value of 62.58% (which is, perhaps coincidentally, close to the White test's p-value), meaning it is statistically insignificant at the 5% level. This implies that any variation in the exchange rate has no direct effect on the change in total exports.

More importantly, this means that changes in nominal exchange rates have hardly any impact on competitiveness, as the latter is more determined by real exchange rates and, perhaps more fundamentally, by total productivity.

- **Conclusion**

The results of each NEO run individually differed significantly; NEO at t was statistically significant, t−1 was the least significant, and t−2 was borderline insignificant but had a negative coefficient. After combining all 3, both NEO change at t and t−1 were significant, which explains that t−1 was suffering from omitted variable bias and that the effect of the change in NEO captures a prolonged horizon. On the other hand, NEO change at t−2's p-value shot up to 48.27% and its coefficient remained negative so we omitted it. We ran a DWT for serial autocorrelation and corrected for it by adding a lagged log change in total exports, giving us our finalized model. We also tested for heteroskedasticity using a White test and got a statistically insignificant result, meaning that heteroskedasticity does not persist in our model, thus making our p-values more reliable.

Furthermore, we added VLU to check if a varying exchange rate had any effect on the change in total exports, which it did not as it was statistically insignificant. This shows that nominal exchange rates are a poor policy measure to stimulate exports.

Overall, with our developed model and the diagnostic tests, we can safely say that the change in new export orders up to a 60+ day horizon is a reliable tool to predict the change in total exports. This could aid policy makers in assessing the health of the trade sector – or the future thereof – and make decisions accordingly.

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