Assignment 3 - Money and Income

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Abstract

Proving a causal link between money supply and income has been an elusive goal in recent decades - research results vary due to choice of testing methods and time period used. Our estimates indicate that there exists some indication of Granger-causality between Industrial Production Index (IPI) and Money supply (M1), however, this varies with the time period and the method used.

Introduction

The link between money and industrial production is interesting to policy makers as they would want to stimulate output. If this policy is to be effective, there needs, however, to be a causal link between money and output. A problem arises however as money supply is in turn determined by previous and forecasted values of output.

A recent paper by Shi *et al.* (2020) provides insightful analysis and summary of recent research in determining causal relation between money and income. Based on their suggestions and conclusions about methods used in this analysis, we continue this discussion by testing whether there exists any causal relationships between money supply (M1) and Industrial Production Index (IPI), that is used to proxy real economic activity. The purpose of this paper is to add and contribute to the existing commentary on the Granger causality.

The remaining sections of this paper are organised as follows. Section 1 provides us with a theoretical background on VAR, VECM and Granger-causality concept. Section 3 and 4 gives a short description of data used and the implementation process. Section 5 describes results obtained by using VECM and VAR models, while Section 6 concludes.

Estimation Process

We are interested in determining whether changes in explanatory variable z_t have some causal effect on dependent variable y_t. For this, the distributed-lag model was introduced, allowing contemporaneous and lagged values of z_t to explain dynamics of y_t. However, since we cannot assume errors being i.i.d., the ADL model was introduced to deal with this, which not only solves the necessity to use HAC standard errors but also is more efficient, see equation 1 (Westerlund, 2019).

$$y_t = a_0 + a_1 y_{t-1} + \ldots + a_p y_{t-p} + c_0 z_t + \ldots + c_r z_{t-r} + \varepsilon_t \qquad (1)$$

A problem with the ADL model is that contemporary effects of z_t on y_t may in term be determined by y_t, giving rise to the problem of feedback and causing z_t to become biased.

A vector autoregressive (VAR) model is simply a multi-equation ADL and, as opposed to only a single equation in ADL, this allows us to pursue simultaneous analysis of multiple variables. See an example of a VAR ($k = 2$)system of equations in 2.1 and 2.2 (Westerlund, 2019).

$$y_t = a_{y1} y_{t-1} + \ldots + a_{yp} y_{t-p} + c_{y1} z_{t-1} + \ldots + c_{yp} z_{t-p} + \varepsilon_{yt} \qquad (2.1)$$

$$z_t = a_{z1} y_{t-1} + \ldots + a_{zp} y_{t-p} + c_{z1} z_{t-1} + \ldots + c_{zp} z_{t-p} + \varepsilon_{zt} \qquad (2.2)$$

Notice that in this form we do not have contamperous values.

To determine how many lags are required, one can still estimate AIC or BIC tests as in the ARMA model. However, to assess whether lags of variable x_t have effect on y_t, i.e., where x_t is said to "Granger cause" y_t (Westerlund, 2019), we must use the Granger non-causality test. Under H_0, lags of x_t have no effect on y_t and it seems unlikely that any x-values would cause y.

Granger causality is defined using the original definition as seen in equation 3, which was provided by Granger (1969).

$u_{1.t+1} = y_{1.t+1} - E[y_{1.t+1} | y_t; \theta]$ (3)

Where $u_{1.t+1}$ is the one-step ahead forecast error of $y_{1.t+1}$which is the realised value at time period t+1. θ is the estimated parameter that is a part of the y equation. Granger-causality means that, given a correct specification of θ, we will be able to reduce the mean square forecast error where the error is defined as by$u_{1.t+1}$.

If there is no granger causality, then θ will not be able to reduce the mean square forecast error. θ does not improve our estimate of future values. In this context, we explore the relation between money and income. A granger causality study concentrates on forecasting outcomes. Money can improve on the forecasts of income and how to affect future income through the use of monetary policy. For example, when quantitative easing regulations were inserted to cover for the 2008 crisis. In order to establish a relation, we use a simplified VAR model.

In general, any combination of non-stationary variables is non-stationary, however, as the sample grows, t-test values will increase and it will become increasingly difficult to reject regressors being statistically insignificant. This results in a spurious result with non-zero R^2 value. A spurious false result will not arise if there exists a linear combination between variables that is stationary, thus leading them to be *cointegrated*. A standard approach for a case when there exists only one cointegrated relationship between the variables is to use the Engle-Granger test. However, should we continue this test for more than two variables (thus possibly having more that 1 cointegrating relationship), we can misinterpret cointegration between variables and erroneously interpret long run effects. Hence, we use the Vector Error Correcting Method (VECM) approach. The Johansson test is then run, which is an extension of the VECM approach. Under H_0, $r = 0$, i.e., cointegration between the variables does not exist.

Data

The data provided consists of 2 sets of variables: money stock (M1) and Industrial Production Index (IPI). They span from January 1959 up until December 2019 on a monthly basis (see Figure 1). The two variables are found to be non-stationary and integrated of order 1.

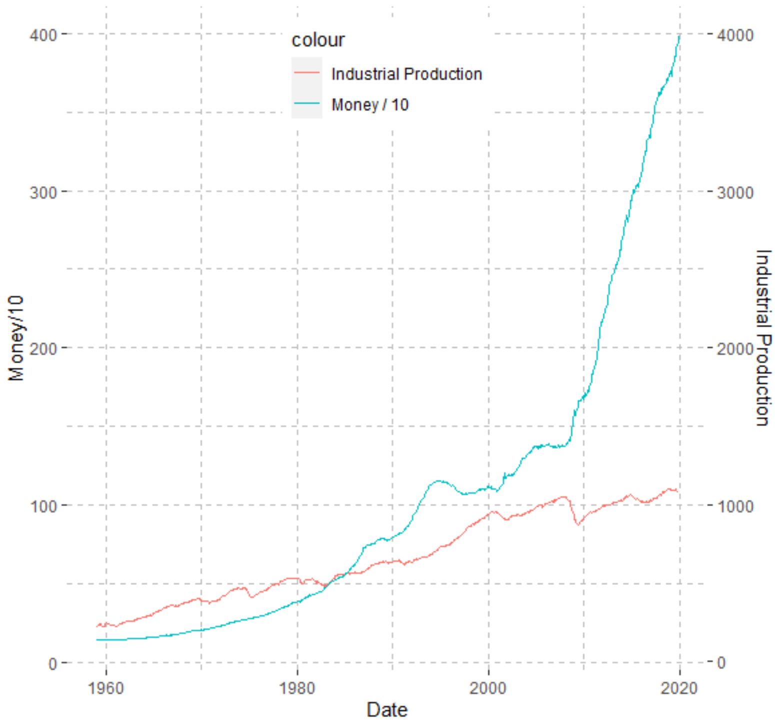

Figure 1. M1 and IPI 1959-2019 (FRED, 2020)

Implementation

Since the data is integrated of order 1, we run the Johansen test procedure run in order to establish if there is a cointegrating relationship. If there is such a relationship we may use it to have greater consistency of our estimates. As per the Johansen procedure run, for the value of $r = 0$, we obtain a test statistic of 254.43, which is greater than the critical value of 1% at 24.60. Our t value is much greater than what is required. Moving on, we fail to reject the null hypothesis in step 2, H_0: r = 1. The rank of the matrix is therefore determined to be 1, at the 1% level. This means that there exists one cointegrating relationship which we will use in the VECM approach.

In the VAR approach we difference the variables and include a constant. We cannot take the level data of the variables as they are non-stationary which would cause trending, but unrelated variables to become significant, despite having no relationship with each other.

The lowest value used in all our approaches (as per the AIC) is 10 lags. We also included monthly dummies due to the monthly frequency of the data in order to capture some seasonality.

Results

When running the VECM with 10 lags and 1 cointegrating relationship, we find that speed of adjustment parameter is insignificant for the industrial production equation, but significant for the money equation. This means that money responds to a disequilibrium in the cointegrating relationship whilst industrial production keeps growing and is not affected by the disequilibrium. We run the model for different time periods in order to check for robustness and since previous literature have found that including data during the 1980s increases the significance between money and income (Shi *et al.*, 2020). We therefore ran the model for the following time periods: pre 1980s, post 1980s and during the 1980s. The only time that the speed of adjustment parameter is significant is in the period post 1980s and for the full sample, but this is in the money equation which goes against the previous literature as money should affect industrial production.

To test the results that industrial production granger causes money holds, we will use a VAR model in first differences. The null hypothesis of the resulting Granger causality test was rejected, which implies that money granger-causes industrial production. We also found that industrial production granger-causes money which is not surprising given the results from our VECM. This may however imply that there is some third underlying factor that causes both money and industrial production. Previous literature indicates that variables that affect industrial production may be prices and interest rates (Shi *et al*., 2020).

As per previous literature we split the sample in order to test the 1980s separately. The periods pre and post 1980s did not make the granger causality significant, but when only looking at the period during the 1980s, we find high significance of granger causality. The effect of money on IPI holds only when examining the 1980s. Industrial production does not, however, granger-cause money during the subsamples but significance is found when looking at the entire sample. When looking at only the period before 1980s we find that industrial production granger causes money, but not vice versa. This relationship does not hold post 1980s as there is no rejection of the null of the Granger causality test.

Conclusion

Based on the results from the VAR and the VECM, we do not find sufficient evidence that money granger-causes industrial production. That is based on that only VAR showed significance when the 1980s is included in the sample. Its relevance for contemporary policy is therefore additionally limited, due to the non-significance when examining the period after the 1980s. Money seems to, in contrast, respond to industrial production in both approaches. Money responds to a disequilibrium in the cointegrating relationship after 1980s and for the full sample whilst in VAR, Granger causality is found in the full and pre 1980s samples.

Furthermore, one interesting result is that in one sample we observed a mutual Granger-causality between IPI and M1 which might be due to a third unobserved/excluded variable. Thus, according to Shi *et al*. (2020) variables that usually are included in VAR are interest rates and prices. One would therefore want to include these variables in following studies to solve this duality. Although the 1980s lend credence to that money granger-causes industrial production, it is unexpected given the previous literature but may result as a fact of the transition from fiscal policy towards monetary policy. Its application to today's policy may however be more limited.

Works cited

Droumaguet, M., A. Warne, and T. Wozniak (2017). Granger causality and regime inference in markov switching var models with bayesian methods. Journal of Applied Econometrics 32(4), 802–818.

Federal Reserve Bank of St. Louis (2020). M1 and Industrial Production index. Available from: https://fred.stlouisfed.org

Granger, CWJ. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica* 37, 424–438.

Shi, S., S. Hurn, and P. C. Phillips (2020). Causal change detection in possibly integrated systems: Revisiting the money–income relationship. Journal of Financial Econometrics 18(1), 158–180

Westernlund, J. (2019). Lecture materials in “Time series analysis”.