An Analysis of the Empirical Modelling Approaches to the Real Business Cycle (RBC) Model and Aggregate Technology

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Abstract

This paper provides analysis of the various econometric modelling methods utilized in Real Business Cycle (RBC) Model to measure aggregate technology shocks. It sheds insight into the concept of employing the Solow residual (purified technology) to determine the shifts in the production function, and/or in essence estimate the shocks to the economy. In addition, it provides a comparative analysis of the different methodologies and findings. The findings in this study can serve as a useful tool for macroeconomic policy formulation and implementation, especially in relation to the whole economy performance, expansion, recession, employment and investments.

Key Words: Economy, Technology shocks, RBC Model, Solow Residual, SVAR

Introduction

The Real Business Cycle (RBC) model in the last few decades has become a dominant platform in macroeconomics. This is primarily through emphasises on the importance of quantitative aspects of business cycles and the provision of a rigorous analysis through dynamic general equilibrium modelling. This is in addition to the model accountability for a sizeable fraction of aggregate fluctuations. An example is the Prescott (1986) study that uses the Solow residual or purified technology as a proxy for technology shocks.

On the contrary, Albergaria de Magalhaes (2005), postulated that the problem with this type of investigation relates to the role played by technology shocks in generating fluctuations, thereby questioning the adequacy of Solow residual as a good proxy for technology shocks. Furthermore, it implies the model depended on the measure of productivity. There is a perceived assertion regarding measures that exclude variable rates of factor-utilization to be weak proxies for technology shocks whilst, those with, tend to have statistical properties close to the theoretical assumptions of RBC models. Studies with similar results include Burnside, Eichenbaum and Rebelo (1996) for the US industry, including Baxter and Farr (2001) using dataset on Canadian firms and US.

On the positive side for RBC, King and Rebelo (2000) suggested that the findings do not necessarily imply a major weakness for RBC modelling. The reason is that models with variable factor-utilization as propagation mechanisms, which tend to amplify shocks with a small magnitude. Equally, Jorgenson and Griliches (1967) using industrial electricity consumption as a proxy to capture variable rates of utilization for capital input. This includes a consideration of input measures that allows for differences in quality and utilization rates. To formulate stylized facts for countries and to explain the main distinctions between artificial and real economies RBC models are useful, for example, Kanczuk and Faria (2000), Val and Ferreira (2001) for Brazil. These models including Kydland and Prescott (1991), used calibration methods but their adequacy is debatable.

Labour – Hoarding, Productivity and True Technology Shocks

In regards to this hypothesis, productivity measures might exhibit a pro-cyclical pattern. For example, in periods of recessions, firms try to maximise their available resources, hence they do not dismiss its entire workforce but reassign some of them to other duties. The difficulty is, it is not possible to capture these activities through official statistics and once the economy begins to come out of recession, the normal observation is a rise in production without a corresponding rise in input use (hours).

This may seem at first as a productivity gain. The fact is firms had this apparent increase in productivity because of labour hoarding. In other words, the observed rise in productivity was spurious. Summers (1986) critique of Prescott (1986) was on this line, while Mankiw (1989) based his own critique on military build up for US over the period 1948 – 85, thereby, characterising it as demand shock. Shea (1999) made use of accident rate to refine the model for technology shock, thus finding effort per hour pro-cyclical and as such a favourable evidence for labor hoarding.

In addition to shocks emanating from labor hoarding, Burnside, Eichenbaum and Rebelo (1993), Burnside and Eichenbaum (1996) examine the sensitivity of TFP measures by using a modified general method of moments (GMM) procedure. This involved estimating a fraction of these measures variance attributable to labour hoarding. The analysis concentrated on the quantitative importance of capacity utilization rates for RBC models. It indicated a propagation mechanism in RBC models through time variable utilization rates. The volatility of productivity shock was low, hence the assumption that capacity utilization under this scenario is endogenous, and causes a gap between true technology shock, which is non-observable, and TFP measure which is observable. Through these observations, the conclusion is that RBC models tend to overestimate the fraction of technology shocks variability that is responsible for business cycles.

The Invariance Properties of Solow's Productivity Residual

One crucial aspect of the Solow residual is the invariance properties. To measure the shift of the production function, Solow (1957), indicate subtracting a Divisia index of input growth from output growth. The main assumptions of the derivation are competition and constant returns to scale (CRS hereafter). Under CRS and competition, the Solow residual measures the shift of the production function. In addition, the method provides a means to measure the trend in productivity, by taking the average rate of growth of the Solow residual as the best measure of the average rate of growth of the Hicks-neutral multiplicative component of the production function.

The question therefore is whether the estimated productivity measures have the same properties as those postulated in the RBC models. As for criticisms of RBC, model characterization of technology shock to the invariance property enunciation is that: "Under competition and constant returns to scale, the Solow residual is uncorrelated with all variables known neither to be causes of productivity shifts nor to be caused by productivity shifts". Therefore, the assumption of perfect competition, implying firms and/or workers receives their marginal products and factor shares to exhaust output. This assumption made it necessary to determine if there is a correlation between measures of productivity and an instrument set. The instruments employed include military spending, international oil prices and the political party of the President; see also Anyalezu (2011, and 2013 respectively). The objective for using the instruments is to capture variables that have no relationship with productivity. However, for Hall (1988), the analysis indicates that the productivity measures used have a correlation with the instrumental variables.

The implication is that productivity may exhibit a pro-cyclical pattern even though the economy's production technology remains relatively the same. Furthermore, Basu and Fernald (BF1997) and others have criticized Hall's choice of instruments. Hartley (1994) argued that the Solow residual may not reliably capture technology shocks by using simulated economies constructed from an adopted Hansen and Sargent (1990) flexible, dynamic linear-quadratic equilibrium macro model. In view that these were simulations, the variability in the series arises only from technology shocks and not market power or labour hoarding. In other words, the Solow residuals reflect a specification error rather than technological change. The reason for this conclusion is the low correlation between controlled technology shocks and the Solow residuals calculated from simulation series.

Evans (1992) using quarterly data tested the exogeneity of the Solow residual for the US over the period 1957 – 83; that is, Granger-causality tests including TFP measures and other macroeconomic variables such as monetary aggregates M1, interest rates, government spending, consumer price index and oil prices. The assumption is that if these macroeconomic variables Granger-cause the Solow residual, then productivity measures is not exogenous. The results showed that TFP measures are Granger-caused by the monetary aggregates used, interest rate and government spending. The other concern relates to the fraction of TFP impulses attributable to demand shocks. On the contrary, Otto (1999), Paquet and Robidoux (2001) using a corrected measure for Canadian economy found these measures are not Granger-caused by any of the macroeconomic variables. This now brings us to the issues of conjectures made by RBC proponents.

Karl Popper (1959, 1972) viewed science as progresses through a series of bold conjectures subjected to severe tests, with some false and accordingly refuted. The truth by definition survives and not refuted. Hartley et al (1997) argued that RBC models are bold conjectures in the Popperian mould and refuted based on the preponderance of the evidence. The assessment of the model focused on the original Kydland and Prescott model and its successor models. Despite all the critiques, there are some novelties with the RBC models. We can explore some of them below.

A Consideration of the Novelty of RBC Models

This section reviews the historical development of the real business cycle model. The Solow (1956, 1970) neoclassical growth model is a very good example to start with. For instance, aggregate output (Y) obtained in the model in accordance to constant returns to scale production function $F(\cdot)$ with aggregate capital K, labor L and a production technology represented by T, hence the production function expression as:

$$Y = F(K, L, T) \qquad (1.0)$$

The model therefore derives consumption from a Keynesian function as:

$$C = (1 - s)Y \qquad (1.1)$$

Where s is the marginal propensity to save with an assumption to achieve long-term growth. Thus, saving (S) is equal to investment (I) ex ante and ex post:

$$\mathrm{I} = \mathrm{S} \qquad (1.2)$$

It is assume, Capital depreciates at the rate δ and grows with investment I. Therefore, expressing the relationship as:

$$\dot{K} = I - \delta K = sY - \delta K \qquad (1.3)$$

where $\dot{K}$ denotes the rate of change of capital with labor growing exogenously at a rate n per unit time, and labor augmenting technology t improving at a rate g per cent per unit time. The effective labour growth at $n + g$ and given the above expressions, the economy will converge to a steady state. Along the steady state growth path, both capital and effective labor will grow at the rate $n + g$. Equally, as the inputs to production are growing at that steady rate, the same will apply to output. Therefore, with the assumption of savings equal to investments, the model will remain in equilibrium but not necessarily in steady state. In which case, whenever the economy moves away from the steady state, a change in s or n, will induce changes in capital and output and as such, adjusts to a new steady state.

Lucas (1975) adopted the Solow growth model to analyse business cycles. In Lucas (1972, 1973), business cycle was viewed as the reaction of workers and firms to expectation errors induced by monetary policy. Therefore, to shift from short-term expectation errors to long run cycles, Lucas provided a distinction between impulses that begin a business cycle and propagation mechanisms that perpetuate a cycle. The assumption is that expectation errors were the impulses responsible for shifting the economy away from the steady state.

The implication of this is that, in terms of the after-shocks, the economy will remain in disequilibria until there is a correction to the expectation errors. The process of adjusting capital in order to return to steady state is the propagation mechanism. In accordance with the new classical economics of transforming macroeconomic to microeconomic foundations, Lucas replaced the stripped-down demand of the Solow growth model with an assumption of utility-maximizing choices of a representative agent. A representative agent chooses consumption and labor supply by solving a dynamic, inter-temporal optimisation problem. However, there is still a fundamental problem with the aggregate demand pathologies. This is because in Lucas's model, the agents use the same savings and investment decisions. In addition, labor supply responded elastically to temporarily high real wages.

In terms of the study by Kydland and Prescott (1982), the perception is very distinct from Lucas's model in that there is no monetary sector, while technology shocks or deviation of t in equation (1.0) above from trend provides the impulse to business cycles. Equally, there are no expectation errors in the model. Therefore, technological change has real effects. It is the finding of impulses in technology shock and the modelling of the economy in continuous equilibrium that distinguishes the real business cycle model from earlier business cycle models, as demonstrated in Anyalezu (2011).

The value of the depreciation rate (δ) is also derived in the same appropriate fashion. Similarly, equations (1.1) and (1.2) represent aggregate demand in the Solow growth model and are substitutes in RBC models by an optimisation problem for a representative agent, holding both the consumer and producer roles. The representative agent maximizes a utility function as:

$$U = U(\{C_t\}, \{L_t\}) \qquad (1.4)$$

This is subject to current and future production constraints given by equation (1.1) in addition to equation (1.0). In this case, the first set $\{C_t\}$ is the set of current and future levels of consumption, while $\{L_t\}$ is the set for current and future supplies of labor. The calibrated model is non-linear and to solve the model, the equation requires reformulation as linear approximations around the unknown steady state. From this point, RBC models abstract from the concerns of traditional growth theory, without seeking any explanation for the steady state but instead concentrated on (equilibrium) deviations from the steady state. Therefore, transforming the Cobb-Douglas production function (1.0) will give

$$Ln(Z) = \ln(Y) - \theta\ln(L) - (1 - \theta)\ln(K), \qquad (1.5)$$

That is, the empirical measure of the technology parameter usually, referred to as the Solow residual or purified technology. Estimating this using actual data will show a trend as explored and modelled in Anyalezu (2011). This means that $g \neq 0$ and therefore must be de-trending before being use as an input to the real business cycle model. Detrended ln(Z) is the state-variable T , or technology shock. Generally, t will be a persistent process; for example, $T_t = \rho T_{t-1} + \varepsilon_t$ with $\rho > 0$ and ε_t an independent, identically distributed random variable. The data used in estimating contractionary effects in Anyalezu (2011) were subject to HP filtering and detrending including, stationary test and heterogeneity test. I will explain about HP filter later. So what are the views from the tests? The next subsection sheds some lights to this question.

Perceptions on Testing

This study has so far extensively focus on the RBC model and as such, it is necessary to ascertain exactly what RBC model is supposed to explain and the applicable test. Real Business Cycle model has traditionally attempted to predict what causes output to fall and then rise again. Therefore, when output declines, the expectation is for employment, income and trade to decline accordingly. Equally, when technology improves, the RBC prediction is that employment will rise. The RBC theorists deem technology as the driving force behind the business cycle.

The structural vector autoregressive model (SVAR) is increasingly becoming the estimation of the most preferred platform that are currently being employed in analysing the role of technological change as a source of permanent fluctuations in labor productivity to identifying technology shocks. An example is the Canova et al (1994) examination of the implications of calibrated RBC model for the dynamic behaviour of various time series. Eichenbaum (1991) provided analysis on the issue of parameter choice by observing that the numerical values of the underlying parameters used to calibrate a real business cycle model are indeed estimates of the true values. The fact is that, true values like depreciation rate or the variance of the shock to the Solow residual are unknown. The problem is because the estimated numbers came from sample data, of which there are associated sampling errors. See also Farmer et al (1993) comparison between RBC model and one with different principles of construction, based on an economy with increasing returns to scale and shocks. Anyalezu (2011), empirically estimate to capture the dynamics of the economy by using vector auto-regression model for the actual economy and the application of the estimated equations to generate the path the economy would follow.

The Impulse Mechanism

A prominent distinguishing feature of the RBC model centres on its ability to locate the impulse to business cycles in technology shocks. The overarching question then is what evidence exists that technology shock is the principal impulse driving the business cycle? The formal answer to the question is, technology shock is the deviation of the parameter t in the aggregate production function, from its steady-state growth path. By averaging, it should reduce the variability of the aggregate shocks relative to the underlying shocks to individual technology level, including changes in the legal and regulatory system within a country[1].

[1] Proponents of RBC models have broadened the scope of technology to include 'changes in the legal and regulatory system within a country' (Hansen and Prescott, 1993, p.281).

Solow (1957) explicitly observed that idle capacity biases the measure and that the measure hinges on the assumption of factors receiving their marginal products. To enable us to explore in more detail the impulse mechanism behind aggregate productivity and aggregate technology, we have to review further the RBC theory.

The Propagation Mechanism

The idea behind the propagation mechanism contained in RBC model predictions is that it should transmit and amplify the impulses to the various cyclical aggregates. In that sense, combining with the shocks it should provide explanation for the pattern of fluctuations in each series and for their co-movements. Take for example, Watson (1993) adoption of a spectral analysis to decompose the power of the real business cycle model to match movements in output at different frequencies. The finding was that the spectral power of RBC model is high at low frequencies (2 – 8 years). Cogley and Nason (1995b) therefore, compared the dynamic pattern of the technology shocks fed into the RBC model with the predicted time-series for output generated by the model. The study found the dynamic properties of the exogenous inputs responsible for determining the properties of the output and not the RBC model itself.

However, Hartley et al., (1997) argued that one of the reasons RBC models seem to do well is due to the reliance on standards of assessment that are not particularly discriminating, especially in its practice of data handling. RBC models predict values for output, consumption, investment and other time series expressed as deviations from the steady state (as discussed above). Therefore, in order to compare these with actual data requires elimination of an estimate of the steady state from these variables, which are trending. The Solow growth model on the other hand suggests that all these variables should grow at rates related to the steady state growth rate. The problem is they are not observable (bearing in mind that RBC models are mainly calibrated simulations). Thus, RBC models follow one of two strategies to generate detrending data: to remove constant exponential trend, which is linear in the logarithm and as such linear detrending, (King et al. (1988)). This is accurate if the rate of growth of the labor force (n) and of technology (ζ) were constant over time.

An alternative strategy is to use a varying trend that effectively allows the steady state growth rate to be variable, and is the option usually implemented using the Hodrick – Prescott (HP) filter (Hodrick and Prescott 1997). The HP filter definition assume, $x_t = \bar{x}_t + \hat{x}_t$ where $\bar{x}_t$ represents the trend component and $\hat{x}_t$ denotes the deviation from trend. The HP filter chooses this decomposition to solve the following problem:

$$\min\left\{(1/T)\sum_{t=1}^{T}\hat{\chi}_t^2 + (\lambda/T)\sum_{t=2}^{T-1}\left[(\bar{\chi}_{t+1}-\bar{\chi}_t)-(\bar{\chi}_t-\bar{\chi}_{t-1})\right]^2\right\} \qquad \lambda > 0 \quad (1.6)$$

Where T is the number of observation and λ is a parameter that controls the amount of smoothness in the series. Therefore, if $\lambda = 0$, the smooth series is identical to the original series and if $\lambda = \infty$, it is a linear trend. The optimal value of λ is $\lambda = \sigma_x^2 / \sigma_c^2$ where σ_x and σ_c are the standard deviation of the innovations in trend and in the cycle[2].

In which case, the HP filter is arguably successful in providing a theoretical estimate of the steady state growth path. Cogley and Nason (1995a) showed that pre- filtered data do not generate cycles in a real business cycle model, while HP-filtered data does. In addition, when the input data serially correlates, HP filter not only generates spurious cycles but also strongly increases the correlation among the predicted values of output, consumption, investment, hours of work and other values from the RBC model. To use HP filter, is to choose λ a priori to isolate cyclical fluctuations belonging to specific frequency band. In addition, Nelson and Plosser (1982) estimated λ to be in the range of $\left[\frac{1}{6},1\right]$ for most of the series they examine. This means that the variability HP filter attributes to the cyclical component is actually part of the trend. The next section therefore, considers a neutral or agnostic approach.

[2] See Canova, Fabio (1998) for complete analysis on "Detrending and business cycle facts", Journal of Monetary Economics 41 (1998) 475 – 512.

Neutrality to Logarithm Level or First Difference Approach

In view of the different views about whether technology shocks drive hours up or down, an alternative approach is to adopt a neutral stance. According to some literatures, estimation in levels or in first differences provide opposite conclusions. The reliance on an agnostic procedure meant that there is no choice between specification in log level or in first difference. The finding in Pesavento and Rossi (2004) is that a positive productivity shock has a negative impact effect on hours as in Francis and Ramey (2001), but the effect is much more short-lived and when it becomes positive as in Christiano et al (2003), it is not significant. Some recent literature has questioned the validity of this theoretical implication. For example, Gali (1999) identifies technology shocks as the only shocks that have an effect on labour productivity in the long run and therefore, estimate a persistent decline of hours in response to a positive technology shock. In addition, other studies that agree or are of similar findings with these conclusions include Shea (1999), Francis and Ramey (2001). The other general equilibrium models that can account for these empirical findings include, Uhlig (2003), Gali and Rabanal (2004), Basu and Fernald (2004).

On the opposing side, Christiano, Eichenbaum and Vigfusson (2003) disagree with these empirical results. They adopted Gali (1999) identifying assumption and found evidence that a positive technology shock drives hours worked up, not down. The estimated effects of technology shocks essentially depend on whether the empirical analysis is a specification of hours and technology in levels or in differences. The studies by Gali, Shea, Francis and Ramey were specifications in first differences with report that hours worked fall after a positive technology shock. The CEV (2003) study used hours in levels and reported that hours worked rose; hence the postulation that, “The difference must be due to different maintained assumptions”. In nutshell, what this means is that, it depends on the treatment of hours worked.

Pesavento and Rossi (2004), argument that whether hours worked is a stationary or exactly integrated process is a key assumption in the current debate on the effects of technology shocks in business cycles. It is difficult to decide between specifications in levels and in first difference solely based on unit root tests. The reason is unit root tests have low power. Equally, impulse responses based on VARs estimated in levels or in first differences have adverse coverage properties as well. This is of course, unless the true data generating process is not persistent; in which case, levels are appropriate. If it has an exact unit root, then first differences are appropriate.

The neutrality (or agnostic) approach as is in Pesavento and Rossi (2003) does not impose a unit root or stationarity test. Similarly, with robustness to the presence of highly persistent processes, it is suitable for analysing the long run effects of technology shocks on hours worked without making assumptions on the integration of the series. It is this reached conclusion that prompted claims of a positive productivity shock with a negative impact effect on hours worked, even though it does disappears quickly (after only 2 quarters), and then becomes positive as in CEV (2003) but not significantly different from zero. In the CEV framework, the level specification implies that the first difference specification is a mis-specification, while the first difference specification indicates that the level specification is correct. The different specification came from the fact that the level VAR allows for a unit root. The impact of these biases depends on the economic problem at hand and on the particular parameters in consideration. Therefore, neglecting the effect may lead to a very different economic outcome in measuring the effects of productivity shocks.

In table 1.0, I provide a summary of research literatures that have investigated the effects of technology shocks and aggregate fluctuations. The listings in the table provided a contrast on findings between those for and against Contractionary effects on hours or employment after a positive technology shocks. In the table, I start by examining some of the empirical studies with similar findings as Gali (1999), followed by those with opposite results. The summary also contains the methodological approaches and a brief explanation of their findings.

Table 1.0 Summaries of Literatures Reviewed: Technology Shocks & Aggregate Fluctuations

Paper	**Method& Data Source**	**For/Against Contraction**	**Explanation**
Anyalezu (2011) Gali & Rabanal (2004)	Panel data & SVAR Annual data,BEID, ONSLFS,OECD, OPEC,WDS-IEA, SPIRI&Jenkins Defence VAR Quarterly US data: Haver USECON database	For for	Two identifying techniques used to model the effects on employment following a technological innovation at the aggregate level. Evidence from the study shows hours worked fall or rise after a positive permanent technology shock, depending on the empirical treatment of hours. The correlation between technology and hours indicates strong positive co-movements. Productivity shows positive co-movement with hours The study questions reliance of changes in aggregate technology as a key factor behind business cycle, in contrast to RBC models claim. They argue that demand factors are the main driver for the strong positive co-movement between output and labour input measures, which characterises RBC models.
Gali (1999& 2004)	Structural VARUS quarterly data: Citi base, and by construction, OECD Quarterly National Accounts (G7)	For	The study identified technology shocks as the only shock with permanent effects on labor productivity in the long run. The study estimated a persistent decline of hours in response to positive technology shocks.
Blanchard, Solow& Wilson (1995)	Instrumental Variable Approach with demand side[3].	For	A regression of changes in unemployment on the filtered productivity growth variable gave a positive coefficient. This means that an increase in productivity drives the unemployment rate upwards while; its dynamic specification sees the effect falling to its original level after three quarters.
Gali (2005)	VAR. Data 1948:Q1 2003:Q4, OECD & USECON	For	A negative comovement between hours and consumption, except for Japan. Technology shock shows major discrepancies with the predictions of standard RBC models.
BFK (1997 & 2004) BF (2002)	Growth Accounting Methodology[4]. Data: Jorgenson dataset, BLS, Haver Analytics	For	Response of estimation to improvements in their measure of technological change indicates a decline on impact for inputs, including labour while output shows no significant change. Post the short run impact, both variables rises with labour input returning to its original level and output attaining a higher level several years after the shock.
Shea (1998)	A DGE Method[5]. Examines time series interactions between measures of technology change e.g. R & D and economic activity. Data from NBER (annual)	Against	Innovation in technology shows no significant change in TFP; however it increases labour inputs in the short run. The VAR specification with a significant increase in TFP in response to positive technology shocks shows inputs moving in opposite direction to TFP.
Blanchard & Quah (1989)	Dynamic Effects VAR model using quarterly US data 1950:2 – 1987:4. Data from BLS. Aggregate	For	In accordance with traditional Keynesian model, the view was that increases in productivity could lead to increase in unemployment in the short run. This is if aggregate demand fails to rise sufficiently to sustain employment[6].

[3] The variables are assumed to be orthogonal to exogenous technological change used as instruments for employment growth. Alternatively, it can be assumed as change in unemployment in a regression featuring productivity growth as a dependent variable. The fitted residual is then interpreted as a proxy for technology driven changes in productivity.

[4] The method allowed various estimations to which includes: increasing returns, imperfect competition, variable factor utilization and sectoral compositional effects. The Purified technology in the model assumed as an effort to correct the measurement error in Solow (1957) residual due to assumptions fundamental in its derivation.

[5] The modelling provided a link between changes in measures of technological innovation and subsequent changes in TFP and hired inputs using industry level data.

[6]The model identified two types of disturbances generating unemployment and output dynamics – permanent and transitory effects (as supply and demand). The demand effect has no LR effect on unemployment or output. The supply disturbances have no effect on unemployment, but may have LR effect on output.

Blanchard (1989)	SVAR Data: (not disclosed in the paper)	Against	A dynamic effect showing a rise in unemployment. The model uses direct restrictions on the contemporaneous SR effects of innovations on the X variable.
Kiley (1997)	Structural VAR[7].	For	The result indicate technology generate a negative correlation between employment and output growth.
Khan & Tsoukalas (2006)	VAR Model Data: Ellen McGrattan and Valerie Ramey datasets, quarterly data & from Groth et al (2005)	For	Reported the response of labor input to neutral and investment specific technology shock in the UK data. The result shows that hours worked decline, which they attribute to the large negative correlation between labour productivity and hours.
Franco & Philippon (2006)	Structural VAR[8]. Aggregate. Synthetic data, Jorgenson & Stiroh sectoral dataset (2000).	For	The model is to examine the role of permanent and transitory shocks for firms and aggregate dynamics. The findings show that technology shocks induce a negative co-movement between output and hours, and uncorrelated across industries.
Francis, Owyang & Theodorou (2003)	A bivariate VAR with labour productivity and labour hours.[9] Data: BLS (1948:Q1 – 2000:Q4) time series.	For	The result indicates a negative response of hours to a positive technology shock. The model also assumes technology is the only shock with a long-horizon impact on labour productivity, irrespective of VAR estimated with labour hours in levels or in first differences. The model also used an agnostic algorithm proposed by Uhlig (1999) to implement a long run (LR) restriction.
Francis & Ramey (2003a)	Structural VAR[10]	For	Both the augmented model with capital tax rates and the model with alternative identifying restrictions indicate similar impulse responses to technology shocks as in Gali (1999). Hours declined in response to a positive technology shock.
Francis & Ramey (2003b)	Structural VAR with long run identifying restrictions.	For	Using long-term UK annual time series, they show evidence of a negative short run impact of technology shocks on labour.
Francis & Ramey (2004)	VAR Data: annual data from BLS, US Census, mini historical stats table HS-3, Econ report of the President 2003 table B-34, Digest of Educ. Stats 2002 H-442, Claudia Goldin – NBER WP H0119	For	The study modifies standard adjustments to generate hour's per capita series that corresponds with theoretical model. The effects of technology on hours are negative.
Carlsson (2000)	This is a variant of BFK (1999) and Burnside et al (1995). Data: Annual aggregate	For	The study created a time series for technological change. The application was for Swedish two digit manufacturing industries. Positive technology shocks show a contractionary effect on hours and a non-expansionary impact on output.
Marchetti & Nucci (2005)	A dynamic cost minimization model with adjustment costs, a variant of BK (1997)[11].	For	Used firm level estimates of technology change to assess the impact on labour input growth. The result shows that positive technology improvements tend to

[7] The SVAR model was an extension of Gali (1999) to data from two-digit manufacturing industries.

[8] The estimated SVAR has three shocks – (1) technology with permanent effects on industry productivity; (2) composition shocks with permanent effects on the industry share in total output and (3) transitory shocks.

[9] This is a variant of the sign restriction algorithm of Uhlig (1999).

[10] The model provided an extension to Gali (1999). Their modification include augmenting the baseline VAR with specification in first differences using a capital tax rate as proxy for the impact of technology shocks from those of permanent changes in tax rates. In addition, technology shock is identified as those with permanent effects on real wages in contrast to labour productivity or hours. The alternative identification restrictions were not rejected when added to a unified (over-identified) model.

[11] The model uses Basu and Kimball (1997) proposed methodology to derive a measure of technology change and estimate the model on firm level panel data for a representative sample of Italian manufacturing firms.

	Data[12]: SIM & CADS for the period 1984 – 1997.		decline labour input on impact. The conclusion was that, the finding is coherent with the prediction of a sticky price model. Thus, provides evidence of a connection at the firm level between the degree of price rigidity and the intensity of the contractionary effect of technology shocks.
Alexius & Carlsson (2005)	SVAR Data: Quarterly & annual - NIPA BEA, Dale Jorgenson database, SNEPQ dataset, OECD MEI, IFS, Mark W. Watson dataset, BLS. Aggregate – U.S & Swedish	For	It estimated technology change from 2 versions of production function approach and 2 SVAR models. Technology improvements are associated with contemporary contractions in input and hours with no significant increase in output.
CEV (2003) (2004)	VAR[13] Data: used the aggregate technology series computed in BFK (1999)[14]	Against	Their result show that hours worked rise after a positive shock to technology. The same identification procedure as in Gali (1999) was used, with hours specified in log level.
CEV (2003)	VAR: for US & Canada. Data: see footnote[15]	Against	The model examines the response of hours worked to a permanent technology shock. With annual data from Canada, hours worked rise after a positive technology shock. It is same result using annual data from the U.S. It contradicts models claiming positive technology shock causes hours worked to fall. They attribute the different results to the models making a specification error in the statistical model or per capita hours worked. They also show that Canadian monetary policy accounted for technology shocks.
Vigfusson (2004)	VAR Data: from the BLS KLEMS dataset, IMF world price of oil	Against	In response to a positive technology shock, a standard flexible price model would have an immediate increase in hours worked. The response by per capita hours worked to a technology shock is initially small but later increases.
Mikhail (2005)	BVAR Data: DRI Economics database Quarterly data 1948:1 –2000:3	Against	This examines the effect of a positive technology shock on per capita hours worked within the class of Bayesian Vector Auto-Regressive (BVAR) models. This was to avoid debate whether specification of per capita hours is in levels or first difference stationary. Six priors were considered after technology shock. The marginal posteriors of the VAR parameters were generated using the Markov Chain Monte Carlo (MCMC) Gibbs sampler, yielding similar results from the VAR. Using CEV data and imposing the identifying restriction, the results indicate per capita hours rise following a positive technology.
Burnside & Eichenbaum (1996)	A GMM dynamic aggregate model - a variant of Hansen (1985) model[16]. Data: US Dept of Commerce (1994), NIPA, BGFRS[17], Citibase for period 1955:Q1 – 1992:Q4.	Against	The model estimated an equilibrium RBC model where capital utilization varies over the business cycle, and is an important source of propagation to business cycle shocks. The result shows hours worked increased follow an impact.

[12] Data sources: SIM = The Bank of Italy's survey of investment in manufacturing;
CADS = the company accounts data service reports.

[13] Using the aggregate technology series computed in BFK (1999), they show the impact on hours worked after a positive shock to technology.

[14] CEV (2003) result based on quarterly US time series data.

[15] The U.S data used is the annual version of the data used in CEV (2003). Due to short span of Canadian quarterly data, they used annual data instead from 1961 (CANSIM).

[16] The model is modified to accommodate factor hoarding expressed as variable capital utilization rates and varying labour effort. It incorporates a different approach to estimating time varying capital utilisation. The distinction between the model measure of hours worked and that of Hansen is that, relate to their low frequency behaviour. Hansen series has a larger degree of high frequency variation.

[17] BGFRS = the Board of Governors of the Federal Reserve System.

Shapiro (1993)	Instrumental Variable. Aggregate, annual & quarterly: Bureau of the Census (Survey of plant capacity), Wayne B. Gray TFP dataset.	Against	Empirical studies of productivity finds short run increasing returns to labour. When capital & hours are in account, there appear to be no short run increasing returns to conventionally measured total factor inputs.
Altig, Christiano, Eichenbaum & Linde (2002) & (2004)	VAR from estimated equilibrium model (simulation). Data: DRI Basic Economics database, quarterly 1959:Q1-2001:Q4. DGEM b/4 aggregate	Against	Their (2002) paper indicates that positive technology shock drives hours worked up. In the (2004) paper, they constructed a DGEM of cyclical fluctuations. Result shows low correlation between inflation, marginal cost and other inflation inertia. It favours the firm specific capital specification due to micro implications.
Alves, Brandao de Brito, Gomes & Souza (2006)	SVAR Data: Eurostat, ECB, EC, OECD, Fagan et al. ((2001) hereafter AWM database)[18] 1970:1 – 2004:Q3	Against	Evidence show hours to go up following technology shock. The result also supports hours as stationary in levels.
Shapiro & Watson (1988)	A Neoclassical Growth regression & IV. Quarterly US data 1951: - 1987:2, from BLS.	Against	The level of output is determined in the LR by supply shocks like technology and labour supply. Positive technology shocks provide evidence for strong growth. No restrictions imposed on SR & LR, but on real interest rate; hence labour was allowed to have a stochastic trend.
Yi Wen (1999)	VAR (a modified Kydland & Prescott model). Data: Citibase	Against	RBC co-moves with output. Technology shock reducing consumption and commove with output.
Pesavento & Rossi (2004)	VAR Data from Christiano et al, DRI Economics database, quarterly: 1948:Q1 – 2001:Q4	Against	Depending whether estimation is in levels or in first difference. The reliance in estimating the model is one of "agnostic" procedure[19]. Hence, a positive productivity shock has a negative impact on hours and then becomes positive at business cycle frequencies[20].
Faust & Leeper (1997)	Bayesian Monte Carlo Procedure in RATS (VAR). Data: (Simulation) considered both quarterly and annual data frequencies.		This investigates the reliance of imposing restrictions on the long run effects of shocks in VAR models. Argued that LR identifying scheme is weak and structural inference by the VAR must satisfy strong dynamic restrictions. Hence, requires care to assess the robustness of inference.
Chang and Hong (2006) & (2003)	VAR of 458 4-Digit US manufacturing industries 1958 – 1996. Data: from NBER (annual) Manufacturing Productivity Database	Against	Their result shows that technological improvement increases employment in many US manufacturing industries.The result differs from those based on labour productivity that found a negative correlation between the permanent component of labour productivity and employment in manufacturing. Their view was that TFP is the best measure for technology because labour productivity reflects the input mix as well as technology.

In table 1.2 below, I show the number of review literatures that are for contraction and the number against in their respective studies. The table also contain the number of studies that used quarterly data, the number that used annual data and the number that used both. In Anyalezu (2011), the research study uses the two forms of data.

[18] AWM = Area-Wide Model database, EC = European Commission.
[19] This implies a sort of `atheist', that is the research does not have to choose whether to do the specification in log levels or in first differences.
[20] The result shows negative effect on hours as in Francis and Ramey (2001), but the effect is much shorter lived than previously found as it disappears after only two quarters. When it becomes positive, it is as in Christiano et al. (2003) but not significantly different from zero.

Table 1.2: Summaries of Reviewed Papers: Technology Shocks & Aggregate Fluctuations

	For Contraction	No of papers Against	Qtr & Annual data	Qtr data	Annual data
No of papers Agg Data Qtr	8	8	3	15	20
No of papers non aggregate	10	9			

Conclusions

This study has identified the various perceptions to RBC model and technology shocks, while acknowledging the importance of TFP. This is more so given that increasing productivity relates to increased economic growth, lower costs and sustained competitiveness. Equally, there is the failure to account for the reason labour productivity increased in accordance with RBC model predictions.

A possible solution therefore, lies in the Solow residual measurement, TFP. This is because using Solow's approach and the concept of TFP as a microeconomic tool can facilitate analysis and separation of labour productivity change in individual firms. In terms of aggregate level, comparisons attributed economic growth to the Solow residual (TFP). Productivity growth is exogenous within the simplest version of Solow's model. In addition, productivity predominates among the sources of economic growth hence, most of growth is exogenously determined. Thus, the reliance on the Solow residual as an explanatory factor is a very powerful indictment of the limitations of the neoclassical framework.

Furthermore, standard neoclassical growth theory has not provided a suitable explanation for the immense inequality in the wealth of nations. Most theories of TFP, for example, ignored the potential role of barriers to capital accumulation in generating aggregate TFP differences, especially across countries or firms. Without doubt, there has been an upsurge of interest in the measurement and explanation of TFP and RBC models because of the development of new theoretical models, the availability of new and better data, including estimation techniques. The advent of advancement of econometrics has made possible the testing of refined hypotheses.
Through the observations from the various modelling approaches, the conclusion drawn is that RBC models perhaps, tend to overestimate the fraction of technology shocks variability that is responsible for business cycles.

Nonetheless, the issues involved are too numerous and too complex. The available empirical evidence is equally too diverse to allow bold conclusions about the measurement and determinants of TFP and RBC models in aggregate fluctuations. Equally, a possible conclusion is that, the impact of the biases, as discussed in the body-text above depends on the economic problem at hand and on the particular parameters in consideration. Therefore, neglecting or ignoring the effect may lead to a very different economic or policy outcome in measuring the effects of productivity shocks.

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