# Macroeconomic Policy and Analysis

## An Investigation of China's Q3 GDP and the Predictive Power of its Leading Indicators

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# Contents

# 1 Introduction

This paper has displays both depth and breath of analysis through the presentation of an overview of the current economic environment in light of recently released data and also an investigation into the use of PMI as a leading indicator with predictive power. This week's release of a slew of new Q3 data comes at a crucial time for the Chinese economy. With heightened scepticism over the dwindling of classic growth engines, namely exports and credit-fuelled expansion, commentators look towards a continued stable but more soft-footed growth figures.

This paper seeks to offer clarity on the data release through the lens of expected economic growth as captured by the PMI indictor. In a proposal covering both the limitations of GDP and the benefits of alternate measures, this paper argues the prefered method of forecasting quarterly GDP is by use of monthly industrial-value added as a more reliable means to an end. Through both graphical and bivariate VAR analysis the forecasting power of PMI as a leading indicator becomes apparent. Thus this investigation suggests a conscientious observer should keep careful watch of PMI and other such business sentiment indicators over the coming months as early warning signs of changes to come.

# 2 A Summary of China Third Quarter Growth

The release of Q3 growth data saw China falling short of expectations with the worse pace growth since the financial crisis. GDP growth fell to 6.5% year-on-year, just missing expectations for 6.6% (Reuters poll). This figure also indicates slowing growth compared to the last quarter which enjoyed a 6.7% year-on-year expansion. In addition to GDP data, the release saw new figures on industrial production, retail sales and fixed asset investment. Industrial production similarly missed forecasters' expectations, growing by 5.8% to September end. Conversely, retail sales showed a 9.2% compared to September last year surpassing expectation and investment similarly beat forecasts with a 5.4% rise year-on-year.

## *2.1 Determinants of Slowing Growth*

The slowing growth can be broadly attributed to the shared influence of the following factors:

- **Deleverage:** The slow down in growth has been heralded unsurprising by many

experts given the financial develeraging process amidst a crackdown on risky credit. This deleveraging trajectory has somewhat slowed with a reversed easing of credit lines in an effort to prop up liquidity and growth.

- **Trade War:** The effect of tit-for-tat tariffs and their contemporaneous effect on headline trade figures remains to fully pass-through to the economy. The full drag on economic growth has been mitigated by firms checking out orders early in anticipation of later restrictions and by the strength of the US economy implying orders are still arriving. Despite this, escalating trade tensions will continue to be a reductionary force on growth.

- **Stock Market Fluctuations:** The Shanghai Composite Index has declined 25% this year and demonstrated a considerable degree of volatility around the release of the Q3 data on Friday. In defence of China's economic position, Yi Gang (People's Bank of China Governor) advocated investors remain level-headed, arguing stock market "abnormal fluctuations" are not reflective of Chinese fundamentals.

**Summary Comment:** The current economic climate is not yet cause for concern and it is likely Beijing will keep growth stable. However, it does appear the growth trajectory is compromised by more uphill struggle than in China's recent economic history."

# 3 A Summary of China PMI

This section examines PMI and its subsidiary metrics, attributing patterns to current developments in the Chinese economy.

In sum, the Producer Managers' Index (PMI) is a metric of confidence in the economy, depicting current expected business performance for the month at hand. The metric, calculated by means of a survey of sampled firms, is avaliable from a number of sources including the China Federation of Logistics  Purchasing (CFLP), Caixin or HSBC. The survey is framed in relative terms, whether performance has improved or worsened since the previous month. Thus an observation equal to 50 represents no change, greater than 50 an improvement and less than 50 a worsening. Thus, we can simply describe PMI as a seasonally adjusted month-on-month (m-o-m) indicator whose numbers reflect what proportion of the companies surveyed report higher/lower output, orders, inventory, exports and other such sub-sections. The key distinguishing feature of PMI is its role as a leading indicator. The PMI data gives a first look into

business plans for the month or two ahead given orders and production plans precede official release of GDP, production, retail sales and export figures. However, one must exercise some caution in placing too much quantitative trust in PMI given firstly, it reflects only a sample of total firms and secondly, is only firms' recorded expectations of the month, not realised output.

## *3.1 Domestic versus Foreign*

We can first identify the severity of impact of the 2008 financial crisis crushing expectations in 2008-2009. This trough is a commonality throughout most analysed series in this paper. Turning to a comparison between total new orders and exports orders, there appears to be little discrepancy over the period observed. The similar trajectory of the two series continues past 2016 despite the creeping influence of trade disputes. This suggests, as aforementioned, that export orders have yet to feel the brunt of obstructing tariffs. We cannot confirm yet whether the slight divergence of the two series is a meaningful sign of export-led struggles or just normal fluctuation. Keeping careful watch of data into the new year will confirm a drop off in export orders.


Figure 1: New Orders and Exports Orders on similar paths with a recent potential divergence

## 3.2 Manufacturing versus Non-Manufacturing

PMI can also be dis-aggregated by sector of firm. By comparing manufacturing versus non-manufacturing firms, we can see non-manufacturing consistently returns higher PMI figures displaying a greater general sense of confidence in production figures. However, the two series have converged somewhat owing to stagnant manufacturing reports hovering around 50 and a decline in non-manufacturing reports. This perhaps is due to a slowing general economic climate reducing consumer capacity for spending on goods such as food or entertainment services. The non-manufacturing service is also less artificially supported by the activity of state owned enterprises.

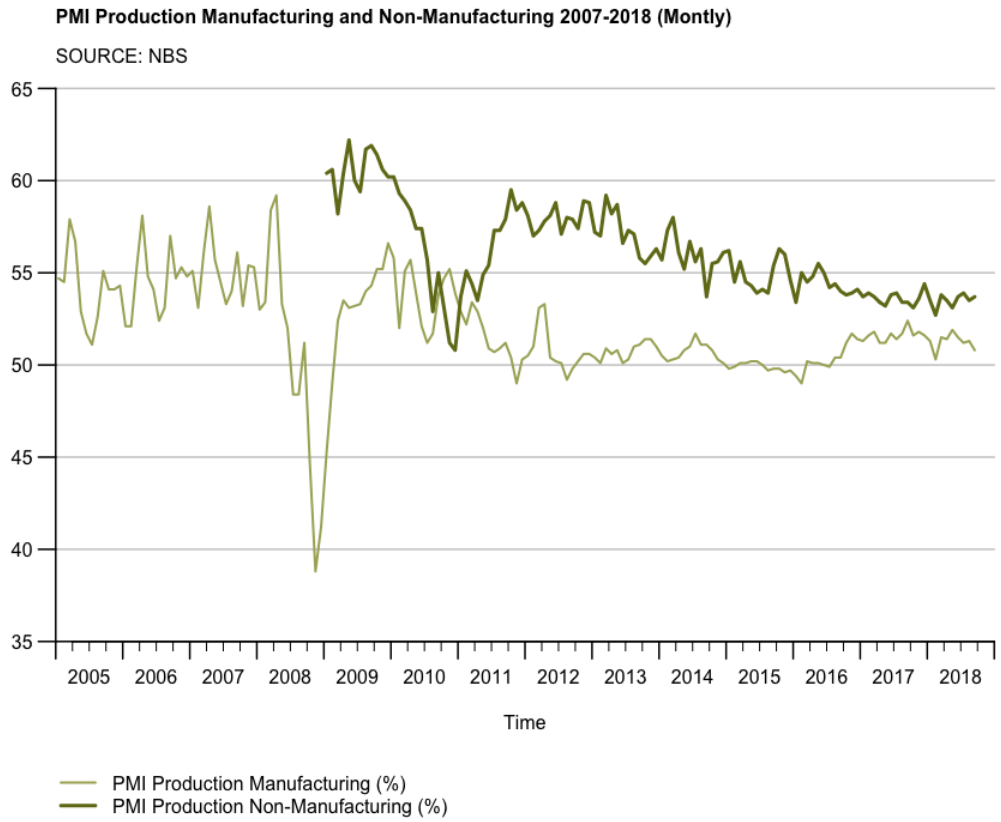


Figure 2: A re-convergence of manufacturing and non-manufacturing PMI

## 3.3 The Role of Expectations

Any index asking agents to form expectations of future economic realisations inherently relies on how expectations are indeed formed. However, production PMI (the standard baseline PMI figure) includes both realised output up until the 20th of the month then forecasts for the remaining 10 or so days. Thus, by the 20th of the month

it is likely most competent firms have a solid idea of how the month will end. One of the sub-categories of PMI is a question specifically focusing on firms' sentiment on business environment. This explicitly extracts expectations for the few months ahead in a more all-encompassing sense. Thus observing the expectations of economic climate is a useful indicator into firms broad sentiment towards the future.

By plotting both production PMI and expectations of business environment PMI, we observe a considerable degree of discrepancy. The underpinning determinants of such incongruence in itself deserves a full-scale investigation. However, it sheds important light on tendency explicated in behavioural economics to over-forecast one's own success in part due to an inability to estimate subjective probability events. The behavioural bias to consistently over-forecast business environment despite a considerable degree of knowledge on realised production demonstrates irrationality of firm managers which we cannot ignore as a variable affecting the broader economy.

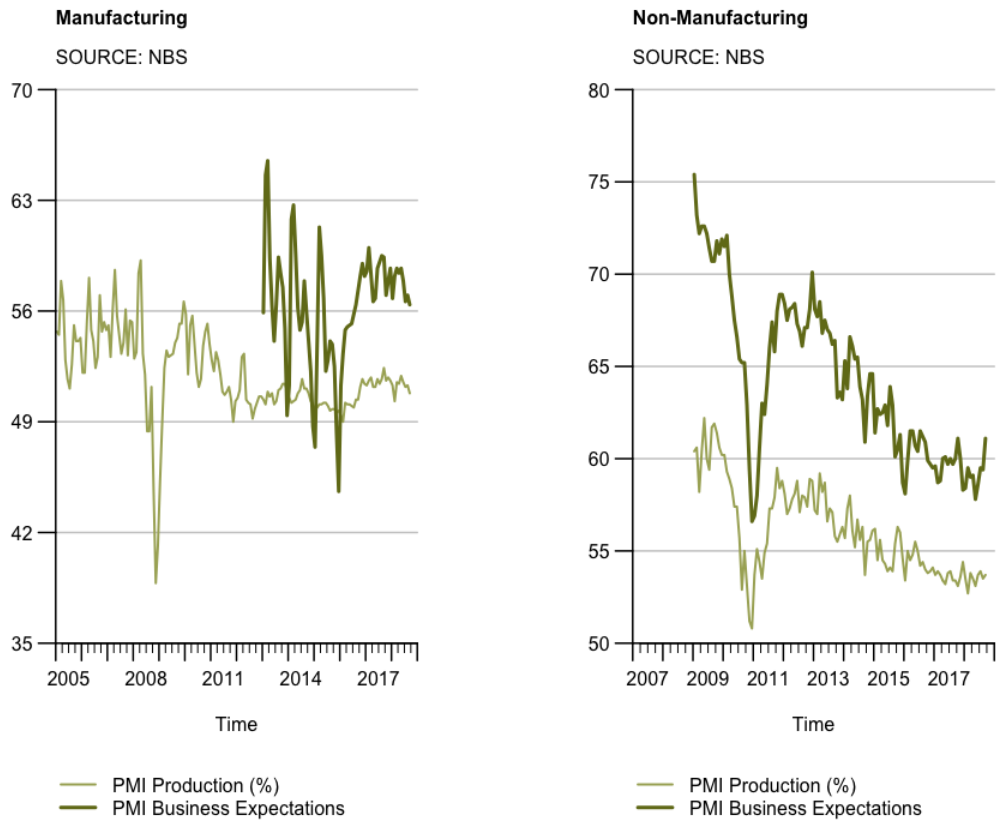


Figure 3: The discrepancy between reported expectation and reported production

# 4 PMI as a Leading Indicator

This section examines PMI as a correlate of key economic indicators.

## *4.1 GDP and its limitations*

**Key Critique:** A criticism re-occurring in these analyses is that of GDP data quality. The aforementioned problems with GDP data and its susceptibility or at best opacity to manipulation raise serious challenges to its use as a headline economic figure. In addition to concerns of validity, GDP is only available in quarterly releases yet PMI is a monthly indicator.

**Key Implication:** Thus, while it was the task to estimate GDP using PMI indicators, this paper argues one can obtain better forecasts of economic performance by predicting values of the composite components of GDP. Monthly figures detailing export growth and industrial value-added are common series used by economists as a proxy for monthly GDP and are more robust to measurement or manipulation worries. As such, hereafter I am concerned with the ability of PMI as a leading indicator of these other same frequency series which in turn determine quarterly GDP. The degree of similarity is apparent in Figure 4, documenting the correlated series of industrial value-added and quarterly GDP.

## *4.2 Export Growth*

By eye, we can observe a fair degree of correlation in the pattern displayed by PMI reported expectations for export orders and export growth year-on-year. The export order sub-category of PMI is particularly useful as a leading indicator given orders for exports will be placed 2-3 months ahead of shipment. Thus, the PMI series predicts changes in export growth before it is identifiable in export volume itself. From observing key peaks and troughs e.g. in 2008, PMI does indeed appear to lead changes in export growth suggesting this is a useful indicator for predicting future developments.

The fairly steep drop-off in the first half of 2018 is particularly noteworthy since the PMI indicator falls below 50 implying firms expect to be worse of in relative terms in the coming periods. This effect has yet to fully be passed through to export orders. As the trade war intensifies the relationship between these two series remains a crucial metric to keep track off.

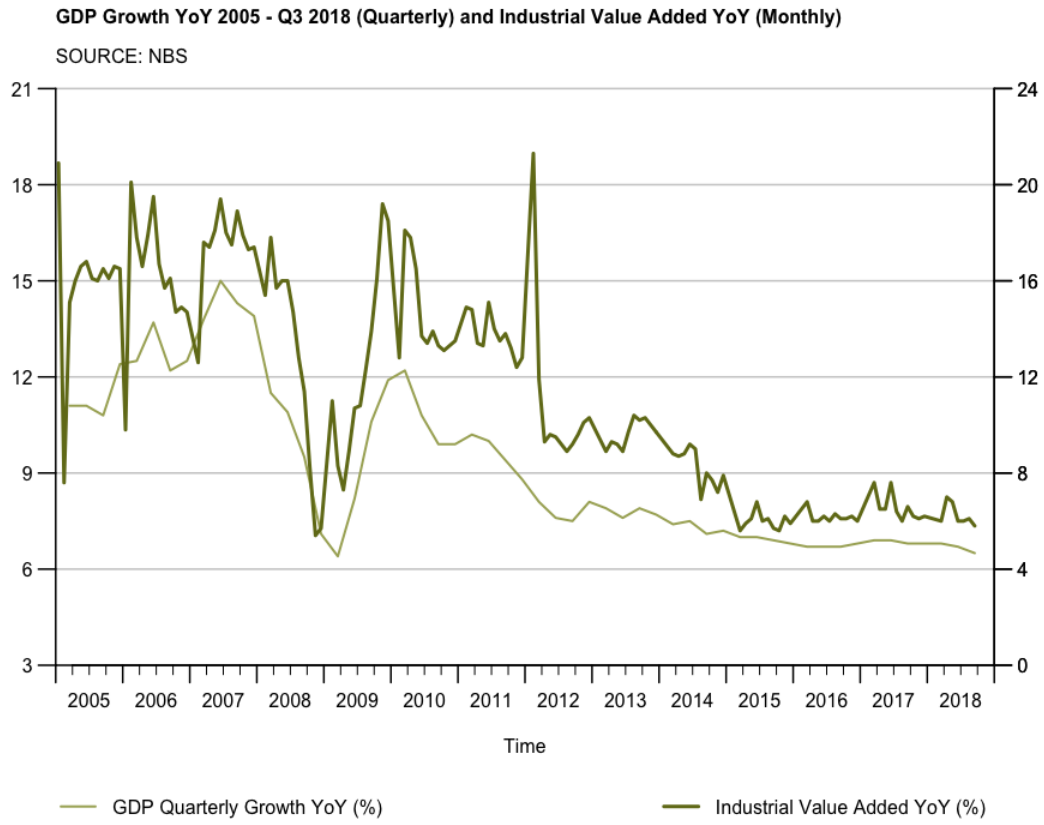


Figure 4: High degree of similarity between quarterly GDP and monthly Industrial Value-Added

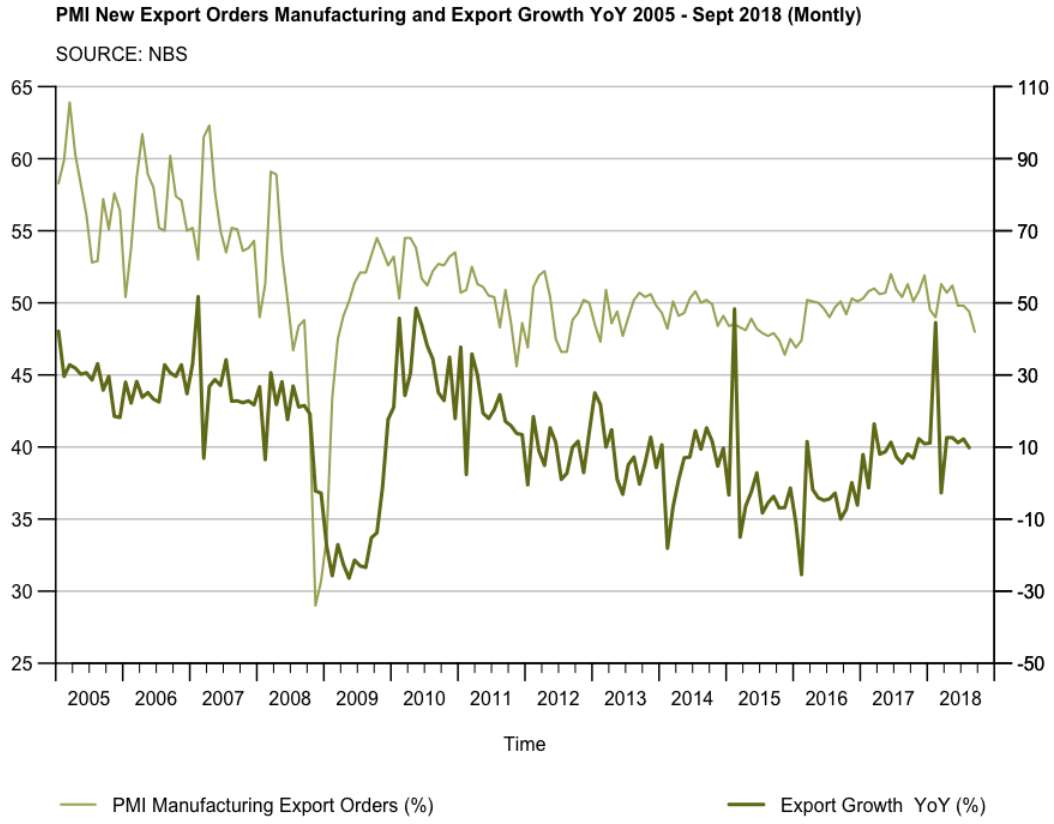


Figure 5: PMI Export Orders as a Leading Indicator of Actual Export Growth

## *4.3 Industrial Value-Added*

Industrial value-added is a monthly metric and common proxy as an estimate of monthly GDP. This dependence is particularly relevant in countries with strong industrial sectors like China. Thus if PMI estimates of manufacturing production can accurately predict industrial value-added we have a sound way to make a best guess of quarterly GDP.

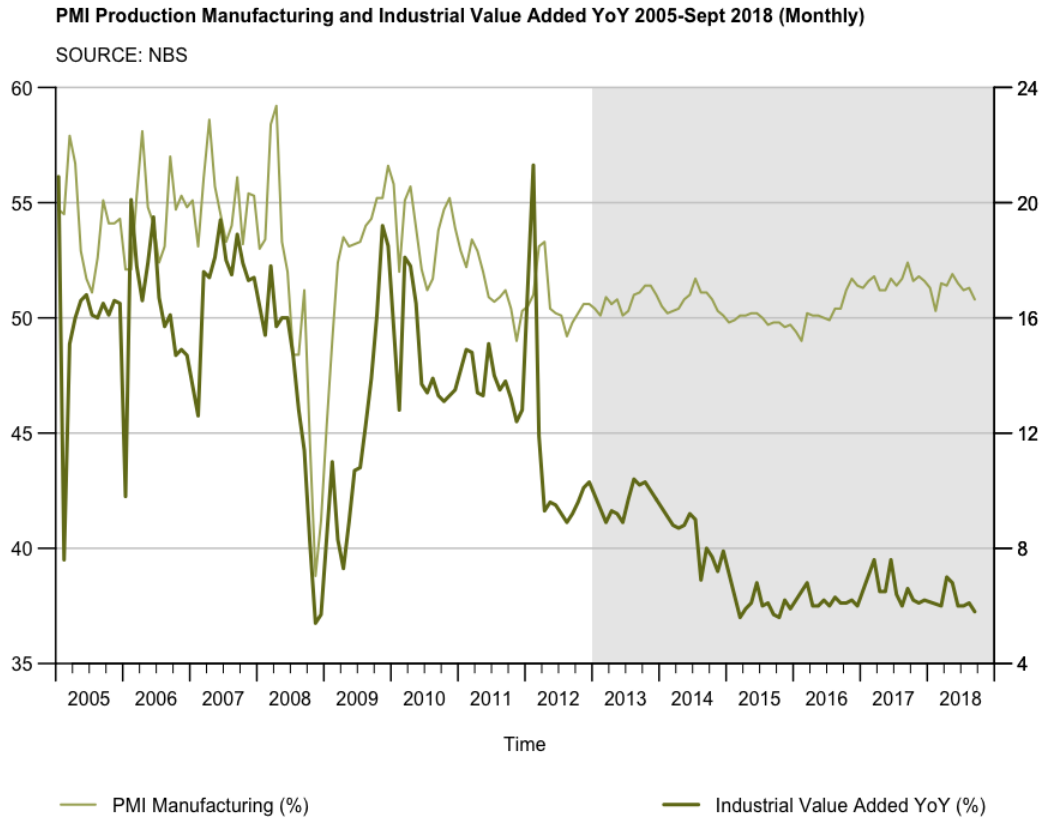


Figure 6: PMI as a Leading Indicator of Industrial Value Added

By observing the long-term co-movements in Figure 6, we can see the series move closely with industrial value-added displaying a slight lag behind PMI. While industrial value added faced a large decline in growth rate beginning in 2012 such scale of change was not apparent in PMI figures. However, by observing a shorter window of the two series (2013-present) we can observe if comovement has been re-established.

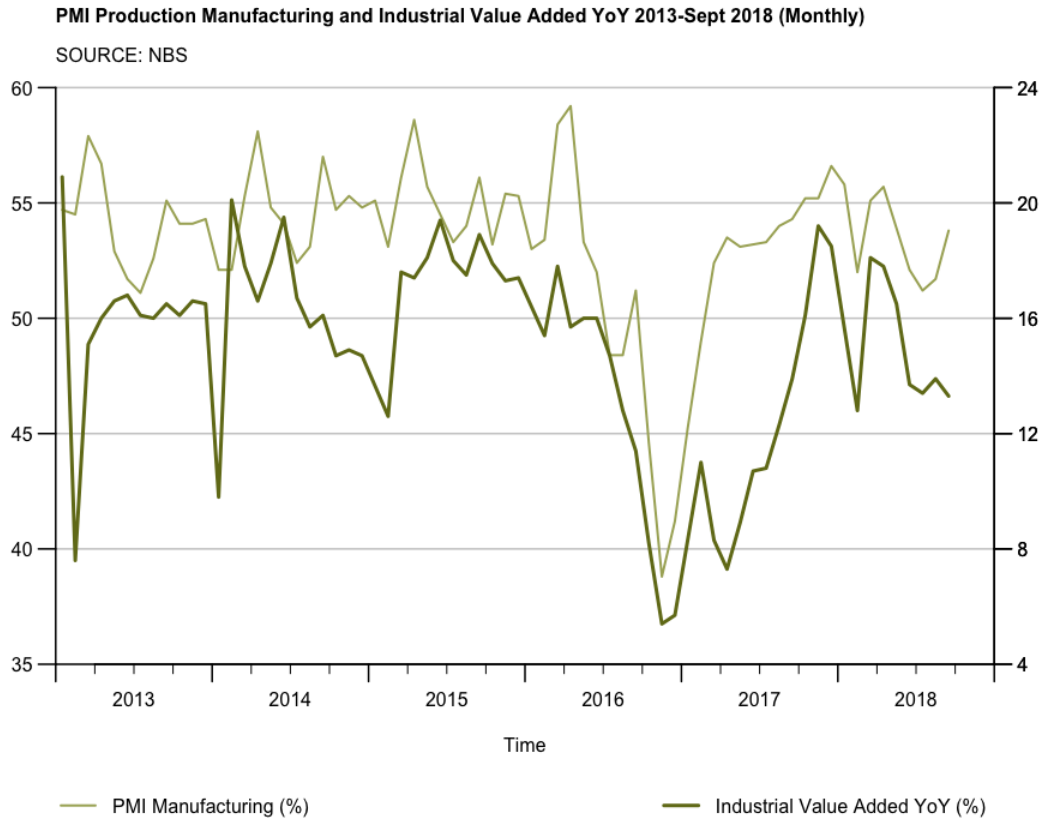


Figure 7: Comovement between series reestablished following 2011 break

Figure 7 demonstrates a fairly decisive re-establishment of comovement between the two series. As before, it appears PMI marginally leads movements in industrial value-added.

**A-priori conclusion:** Before identifying and modelling a relationship between the two time series, just an observation of the patterns of these two series already suggests a strong co-movement and a partial lag of industrial value-added to a lead of PMI manufacturing production estimates. To confirm this relationship, this paper applies time series econometics in the form of a bivariate var model outlined in the subsequent section.

# 5 Bi-variate VAR Forecasting

## *5.1 Theory*

**Vector Autoregressive (VAR) models** are used for multivariate time series analysis. The structure defines each variable as a linear function of past lags of itself and past lags of the other variables.
A reduced form VAR model is defined as:

$$x_t = A_1 x_{t-1} + ... + A_p x_{t-p} + CD_t + u_t$$

where $p$ is the lag-order of the model.
We can further define $x_t$ in a VAR model with $K$ endogenous variables:

$$x_t = (x_{1t}, ..., x_{Kt})' \rightarrow (K \times 1) \text{ random vector}$$

$$A_i = (K \times K) \text{ coefficient matrix}$$

$$D_t = \text{deterministic vector}, C = \text{associated coefficient matrix}$$

$$u_t = (u_{1t}, ..., u_{Kt})' \sim N(0, \sigma_\epsilon^2) \text{ in } K\text{dimensions} \Rightarrow \text{ White Noise Process}$$

Under this framework, we can define a **bi-variate VAR (BVAR)** as the integration of a pair of variables. In this case, we use one measure of real economic activity (industrial value added) and one expectations measure (PMI production). Once estimated we can test the forecasting performance of the model against a basic $AR(p)$ model which contains only lags of the variable at hand. If PMI is contains useful predictor information then the VAR model incorporating its influence will outperform the AR model.

## 5.2 Imputation of Missing Values by Kalman Filtration

As stated on the NBS website, monthly measurements for January and occasionally February are omitted from the published series for season adjustment checks. As such the industrial value added series had numerous missing values. In order to circumvent this problem, a Kalman filter imputation method is applied.

**The Kalman filter** is based upon the representation of a dynamic system in a state-space form. It applies an algorithm for sequentially updating a linear projection for a given system of relationships. The Kalman filter calculates one-step ahead forecasts recursively, proceeding from unconditional projection at time $t = 1$ to conditional production for $t = 2$ i.e.:

$$\hat{E}(\delta_1) = \hat{\delta}_{1|0}$$

$$\rightarrow \hat{E}(\delta_2|\Omega_1 = (y_1, x_1)) = \hat{\delta}_{2|1}$$

In general terms this can be written as:

$$\hat{\delta}_{t+1|t} = \hat{E}(\delta_{t+1}|\Omega_t)$$

$$\hat{\delta}_{t+1|t} = F \bullet \hat{E}(\delta_t|\Omega_t) + \hat{E}(v_{t+1}|\Omega_t)$$

$$\hat{\delta}_{t+1|t} = F \bullet \hat{\delta}_{t|t} + 0.44$$

Figure 8 presents the full series with imputed values included.

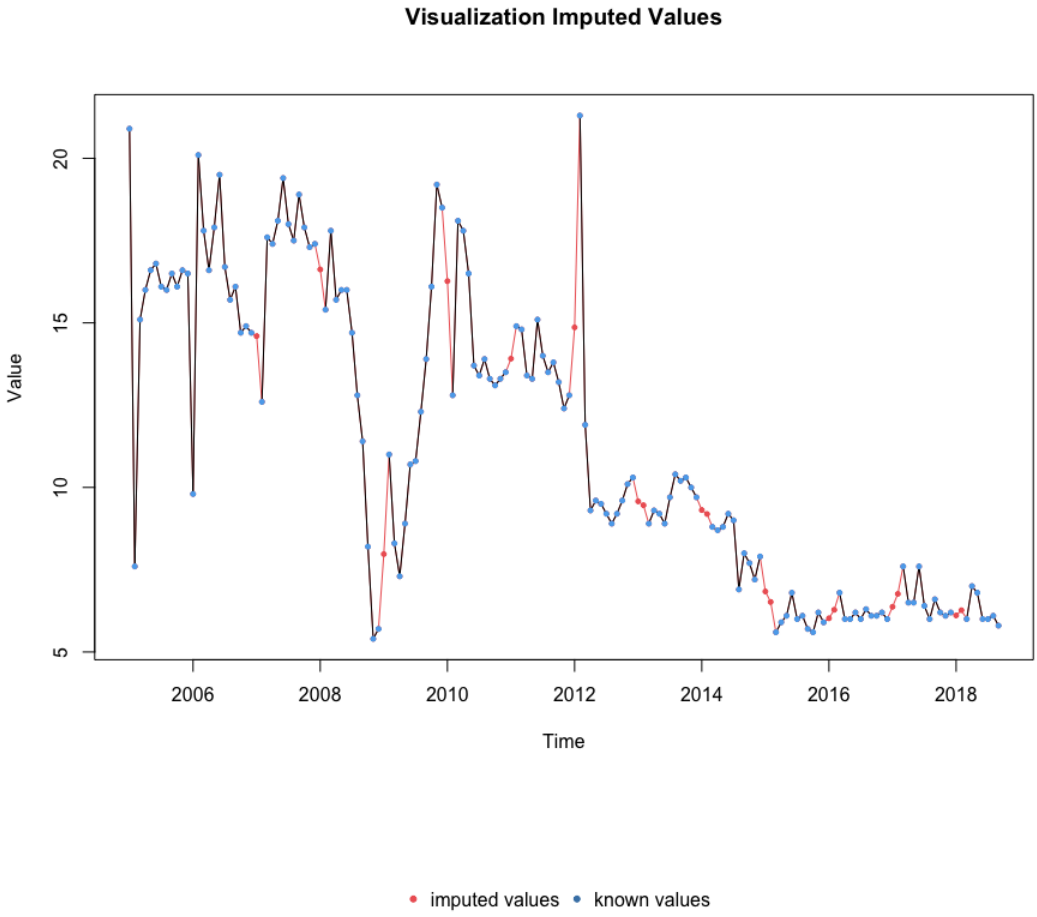


Figure 8: Imputed missing values using the Kalman Filter Method

## *5.3 Validity Tests*

Before using either series we must ensure the system is **stationary**. Both series are first-differenced and the resulting variables are indeed stationary as confirmed by the ADF tests presented in Table 1.

| Variable | Dickey-Fuller | p-value | Result |
|---|---|---|---|
| Diff(Industrial Value Added) | -5.54 | 0.01 | Reject $H_0$ in favour of the alternative hypothesis of stationarity |
| Diff(PMI Production) | -5.63 | 0.01 | Reject $H_0$ in favour of the alternative hypothesis of stationarity |

Table 1: Augmented Dickey Fuller Tests for Stationarity

An **Akaike Information Criteria (AIC)** is used to selected the order of the VAR model with 10 lags specified as the maximum. The suitable number of lags by this criterion is $p = 3$ thus a $VAR(3)$ model is fitted. This can be summarised as:

$$d.pmi = d.indprod.l1 + d.pmi.l1 + d.indprod.l2 + d.pmi.l2 + d.indprod.l3 + d.pmi.l3 + const$$

We can conduct a misspecifiation test to identify serial correlation using the **Portmanteau test**. If $H_0$ is rejected this suggests the VAR model should be rerun with other lags. Given the p-value we do not reject $H_0$ and conclude the model is correctly specified. Finally, we can also conduct an **ARCH test for Autoregressive Conditional Heteroscedasdicity**. The p-value suggests we do not reject $H_0$

| Test | p-value | Result |
|---|---|---|
| Portmanteau | 0.1995 | Do Not reject $H_0$ in favour of the alternative hypothesis of correct specification |
| ARCH | 0.211 | Do not reject $H_0$ in favour of no conditional heteroscedasdicity |

Table 2: Tests of $VAR(3)$ Specification and Assumptions

## *5.4 Predictions*

Figure 9 presents this paper's best estimates of 4 quarter ahead developments in Industrial Production. Figure 10 presents these forecasts with confidence intervals as a fan chart.

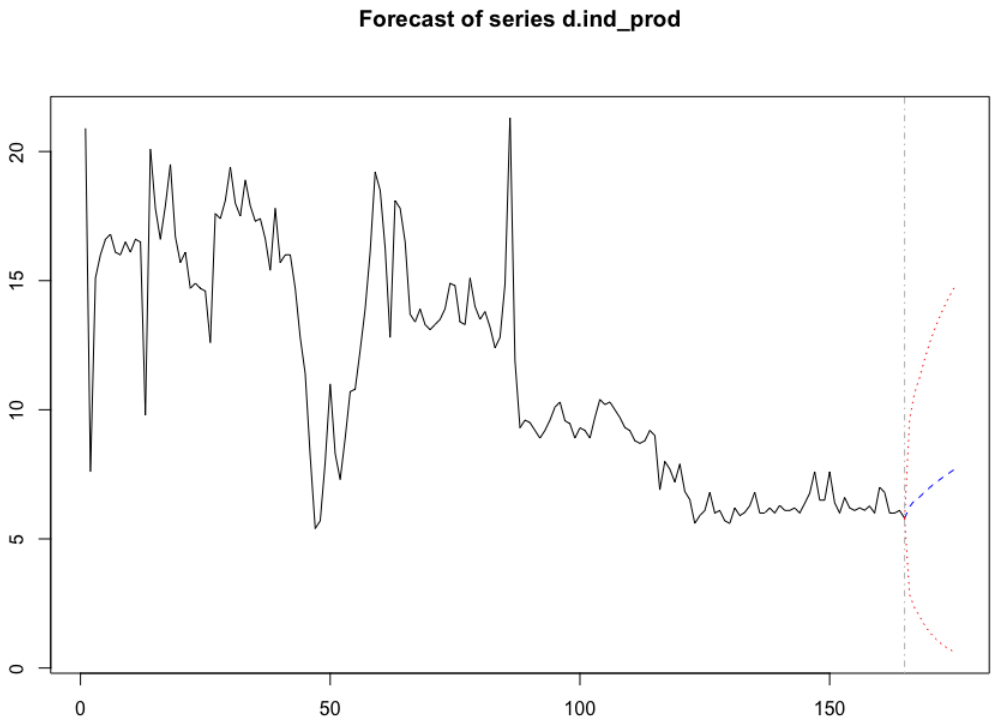


Figure 9: Forecasted development in Industrial Value Added

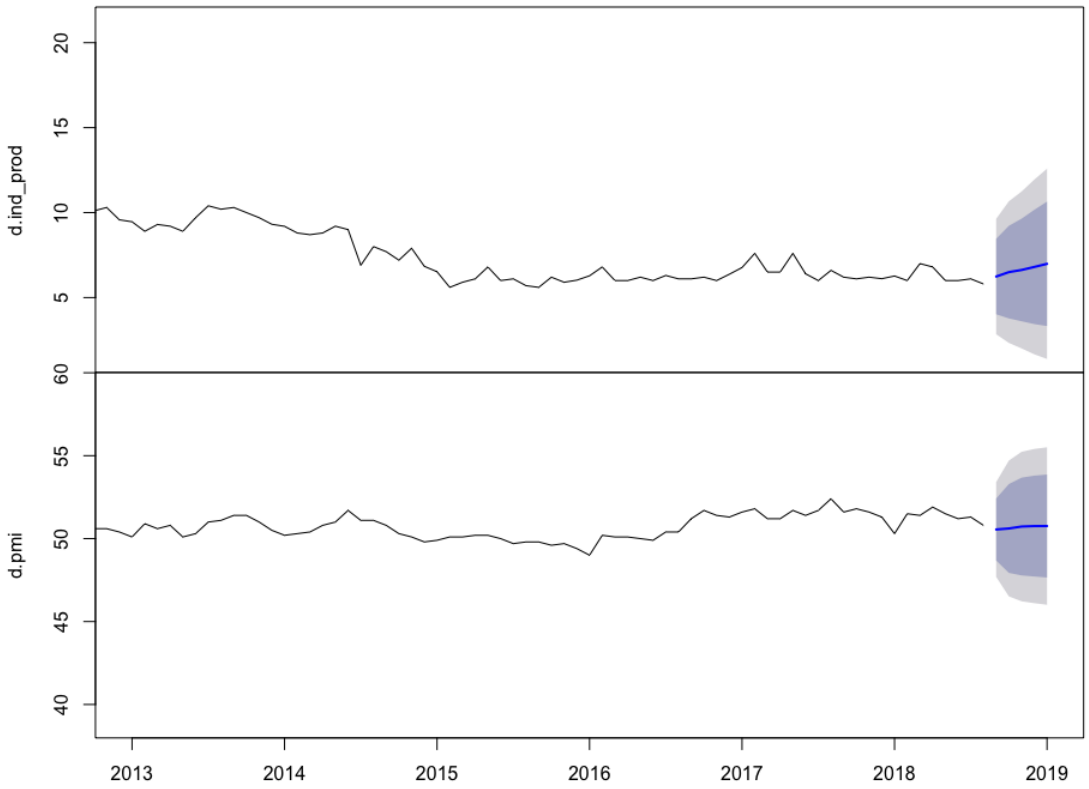


Figure 10: Forecasted Fan Charts from Bivariate Var (3)

## *5.5 Comparison to AR Model*

We can compare the effectivness of the VAR(3) model by calculating the **Relative Root Mean Squared Error (RRMSE)**. The ratio of the RSME of each model suggests the relative forecasting ability of each model. Table 3 presents the estimates for each of the $h$ forecasted lags ahead. A value of less than 1 indicates the $VAR(3)$ model utilising the PMI information is a better predictor than the $AR$ model using only lags on industrial value-added itself. All values for all calculated lags are less than 1 indicating the VAR model does indeed outperform the AR.

| Predicting Variable | $h = 1$ | $h = 2$ | $h = 3$ | $h = 4$ |
|---|---|---|---|---|
| PMI in VAR(3) | 0.46 | 0.35 | 0.48 | 0.75 |

Table 3: Relative Root Mean Square Error Calcuation

# 6 Conclusion

This paper has displays both depth and breath of analysis through the presentation of an overview of the current economic environment in light of recently released data and also an investigation into the use of PMI as a leading indicator with predictive power. In covering this ground, the analysis begins to show how PMI can forecast higher frequency and reliability elements of GDP which in turn can be used to give headline predictions of the health of the Chinese economy. Such leading indicators will become valuable metrics to observe over the coming months to determine both the source and severity of the slowdown in growth.