



Munich Personal RePEc Archive

The behaviour of disaggregated output over the economic cycle

Mashabela, Juliet and Raputsoane, Leroi

7 February 2018

Online at <https://mpra.ub.uni-muenchen.de/122906/>
MPRA Paper No. 122906, posted 10 Dec 2024 14:26 UTC

The behaviour of disaggregated output over the economic cycle

Juliet Mashabela* and Leroi Raputsoane**

February 7, 2018

Abstract

This study examines the behaviour of disaggregated output over the economic cycle in South Africa. Sectoral and industry level output is decomposed into its transitory and permanent components. The transitory components of sectoral and industry level output are then examined for comovement with the transitory component of aggregate output. The results show a strong positive comovement of the transitory components of all the economic sectors and majority of the industries with that of aggregate output. This is particularly the case with mining and quarrying, wholesale, retail trade and accommodation as well as finance, real estate and business services. The results particularly show a weak comovement of the transitory components of general government services as well as community, social and personal services with that of aggregate output which highlights a laissez faire approach of government to economic management. The results further show no distinction of industries, such as defensive, cyclical and sensitive industries, in contrast to the finance literature.

JEL Classification: C11, D20, E32

Keywords: disaggregated output, Economic cycle, Comovement

*Juliet Mashabela, sebolelom4@gmail.com, Johannesburg

**Leroi Raputsoane, lrputsoane@yahoo.com, Pretoria

Introduction

Studying the economic cycle is a long tradition in macroeconomics. Early contributions on the subject include Burns and Mitchell (1946) while the recent contributions include Kydland and Prescott (1990), Romer (1993) and Stock and Watson (1999). Hodrick and Prescott (1997) as well as Baxter and King (1999), among others, further advanced the literature on the isolation the economic cycle. The prominent areas of interest of this literature include dating of the phases of the economic time series as well as decomposing the economic time series into its components. The two strands of literature highlight the importance of the different shocks to the economy that include the demand and supply side policies, market rigidities as well as investor and consumer sentiments. The literature also highlight the effects of different shocks on the phases and components of the economy. Diebold and Rudebusch (1970) and Romer (1993) argue that the different economic sectors and industries respond differently to economic shocks. Thus comovement of the fluctuations of different economic sectors and industries could be because they are partially driven by common shocks due to the factors that include economic policies, investment as well as consumption decisions.

Calibrating policy formulation as well as investment and consumption decisions to economic fluctuations necessitates an understanding of how different industries behave relative to the economic cycle. For instance, according to the European Central Bank (ECB). (2012) and Morgan Stanley Capital International (MSCI). (2014), the investment literature distinguishes between types of industries, categorised into defensive, cyclical and sensitive industries, based on how they respond to economic fluctuations. The endogenous and exogenous shocks drive the phases of the economic cycle where the short term cycle is determined by demand side shocks while the long term cycle is determined by supply side shocks. The short term economic fluctuations, or the transitory component, emanate from changes in monetary, financial and fiscal policies as well as consumer and business sentiment. The long term economic fluctuations, or potential component, emanate from the nominal rigidities that include changes in technological advancement, privatisation, deregulation as well as multilateral agreements. The discussion on macroeconomic shocks can be found in (Nelson and Plosser, 1982), Kydland and Prescott (1990), Nelson (2005) and Christiano et al. (2005) while Diebold and Rudebusch (1970), Blanchard et al. (1986) and Campbell and Mankiw (1987) discuss the interaction of macroeconomic policies and the economic fluctuations.

This study examines the behaviour of disaggregated real output over the economic cycle in South Africa. Sectoral and industry level output are decomposed into their transitory and potential components. The transitory components of sectoral and industry level output are then examined for their comovement with that of aggregate output which approximates the total economy. The aim is to uncover the similarities as well as the differences in fluctuations, or procyclicality as opposed to countercyclicality, of sectoral and industry level output relative to output of the total economy over the short and long term horizons. This is important because economic policy formulation as well as investment and consumption decision making aimed to influence the macroeconomic fluctuations could have undesired results to the microeconomic fluctuations of the economy. This is particularly relevant for the economic sectors and industries whose short term and long term fluctuations do not match the fluctuations of the total economy overtime. Thus the paper is of particular interest to policy makers in that it will help to promote coherent sectoral and industry specific policy formulation as well as investment and consumption decision making in the economy.

The paper is organised as follows. Next is the discussion of the data. Then is the specification of the empirical model. This is followed by the presentation and interpretation of empirical results as well as the discussion of the policy implications. Last is the conclusion.

Data

The study uses data from Statistics South Africa spanning the period 1994 to 2015. The data comprises aggregate output, as well as output of the 3 main sectors and 10 industries. The industries are consistent with Statistics South Africa's Standard Industrial Classification (SIC) of all economic activities of 2012. The 3 main sectors are the primary sector, secondary sector and the tertiary sector. The 10 main industries are agriculture, forestry and fishing and mining and quarrying, which constitute the primary sector, Manufacturing, electricity, gas and water as well as construction, which make up the secondary sector, Wholesale, trade, catering and accommodation, transport, storage and communication as well as finance, real estate and business services, which represent the tertiary sector. General government services as well as community, social and personal services are excluded from the sectoral classification. Aggregate output, the the output of the 3 economic sectors and 10 economic industries is measured as real value added. The transitory components of the output measures are isolated from potential components, or periodicities, to uncover the similarities as well as the differences of their fluctuations over the short term horizon.

The transitory and potential components are achieved by first decomposing real output into the cyclical and the trend components using the Hodrick and Prescott (1997) filter. However, these cyclical and the trend components still contain the volatile and the permanent components, respectively. Therefore, both components are decomposed further to isolate the transitory and volatile component as well as the potential and permanent component, respectively. Thus, the duration of the volatile component is calibrated as a period of less than 2 years, the transitory component is about 3 to 5 years, the potential component is about 6 to 10 years, while the permanent component is a period of more than 10 years. The periodicities are identified by calculating the number of years that each component complete a full cycle consistent to those identified by the Business Cycle Dating Committee at the National Bureau of Economic Research (NBER). The economic cycle literature normally identifies 2 components while Baxter (1994) identifies 3 components that comprise the trend, cyclical and irregular components. The end point corrections are made to the components data series following Baxter and King (1999) as well as Kaiser and Maravall (2012).

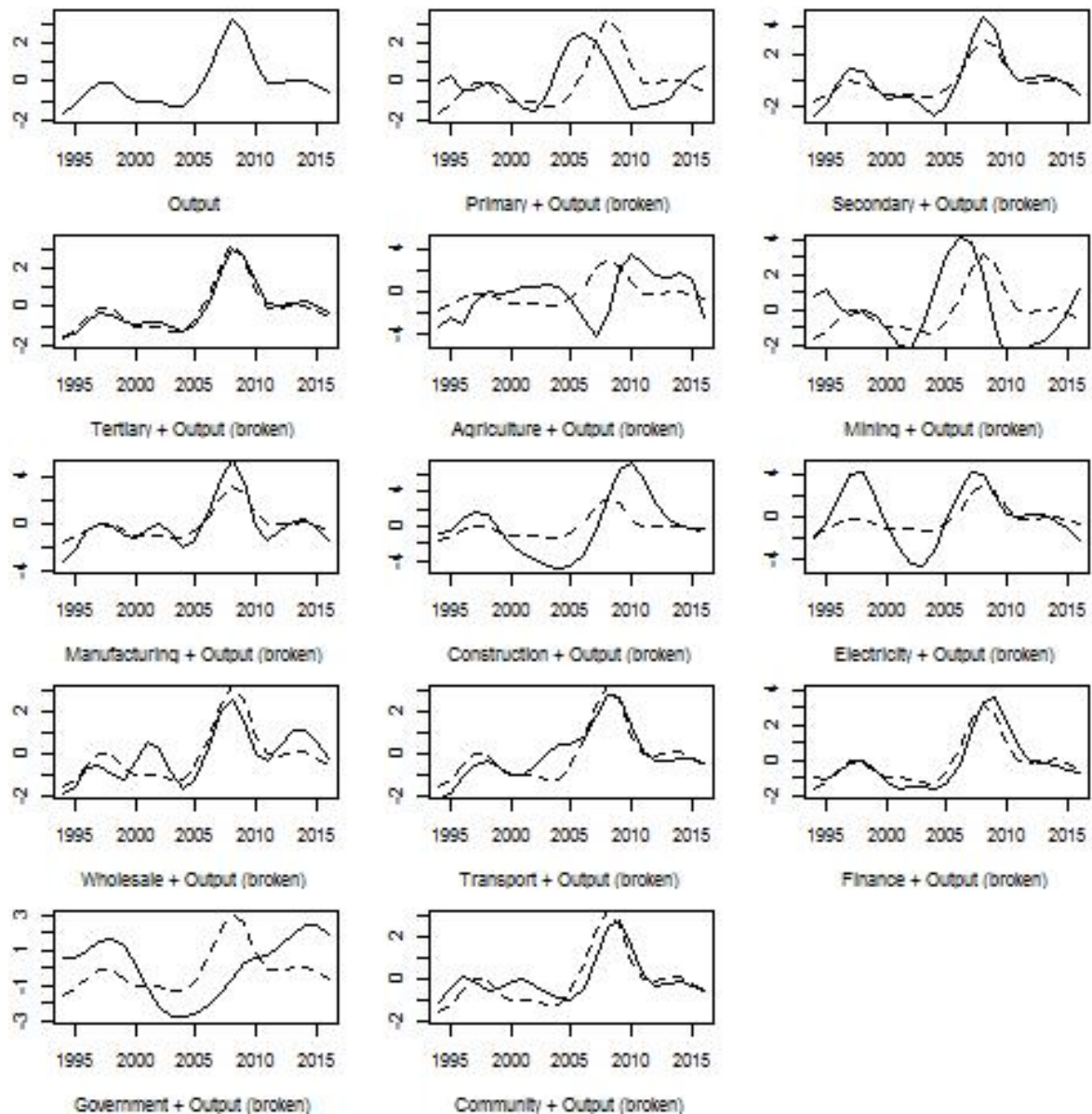
The descriptive statistics of the transitory components of aggregate output as well as output of the 3 main economic sectors and the 10 industries are presented in Table 1. The maximum value of aggregate output is about 3.2, mainly on account of real output of the secondary sector. The minimum value of aggregate output is about -1.6, also mainly on account of the secondary sector. As a result, the standard deviation of the secondary sector is the biggest compared to those of the primary and the secondary sectors implying higher volatility. The industries that realised the extreme maximum values during the sample period are construction, manufacturing, mining and quarrying, as well as electricity, gas and water. In the same period, the extreme minimum values were recorded by construction, electricity, gas and water, agriculture, forestry and fishing as well as manufacturing. The mean values of all the transitory components are about 0 given that all the components data series are deviations from their long term trend values. The transitory components of agriculture, forestry and fishing, construction, electricity, gas and water as well as mining and quarrying have the biggest standard deviations compared to those of the other industries.

	Maximum	Minimum	Mean	Std.Dev.
Output	3.172986	-1.621214	-0.098096	1.256560
Primary	2.552061	-1.572883	-0.045848	1.172615
Secondary	4.744619	-2.711067	-0.101650	1.924876
Tertiary	2.928783	-1.541787	-0.090768	1.210091
	Maximum	Minimum	Mean	Std.Dev.
Agriculture	3.518280	-4.085274	-0.241664	2.060928
Mining	4.049341	-2.852676	-0.044092	1.938303
Manufacturing	5.286347	-3.280508	-0.183558	1.986714
Construction	7.253434	-4.831704	0.002192	3.372792
Electricity	4.303795	-4.725057	0.121428	2.679630
Wholesale	2.545441	-1.922662	-0.090028	1.183899
Transport	2.781601	-2.146144	-0.054931	1.243341
Finance	3.628669	-1.639766	-0.130640	1.511721
Government	2.441923	-2.816379	0.114790	1.720897
Community	2.722267	-1.161521	-0.014114	1.005249

Notes: Own calculations with data from Statistics South Africa. Maximum measures the the biggest value of real output during the sample period, Mean shows the average value of real output, Minimum is the smallest value of real output and Std.Dev. is the standard deviation of real output during the sample period.

Table 1: Descriptive statistics of the transitory components

The graphs of the transitory components are depicted in Figure 1. The transitory component of aggregate output increased between 1994 and 1997 and then decreased from 1998 and reached a low in late 2003. It subsequently accelerated sharply reaching an all time high in late 2008 where it fell abruptly to 2012. The steady but slow growth of the transitory component of aggregate output between 2011 and 2014 was followed by the decrease to the end of the sample. The transitory components of the secondary and tertiary sectors tend to move closely with that of aggregate output while the opposite is true for the primary sector. The transitory components of most industries move closely with aggregate output, in particular, wholesale trade, catering and accommodation, transport, storage and communication as well as finance, real estate and business services while the opposite is true for agriculture, forestry and fishing, mining and quarrying as well as general government services.



Notes: Own calculations with data from Statistics South Africa. The transitory components are measured as percentage deviation and are derived by isolating the volatile component from the short term component.

Figure 1: Graphs of the transitory components

Methodology

The behaviour of disaggregated real output over the economic cycle is analysed using Bayesian Model Averaging (BMA). Bayesian Model Averaging (BMA) method was proposed by Leamer (1978), introduced by Bartels (1997) and is described in detail in Hoeting et al. (1999). Bayesian Model Averaging (BMA) emphasises variable importance when selecting the relevant variables in high dimensional data where information may usually be scattered through a large number of potential explanatory variables. Bayesian Model Averaging (BMA) accounts for the model uncertainty inherent in variable selection. The method also overcomes the omitted variable bias by averaging over the best models providing an optimal way to capture the underlying relationships between the variables. Thus, according to Hoeting et al. (1999), Bayesian Model Averaging (BMA) efficiently minimises the estimated parameters towards the stylised representation of the data leading to sound inference.

The empirical Bayesian Model Averaging (BMA) model is specified following Feldkircher and Zeugner (2015) where the details can be found. Given a vector of the dependent variable y_t , which contains the transitory and potential components of output, and a matrix of explanatory variables X_t , which contains the transitory and potential components of disaggregated real output, Bayesian Model Averaging (BMA) model is specified as follows

$$y_t = \alpha_{\gamma t} + X_{\gamma t} \beta_{\gamma t} + \epsilon_t \quad , \quad \epsilon_t \sim N(0, \sigma^2) \quad (1)$$

where $\alpha_{\gamma t}$ is a constant, $\beta_{\gamma t}$ are coefficients, ϵ_t is the error term with mean 0 and variance σ^2 . In the event of high dimensional data, the variable selection approach estimates all the possible combinations of $X_{\gamma t}$ and constructs a weighted average over them to circumvent the problem of identifying the explanatory variables to include in the model. Thus $X_{\gamma t}$ contains K variables where 2^K variable combinations are estimated resulting in 2^K models.

The model weights for Bayesian Model Averaging (BMA) are derived from posterior model probabilities using Bayes theorem as follows

$$p(M_\gamma | y, X) = \frac{p(y | M_\gamma, X) p(M_\gamma)}{p(y | X)} = \frac{(y | M_\gamma, X) p(M_\gamma)}{\sum_{\gamma=1}^{2^K} p(y | M_s, X) p(M_s)} \quad (2)$$

where $p(M_\gamma | y, X)$ is the posterior model probability, M_γ is the true model, $p(y | M_\gamma, X)$ is the marginal likelihood of the model, $p(M_\gamma)$ is prior model probability and $p(y | X)$ is the constant integrated likelihood over all models. The Posterior Model Probability (PMP) is

$$p(y | X) p(\beta_\gamma | y, X) = \sum_{\gamma=1}^{2^K} p(\beta_\gamma | M_\gamma, y, X) p(M_\gamma | y, X) \quad (3)$$

where β_γ are the parameters of the model. The unconditional coefficients of the model are

$$E(\beta_\gamma | y, X) = \sum_{\gamma=1}^{2^K} p(\beta_\gamma | M_\gamma, y, X) p(M_\gamma | y, X) \quad (4)$$

where the Prior Model Probability (PMP) has to be proposed based on prior knowledge or believe. According to Varian (2014), Bayesian Model Averaging (BMA) analyses models with high dimensional data revealing the interdependence among the variables hence the method leads to new ways to understand the underlying relationships between the variables.

Results

Bayesian Model Averaging (BMA) uses Bayesian statistics hence it requires the specification of the prior distributions on the model parameters and the model space, the Markov Chain Monte Carlo (MCMC) sampler, the number of draws that the sampler runs, or iterations, and the number of the first iterations, or burnins, to be omitted from the estimation results. The number of draws refers to the number of iterations that that the MCMC sampler runs. Burn ins are the number of initial iterations to be omitted. MCMC is the Markov chain Monte Carlo sampler to be used in estimation. Model prior is the mass on model size and g Prior is the hyper parameter that determines the degree of prior uncertainty. The following pre estimation model statistics were chosen for all estimations. The number of draws and burnins for the MCMC sampler were set to 1 000 000 and 100 000, respectively. The MCMC sampler is birthdeath while the hyper parameter on the Zellner (1986) g-prior is BRIC.

The model statistics of the comovement between the transitory components are presented in Table 2. The model space is 8.000 and 1024.000 given the 3 economic sectors and 10 economic industries, respectively. The mean number of regressors, which shows the average number of regressors with relatively high probability of inclusion in the estimated models, is 2.900 for the economic sectors model and 5.329 for the economic industries model. Thus economic sectors and the economic industries models predict about 2 and 5 variables on average with high probability of inclusion in the estimated models, respectively. PMP Correlation shows that the degree of convergence between the prior and the posterior model probabilities is reasonably high for all the estimated models at 1.000 for the economic sectors model and 1.000 for the economic industries model. The Shrinkage factor, which is a goodness of fit indicator, is 0.958 for the economic sectors model and is 0.990 for the economic industries model which show an almost perfect goodness of fit for both the estimated models.

	Economic sectors	Economic industries
Model space	8.000000	1024.000
Mean regressors	2.909900	5.328800
PMP correlation	1.000000	0.999700
Shrinkage factor	0.958300	0.990100

Notes: Own calculations with data from Statistics South Africa. Model space measures the variable combinations in the estimated models. Mean Regressors are covariates with high probability of inclusion in the estimated models. PMP Correlation is the degree of convergence between the prior model probability and posterior model probability and Shrinkage Factor is the goodness of fit indicator of the estimated models.

Table 2: Model statistics of the transitory components

The results of the comovement between the transitory components are presented in Table 3. The top panel presents the results of the economic sectors while the bottom panel presents the results of the economic industries. The results of the economic sectors show a strong positive correlation between the secondary and tertiary sectors and aggregate output, while it shows a weak positive correlation of the primary sector and the aggregate output. The posterior inclusion probabilities show that the primary, secondary and tertiary sectors are included in over 90 percent of the models that explain aggregate output. The posterior mean shows that a 1 percent increase in transitory component of primary, secondary and tertiary sectors is associated with 0.133, 0.281 and 0.531 percent increase in the aggregate output, respectively. The conditional position signs of the main sectors are all 1.000, which show a 100 percent certainty of a positive relationship between output of the economic sectors and aggregate output. Thus the comovement between the secondary and tertiary sectors and aggregate output is a strong and positive while that of the primary sector is weak.

The results of the main economic industries show a strong correlation between the manufacturing, transport, storage and communication as well as finance, real estate and business services with the aggregate output. Mining and quarrying as well as general government services show a weak correlation with the aggregate output while agriculture, forestry and fishing show virtually no correlation with the economic cycle. The posterior inclusion probabilities show that mining and quarrying, wholesale, retail trade and accommodation as well as finance, real estate and business services industries are included in over 70 percent of models that explain the aggregate output. The opposite is true for general government services and community, social and personal services which are included in only about 16 percent of the models that explain the aggregate output. The posterior mean shows that a 1 percent increase in the transitory components of finance, real estate and business services, manufacturing as well as wholesale, retail trade and accommodation lead to 0.28, 0.19 and 0.17 percent increase in the transitory component of the aggregate output, respectively while a 1 percent increase in general government services as well as community, social and personal services is somehow associated with virtually no increase in the aggregate output.

	Corr.Coef	Post.Inc.Prob	Post.Mean	Con.Pos.Sign
Primary	0.272941	0.949834	0.133282	1.000000
Secondary	0.973593	0.970248	0.280961	1.000000
Tertiary	0.977752	0.989714	0.531355	1.000000
Economic industries	Corr.Coef	Post.Inc.Prob	Post.Mean	Con.Pos.Sign
Agriculture	-0.015786	0.492615	0.020723	0.676857
Mining	0.228654	0.739346	0.093783	1.000000
Manufacturing	0.931622	0.661032	0.185343	0.999991
Construction	0.594637	0.503337	0.040920	0.772155
Electricity	0.691808	0.558648	0.036152	0.937730
Wholesale	0.820575	0.703269	0.170245	0.999989
Transport	0.879496	0.603666	0.125681	0.992057
Finance	0.935567	0.745828	0.288176	1.000000
Government	0.052605	0.156589	0.000421	0.566291
Community	0.883629	0.155750	-0.004840	0.407801

Notes: Own calculations with data from Statistics South Africa. Corr.Coef is the correlation coefficient and the associated p value, Post.Inc.Prob is the posterior inclusion probability, Post.Mean is the posterior mean and the associated posterior standard deviation and Con.Pos.Sign is the probability of positive coefficient.

Table 3: Model results of the transitory components

The conditional position signs show a strong probability of a positive relationship between all the economic sectors and most economic industries, that include Mining and quarrying as well as finance, real estate and business services, and aggregate output. The opposite is true for agriculture, forestry and fishing as well as general government services which show a weak probability of a positive relationship with real output while community and personal services show a weak probability of a negative relationship with aggregate output. Thus the comovement between the Mining and quarrying, manufacturing, retail trade and accommodation as well as finance, real estate and business services and aggregate output is a strong and positive while there generally a weak comovement between agriculture, forestry and fishing, general government services as well as community, social and personal services. In particular, not only are the coefficients associated with the agriculture, forestry and fishing, general government services as well as community, social and personal services industries small but their signs of the relationship with aggregate output are largely inconclusive.

As discussed above, calibrating policy, investment and consumption decisions to economic fluctuations necessitates an understanding of how different economic sectors and industries behave relative to the economic cycle. This is because industries respond differently to economic fluctuations hence the comovement of different industries in the economy may be because they are driven, to a large extent, by common shocks. The results have provided evidence of a generally strong positive relationship between the transitory of the tertiary sector, in particular, the finance, real estate and business services industry, while the opposite is true for the transitory of the primary sector, in particular, the agriculture, forestry and fishing industry. Contrary to the investment literature, there does not seem to be a clear distinction between the different economic industries by categories, such as the defensive, cyclical and sensitive industries. Consequently, the paper has enhanced the understanding of how the different economic sectors and industries behave relative to the economic cycle in the short run in quest to promote coherent sectoral and industry level policy formulation as well as to foster informed investment and consumption decision making in the economy.

Conclusion

This study examined the behaviour of disaggregated sectoral and industry level output over the economic cycle in South Africa. The transitory components of aggregate output as well as the sectoral and industry level output were isolated from their permanent components. The transitory components of the main economic sectors and industries were then examined for their comovement with those of the aggregate output. The results show a strong positive comovement between all the economic sectors and aggregate output. They further show somewhat strong positive comovement of the Mining and quarrying, wholesale, retail trade and accommodation as well as finance, real estate and business services industries and aggregate output, while the opposite is true for general government services and community, social and personal services. Contrary to the investment literature, there does not seem to be a clear distinction between the comovement of economic sectors and industries with the aggregate output by categories, such as defensive, cyclical and sensitive industries. A weak comovement of general government services and community, social and personal services with aggregate output show a laissez faire approach to economic management by government.

References

- Bartels, L. M. (1997). Specification Uncertainty and Model Averaging. *American Journal of Political Science*, 41(2):641–674.
- Baxter, M. (1994). Real Exchange Rates and Real Interest Differentials: Have We Missed the Business Cycle Relationship? *Journal of Monetary Economics*, 33(1):5–37.
- Baxter, M. and King, R. G. (1999). Measuring Business Cycles: Approximate Band Pass Filters for Economic Time Series. *Review of Economics and Statistics*, 81(4):575–593.
- Blanchard, O. J., Hall, R. E., and Hubbard, R. G. (1986). Market Structure and Macroeconomic Fluctuations. *Brookings Papers on Economic Activity*, 1986(2):285–338.
- Burns, A. F. and Mitchell, W. C. (1946). Measuring Business Cycles. *NBER Books*. National Bureau of Economic Research Inc.
- Campbell, J. Y. and Mankiw, N. G. (1987). Permanent and Transitory Components in Macroeconomic Fluctuations. *American Economic Review*, 77(2):111–117.

- Christiano, L. J., Eichenbaum, M., and Evans, C. L. (2005). Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy. *Journal of Political Economy*, 113(1):1–45.
- Diebold, F. X. and Rudebusch, G. D. (1970). Measuring Business Cycles: A Modern Perspective. *Review of Economics and Statistics*, 78(1):67–F77.
- European Central Bank (ECB). (2012). Stock Prices and Economic Growth. *Monthly Bulletin*, October.
- Feldkircher, M. and Zeugner, S. (2015). Bayesian Model Averaging Employing Fixed and Flexible Priors. *Journal of Statistical Software*, 68(4):1–37.
- Hodrick, R. and Prescott, E. C. (1997). Postwar U.S. Business Cycles: An Empirical Investigation. *Journal of Money, Credit and Banking*, 29(1):1–16.
- Hoeting, J. A., Madigan, D., Raftery, A. E., and Volinsky, C. T. (1999). Bayesian Model Averaging: A Tutorial. *Statistical Science*, 44(4):382–401.
- Kaiser, R. and Maravall, A. (2012). *Measuring Business Cycles in Economic Time Series*, volume 154. Springer Science and Business Media, 3 edition.
- Kydland, F. E. and Prescott, E. C. (1990). Business Cycles: Real Facts and a Monetary Myth. *Quarterly Review*, 4:3–18. Federal Reserve Bank of Minneapolis.
- Leamer, E. E. (1978). *Specification Searches: Ad Hoc Inference with Non Experimental Data*. John Wiley and Sons Inc.
- Morgan Stanley Capital International (MSCI). (2014). Cyclical and Defensive Sectors. *Indexes Methodology*, June. Morgan Stanley Capital International.
- Nelson, C. R. and Plosser, C. R. (1982). Trends and Random Walks in Macroeconomic Time Series: Some Evidence and Implications. *Journal of Monetary Economics*, 10(2):139–162.
- Nelson, E. (2005). Monetary Policy Neglect and the Great Inflation in Canada, Australia and New Zealand. *International Journal of Central Banking*, 1(1):133–179.
- Romer, C. D. (1993). Business Cycles. In Henderson, D. R., editor, *The Fortune: Encyclopedia of Economics*, volume 330.03 F745f. Warner Books.
- Stock, J. H. and Watson, M. W. (1999). Business Cycle Fluctuations in US Macroeconomic Time Series. *Handbook of Macroeconomics*, 1(Part A):3–64.
- Varian, H. R. (2014). Big Data: New Tricks for Econometrics. *Journal of Economic Perspectives*, 28(2):3–28.
- Zellner, A. (1986). On Assessing Prior Distributions and Bayesian Regression Analysis with g Prior Distributions. *Bayesian Inference and Decision Techniques*, 6:233–243.