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ASYMMETRIC EFFECTS OF LOCAL AND GLOBAL BUSINESS CYCLE VARIATIONS ON THE SECTORAL INDUSTRIAL PRODUCTION IN SINGAPORE

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Abstract:
This paper investigates the sensitivities of Singapore's sectoral industrial production to local and global business cycle variations using the auto-regressive distributed lag (ARDL) model in the nonlinear and asymmetric cointegration framework. By employing monthly time series data from Jan 1983 to Dec 2022 the study corroborates the commonly held view that durable industries are pro-cyclic to thelocal business cycle. However, the nature of cyclic sensitivity is different if viewed from a global perspective. Industries including pharmaceutical, computer, and motor vehicles industries flourish in both the local and global business cycle booms. Almost all industries having long-run linkages with global industrial production are also affected by global production growth in the short run. However, consistent with earlier studies for Southeast Asian countries, very few industries exhibit short-run asymmetries in their relationship with local and global business cycles. We found that incorporating long-run information also improves the forecasting ability of sectoral industrial production growth in Singapore.

Key words: *Business cycle, industry cyclicality, durable goods*

1. Introduction

It is well known to economists, policymakers, and business managers that different businesses and industries react differently to aggregate economic fluctuations. Generally, industries related to consumer discretionary products and durable items are considered cyclic implying that the businesses engaged in the production, transportation, and distribution of these items enjoy a windfall revenue around a peak in economic activity. Conversely, the associated industries are hit hard during economic recessions. On the other hand, non-cyclic industries, i.e. those producing consumer staple items, and non-durable industries are relatively less or even unaffected by aggregate economic fluctuations. Industries are defined as counter-cyclic if the output of these industries is negatively correlated with national aggregate output. As Petersen and Strongin, (1996) argue that durable-goods industries are characterized by stronger cyclical dynamics than nondurable-goods industries which in turn are considered to have more pronounced cyclicality than service industries. In their empirical study at a highly disaggregated level for the US, they found that durable goods industries are three times more cyclical than non-durable goods industries.

Iqbal (2021) deliberates on the importance of assessing firms and industries being cyclic or otherwise. For example, the cyclic sensitivities of industries provide a key input for decision making leading to the formulation of business agglomerates to diversify business cycle risk. In the investment and financial context, the stock price volatility of the firms related to a cyclic industry is high and such firms are exposed to non-diversifiable riskand thus require extrapremiums for holding their stocks in a portfolio.

Despite the important economic and financial implications of assessing the business cycle exposure of manufacturing industries, very few empirical studies are conducted in this area. Notable studies specifically aimed at measuring business cycle sensitivities of industries include Peterson and Strongin (1996) for the US; Konovalova and Maksimov (2017) for Canada and Russia; Baig et al. (2020) for Pakistan, and Iqbal (2021) for the four Southeast Asian countries.

These studies employ regression of the growth rates of either value added, production, or employment of individual industries on the growth rates of aggregate economy in essentially a short-run static framework assuming stationarity and disregarding the information contained in the levels of times series. However, the trade flow between open economies compriseslargely durable goods. Consumers do not derive utility directly from spending on durable goods in the current period, but the flow of services of durable goods extends over a longer time. Also, abusiness cycle spreads over several years and is therefore a long-run time series movement. Theseconsiderationsnecessitate the study of long-runexposures of durable and non-durable industrial activity to the business cycle i.e. an analysis withinthe long-run cointegration framework.

A stylized fact observed in the business cycle is that economic expansions are longer but less sharp than downturns. As Tan (2011) highlights that economy is essentially asymmetric and dynamic and industrial activities e.g. innovation, growth, firm entry, exit, cluster, etc. change and interact over time. The asymmetry and non-linearity in an individual's consumption expenditure and economic aggregates e.g., employment is well studied in the literature. Dekimpe and Deleersnyder (2018) note that consumers are quick in cutting back on their durable expenditures in a recession period, while upward adjustments after the contraction are not that fast. The prospect theory of Tversky and Kahneman (1991) posits that people react more extensively to unfavorable changes than to comparable gains. Neftci (1984) found that U.S. unemployment displays asymmetric adjustment over the business cycle. Acemoglu and Scott (1994) have also shown asymmetries in the cyclical behavior of UK labor markets. Harris and Silverstone (1999) and Silvapulle et al., (2004) testing the asymmetric adjustment in specifications of Okun's law found that the short-run effects of positive cyclical output on cyclical unemployment are quantitatively different from those of negative ones; as such, the relationship between labor market indicators and aggregate income is asymmetric. Kandil (2006) found strong evidence concerning the asymmetric effects of aggregate demand shocks on the US manufacturing industries. For their comparative study of Australia and the US, Black and Cusbert (2010) found a stronger relationship between household spending on durables and income during the fall in economic activity than during increases in these variables. A similar nature of the relationship was observed in the relationship between business investment and GDP growth.

Singapore is a vibrant open economy with wide-ranging international trade including petroleum products, food and beverages, electronic components, chemicals, textiles and garments, transport, and telecommunication equipment. The manufacturing sector is the backbone of Singapore's economy and contributes 20-25% of the city state's GDP. Singapore is also home to 7000 multinational companies and one of the world's busiest ports. In addition, the Singapore Department of Statistics provides high-quality historical time series data on production indices of individual industries at both monthly and annual frequencies. This makes Singapore's industrial sector an attractive case study for investigating both the local and global business cycle sensitivities in an asymmetric cointegration framework.

Accordingly, this paper investigates the long-run co-movement of individual manufacturing industries' production in Singapore with aggregate measures of business cycle activity in an asymmetric and non-linear cointegration framework based on the ARDL model. The real business cycle model suggests a large fraction of fluctuations in aggregate output as technological or taste shocks. These later disturbances to technology are likely to induce industry-specific components of output growth that are common across nations hence of a global nature. Consistent with this our model specifies individual industry output as dependent on both the local and global aggregate production growth.

2. Literature Review

The literature on business cycle exposure and cyclicality of individual industrial sectors of an economy is very rare.Much of the available literature is related to various demand and supply shocks to aggregate industrial production. Petersen and Strongin (1996) were among the firststudies aimed at assessing the cyclicality of individual US industries' value added. Using a highly disaggregated four-digit SIC code level industries using annual data over the period 1958-1986 they found that durable goods industries are on average three times more cyclical than nondurable industries.The proportion of variable input factors, labor hoarding, and market structure characteristics emerged as the main determinants of cyclicality.

By employing final demand and employment at the industry level Berman and Pfleeger (1997) investigated the sensitivities of the US industries to business cycle fluctuations using annual data over the 1977-2005 period. The sample involved 183 individual industries aggregated into 12 groups. Their methodology involves a simple correlation between individual industries and business cycles measured by GDP. They concluded that both employment and final demand are highly correlated with the business cycle in industries such as household furniture, motor vehicles and equipment, retail trade, and carpets and rugs. Neither employment nor final demand is highly correlated with the business cycle in industries such as drugs, educational services, insurance carriers, and food-related industries. Thus, the findings in their study are in line with Petersen and Strongin's (1996) work.

By employing a three-digit industry (NAICS) classification and using monthly data from January 1991 to May 2013 on 86 industries, as recent evidence, Camacho, and Leiva-Leon (2019) found the US goods-producing industries, complementary businesses, and wholesale and retail industries are among the first to hit by the recession. On the other hand, durable goods industries, transport, and warehouse sectors experience a delayed reaction in a reduction in employment. Also, businesses engaged in education and training, health care, and social assistance utility industries are less sensitive, particularly to the 2001 local recession.

In contrast to the US industries, evidence from Konovalova and Maksimov (2017) show that the Canadian durable and non-durable industries are equally affected by the business cycle. However, in their study, the Russian durable and non-durable industries'reaction is like the US counterpart. Their sample extended over the period 2003-2013 for Russia and 1981-1997 for Canada.

There are arguments that the nature and characteristics of cyclic fluctuations may be different across countries at different levels of development (Rand and Tarp, 2002). Earlier, Ang et al. (2000) show that booms and busts do not occur synchronously in all countries as there are differences in the timing of peaks and troughs. Also, the recession intensities are not equally severe in all countries and some countries may not be hit at all. Male (2011) found that the amplitude of expansion is larger in Asian countries than the developed countries. Consistent with this idea, the evidence provided by Iqbal (2021) for the four Southeast Asian countries (Indonesia, Malaysia, Philippines, and Singapore) indicates that generally, the sensitivities of manufacturing industries to booms and recessions are different from the pattern observed in the US and Russia. Thus, the commonly held view among economists and business managers that demand for durable goods flourishes in booms and falls in recessions does not appear to find support for these Asian countries. However, the analysis of panel data reveals the expected pattern of industrial sensitivities to the local business cycle only.

Using annual time series data of sales and profits on ten major nonfinancial industries over the period 1976–2017, Baig et al. (2020) employed the seemingly unrelated regression (SUR) estimator to estimate the sensitivities of Pakistani industries concerning local and global business cycle. Their findings were mixed in that cement, chemicals, engineering, fuel and energy, and transport and communication, industries were found to be cyclic concerning local business cycles. On the other hand, the cement, chemicals, fuel and energy, paper and board, sugar, textiles, and transport and communication industries are found to be noncyclic with respect to global GDP growth.

Within the essentially static regression framework employed in Konovalova and Maksimov (2017), the asymmetric exposure of industries to booms and recessions of the business cycle was measured by regressing the growth rates in value-added on individual industry on both the net growth rate of GNP over and above its average value as well as the absolute value of the net growth rate of GNP. On the other hand, Iqbal (2021) employed an F test of the equality of the coefficient of the first and third quartile interaction terms of the respective dummy variables with the GDP growth. The two dummy variables represented the movement of GDP growth below the 25th percentile and above the 75th percentile respectively.

Fortunately, within the long-run cointegration framework that the present paper intends to employ, an appropriate Nonlinear Autoregressive Distributed Lag (NARDL) model pioneered by Shin, and Greenwood-Nimmo (2014) is available for assessing the potential long-run and short-run asymmetric exposures of individual industries to boom and recession of the aggregate business cycle.

3. Data and Methodology

Monthly data on the individual industrial production indices and overall production index (2019 = 100) is available from the website of the Singapore Department of Statistics[1] over the periodfrom Jan 1983 to Dec 2022. Macroeconomic variables including consumer prices, interest rate, and exchange rate for Singapore are also obtained from this source. Some of the indices and macroeconomic variables have shorter sample sizes. Global aggregate production is measured by OECD monthly production index[2]. Oil prices (WTI) are obtained from FRED[3]. A preliminary graphical assessment shows that the production indiceshave strong seasonality. We employ Census X-13 ARIMA to adjust the seasonality of Singapore production indices. The OECD industrial production index is already available in seasonally adjusted form. The analysis begins with a description ofthe main numerical features of the growth rates of individual and aggregated seasonally adjusted production indices and macroeconomic variables in Table 1.

Table1: Descriptive statistics of the variables under study

Variable	Sample Size	Mean	SD	Min	Max	Skew	JB
Apparel	479	-0.578	15.292	-73.652	61.553	0.070	163.4*
Chemicals	371	0.434	7.734	-45.379	25.099	-0.820	501.1*
Computer	323	0.373	7.537	-36.975	32.299	-0.098	152.5*
Electrical	479	0.401	8.766	-49.801	49.297	0.196	1054.9*
Food	469	0.178	6.936	-32.229	32.352	0.141	241.4*
Furniture	323	-0.465	15.943	-79.225	134.421	1.341	4120.7*
Leather	479	-0.213	15.843	-89.931	61.800	0.222	210.5*
Machinery	479	0.428	9.077	-46.084	33.699	-0.243	209.4*
Metal Products	479	0.129	6.506	-32.581	30.154	0.297	269.3*
Metals	479	0.051	16.952	-94.593	111.547	0.274	1331.9*
Minerals	479	-0.400	11.337	-119.958	63.651	-1.863	17207.6*
Motor Vehicles	191	0.339	10.946	-56.536	35.463	-0.477	195.7
Other Manufacturing	323	0.492	11.367	-48.719	55.138	0.106	192.1*
Other Transport	479	0.396	8.011	-43.019	28.892	-0.329	262.7*
Paper	479	0.006	8.854	-47.879	56.160	0.237	857.3*
Petroleum	479	0.103	8.555	-31.013	38.236	0.038	49.5*
Pharmaceuticals	371	0.909	39.713	-226.783	149.929	-0.578	337.5*
Printing	479	-0.048	6.600	-26.995	36.712	0.957	817.3*
Rubber	479	-0.054	7.178	-22.467	41.540	0.573	482.0*
Textile	479	-1.141	16.577	-149.281	98.703	-0.563	7961.8*
Wood	479	-0.326	13.209	-92.432	110.126	0.302	5913.0*
Local Production	479	0.503	6.596	-25.584	28.827	0.021	121.4
Global Production	475	0.157	1.071	-15.624	7.262	-6.639	222150.5*
Interest Rate	419	-0.133	12.209	-60.613	71.20	0.518	700.4*
Exchange Rate	419	-0.096	1.261	-5.594	6.193	0.271	124.4*

Consumer Prices	479	0.139	0.340	-1.086	1.520	0.329	23.8*
Oil Prices	443	0.272	0.855	-56.812	54.562	-0.666	987.5*

Note: This table reports the descriptive statistics, including the average, standard deviation, minimum, maximum, skewness, and the Jarque-Bera test of normality of the percentage growth rates of the seasonally adjusted indices and macroeconomic variables The asterisks * indicate a rejection of the null hypothesis of normality 5% levels of significance.

It appears that the pharmaceutical production index has on average the highest percentage growth rate of 0.91% per month and textile has the lowest average growth of -1.14%. The growth rates of the pharmaceutical, textile, apparel, furniture, and leather sectors have been quite volatile. None of the production indices growth rates under study and macro variables appear to be normally distributed. The distribution of industrial growth rates appears to be positively skewed for some industries (e.g. furniture, printing, rubber) and negative for other industries (e.g. minerals, pharmaceutical, and textile).

Table 2 reports the ADF and KPSS tests to examine the stationarity properties of the production indices and macro variables. The former test assumes non-stationarity under the null hypothesis, whereas the latter testassumes stationarity. The tests are performed for both the level and first difference. The decision on whether to use no intercept, intercept only, or both intercept and trend in these tests are made by a visual inspection of the time series under study. All the indices are found to be integrated of order 1 as they are non-stationary at the level and stationary at the first difference as revealed byboth of thesetests. Also, none of the indices appears to be integrated of order 2. This indicates that we can safely proceed to the ARDL-based test of cointegration. In the case of the consumer price series, the KPSS test indicates the stationarity of the level series. But the correlogram presents the typical pattern of a non-stationarity series.

Table 2: ADF and KPSS Tests of Unit Root

	Level		**First Difference**	
Variable	**ADF**	**KPSS**	**ADF**	**KPSS**
Apparel	-0.863	2.456*	-5.211*	0.132
Chemicals	-1.357	0.217*	-6.854*	0.087
Computer	-2.621	0.232*	-5.004*	0.165
Electrical	-1.238	0.513*	-6.167*	0.326
Food	-2.047	0.294*	-6.649*	0.057
Furniture	-2.758	0.215*	-4.907*	0.319
Leather	-1.565	2.538*	-9.157*	0.105
Machinery	-2.468	0.357*	-4.976*	0.227
Metal Products	-2.323	0.456*	-5.648*	0.248
Metals	-2.033	2.320*	-8.224*	0.069
Minerals	-1.792	1.649*	-5.274*	0.221
Motor Vehicles	-2.600	0.206*	-3.390*	0.495
Other Manufacturing	-0.106	0.529*	-5.634*	0.172
Other Transport	-2.703	0.246*	-6.197*	0.110
Paper	-3.007	0.159*	-27.017*	0.066
Petroleum	-2.113	1.194*	-8.079*	0.085
Pharmaceuticals	-2.246	0.389*	-5.678*	0.204
Printing	-1.213	0.651*	-4.376*	1.253
Rubber	-1.565	1.171*	-7.223*	0.071
Textile	-3.384	0.386*	-4.382*	0.253
Wood	-3.299	0.342*	-16.183*	0.245
Local Production	-2.282	0.462*	-25.632*	0.140
Global Production	-2.465	0.541*	-15.839*	0.207
Interest Rate	-2.303	1.646*	-18.644*	0.087
Exchange Rate	-2.237	0.150*	-14.572*	0.174

Consumer Prices	-1.746	0.133	-8.790*	0.101
Oil Prices	-2.206	2.109*	-16.331	0.044

Note: Intercept or linear trend options to be used in the test equation were determined by visual inspection of the time series. Optimal lags are determined using AIC criteria.

3.1 Linear ARDL Approach to Cointegration

Pesaran et al. (2001) proposed a test of cointegration using the following ARDL modeling setup:

$$\Delta Y_t = \alpha + \delta Y_{t-1} + \boldsymbol{\beta X_{t-1}} + \sum_{j=1}^{p} \delta_{1j} \Delta Y_{t-1} + \sum_{j=0}^{q} \delta_{2j} \Delta \boldsymbol{X_{t-1}} + \sum_{j=0}^{r} \delta_{3j} \Delta \boldsymbol{Z_t} + \epsilon_t \quad (1)$$

Here $\boldsymbol{X_t}$ is a vector of regressors that is being tested to contain long-run information and $\boldsymbol{\beta}$ is the conformable vector of parameters. In the present case, Y_t is the logged industrial production index. $\boldsymbol{X_t}$ includes local aggregate industrial production as well as global aggregate industrial production.Here $\boldsymbol{Z_t}$ is the set of deterministic regressors. We employ monthly seasonal dummy variables and dummy variables for the Asian financial crisis, the global financial crisis, and Covid19. Industrial production is also expected to be affected by macroeconomic variables including interest rate, exchange rate, consumer prices, and oil prices. These variables are also contained in $\boldsymbol{Z_t}$. As we have monthly data, we initially set maximum lags as 12. Specifically, we estimated the following equation.

$$\begin{aligned}\Delta Industry_t = {} & \beta_0 + \beta_1 Industry_{t-1} + \beta_2\ Local\ Y_{t-1} + \beta_3\ Global\ Y_{t-1} + \sum_{j=1}^{p} \delta_{1j} \Delta Industry_{t-1} \\ & + \sum_{j=0}^{q} \delta_{2j} \Delta Local\ Y_{t-1} + \sum_{j=0}^{r} \delta_{3j} \Delta Global\ Y_{t-1} + \sum_{j=0}^{s} \delta_{4j} \Delta CPI_{t-1} \\ & + \sum_{j=0}^{t} \delta_{5j} \Delta EXRATE_{t-1} + \sum_{j=0}^{u} \delta_{6j} \Delta INTRATE_{t-1} + \sum_{j=0}^{v} \delta_{7j} \Delta OIL_{t-1} + \sum_{j=1}^{11} \gamma_j Dum_{jt} \\ & + \gamma_{12} GFC07_t + \gamma_{13} Currency97_t + \gamma_{14} Covid19_t + \epsilon_t \end{aligned} \quad (2)$$

Here $Industry_t$ is the individual industry production index, and $Local\ Y_t$ and $Global\ Y_t$ are aggregate Singapore and OECD industrial production indices respectively and intend to measurethe local and global business cycles variation. The CPI, EXRATE, INTRATE, and OIL represent the consumer price index of Singapore, the exchange rate (Singapore dollar per unit of US dollar), Singapore's short-term interest rate, and WTI oil spot prices respectively. In this model, there are many variablesand their lags,so parsimony is desired to achieve precise estimates. Weuse a general to specific modeling approach in selecting appropriate lags via the stepwise backward selection procedure with lags of individual industry production index and lags of $Local\ Y_t$ and $Global\ Y_t$ included in all regressions. The F statistic of Pesaran, Shin, and Smith (2001) is applied to test the absence of linearcointegration hypothesis H_0: $\beta_1 = \beta_2 = \beta_3 = 0$. Their bound test furnishes two sets of critical values; one assuming all regressors as I(0) and the other where all regressors are assumed I(1). If the F test statistic value exceeds the upper bound, the null of no cointegration is rejected and so evidence in favor of cointegration is established. On the other hand, if the test statistic is less than the lower bound, there is no cointegration. The test is inconclusive if the F statistic falls between I(0) and I(1) bounds. Iqbal (2011) found that in comparison to the Engle-Granger and Johansen approaches, the ARDL-based error correction model provides superior long-run forecasts of exchange rate and money supply. Also essentially exogenous nature of local and global industrial production and macroeconomic variables for individual industry production requires a single equation approach of cointegration for which the Pesaranet al. (2001) ARDL based cointegration is appropriate.

3.2 Non-Linear ARDL Approach to Cointegration

As argued in the introduction, the business cycle exposure to some individual industries' production may be asymmetric. We also test asymmetric cointegration for which the appropriate modeling approach is the non-linear ARDL (NARDL) developed byShin, and Greenwood-Nimmo (2014). Here a regressor $x_t$that contains potentially long-run information is partitioned as a partial sum process as follows:

$$x_t = x_0 + x_t^+ + x_t^-$$

$$x_t^+ = \sum_{i=1}^{t} \Delta x_j^+ = \sum_{i=1}^{t} \max(\Delta x_j, 0) \tag{3}$$

$$x_t^- = \sum_{i=1}^{t} \Delta x_j^- = \sum_{i=1}^{t} \min(\Delta x_j, 0) \tag{4}$$

Thus, the conditional asymmetric error correction is specified as follows:

$$\Delta Y_t = \alpha + \delta Y_{t-1} + \boldsymbol{\beta_1 X_{t-1}^+} + \boldsymbol{\beta_2 X_{t-1}^-} + \sum_{j=1}^{p} \delta_{1j} \Delta Y_{t-1} + \sum_{j=0}^{q} \delta_{2j}^+ \Delta \boldsymbol{X_{t-1}^+} + \sum_{j=0}^{q} \delta_{2j}^- \Delta \boldsymbol{X_{t-1}^-} + \sum_{j=0}^{r} \delta_{3j} \Delta \boldsymbol{Z_t} + \epsilon_t \tag{5}$$

Specifically, the following NARDL equation is specified:

$$\begin{aligned} \Delta Industry_t = {} & \beta_0 + \beta_1 Industry_{t-1} + \beta_2\, Local\, YPos_{t-1} + \beta_3\, Local\, YNeg_{t-1} \\ & + \beta_4\, Global\, YPos_{t-1} + \beta_5\, Global\, YNeg_{t-1} + \sum_{j=1}^{p} \delta_{1j} \Delta Industry_{t-j} \\ & + \sum_{j=0}^{q} \delta_{2j} \Delta Local\, YPos_{t-j} + \sum_{j=0}^{r} \delta_{3j} \Delta Local\, YNeg_{t-j} \\ & + \sum_{j=0}^{s} \delta_{4j} \Delta Global\, YPos_{t-j} + \sum_{j=0}^{t} \delta_{5j} \Delta Global\, YNeg_{t-j} + \sum_{j=0}^{u} \delta_{6j} \Delta CPI_{t-j} \\ & + \sum_{j=0}^{v} \delta_{7j} \Delta EXRATE_{t-j} + \sum_{j=0}^{w} \delta_{8j} \Delta INTRATE_{t-j} + \sum_{j=0}^{x} \delta_{9j} \Delta OIL_{t-j} + \sum_{j=1}^{11} \gamma_j Dum_{jt} \\ & + \gamma_{12} GFC07_t + \gamma_{13} Currency97_t + \gamma_{14} Covid19_t + \epsilon_t \end{aligned} \tag{6}$$

Here '*Local Y Pos*' is the partial sum related to positive changes in the Singapore's local aggregate production index, 'Global Y Neg' indicates negative partial sum associated with the world (OECD) production index. Other aggregate production terms are similarly defined.

Within this model, the long-run non-linear cointegration relationship is tested as the null hypothesis: H_0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$with Pesaran, et al. (2001) critical values. Additionally, within the NARDL framework, one can also test the asymmetry of individual industrial production and local and global business cyclesrelationship as follows:
Long-run symmetric industry local business cycle relationship: $\beta_2 = \beta_3$
Long-run symmetric industry global business cycle relationship: $\beta_4 = \beta_5$
Short-run symmetric industry local business cycle relationship:$\sum_{j=0}^{q} \delta_{2j} = \sum_{j=0}^{r} \delta_{3j}$
Short-run symmetric industry global business cycle relationship:$\sum_{j=0}^{s} \delta_{4j} = \sum_{j=0}^{t} \delta_{5j}$
These hypotheses are conducted using the standard Wald test. Finally, we can recover the long-run dynamic multipliers of a unit change in positive and negative shocks to local and global business cycles as follows: $\beta_2^+ = {}^{\beta_2}/_{\beta_1}$, $\beta_2^- = {}^{\beta_3}/_{\beta_1}$.

Depending on the non-rejection of the long-run or short-run asymmetries or both the NARDL model reduces to a partial NARDL or linear ARDL model.

There is a caveat in Shin, and Greenwood-Nimmo (2014)'s procedure. Their test crucially relies on the partial sums defined in eq (3) and (4). However, these partial sums related to asymmetric terms use zero as a threshold which can result in a low sample variability of these variables. This fact may invalidate the associated coefficients[1]. This is especially a problem in the small sample sizes. Our use of monthly data in the present study effectively increases sample size and is therefore an attempt to mitigate the issue associated with low variability of the partial sums. Also,for the present study,the positive and negative partial sums around the zero threshold are economically interpretable as related to movements during boom and recession respectively.

3.3 Long-run parameter estimation

One of the popular single equation estimators of the cointegration parameters is the Dynamic OLS of the Stock and Watson (1993). This estimator is known for its superior performance in small samples and its ability to account for potential simultaneity among the regressors. The estimation equation includes leads and lags of the first differences regressors. Their inclusion corrects the potential endogeneity and serial correlation in the error term. The estimator also remains valid in the presence of variables with different orders of integration. Hence Stock and Watson (1993) contend that adding leads and lags of first difference explanatory variables in the regression in combination with the Newey-West heteroskedasticity and autocorrelation (HAC) correction yields consistent standard errors. The long-run model to be estimated by DOLS is specified as follows:

$$
\begin{aligned}
Industry_t = {} & \beta_0 + \beta_1\ Local\ Y\ Pos_t + \beta_2\ Local\ Y\ Neg_t + \beta_3\ Global\ Y\ Pos_t \\
& + \beta_4\ Global\ Y\ Neg_t + \sum_{j=-k}^{k} \delta_{1j} \Delta Local\ Y\ Pos_{t-j} \\
& + \sum_{j=-k}^{k} \delta_{2j} \Delta Local\ Y\ Neg_{t-j} \sum_{j=-k}^{k} \delta_{3j} \Delta Global\ Y\ Pos_{t-j} \\
& + \sum_{j=-k}^{k} \delta_{4j} \Delta Global\ Y\ Neg_{t-j} + \delta_3 \Delta INTEREST_t + \delta_4 \Delta EXRATE_t + \delta_5 \Delta CPI_t \\
& + \delta_6 \Delta OIL_t + \sum_{j=1}^{11} \gamma_j Dum_{jt} + \gamma_{12} GFC07_t + \gamma_{13} Currency97_t + \gamma_{14} Covid19_t \\
& + \varepsilon_t
\end{aligned}
\quad (7)
$$

4. Results of Empirical Analysis

4.1 Bound Tests of Cointegration

Table 3 reports the Bound test of both the linear and non-linear cointegration. It is noted that generally, the results of the test for both the linear and non-linear cointegration yield similar conclusions regarding the presence of a long-run relationship. A notable exception is for the rubber and computer industries where there is no evidence of linear cointegration, yet the NARDL test indicates significant non-linear cointegration. Alsofor the apparel industry, there appears to be no linear cointegration but the nonlinear cointegration evidence is inconclusive. As non-linearity is a more general mathematical characteristic, it can be safely concluded that long-run cointegration is essentially asymmetric in many industries. We observethat 6 of the 10 non-durable industries' production show long-run non-linear relationships with the local and global business cycles. Except for furniture, evidence of significant long-run asymmetric long-run cointegration is found for all durable industries.

4.2 Test of long-run and short-run asymmetry

After the establishment of asymmetric cointegration, we proceed to test for asymmetry in both the long-run and the short-run relationships of sectoral production and local and global business cycles. Specifically, we test whether the coefficients of the variables corresponding to the positive and negative partial sums are equal.

Table 3: Bounds Test for Linear and Non-Linear Cointegration

	Linear		Non-Linear	
Variable	**F-statistic**	**Result**	**F-statistic**	**Result**
Non-Durable				
Apparel	0.363	No Cointegration	4.590	Inconclusive
Chemicals	3.489	No Cointegration	2.027	No Cointegration
Food	4.215	Inconclusive	4.594	Inconclusive
Leather	2.341	No Cointegration	1.412	No Cointegration
Paper	9.736*	Cointegration	7.452*	Cointegration
Petroleum	6.822*	Cointegration	6.273*	Cointegration
Pharmaceuticals	7.882*	Cointegration	8.753*	Cointegration
Printing	6.553*	Cointegration	9.118*	Cointegration
Rubber	1.713	No Cointegration	5.406*	Cointegration
Textile	4.815	Inconclusive	7.043*	Cointegration
Durable				
Computer	2.914	No Cointegration	5.244*	Cointegration
Electrical	5.093*	Cointegration	10.154*	Cointegration
Furniture	5.496*	Cointegration	3.131	Inconclusive
Machinery	7.661	Cointegration	6.358*	Cointegration
Metal Products	6.372*	Cointegration	7.226*	Cointegration
Metals	8.543*	Cointegration	7.628*	Cointegration
Minerals	5.675*	Cointegration	6.596*	Cointegration
Motor Vehicles	7.285*	Cointegration	7.675*	Cointegration
Other Manufacturing	4.083	Inconclusive	5.948*	Cointegration
Other Transport	12.624*	Cointegration	5.831*	Cointegration
Wood	5.761*	Cointegration	5.465*	Cointegration

Note: * indicates significance at 5% level. Test of Null of Cointegration: ($\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$). The 5% critical values are from Pesaran et al. (2001) case III with k = 2. The 5% critical values corresponding to I(0) and I(1) are 3.79 and 4.85. Starting with 12 lags, the optimal lags terms are selected using general to specific modeling with a backward stepwise selection. Growth rates/changes in consumer prices Inflation, interest rate, exchange rate, oil prices, monthly season dummy variables and dummy variables for Asian Currency Crisis (1997-98), Global Financial crisis (2007-08), and Covid19 (2020) are added as search regressors in each stepwise ARDL equation. The classification of industries into durable and non-durable follows North American Industry Classification System (NAICS).

4.3 Test of long-run and short-run asymmetry

After the establishment of asymmetric cointegration, we proceed to test for asymmetry in both the long-run and the short-run relationships of sectoral production and local and global business cycles. Specifically, we test whether the coefficients of the variables corresponding to the positive and negative partial sums are equal. The tests are conducted separately for the local and global business cycles respectively. The rejection of the test establishes asymmetry. Table 4 reports the Wald test statistics (p-values in parentheses) for the long and short-run asymmetry in the ARDL modeling framework. Among the non-durable industries, we found significant long-run asymmetry wrt the local business cycle in half of all industries, especially for the apparel, food, printing, rubber, and textile industries. Test for global long asymmetry yields a similar conclusion. Among the durable industries, significant long-run asymmetries are found for the electrical, furniture, machinery, metals, and wood. Generally, industrial production in the same industries is found to have asymmetric reactions to long-run local and global business cycles. These results contrast withcyclicality(section 4.4) where we found generally the opposite conclusion. Except for very few industries, evidence of short-run asymmetries is not found wrt to both the local and global business cycles and both the durable and non-durable industries in Singapore. These results of short-run symmetry corroborate the findings of Iqbal (2021) who found that only very few industries in the four Southeast Asian countries follow an asymmetric pattern. One reason for this apparent similarity is that essentially the framework used by Iqbal (2021) involved the tests of only the short-run asymmetries since his regression modeled only the short-run changes and therefore devoid of the long-run information contained in the level of variables. The present study indicates that indeed inclusion of long-run information makes a difference in that at least half of all the industries show long-run asymmetric responses to both the local and global business cycles.

Table 4: Test of long and short-run asymmetry

Industry	Local Long Run	Global Long Run	Local Short Run	Global Short Run
Non-Durable				
Apparel	19.529* (0.000)	19.510*(0.000)	0.557(0.465)	0.611(0.435)
Chemicals	0.737(0.390)	0.382(0.536)	0.772(0.379)	0.551(0.459)
Food	5.902**(0.015)	7.911*(0.005)	1.927(0.166)	2.009(0.157)
Leather	0.108(0.741)	0.121(0.728)	0.074(0.785)	7.582*(0.006)
Paper	3.772(0.052)	2.082(0.148)	0.423(0.515)	0.001(0.975)
Petroleum	2.802(0.098)	1.028(0.311)	0.029(0.865)	6.468**(0.011)
Pharmaceuticals	0.028(0.867)	0.221(0.638)	0.050*(0.006)	1.101(0.295)
Printing	21.557*(0.000)	0.264(0.607)	5.569**(0.019)	2.522(0.115)
Rubber	19.677*(0.000)	1.433(0.231)	2.085(0.149)	7.246*(0.007)
Textile	11.568*(0.005)	20.262*(0.000)	1.453(0.229)	8.811*(0.003)
Durable				
Computer	3.544(0.068)	7.578*(0.006)	1.394(0.239)	0.301(0.583)
Electrical	0.219(0.639)	4.017**(0.048)	5.862**(0.016)	0.609(0.406)
Furniture	7.715*(0.005)	7.682*(0.000)	0.405(0.525)	0.617(0.433)
Machinery	4.792*(0.002)	5.787**(0.016)	1.698(0.193)	0.957(0.328)
Metal Products	9.542*(0.002)	0.103(0.746)	0.477(0.490)	0.974(0.324)
Metals	4.736**(0.030)	7.096*(0.008)	2.321(0.128)	1.697(0.193)
Minerals	3.658(0.056)	0.027(0.867)	0.204(0.651)	2.204(0.138)
Motor Vehicles	5.869**(0.016)	1.292(0.257)	1.354(0.254)	1.712(0.200)
Other Manufacturing	6.790*(0.009)	0.005(0.943)	0.386(0.036)	0.336(0.562)
Other Transport	0.817(0.366)	0.059(0.808)	1.731(0.189)	0.443(0.506)
Wood	5.469**(0.012)	6.299**(0.0123)	0.115(0.733)	0.246(0.619)

Note: The table presents the values of the standard Wald F test statistics of the long-run test of asymmetry and of the short-run symmetry (Eq. 6). For the long-run test, the model is estimated using a general to specific strategy with stepwise backward selection regression. For the short-run model, 12 lags are used for the first difference regressor terms. In addition, the lags of the growth rate of interest rate, exchange rate, consumer, and oil prices are included in all equations. Also, monthly season dummy variables and dummy variables for the Asian Currency Crisis (1997-98), Global Financial Crisis (2007-08), and Covid-19 (2020) are added as search regressors in each of the ARDL equations. * and ** indicate significance at 1% and 5% level of significance respectively.

4.4 Results of NARDL Estimation

Table 5 presents estimates and tests for equation (6). We employ a general to specific modeling strategy to select terms involving the first difference variables. Adjusted R square and LM test of serial correlations of order 12 are also reported. Except for the paper and wood industries serial correlations were not significant. However, we found evidence of heteroskedasticity in most of the industries' residuals. Hence, we report tests that involve the HAC-corrected standard errors. It can be noted that the lag sectoral industrial production term is significant (at a 1% level of significance for most of the cases) and is negative for all cases except the printing industries. Thus, the estimated NARDL models are found stable.

Also because of the collinearity between lags of the same right-hand first difference variables, the individual coefficients are not very informative. Hence for these cases where there is more than one lag term of the same variable selected by the general to a specific methodology, we report the sum of the coefficients, instead of individual coefficients, with an indication of statistical significance by stars. We report the results for only the industries whose production indices have long-run non-linear relationships, as indicated by the Bound tests, with aggregated local production and with OECD industrial production. The short-run lagged difference terms of industrial production indices are significant and negative in almost all cases. Thus, Singapore's industrial production growth can be significantly predicted from their past growth rates. For many industries macroeconomic variables also have predictive contents. Durable goods generally have much higher interest elasticities of interest demand than non-durables and thus should be much more sensitive to interest rate changes. This effect is observed in electrical, metal and metals products, and wood industries which are significantly interest rate sensitive as expected. We note that short-run changes in both local and global production significantly affect current growth in almost all durable and non-durable industries. This is expected owing to the Singapore economy being globally integrated into the world economy.

As far as the financial crises dummy variables are considered, only the rubber industry production growth appears to be negatively affected by the Asian financial crisis of 1997. However, the global financial crisis 2007-08, has positively affected production in five industries (electrical, furniture, minerals, metals, and metal products). Finally, while the recent Covid19 crisis negatively affected growth in the 'other transport' sector, the textile sector gained during the crisis period. Production growth in some industries hasa seasonal pattern. In particular, production in February is significantly higher than in other months in the paper, textile, electrical, metal products, minerals, and motor vehicles sectors.

It can be noted that in Table 5, for the linear or non-linear ARDL models the long-run coefficients or elasticities are calculated indirectly as a non-linear function of the model parameters. Both the estimates and the standard error may therefore involve numerical and asymptotic inaccuracies. Our analysis of the long-run coefficients and associated assessment of the cyclicality of industries is therefore based on the Dynamic OLS discussed in the next subsection. This method yields the long-run estimates directly.

Table 5: Estimates and tests of the NARDL model

Paper		*Petroleum*		*Pharmaceutical*	
$Industry_{t-1}$	-0.161*	$Industry_{t-1}$	-0.137*	$Industry_{t-1}$	-0.262*
$Local\ Y_{t-1}$	0.042*	$Local\ Y_{t-1}$	-0.023	$Local\ Y_{t-1}$	0.453*
$Global\ Y_{t-1}$	-0.102	$Global\ Y_{t-1}$	0.115	$Global\ Y_{t-1}$	0.851*
$\sum \Delta Industry_{t-i}$	-1.699*	$\sum \Delta Industry_{t-i}$	-0.867*	$\sum \Delta Industry_{t-i}$	-0.958*
$\sum \Delta Local\ Y_{t-i}$	0.826*	$\Delta Global\ Y\ Pos_{t-3}$	-1.341**	$\sum \Delta Local\ Y\ Pos_{t-i}$	6.767*
$\Delta EXRATE_{t-2}$	-0.479**	$\sum \Delta Global\ Y\ Neg_{t-i}$	1.974	$\sum \Delta Local\ Y\ Neg_{t-i}$	7.236*
$\sum \Delta OIL_{t-i}$	0.130*	ΔOIL_{t-5}	-0.088**	$\sum \Delta Global\ Y_{t-i}$	-10.406*
ΔCPI_{t-11}	2.239**	$\sum \Delta EXRATE_{t-i}$	-1.302*	$\Delta INTRATE_{t-2}$	-0.208**
Feb	0.026**	$\Delta INTRATE_{t-4}$	0.058**	$\sum \Delta EXRATE_{t-i}$	-4.638*
		Apr	-0.028**	$\sum \Delta OIL_{t-i}$	-0.387

				$\sum \Delta CPI_{t-i}$	-0.606
				Jun	-0.093**
Long-run symmetric/ asymmetric effects					
Local Y	0.261**	Local Y	-0.172	Local Y	1.886*
Global Y	-0.632	Global Y	0.823	Global Y	2.752**
Model diagnostics and goodness of fit					
Adj R^2	0.524	Adj R^2	0.231	Adj R^2	0.711
LM (SC 12)	1.941**	LM (SC 12)	0.341	LM (SC 12)	1.058

Note: The table presents estimated coefficients of linear or non-linear ARDL models. Statistical significance using the HAC corrected standard errors is indicated by * significance at 1% and ** significance at 5% respectively. For variables with multiple lag terms the test sums are reported with the test of significance indicated. The second part indicates long-run symmetric or asymmetric coefficients. Finally, the adjusted R square and BG test of order 12 serial correlation.

Printing		*Rubber*		*Textile*	
$Industry_{t-1}$	-0.013	$Industry_{t-1}$	-0.136*	$Industry_{t-1}$	-0.146*
$Local\ Y\ Pos_{t-1}$	0.023	$Local\ Y\ Pos_{t-1}$	0.155**	$Local\ Y\ Pos_{t-1}$	-0.255*
$Local\ Y\ Neg_{t-1}$	0.023	$Local\ Y\ Neg_{t-1}$	0.189*	$Local\ Y\ Neg_{t-1}$	-0.312*
$Global\ Y_{t-1}$	-0.008	$Global\ Y_{t-1}$	-0.123**	$Global\ Y\ Pos_{t-1}$	-0.004
$\sum \Delta Industry_{t-i}$	-1.493*	$\sum \Delta Industry_{t-i}$	-0.579*	$Global\ Y\ Neg_{t-1}$	0.956*
$\sum \Delta Local\ Y\ Pos_{t-i}$	0.365**	$\sum \Delta Local\ Y_{t-i}$	0.751**	$\sum \Delta Industry_{t-i}$	-0.746*
$\sum \Delta Local\ Y\ Neg_{t-i}$	0.145	$\Delta Global\ Y\ Neg_t$	1.344*	$\sum \Delta Local\ Y_{t-i}$	0.574*
$\Delta Global\ Y\ _{t-1}$	1.946*	$\sum \Delta CPI_{t-i}$	-0.922	$\sum \Delta Global\ Y\ Pos_{t-i}$	2.353
$\sum \Delta INTRATE_{t-i}$	0.129*	$\sum \Delta OIL_{t-i}$	0.154*	$\sum \Delta Global\ Y\ Neg_{t-i}$	11.355*
$\Delta EXRATE_{t-2}$	-0.471*	*Currency97*	-0.030**	$\sum \Delta INTRATE_{t-i}$	-0.275*
$\sum \Delta OIL_{t-i}$	0.038			$\Delta EXRATE_{t-4}$	1.191**
ΔCPI_{t-1}	1.715*			ΔCPI_{t-10}	5.369*
Jan	-0.018**			Covid19	0.143*
Feb	0.033*			*Feb*	0.076*
Long-run symmetric/ asymmetric effects					
Local Y Pos	0.704	Local Y Pos	1.139*	Local Y Pos	-1.741**
Local Y Neg	2.331	Local Y Neg	1.381*	Local Y Neg	-2.130**
Global Y	-0.625	Global Y	-0.902**	Global Y Pos	-0.032
				Global Y Neg	6.549*
Model diagnostics and goodness of fit					
Adj R^2	0.608	Adj R^2	0.526	Adj R^2	0.569
LM (SC 12)	0.781	LM (SC 12)	0.876	LM (SC 12)	0.750

Electrical		*Furniture*		*Machinery*	
$Industry_{t-1}$	-0.102*	$Industry_{t-1}$	-0.076*	$Industry_{t-1}$	-0.108*
$Local\ Y_{t-1}$	0.068	$Local\ Y\ Pos_{t-1}$	-0.185	$Local\ Y\ Pos_{t-1}$	0.238*
$Global\ Y\ Pos_{t-1}$	-0.167	$Local\ Y\ Neg_{t-1}$	-0.204	$Local\ Y\ Neg_{t-1}$	0.231*
$Global\ Y\ Neg_{t-1}$	-0.282*	$Global\ Y\ Pos_{t-1}$	0.174	$Global\ Y\ Pos_{t-1}$	-0.327*
		$Global\ Y\ Neg_{t-1}$	0.160	$Global\ Y\ Neg_{t-1}$	-0.202**
$\sum \Delta Industry_{t-i}$	-0.698*	$\sum \Delta Industry_{t-i}$	-0.628*	$\sum \Delta Industry_{t-i}$	-0.578
$\sum \Delta Lobal\ Y\ Pos_{t-i}$	0.060	$\sum \Delta Global\ Y_{t-i}$	9.469*	$\Delta Local\ Y_t$	0.388*
$\sum \Delta Lobal\ Y\ Neg_{t-i}$	0.306**	$\sum \Delta CPI_{t-i}$	10.143*	$\sum \Delta Global\ Y_{t-i}$	1.751*
$\sum \Delta Global\ Y_{t-i}$	4.608*	$\sum \Delta OIL_{t-i}$	-0.564*	$\sum \Delta EXRATE_{t-i}$	-1.547*

$\sum \Delta INTRATE_{t-i}$	0.015	*GFC*	0.082*		
$\sum \Delta CPI_{t-i}$	0.857	*Jun*	0.051**		
ΔOIL_{t-9}	0.074**				
GFC	0.074**				
Feb	0.051*				
Aug	0.025**				
Long-run symmetric/ asymmetric effects					
Local Y	0.670	Local Y Pos	-2.442	Local Y Pos	2.194*
Global Y Pos	-1.624	Local Y Neg	-2.691	Local Y Neg	2.134*
Global Y Neg	-2.748*	Global Y Pos	2.299	Global Y Pos	-3.019*
		Global Y Neg	2.107	Global Y Neg	-1.863**
Model diagnostics and goodness of fit					
Adj R^2	0.545	Adj R^2	0.500	Adj R^2	0.412
LM (SC 12)	1.128	LM (SC 12)	1.027	LM (SC 12)	1.045

Products		*Metals*		*Minerals*	
$Industry_{t-1}$	-0.067*	$Industry_{t-1}$	-0.304*	$Industry_{t-1}$	-0.056*
$Local\ Y_{t-1}$	0.022	$Local\ Y\ Pos_{t-1}$	0.099	$Local\ Y_{t-1}$	-0.061
$Global\ Y_{t-1}$	-0.095	$Local\ Y\ Neg_{t-1}$	0.062	$Global\ Y_{t-1}$	0.076
$\sum \Delta Industry_{t-i}$	-1.006*	$Global\ Y\ Pos_{t-1}$	-0.251	$\sum \Delta Industry_{t-i}$	-0.158**
$\sum \Delta Local\ Y_{t-i}$	0.036	$Global\ Y\ Neg_{t-1}$	0.086	$\sum \Delta Local\ Y_{t-i}$	0.388*
$\sum \Delta Glocal\ Y_{t-i}$	4.894*	$\sum \Delta Industry_{t-i}$	-0.769*	$\sum \Delta Glocal\ Y_{t-i}$	11.108*
$\sum \Delta INTRATE_{t-i}$	0.099*	$\sum \Delta Local\ Y_{t-i}$	1.032*	$\sum \Delta CPI_{t-i}$	3.007
$\sum \Delta CPI_{t-i}$	1.636	$\sum \Delta Glocal\ Y_{t-i}$	1.619*	ΔOIL_{t-7}	-0.115**
$\sum \Delta OIL_{t-i}$	0.014	ΔCPI_{t-2}	5.814*	*GFC*	0.092*
GFC	0.028**	ΔOIL_t	0.171**	*Feb*	0.082*
Jan	-0.026*	$\Delta INTRATE_{t-11}$	0.191*		
Feb	0.023*	*GFC*	0.089**		
		Jun	-0.050**		
Long-run symmetric/ asymmetric effects					
Local Y	0.325	Local Y Pos	0.327	Local Y	-1.092**
Global Y	-1.410	Local Y Neg	0.204	Global Y	1.363
		Global Y Pos	0.204		
		Global Y Neg	0.284		
Model diagnostics and goodness of fit					
Adj R^2	0.574	Adj R^2	0.462	Adj R^2	0.479
LM (SC 12)	1.477	LM (SC 12)	1.017	LM (SC 12)	0.860

Motor Vehicles		*Other Manufacturing*		*Other Transport*	
$Industry_{t-1}$	-0.159*	$Industry_{t-1}$	-0.063**	$Industry_{t-1}$	-0.066*
$Local\ Y\ Pos_{t-1}$	-0.331*	$Local\ Y\ Pos_{t-1}$	-0.030	$Local\ Y_{t-1}$	-0.008
$Local\ Y\ Neg_{t-1}$	-0.377*	$Local\ Y\ Neg_{t-1}$	-0.048	$Global\ Y_{t-1}$	0.283*
$Global\ Y_{t-1}$	0.911*	$Global\ Y_{t-1}$	-0.514	$\sum \Delta Industry_{t-i}$	-1.029*
$\sum \Delta Industry_{t-i}$	-1.241*	$\sum \Delta Industry_{t-i}$	-1.375*	$\sum \Delta Local\ Y_{t-i}$	0.023
$\sum \Delta Local\ Y_{t-i}$	1.708*	$\Delta Local\ Y_t$	0.190**	$\sum \Delta Glocal\ Y_{t-i}$	1.435**
$\sum \Delta Glocal\ Y_{t-i}$	1.109	$\sum \Delta Glocal\ Y_{t-i}$	1.581*	$\sum \Delta EXRATE_{t-i}$	-0.740

$\Delta EXRATE_{t-11}$	-1.732*	$\sum \Delta EXRATE_{t-i}$	-0.495	$\sum \Delta CPI_{t-i}$	7.065*
$\sum \Delta OIL_{t-i}$	0.684*	ΔCPI_{t-5}	-3.618*	$\sum \Delta OIL_{t-i}$	-0.021
GFC	-0.124*	ΔOIL_{t-2}	-0.176*	*Covid19*	-0.062*
Jan	-0.026*			*Mar*	0.026**
Feb	0.023*				
Long-run symmetric/ asymmetric effects					
Local Y Pos	-2.074**	Local Y Pos	-0.481	Local Y	-0.132
Local Y Neg	-2.360**	Local Y Neg	-0.766	Global Y	4.247*
Global Y	5.705*	Global Y	0.811		
Model diagnostics and goodness of fit					
Adj R^2	0.593	Adj R^2	0.496	Adj R^2	0.412
LM (SC 12)	1.061	LM (SC 12)	1.098	LM (SC 12)	1.068

Wood		*Computer*	
$Industry_{t-1}$	-0.134*	$Industry_{t-1}$	-0.066**
$Local\ Y\ Pos_{t-1}$	-0.039*	$Local\ Y_{t-1}$	-0.002
$Local\ Y\ Neg_{t-1}$	-0.014*	$Global\ Y\ Pos_{t-1}$	0.072
$Global\ Y\ Pos_{t-1}$	0.113*	$Global\ Y\ Neg_{t-1}$	-0.015
$Global\ Y\ Neg_{t-1}$	0.110		
$\sum \Delta Industry_{t-i}$	-0.869*	$\sum \Delta Industry_{t-i}$	-1.035*
$\sum \Delta Local\ Y_{t-i}$	0.583*	$\sum \Delta Local\ Y_{t-i}$	1.409*
$\Delta Glocal\ Y_{t-5}$	0.781**	$\Delta INTRATE_{t-8}$	-0.050**
$\sum \Delta INTRATE_{t-i}$	0.161**		
$\Delta EXRATE_{t-2}$	-0.758**	$\sum \Delta CPI_{t-i}$	-6.072*
ΔOIL_{t-1}	0.108**	$\sum \Delta OIL_{t-i}$	0.237*
ΔCPI_{t-3}	3.423**		
Long-run symmetric/ asymmetric effects	-0.645		
Local Y Pos	-0.487		
Local Y Neg	1.652	Local Y	-0.043
Global Y Pos	0.076	Global Y Pos	1.089
Global Y Neg		Global Y Neg	-0.226
Model diagnostics and goodness of fit			
Adj R^2	0.381	Adj R^2	0.520
LM (SC 12)	2.296*	LM (SC 12)	1.109

4.4 Assessment of Cyclicality

Assessment of long cyclicality requires estimated long-run elasticities of sectoral industrial production with respect to both the local and global aggregate industrial productions. The long-run parameters are estimated using the Dynamic OLS (eq 7).The estimated long-run elasticities reported in Table 6 correspond to the parameters β_1 through β_4. The number of first difference lead and lag terms 'k' is selected by Akaike's information criterion. We also use macroeconomic variables in growth form, crisis-related dummy variables, and monthly season dummy variables as fixed regressors in equation 7. We present the results for only those manufacturing industries for which production is found to be cointegrated with local and global business cycle variation through the Bound test for the NARDL model. These industries include paper, petroleum, pharmaceutical, printing, rubber, textile among non-durable industries and computer, electrical, machinery, metals, metals products, minerals, motor vehicles, other manufacturing, other transport, and wood among durable industries. The resulting estimated coefficient's signs and statistical significance are used to assess the cyclicality of industries. We classify industries as cyclic, counter-cyclic, or non-cyclic as per the Berman and Pfleeger (1997) definitions. We use the estimated elasticities to assess the cyclicality of industrial productionwrt to both the local and global business cycles. Generally, our estimates for the local business cyclicality corroborates the commonly held view that durable industries are pro-cyclic as except for the metal products, minerals, and wood industry, all the durable industries are found pro-cyclic wrt the local business cycle as indicated by significant and positive elasticities corresponding to both the positive and negative partial sums variables. However, counter intuitively, pharmaceutical industry is found local business cyclic. The paper industry is also found to boom during the local business cycle. It is also interesting to note that except paper, non-durable industries are found cyclic with respect to the global business cycle. So is the case with computers, minerals and motor vehicles among the durable industries. Generally, the nature of local cyclicality direction is opposite of the global cyclicality. Only the computer and motor vehicle industries are found cyclic wrt to both the local andglobal business cycles. Generally, the view that nondurable goods industries act as noncyclic or counter-cyclic appears to be true only wrt to the local business cycle for Singapore industries.

We also note that our estimates are robust to the inclusion or exclusion of macroeconomic variables as deterministic regressors as the estimated elasticities are very close in both cases. Table A1 in the appendix, shows that the general conclusion on cyclicality remainsthe same if the long-run equation uses asymmetric positive and negative partial sum variables for local and global business cycle variables.

Table 6: Estimates of long-run elasticities using the Dynamic OLS

Industries	Without Macroeconomic Variables		With Macroeconomic Variables		Local Cyclicality	Global Cyclicality
	Local Ind. Production	Global Ind. Production	Local Ind. Production	Global Ind. Production		
Non-Durable						
Paper	0.408*	-0.922*	0.449*	-1.399*	Cyclic	Counter Cyclic
Petroleum	-0.036	0.765**	-0.091	0.675**	Non Cyclic	Cyclic
Pharmaceutical	2.223*	1.247**	2.195*	1.358**	Cyclic	Cyclic

Printing	-0.954*	3.583*	-1.075*	3.065*	Counter Cyclic	Cyclic
Rubber	-0.754*	2.054*	-0.733*	1.593*	Counter Cyclic	Cyclic
Textile	-2.889*	4.100*	-3.205*	3.930*	Counter Cyclic	Cyclic
Durable						
Computer	0.375*	1.247*	0.359*	1.372*	Cyclic	Cyclic
Electrical	1.294*	-2.504*	1.308*	-2.813*	Cyclic	Counter Cyclic
Machinery	1.866*	-2.735*	1.878*	-2.645*	Cyclic	Counter Cyclic
Metal Products	-0.084	0.695	-0.029	-0.145	Non Cyclic	Non Cyclic
Metals	0.446*	-0.612	0.430*	-0.519	Cyclic	Non Cyclic
Minerals	-0.955*	2.051*	-1.093*	1.888*	Counter Cyclic	Cyclic
Motor Vehicles	0.700*	4.912*	0.698*	4.918*	Cyclic	Cyclic
Other Manufacturing	1.064*	0.706	1.091*	0.644	Cyclic	Non Cyclic
Other Transport	0.950*	-0.079	0.894*	0.237	Cyclic	Non Cyclic
Wood	-0.469*	-0.076	-0.542*	0.375	Counter Cyclic	Non Cyclic

Note: The long-run parameters are estimated via Dynamic OLS. The number of lead and lag terms of the first difference right hand side variables are selected by Akaike's information criterion. The fixed regressors include seasonal monthly dummies, the dummy variables for Asian Financial Crisis, GFC, and Covid19. The results correspond to the two cases whether the macroeconomic variables are included or not included as fixed regressors. The significance of the coefficients via a t statistic involves the HAC corrected standard errors.

4.5 Forecasting efficacy of industrial growth rates

We now focus on the predictive ability of our linear and non-linear ARDL models to investigate the information contents of the asymmetric local and global business cycle effects on industrial production growth. We estimate the linear and non-linear ARDL models using the data from the start of the sample period to December 2021 and forecast industrial production growth for the 12 months of 2022. The forecasting accuracy is measured using the root mean square error (RMSE) and is reported in Table 7. It can be observed that for two-thirds (specifically 14 out of 21) of all the industries under study, either the symmetric or asymmetric cointegration-based ARDL model yields superior forecasting performance as compared to the ARDL model which does not include long-run level information related to both the local and the global business cycle variations. This observation highlights the potential gain in accuracy that earlier studies could have exploited by benefiting from the long-run cointegration framework in the prediction and assessment of the cyclicality of industrial production growth. It can also be noted that apart from some exceptions, those industries for which production is either linearly or non-linearly cointegrated with local and global business cycles also show up as yielding superior forecasting ability.

Table 7: Root Mean Square Error (RMSE) of industrial production growth forecasts.

Industries	ARDL with no cointegration	ARDL with symmetric cointegration	ARDL with asymmetric cointegration
Apparel	0.2577*	0.2650	0.2733
Chemicals	0.0702	0.0631	0.0571*
Computer	0.0924	0.0848	0.0739*
Electrical	0.0833	0.0746	0.0656*
Food	0.0738	0.0735*	0.0865
Furniture	0.1463*	0.1492	0.3650
Leather	0.2198*	0.2220	0.2604
Machinery	0.0680	0.0655*	0.0953

Metal Products	0.0980	0.0906	0.0844*
Metals	0.2483	0.2380*	0.2489
Minerals	0.1209	0.1159*	0.1295
Motor Vehicles	0.0903*	0.1135	0.1429
Other Manufacturing	0.1710	0.1588*	0.1854
Other Transport	0.0825	0.0818*	0.0934
Paper	0.1171	0.1094*	0.1560
Petroleum	0.0643	0.0622*	0.0849
Pharmaceuticals	0.2486	0.2097*	0.2663
Printing	0.0810*	0.0821	0.0824
Rubber	0.0689*	0.0724	0.0858
Textile	0.2603*	0.2695	0.2625
Wood	0.1340	0.1234	0.1146*

Note: The minimum of RMSE corresponding to each industry is indicated by *.

5. Results and Discussion

The bound test of both the linear and non-linear cointegration yields similar conclusion regarding the cointegration for most the industries except the rubber and computer industries where there is no evidence of linear cointegration, yet the NARDL test indicates significant non-linear cointegration. Also, for the apparel industry, there appears to be no linear cointegration but the nonlinear cointegration evidence is inconclusive. Generally, it can be concluded that long-run cointegration is essentially asymmetric in many industries. In the majority of non-durable industries, production shows non-linear long run relationships with the local and global business cycles. Our results of short-run symmetry corroborate the findings of Iqbal (2021) who found that only very few industries in the four Southeast Asian countries follow an asymmetric pattern. One reason for this apparent similarity is that essentially the framework used by Iqbal (2021) involved the tests of only the short-run asymmetries since his regression modeled only the short-run changes and therefore devoid of the long-run information contained in the level of variables. The present study indicates that indeed inclusion of long-run information makes a difference in that at least half of all the industries show long-run asymmetric responses to both the local and global business cycles.

Overall findings indicate that the reactions of Singapore’s manufacturing industries to local and global business cycles are not the same for all industries. Thus, imposing a linear reaction of industrial production to the business cycles may lead to model misspecification in at least half of all non-durable as well as durable industries, especially in the long-run model.

The results also indicate that industrial production growth can be significantly predicted from their past growth rates. In addition to history, some macroeconomic variables have predictive contents for many industries production. As per theoretical expectation durable goods generally have much higher interest elasticities of interest demand than non-durables that is observed in electrical, metal and metals products, and wood industries which are significantly interest rate sensitive. Most industries considered are also affected by global oil price changes. This is expected owing to the Singapore economy being globally integrated into the world economy. There is also evidence of the recent Covid19 crisis to negatively affect growth in the ‘other transport’ sector, whereas the textile sector actually gained during the crisis period.

The results of cyclicality of Singapore's industrial appears to be similar to that reported earlier studies e.g., Konovalova and Maksimov (2017) for Russia, Petersen and Strongin (1996) for the US , and the panel data evidence by Iqbal (2021) for the Southeast Asian countries. However, except Iqbal (2021), the previous studies did not investigate the global business cycle sensitivities of the local industries. The empirical results in the present study highlight the effects of global economic cycle on manufacturing industries.

It can also be observed that forecasting ability of industries production is enhanced when the industries are found more cointegrated with the Singapore's local and global GDP growth.

6. Conclusion

This paper conducts an empirical econometric investigation of the local and global business cycle sensitivities of Singapore's sectoral industrial production. By employing monthly seasonally adjusted production indices from 11 durable and 10 non-durable manufacturing industries, this paper examines the presence of long-run symmetric and asymmetric relationshipsof sectoral production indices with the local and global business cyclevariationswithin an ARDL and NARDL framework and by estimating the long-run parameters using the Dynamic OLS estimator. It is found that the nature of cyclic sensitivity is different if viewed from a local or global economic perspective. Also, this study corroborates the commonly held conception that durable industries are pro-cyclic, we also note that this conclusion is valid more for the local economy than the global business cycle. Viewing from a global economy perspective, generally non-durable industries are seen to enjoy higher production levels during a global boom. Thus, while generally, the durable manufacturing industries enjoy high production during the local booming economy, the global business cycle sensitivities of these industries are different. Some exceptions are the computer and motor vehicles industries which are found to flourish in both the local and global business cycle booms.

Also, while we found a significant long-run asymmetric relationship between sectoral industrial production and aggregate local and global industrial production, very few industries exhibit evidence of short-run asymmetries wrt to both the local and global business cycles for both the durable and non-durable industries. This conclusion is in line with earlier findings where similar patterns in the industries of four Southeast Asian countries including Singapore were found.

Finally, a forecast comparison shows that the forecasting of sectoral industrial production growth can be improved by incorporating long-run information about the local and global economic cycles. Thus, empirical evidence in this paper indicates thatthe long-run relationship of Singapore's industries with local and global business cycle variations yields improvement inthe prediction and assessment of the cyclicality of sectoral industrial production growth.

7. References

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[1]https://www.singstat.gov.sg/
[2]https://stats.oecd.org/viewhtml.aspx?datasetcode=MEI_REAL&lang=en
[3]https://fred.stlouisfed.org/tags/series?t=monthly%3Bwti
[4]Cho et al. (2023) describe ways to treat the threshold as an unknown parameter to be estimated resulting in the threshold ARDL (TARDL) model. However, yet this model has not gained popularity in applied research.

Appendix Table A1: Estimates of long-run elasticities using the Dynamic OLS

	Local B. Cycle +	Local B. Cycle-	Global B. Cycle +	Global B. Cycle-	Local Cyclicality	Global Cyclicality
Non-Durable						
Paper	0.467*	0.429*	-1.505*	-1.071*	Cyclic	Counter Cyclic
Petroleum	1.557*	1.723*	-1.277*	-0.541**	Cyclic	Counter Cyclic
Pharmaceuticals	-0.263	-0.742	2.594*	3.661*	Non Cyclic	Cyclic
Printing	2.239*	2.289*	-2.814*	1.466	Cyclic	Counter Cyclic
Rubber	1.203*	1.524*	-0.462**	-1.031*	Cyclic	Counter Cyclic
Textile	0.503	0.949**	-0.482	0.147	Cyclic	Non Cyclic
Durable						
Computer	1.058**	1.554*	2.802*	-1.532	Cyclic	Cyclic
Electrical	0.640**	0.548**	-1.861*	-1.803*8	Cyclic	Counter Cyclic
Machinery	1.673*	1.063*	-4.945*	1.158	Cyclic	Counter Cyclic
Metals Products	1.507*	1.452*	-2.632*	0.583	Cyclic	Counter Cyclic
Metals	0.500*	0.413**	-1.098*	-0.199	Cyclic	Counter Cyclic
Minerals	2.813*	3.337*	-2.695*	-2.458*	Cyclic	Counter Cyclic
Motor Vehicles	-2.055	-2.761**	5.885*	8.383*	Counter Cyclic	Cyclic
Other Manufacturing	-1.094*	-1.227*	3.263*	1.671*	Counter Cyclic	Cyclic
Other Transport	1.123*	0.511	-3.163*	3.355*	Cyclic	Uncertain
Wood	-1.011*	-0.967*	1.303**	0.094	Counter Cyclic	Cyclic

Note: The long-run parameters are estimated via Dynamic OLS. The number of lead and lag terms of the first difference right hand side variables are selected by Akaike Information Criteria. The fixed regressors include seasonal monthly dummies, the dummy variables for the Asian Financial Crisis, Global Financial Crisis, and Covid19. The macroeconomic variables are also included as fixed regressors. The significance of the coefficients via a t statistic is based on the HAC corrected standard errors.