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Is British Output Growth Related to its Uncertainty? Evidence using Eight Centuries of Data

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Abstract

We examine the empirical relationship between output variability and output growth for Britain using data for eight centuries covering the 1270 to 2014 period. Drawing on the economic history literature, we split the full sample period in four subperiods and use GARCH models to measure output growth uncertainty and estimate its effect on average growth. Within each sub-sample we allow output growth to depend on the state of the system, e.g. 2-regime switching model would switch between high-growth and low-growth regimes. We find that the effect of uncertainty on growth differs depending on the existing growth regime. Low-growth regimes are associated with a negative effect of uncertainty on growth, and medium or high-growth regimes are associated with a positive effect. These findings are consistent across the four states of economic development. Our results indicate why the empirical literature to date has found mixed results when examining the effect of uncertainty on growth.

Keywords: output variability, output growth, GARCH models, regime switching

JEL Classification: C22, C51, C52, E32

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1 Introduction

Until the early 1980s, macroeconomic theorists treated the analysis of the real business cycle (RBC) as separate from the study of economic growth. In the 1980s, three important contributions in business cycle theory by Kydland and Prescott (1982), Long and Plosser (1983) and King *et al.* (1988) integrated the theories of the business cycle and economic growth in their models. However, these models did not consider the possibility that the variability of the business cycle might relate to the rate of economic growth. Similarly, for the most part, developments in growth theory have been made without consideration of the variability in the business cycle. The scene has changed recently at both the theoretical and empirical front. At the theoretical level, Blackburn and Pelloni (2005) and a number of studies summarised by these authors examine how cyclical fluctuations might relate to long-run economic growth. At the empirical level, studies by McConnell and Perez-Quiros (2000) and Stock and Watson (2002) highlight the importance of the reduction in US GDP growth volatility in the last two decades and its implications for growth theory. The early dichotomy in macroeconomic theory between economic growth and the variability of economic fluctuations can be reconsidered in relation to several theoretical approaches. These theories predict a positive, negative or no association between the two variables. The empirical evidence to date, based on cross-section country studies, panel data studies, or time-series analyses of individual countries is also quite mixed. The conflict in relation to the theoretical models, as well as the mixed empirical findings are summarized in Bakas *et al.* (2018). The theoretical and empirical ambiguity surrounding the RBC variability-economic growth relationship provides us with the motivation to expand on the empirical aspects of this issue.

We examine the extent and the importance of growth uncertainty by employing a long span of annual output data for England/Great Britain, that starts in the 13^{th} century and runs up to the present. Our source of data is Broadberry *et al.* (2015) and Hills *et al.* (2010). The historical setting has a number of advantages over the relatively short samples adopted by existing studies in the literature. First, we are able to analyze the RBC variability-growth relationship over a period that spans a number of centuries, thus including in our analysis periods of significant variation in output growth associated with famines (such as the Great Famine of 1315-17), major diseases (such as the Black Death of 1348-49), wars (such as the Napoleonic wars, and the two World Wars), economic crises (such as the Great Depression, the volatile 1970s), and periods of prosperity (such as the Great Moderation).[1] Second, the use of annual data allows us to perform a more appropriate test of the Black (1987) hypothesis that predicts a positive effect of output variability and uncertainty on the growth rate of output. Black's argument is based on the response of investment and output growth to a change in uncertainty regarding the profitability of investment projects, and hence can be better tested in a study that uses low-frequency data (see Caporale and McKiernan, 1998). Finally, our study is the first (as far as we are aware) to empirically examine the extent of economic and in particular growth uncertainty through the lens of an economy moving from primarily agrarian structure to economic powerhouse during the *First Industrial Revolution*, to the decline in manufacturing during the *Second Industrial Revolution* and the emphasis on services.

Our primary focus is to examine the impact of growth uncertainty on output growth. Given the established theoretical literature, we focus solely on the relationship between growth uncertainty on output growth.[2] Our methodological approach includes univariate GARCH models (both symmetric and asymmetric) and regime switching models to develop a proxy for output growth volatility or uncertainty. These models have been to the forefront of empirical macroeconomic models over the last fifteen years in modelling uncertainty in various macroeconomic variables (Hamilton, 2008).[3] Our contribution to the economics literature is three fold and may be summarized within the context of economic modelling, macroeconomic uncertainty literature and economic policy. First, we employ a very long sample

[1]While previous studies have highlighted the limited evidence of economic growth prior to the 17^{th} century, see Crafts and Mills (2017), we examine a much larger sample of data. Although our chosen sample includes limited evidence of sustained economic growth for the per-17^{th} century, there is ample evidence of economic growth volatility. The interaction between economic growth and growth uncertainty forms a significant contribution to our study. Further details on both economic growth and levels of volatility will be presented later in the empirical results section.

[2]Although theoretical as well as empirical studies have reported ambiguous results, we none the less have a solid theoretical foundation in terms of examining the relationship between growth uncertainty on output growth. The business cycle models, indicate there should be no influence, with output growth being determined by real factors such as technological changes. An alternative is the endogenous growth caused by learning-by-doing which shows that business cycle volatility raises the long-run growth of the economy, see Black (1987). Finally, according to Bernanke (1983) and Pindyck (1991), the negative relationship between output volatility and growth arises from investment irreversibility at the firm level.

[3]Given the lack of a clear theoretical model, we do not formally examine the impact of output growth on growth uncertainty. However, we do model uncertainty assuming different growth regimes and so do take account of different growth regimes on output uncertainty.

covering almost eight centuries and thus our setting is better suited to capturing the effects of uncertainty on growth which are expected to be long-run in nature. Secondly, we allow for regimes in the growth series and we are more likely to detect the differential effects of uncertainty on growth between low and high growth regimes. We see this as a critical innovation towards understanding the ambiguous empirical relationship between growth uncertainty and output growth that has been highlighted by Bakas *et al.* (2018). Finally, we evaluate the extent of growth uncertainty over an eight century sample, with a particular emphasis on the phases of economic development and the industrial revolution in particular. This is relevant for policy makers in understanding the interaction between economic development, output growth and the role of uncertainty.

Our results show the presence of strong time varying volatility effects in annual output growth that cover the period 1270-2014. We first estimate symmetric and asymmetric GARCH models for the full sample period and find that uncertainty about output growth affects output growth negatively as suggested by various economic theories. Drawing on Broadberry *et al.* (2012), we also split the sample period into four subperiods and consider three different regimes of output growth (low, intermediate, and high). These regime changes are anticipated given the length of our sample and the large number of exogenous events happening over the long sample period, such as the Great Famine, the Black Death and the Industrial Revolution. Although expected, this is the first study to formally model regime switches in British GDP over such a long sample of data. We find that in each of the four periods examined, output growth volatility has a consistent effect on output growth. However, the effect of uncertainty on growth differs depending on the output-growth regime: in low-growth regimes the effect is negative and in high-growth regimes the effect is positive. These findings have important implications for macroeconomic theory, but the empirical literature in particular. At the most fundamental level, our results suggest that macroeconomic modelling should consider the theory of economic growth in tandem with real business cycle models and not separately. With the specific macro literature in mind, our study clearly indicates why the literature to date has found mixed results. It is only when we examine growth via the long sample (regime switching) lens that we correctly identify the relationship between output uncertainty and output growth.

The paper is structured as follows. The following section provides a summary of the theoretical and empirical literature, with section 3 examining a historical analysis of GDP growth. Section 4 outlines our empirical methodology and section 5 describes the data and presents the estimation results. Section 6 discusses the major results in the light of the relevant literature and, finally, section 7 concludes the paper and offers some implications for macroeconomic theory.

2 Literature Review

2.1 Theoretical background

According to macroeconomic theory there are three possibilities as far as the impact of output variability on output growth is concerned. First, there is the possibility of independence between output variability and growth. In other words, the determinants of the two variables are different from each other. According to some business cycle models, output fluctuations around the natural rate are due to price misperceptions in response to monetary shocks. In contrast, output growth changes arise from real factors such as technology (Friedman, 1968).

The second scenario predicts a negative association between output variability and average growth and can be traced to Keynes (1936). In his General Theory he argued that entrepreneurs, when estimating the return on their investment, take into consideration the fluctuations in economic activity. The larger the output fluctuations, the higher the perceived riskiness of investment projects and, hence, the lower the demand for investment and output growth. This result confirms the literature on sunspot equilibria (Woodford, 1990). Bernanke (1983) and Pindyck (1991) argue that the negative relationship between output volatility and growth arises from investment irreversibilities at the firm level. Ramey and Ramey (1991) show that in the presence of commitment to technology in advance, higher output volatility can lead to suboptimal ex post output levels by firms (due to uncertainty-induced planning errors) and hence, lower mean output and growth.

Finally, the positive impact of output variability on growth derives from several economic theories. First, more income variability (uncertainty) would lead to a higher savings rate (Sandmo, 1970) for precautionary reasons, and hence, according to neoclassical growth theory, a higher equilibrium rate of economic growth. This argument has been advanced by Mirman (1971). An alternative explanation is due to Black (1987) and is based on the hypothesis that investments in riskier technologies will be pursued only if the expected return on these investments (average rate of output growth) is large enough to compensate for the extra risk. As real investment takes time to materialize, such an effect would be more likely to obtain in empirical studies utilizing low-frequency data. Another strand of the literature, the so-called Oi-Hartman-Abel effect, argues that uncertainty may lead to higher growth if profits are convex in demand or costs (Oi, 1961; Hartman, 1972; Abel, 1983). Under this condition, a higher demand or cost uncertainty will increase expected profits. The above argument is more valid in the medium to long run due to the prevalence of higher adjustment costs in the short run. Another argument for a positive effect of growth on volatility has been advanced by the growth options literature (Bar-Ilan and Strange, 1996). If there are investment lags in the sense that the completion of a project is subject to delays, an increase in mean-preserving risk leads to a higher expected profit and investment. In other words, only good news are relevant in growth options. The option to close down a bad project makes bad news irrelevant. More recently, Blackburn (1999) using a model of endogenous growth generated by learning-by-doing shows that business cycle volatility raises the long-run growth of the economy.

The effect of output volatility on growth is ambiguous. A number of studies (Smith, 1996; Grinols and Turnovsky, 1998; Turnovsky, 2000) show that, with preferences represented by a constant elasticity utility function, the growth rate is positively related to volatility provided the coefficient of risk aversion exceeds one. Smith (1996) shows that the sign of the growth-volatility relationship depends on whether the intertemporal elasticity of substitution exceeds or falls short of one. The above papers all refer to a closed economy. Turnovsky and Chattopadhyay (2003) in a stochastic general equilibrium small-open economy model of a developing country examine the effect of output volatility on output growth allowing for three additional types of volatility (in the terms of trade, government spending and money supply) to have an impact on output growth. The theoretical model implies that output volatility has an ambiguous effect on growth. This result is confirmed by numerical simulations that show that the effect is small.

Recently, a growing theoretical literature has developed that examines the correlation between average output growth and its variability in an endogenous growth setup (Blackburn and Galinder, 2003; Blackburn and Pelloni, 2004, 2005). Blackburn and Galinder (2003) focus on the importance of the source of technological change for the sign of correlations between output growth and its volatility. In a stochastic real growth model the authors show that positive (negative) correlation will most likely arise in a framework of internal (external) learning where the agents improve their productive efficiency by investing time in learning (benefit from knowledge spillovers taking place among agents).

In a stochastic monetary growth model Blackburn and Pelloni (2004) show that the correlation between output growth and its variability is a function of the type of shocks buffeting the economy. The study concludes that the correlation will be positive (negative) depending on whether the real (nominal) shocks dominate. In a richer setting, Blackburn and Pelloni (2005) use a stochastic monetary growth model with three different types of shocks (technology, preference and monetary) that have permanent effects on output due to wage contracts and endogenous technology. The authors show that output growth and output variability are negatively correlated irrespective of the type of shocks causing fluctuations in the economy.

2.2 Empirical Evidence

Given the absence of a theoretical consensus, the anticipated relationship between output variability and economic growth remains largely an empirical issue. The empirical evidence to date on the association between output variability and output growth is quite large but inconclusive. Early studies employed cross section (Kormendi and Meguire, 1985) or pooled data (Grier and Tullock, 1989) and find evidence for a positive association. Ramey and Ramey (1995) use a panel of 92 countries and a sample of OECD countries (for the 1960-1985 period) and find strong evidence that countries with higher output variability have lower growth. A similar result is obtained by Zarnowitz and Moore (1986), Kneller and Young (2001) and Turnovsky and Chattopadhyay (2003).

More recent studies use the time series techniques of Generalised Autoregressive Conditional Heteroskedasticity (GARCH) models to proxy for output uncertainty rather than variability (Caporale and McKiernan, 1996, 1998; Speight, 1999)[4]. The first two papers use UK and US data, respectively, and find a positive association between output variability and growth, whereas the last paper uses UK data and finds no association. Grier and Perry (2000) using the GARCH-M model and monthly US data find no evidence that uncertainty about output growth affects the rate of output growth. Henry and Olekalns (2002) find evidence in favour of a negative association using post-war real GDP data for the United States. Allowing for asymmetries, Grier *et al.* (2004) find US evidence for a positive effect. Fountas *et al.* (2002) find no evidence for an effect of output uncertainty

[4] In this paper the terms uncertainty, variability, and volatility are used interchangeably.

on growth using data from Japan and a bivariate GARCH model that includes inflation and output growth. This result is confirmed in Fountas *et al.* (2004) using Japanese data and three different univariate GARCH models.

The motivation for our empirical study comes from, first, the inconclusiveness of the existing empirical time series literature, and second the sparsity of evidence using international data that cover a long horizon. We, therefore, attempt to provide more robust evidence on the relationship between output growth and output growth uncertainty using annual data that span over an eight-century period for the UK. In this set up, the issue or regimes shifts becomes important.

3 GDP Growth Over Eight Centuries

Drawing on Broadberry *et al.*, (2012) our long sample can be split into four separate periods. From 1270-1499 represents the medieval period, 1500-1699 the early modern period, 1700-1869 representing the industrialization period and 1870-2014 representing the modern economic period. The medieval period represents a sample in which output was dominated by the agricultural sector. As a result there were prolonged stages of considerable fluctuations, primarily as a result of adverse weather and disease. This was particularly the case during the first half of the 14^{th} century, with economic conditions deteriorating further during the Black Death. Both harvest failure and the plague had a detrimental effect on output growth, although the cause was very different. Clearly livestock disease and crop failures led to a fall in output, with overall English output being dominated by agriculture. However, the plague led to a dramatic reduction in population, which economic theory would indicate would lead to higher nominal wages. Evidence indicates that the reduction in output was less than the reduction in population and that output per capita rose after 1350 (see, Pamuk, 2007).

The early modern period reflects an increased share of industry and services in English output, although still dominated by agriculture. The 16^{th} and 17^{th} century were heavily influenced by a number of incidents of extremely sharp reductions in agricultural output, which lead to a subsequent sustained mortality crisis. While, the first half of the early modern period was relatively peaceful, this changed with the advent of the civil war between 1642-1651 and subsequent conflicts (see Nef, 1942).

Between the last two periods, the English population doubled in size from 4.2 million in 1600 to 8.7 million in 1800 (see, Broadberry *et al.*, (2015)) .

The fourth period, i.e., the modern economic period, shows a considerable reduction in growth volatility.[5] While fluctuations in output as a result of harvest productivity continues to be an issue, there was a greater influence of wars and commerce on the emerging industry and service sector. Broadberry *et al.*, (2015) provides considerable details on both determinants during this period. The key drivers of growth during the first half of the modern economic period was primarily agriculture and services. However, employment structure was changing dramatically, with those employed in services increasing considerably, from 13.4% (of the labour force) in 1710 to 35.2% in 1871 (see, A'Hearn, 2014). Comparable figures for agriculture during this period reflect the significant gains in productivity, with those employed falling from 48.7% in 1710 to 21.3% in 1871 (see, A'Hearn, 2014).

At the peak of the *First Industrial Revolution* in the mid 18^{th} century Britain was universally viewed as the engine of world economic growth. However, with new technologies emerging in light engineering and organic chemicals Britain lost ground to both Germany and the US towards the end of the 18^{th} century (see Harley, 2014). Our final sub-sample is certainly associated with a decline in the manufacturing sector and textiles, with unemployment and in particular unemployment, in regions associated with economic success in the previous period, being a serious issue.[6] The fundamental technological advances associated with the late nineteenth century, *Second Industrial Revolution*, were more likely to be located in the US and Germany in particular, (see Harley, 2014). Nicholas (2014) highlights the lack of technological advances as a key reason for the decline of the British economy since the *First Industrial Revolution*.[7]

[5]As highlighted by Broadberry *et al.*, (2012) this could be due to the move from probate sources to farm accounts for the agricultural sector.

[6]Kitson and Michie (2014) highlight 1870 as the high point in relation to manufacturing. The author's point to the period 1870-1913, as an age of maturity in manufacturing, 1919-1939 as an age of uncertainty, 1950-1973 representing the transition and finally 1973-2007 as the age of decline. The decline in manufacturing since 1960 has been both relative to other sectors in the economy and relative to other countries, see Kitson and Michie (2014). The textile industry declined primarily due to increasing overseas competition. Singleton (1991) provides a detailed analysis of the cotton industry. This has been particularly the case post WW2, where global textile production networks have been to the fore.

[7]Harley (2014) also highlights that during this period, the British economy made significant advances in the services sector, namely the development of international finance and services related to globalized business.

4 Methodology

In this section we introduce the STAR-EGARCH-in-mean model that enables us to test the time-varying behavior of the growth uncertainty on the levels of growth. Before presenting the time varying volatility model, we examine the case of a regime switching smooth transition autoregressive (STAR) model. Consider the time series of growth rates y_t, $t = 1, ..., n$, the stochastic properties of which are assumed to be described by the following model:

$$
\begin{aligned}
y_t = &\left(\phi_{0,L} + \textstyle\sum_{k=1}^{P} \phi_{1,L}^{k} y_{t-k} + \psi_{1,L}\sigma_{y_t}\right) G(s_t;\gamma,c) \\
+ &\left(\phi_{0,H} + \textstyle\sum_{k=1}^{P} \phi_{1,H}^{k} y_{t-k} + \psi_{1,H}\sigma_{y_t}\right) [1 - G(s_t;\gamma,c)] + u_t
\end{aligned}
\tag{1}
$$

where $\phi_{1,i}$ [i = low state of the economy (L) and high state of the economy (H)] captures the conditional mean according to the state of the economy, while $\phi_{1,i}^{k}$ captures any possible own past growth effects (k, denotes the lag order, in our case the appropriate lag is equal to one). Similarly, parameters $\psi_{1,i}$ capture the growth uncertainty effects on growth for each state of the economy.

To capture temporal changes in the economy we employ the logistic function by letting $G = G(s_t;\gamma,c)$;

$$
G(s_t) = \{1 + exp[-\gamma(s_t - c)]\}^{-1} \qquad where \quad \gamma > 0 \tag{2}
$$

where s_t is the transition variable, and γ and c determine the smoothness and location, respectively, of the transition between the regimes. The transition variable is described as a function of lag growth rates: $s_t = y_{t-1}$.[8]

The resulting model is able to capture a wide variety of patterns of change. Differing values for c suggest that at different growth rates the effects of $\phi_{1,i}, \phi_{1,i}^{k}$, and $\psi_{1,i}$ may be different for each state of the economy. The pace of change is determined by the slope parameter γ. This change is abrupt for large γ, and becomes a step function as $\gamma \to \infty$, with more gradual change represented by smaller values of this parameter.

[8]In practice, we scale $(y_{t-1} - c)$ by σ_{t-1}, the standard deviation of the transition function, to make estimates of γ comparable across different sample sizes. In principle, any variable can act as a transition variable.

In addition the error term (in equation 1) is assumed to follow the following process;

$$u_t|I_{t-1} \sim N(0, \sigma_t^2) \tag{3}$$

where I_{t-1} is the information set consisting of all relevant information up to and including time $t-1$, and N denotes the normal distribution. σ_t^2 is the conditional variance of the error term and follows a time-varying structure given by a time-varying volatility EGARCH process;

$$\begin{aligned} \sigma_t^2 = \exp\{\alpha_{0,L}G(s_t) + \alpha_{0,H}[1 - G(s_t)] \\ +\{\alpha_{1,L}G(s_t) + \alpha_{1,H}[1 - G(s_t)]\}f(z_{t-1}) \\ +\beta_L G(s_t) ln(\sigma_{t-1}^2) + \beta_H[1 - G(s_t)] ln(\sigma_{t-1}^2)\} \end{aligned} \tag{4}$$

where $z_{t-1} = \epsilon_{t-1}/\sigma_{t-1}$ are the standardized shocks with

$$f(z_{t-1}) = (|z_{t-1}| - E|z_{t-1}| + \zeta z_{t-1}) \tag{5}$$

As for the interpretation of the parameters of the error process, similar to the parameters in equation (1) the constant parameters, $a_{0,i}$, of equation (4) are allowed to vary when the transition variable takes values below or above the threshold value. By incorporating this feature into the model, we are able to assess whether the effect of growth volatility is, on average, different across the regimes. By assuming a regime dependent behavior on rest of the parameters, notably $\alpha_{1,i}$ (short run volatility effects) and β_i (volatility persistence effects) the model is capable of accommodating systematic changes in the amplitude of the volatility clusters. Parameter ζ captures possible asymmetric effects of shocks on growth volatility (i.e., the possibility that negative shocks on growth have greater impact on volatility compared to positive shocks of the same magnitude, and vice versa). The model is estimated using maximum likelihood techniques.

5 Data and Empirical Results

5.1 Data

Our measure of output is real GDP at factor cost for England (1270-1700) and Great Britain (1700-2014) and is a combination of a number of data sources. The primary source of data is from Broadberry *et al.* (2015), while the latter part of the sample has been complied by Hills *et al.* (2010). The data detailed in Hills *et al.* (2010) is from 1830 to the present and for 1830-1855 incorporates the Feinstein (1972) extensions to Deane's (1968) data, which is available in Mitchell (1988), as well as data from Solomou and Weale (1991), Sefton and Weale (1995) and from the ONS. Detailed information on the data is provided in appendix 5.3 in Broadberry, *et al.* (2015) and the appendix to Hills *et al.* (2010).

Drawing on Broadberry *et al.*, (2012) we split the complete sample into four separate periods. From 1270-1499 represents the medieval period, 1500-1699 the early modern period, 1700-1869 representing the industrialization period and 1870-2014 representing the modern economic period. Besides the sample divisions representing conventional periods in economic history, there is also differences in the sources of data within each sub-sample. For example, the source of data within the agricultural sector varies considerably depending on the period chosen. Manorial accounts are the primary source for the medieval period (see Campbell, 2010), probate inventories for the early modern (see Overton, 1984 and Overton *et al.*, 2004) and farm accounts for the modern period (see Turner *et al.*, 2001).[9] [10]

5.2 Empirical Results

We first present some summary statistics (Table 1). These statistics indicate a clear trend towards rising mean growth rates over the four periods and falling variability in growth rates. The latter point is particularly evident from the Figure 1 plot of annual percentage growth rates over the full sample. The first two periods report very high volatility in comparison to the following periods, with the first period even report negative mean growth. The last two periods report quite significant growth, yet were particularly stable, with average growth rates (standard deviations) of 1.322% (4.257%) and 1.971 % (3.138%). This finding is consistent with results previously reported by Craft and Mills (2017). In fact, mean growth doubled in the third period (driven by the *First Industrial Revolution*) in relation to the previous period. The time series plot in Figure 1 certainly points towards evidence of time variation in the volatility associated with output growth.

[9] An additional motivation for the chosen sample splits is the establishment of Great Britain under the Act of Union in 1707. The third and fourth sub-period refer to Great Britain.

[10] A further issue is the smaller sample of observations for each year for probate, than the case of manorial accounts.

We estimate two time-varying volatility models, a standard GARCH and an EGARCH model for the four sample periods assuming one regime for mean growth[11] Tables 2 and 3 report the results of the GARCH estimation and Tables 4 and 5 report the results of the EGARCH estimation. The GARCH estimation (Tables 2 and 3) indicates considerable evidence for time-varying uncertainty in all four sub-periods. They also indicate a large degree of uncertainty persistence which seems to be higher in the medieval and early modern periods. The EGARCH estimation results (Tables 4 and 5) show that time-varying uncertainty does exist in the output growth series, but in particular for the first three sub-samples. However, the nature of the time series behaviour for both growth and its uncertainty is very different for both samples, with considerable uncertainty persistence for the first three samples. It seems there is no evidence for uncertainty asymmetry for each of the subperiods. The effect of uncertainty on growth is negative in all subperiods, but it is insignificant in the GARCH model and significant only in the first period in the EGARCH model. The final two samples, with both periods driven by industrial and services growth, report mixed evidence in terms of the drivers of time varying uncertainty and there is no evidence of volatility having any effect on output growth.

The regime switching model is estimated using one lag according to the AIC and SIC criteria. The results are robust to an alternative lag choices. To analyse the models for regime switching, the linear model is adopted as the null hypothesis for testing linearity against the smooth transition type non-linearity using the tests of Luukkonen *et al.*, (1988) and Teräsvirta (1994). The P-value for the LM test to determine nonlinearity is reported in the last row of Tables 2-5 and indicates consistent evidence of regime switching. Having established evidence of non-linearity, we estimate a regime switching model for each subperiod. As a starting point, we allow for two regimes (low and normal growth). The results are reported in Tables 6 and 7. Once we take account of regime switching, there is considerable evidence of a relationship between growth uncertainty and growth. In three out of the four samples, uncertainty during low growth regimes has a negative effect on growth. Of particular importance is that the coefficient size rises during each of the samples. In all samples examined there is considerable persistence in uncertainty during the low growth regime. There is similar

[11] In addition to our choice to divide the sample into four subperiods on the basis of economic history, we also employed an endogenous identification procedure to identify suitable sub-samples. The sub-samples are very consistent with those implied by the economic history literature. The results revealed 3 break points splitting the sample in the following sub-periods; 1272-1505, 1506-1691, 1692-1881 and 1882-2014.

evidence of uncertainty effects on economic growth for the normal growth regime, with uncertainty having a positive effect and again with a larger impact over time.

Second, the estimated smoothness coefficients (the $\gamma's$) indicate that there is relatively smooth adjustment between regimes with the fastest adjustment taking place in the medieval and the modern economic period. The relatively large coefficient for the medieval period is consistent with growth being dominated by agriculture and so economic activity being particularly sensitive to crop failures and livestock disease. The γ for period 3 is quite low indicating a slow switch between regimes, with the regime threshold at 1.72%.

Third, the estimated threshold varies substantially among the four periods and is negative in the medieval period, but positive in the other periods. This is not surprising given the large swings between positive and negative growth rates in the medieval and early modern periods. There is also a quite dramatic upward trend in the threshold value over the eight centuries. For example in period 1, the threshold at which the switch occurs is -0.478%, while in the last period it has risen to 2.274%. Finally, there is much greater evidence of asymmetry in uncertainty, once we take account of separate regimes. The asymmetry parameter ζ is significant for the first 3 samples, although there is inconsistency in relation to the sign. The LM test to determine remaining nonlinearity (Luukkonen *et al.*, 1988, and Terasvirta, 1994) in the two-regime model show that the null hypothesis (no remaining non-linearity) is rejected in most cases, the only exception being the industrialization period.

As a next step, we allow for three different regimes depending on the level of output growth (low, medium, and high). We report the results for the four subperiods in Tables 8 and 9. The multiple regime switching model further emphasizes the role of time varying uncertainty on output growth. Again, in three out of the four samples, uncertainty during low-growth regimes has a negative effect on growth. Taking into account the three separate regimes, results in quite a consistent effect over the different samples. In addition, the persistence term for uncertainty is consistent in terms of sign and statistical significance. The in-mean effect of the uncertainty is considerably larger for the uncertainty during high-growth regimes (*good uncertainty*) versus the low-growth regimes (*bad uncertainty*). For instance, in the medieval period 1272-1499 in the low-growth regime, uncertainty negatively affects average growth. More specifically, one standard deviation increase in (bad) uncertainty reduces average growth by approximately 3.8 per cent. In contrast, in high growth regime one standard deviation increase in (good) uncertainty increases average growth by approximately 4.2 per cent. In the medium-growth regime the effect is still positive but insignificant. A similar pattern holds for all subperiods. Table 10 summarises the sign and significance of the in-mean coefficients across the four periods. It is obvious that there is consistency across the four periods as the in-mean coefficient is negative for the low-growth regime and positive for the high-growth regime.

There is also far more consistency in relation to the speed of transition between regimes. There is relatively smooth adjustment between the multiple regimes for all samples, with the marginally fastest adjustment taking place in the industrialization period. In addition, the *fast* transition speeds in particular for the medieval and the modern economic period for the two-regime case are now far smoother once we take account of multiple regimes. Although the multiple regime model eliminates any further non-linearity, there is mixed evidence in terms of the certainty associated with the threshold values. The empirical results presented in Tables 8 and 9 clearly depict the low-growth, normal-growth and high-growth regimes, in particular in relation to the threshold values. While, the lack of statistical significance is a concern, the LM test results highlight the importance of the expanded model.

Figures 2-5 show the first estimated transition function and the observed growth rates in the four subperiods. The transition function equals one for the low growth regime and zero for the medium (normal) growth regime. It is obvious that there is quite large variation in the transition function indicating regimes alternate quite often during the medieval and early modern periods. In particular, in Figure 2 and 3, output tends to be equally distributed between the normal and low growth regime. For the industrialization and modern economic periods (Figure 4 and 5), there is far greater indications of the medium regime being the norm and relatively minor switches to low-growth regimes. For example in Figure 4, it is evident that the medium growth regime is more prevalent and coincides to a large extent with the *First Industrial Revolution* between 1760 and 1830. Figure 5 shows more clearly the various regimes that apply in the modern economic period, with continued evidence of the medium regime being the norm. The high-growth regimes associated with the two world wars are also evident. In addition, the high-growth regime linked with the post world war two reconstruction and fast-growth period is also obvious in the figure. The high-growth regime also is highlighted by the post-mid 1990s period which is associated with the Great Moderation. Finally, Figure 5 indicates the temporary low-growth regime caused by the recent Great Recession.

6 Discussion

We have examined the uncertainty-growth relationship over a very long period that spans eight centuries using British data allowing for regime switching where the economy may shift from a low-growth regime to a high-growth regime. Our first contribution relates to the potential influence of the regime on the uncertainty-growth relationship. We have shown that the uncertainty-growth relationship differs across high-growth and low-growth regimes. In other words, our results from the models allowing for regimes (two or three) are quite interesting and highlight the influence of the regime on the sign of the in-mean coefficient that captures the effect of output growth uncertainty on average growth. Our major findings regarding the first contribution can be summarized as follows. First, in both the two- and three-regime models, the low-growth regime is associated with a negative effect of output growth uncertainty on growth (for most sample periods). This finding supports the Keynesian theory which argues that periods of high uncertainty are associated with a lower demand for investment and hence average growth. Second, periods of medium growth (in the two-regime model) or high growth (in the three-regime model), are associated with a positive effect of output growth uncertainty on growth. This finding is consistent with the theory advanced by Black (1987), Blackburn (1999), Mirman (1971), Oi (1961), and others. This result seems rather intuitive as during medium- or high-growth periods, investors feel quite optimistic and decide to invest even in the presence of more uncertainty about the growth prospects of the economy.

Our finding that in the low-growth regime, uncertainty has a negative effect on growth may explain why this negative effect is more prominent in low-income developing countries. Indeed, this finding may explain the evidence obtained by Bakas et al (2018) that the negative relationship is stronger for developing countries which are in low-growth regimes and have considerable *bad uncertainty*. Our evidence can also explain the finding of Aghion et al (2010) that countries characterized by financial underdevelopment have higher volatility which is associated with a negative impact on growth.

Our second contribution relates to the consideration of four historical periods in our sample (the medieval, early modern, industrialization, and modern economic periods) in order to study the impact of the level of economic development on the uncertainty-growth nexus. Our unconditional results show that the only difference that applies across subperiods is that early stages in British history (the medieval and early modern period) indicate low growth and high volatility, whereas later stages (industrialization and modern period) indicate high growth and low volatility. Using our GARCH approach, we find consistent evidence that in all phases of economic development volatility affects growth negatively during low-growth regimes and positively during high-growth regimes. The only exception to this strong conclusion is the early modern period where the negative effect in the low-growth regime is statistically insignificant. Therefore, we can conclude that the state of economic development has no bearing on the uncertainty-growth relationship.

As highlighted earlier in the paper, the empirical literature on the relationship between output uncertainty and output growth has produced mixed results. This is not surprising given the variety of empirical methodologies employed (panel, cross section, or time series studies), the number of countries involved in time series studies, and the variation of the sample periods chosen. However, with very few exceptions, all previous time series studies used a short time period covering a few decades. None of the previous studies considered regime changes. Fountas and Karanasos (2008) employed annual data starting in the 19th century for five industrial countries, including the UK (roughly the last subperiod of our study). No consideration of different growth regimes was given in this paper. The authors found that in three countries (France, Germany and UK), the effect of uncertainty on growth is positive. This result is broadly consistent with our result that in high-growth regimes (as one could classify the last subsample, relative to the previous three subsamples) the effect of uncertainty on growth is positive. Speight (1999) estimates the uncertainty-growth relationship using GARCH models for post WWII UK monthly data. He finds that uncertainty about growth does not affect the average growth rate significantly. However, this result is not directly comparable to our analysis as there is no consideration of regime switching.

7 Conclusions

We examine the empirical relationship between output variability and output growth for Britain using data for eight centuries for the period 1270-2014. Our sample includes the pre-industrial period with its primary focus on agricultural production and the first, second and third industrial revolutions. This period also includes catastrophic events such as the Great Famine (1315-17) and the Black Death (1348-49), as well as, a large number of wars. We split the full sample period in four subperiods, on the basis of economic historians and use GARCH models to measure output growth uncertainty and estimate its effect on average growth. Using a comprehensive range of GARCH models, including symmetric, asymmetric, and regime switching, we estimate the uncertainty-growth relationship and make two contributions to the literature. First, we analyze the uncertainty-growth relationship over an eight-century period allowing for switching between low- and high-growth regimes. Second, we consider the effect of the state of economic development on the uncertainty-growth relationship by dividing the eight-century period into four distinct subperiods; the medieval period, the early modern period, the industrialization period, and the modern economic period. Regarding the first contribution, when considering a single-regime model, uncertainty about output growth has a significant and negative effect on output growth in the medieval and early modern periods. In addition, allowing for three different regimes of the growth level (low, medium, and high), we find that the effect of uncertainty on growth differs depending on the existing growth regime. Low-growth regimes are associated with a negative effect of uncertainty on growth, and medium- or high-growth regimes are associated with a positive effect of uncertainty on growth. Regarding the second contribution, we find that for each of the four subperiods considered, the effect of uncertainty on growth is negative for the low-growth regime and positive for the high-growth regime. In other words, under all states of economic development (whether the leading sector of the economy was the agricultural or the industrial sector), the effect of uncertainty on growth remains similar and depends on the growth regime (low or high growth).

Our results are in agreement with the variety of the predictions of economic theories regarding the effects of uncertainty about the rate of output growth on average growth. For low-growth regimes, we find support for the Keynesian theory that more uncertainty discourages the demand for investment and leads to lower growth. On the other hand, for medium or high-growth regimes, we find evidence supporting the theories advanced by Black (1987) and Mirman (1971). These results have important implications for macroeconomic modelling as they highlight the importance of treating output variability (or uncertainty) and growth in tandem rather than separately. Hence, macroeconomic theorists should direct their efforts in modelling the variability of the business cycle simultaneously with the growth rate in order to better understand the determinants of long-run growth.

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Figure 1: Output Growth in England/Great Britain

1270 - 2014

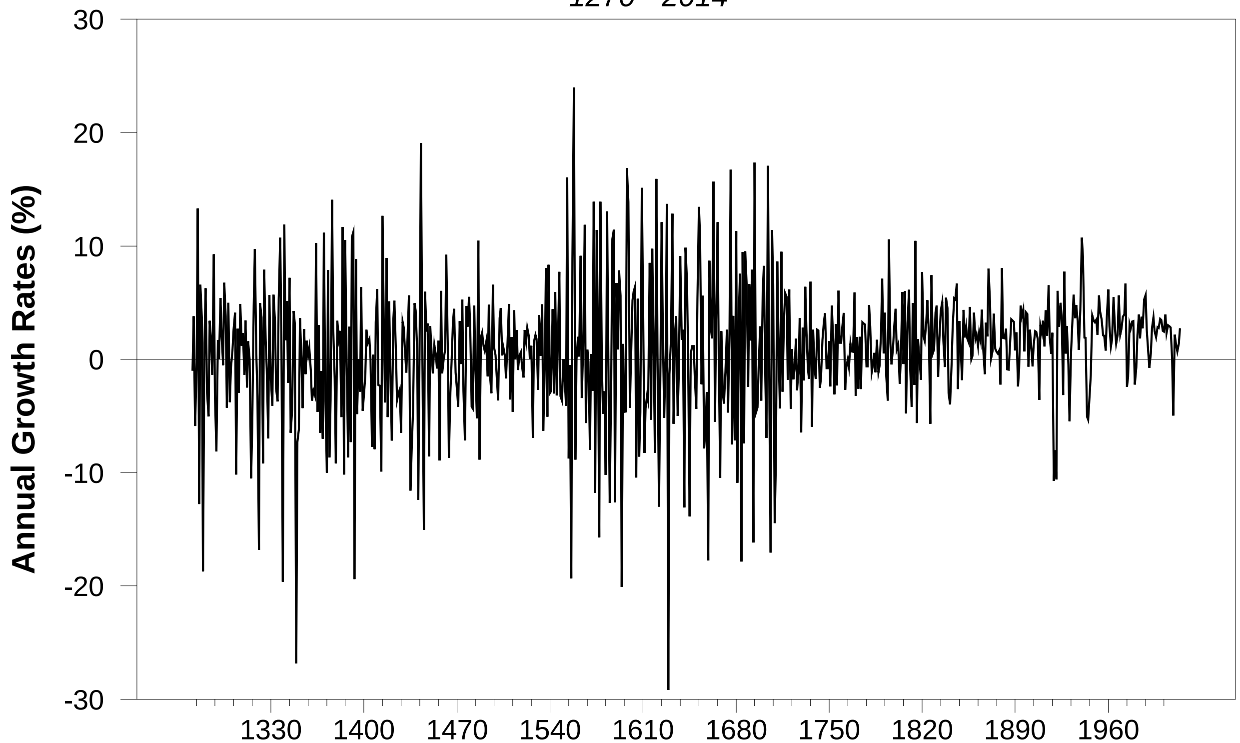

Figure 2: Output Growth and Recession Transition Function

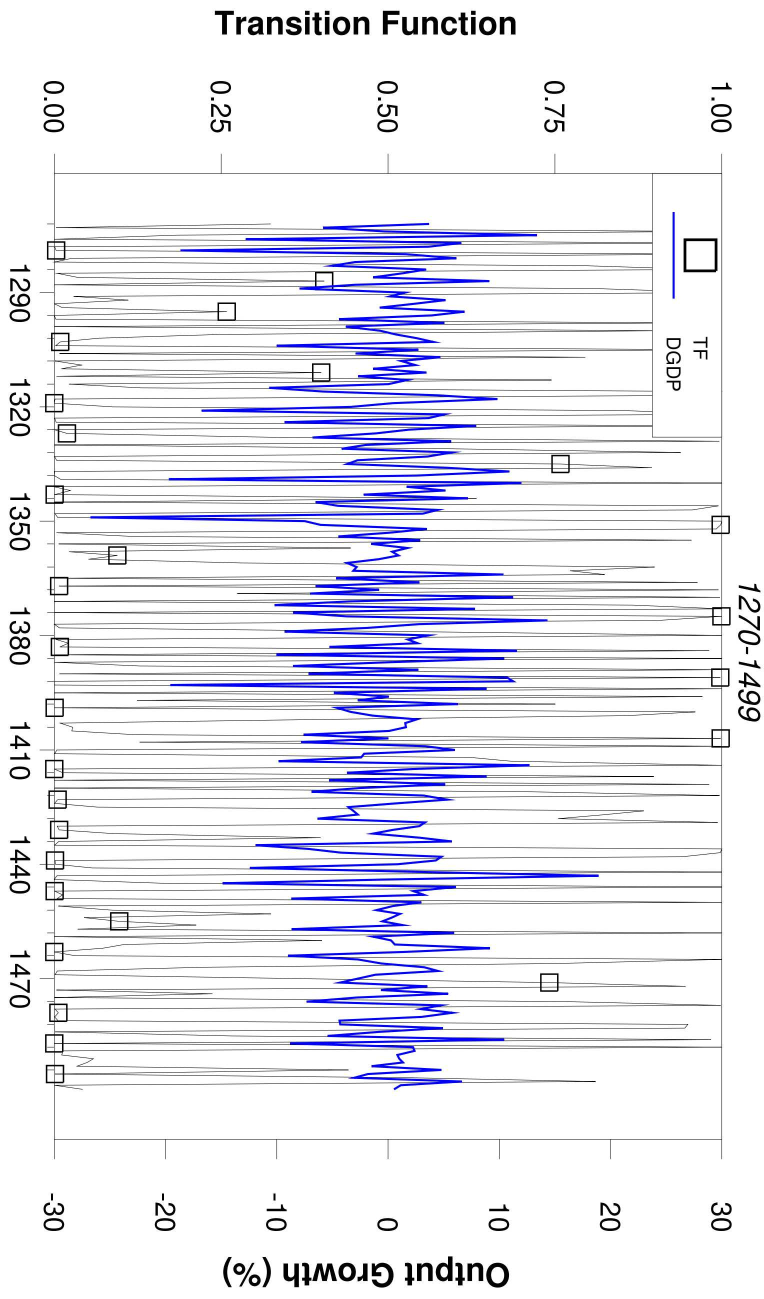

Figure 3: Output Growth and Recession Transition Function

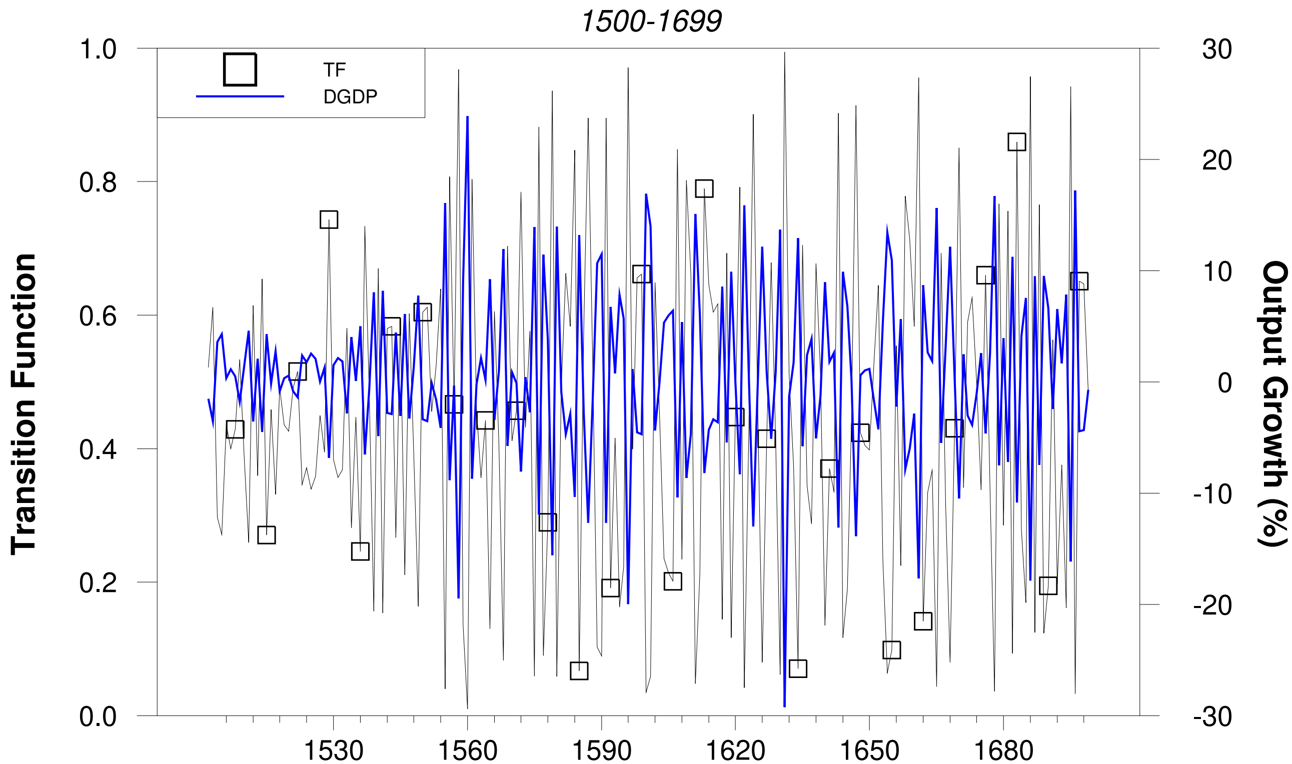

Figure 4: Output Growth and Recession Transition Function

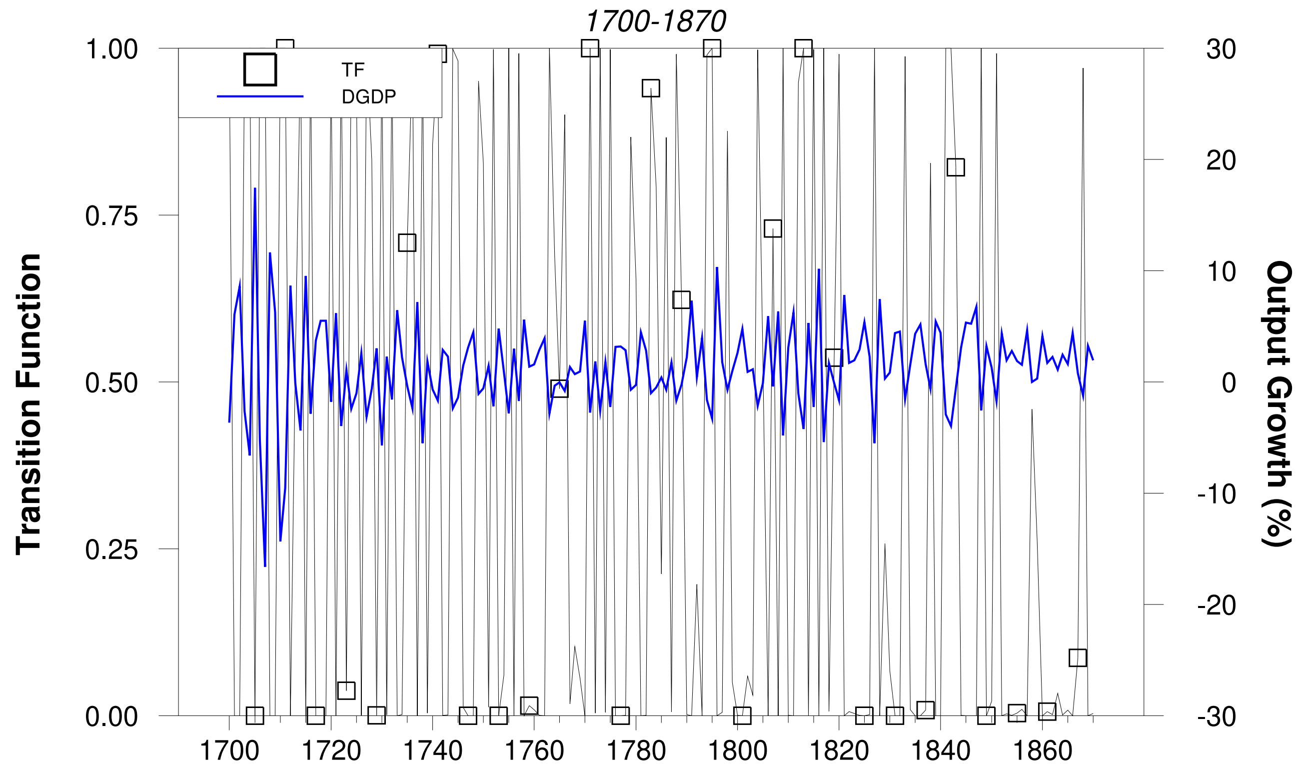

Figure 5: Output Growth and Recession Transition Function

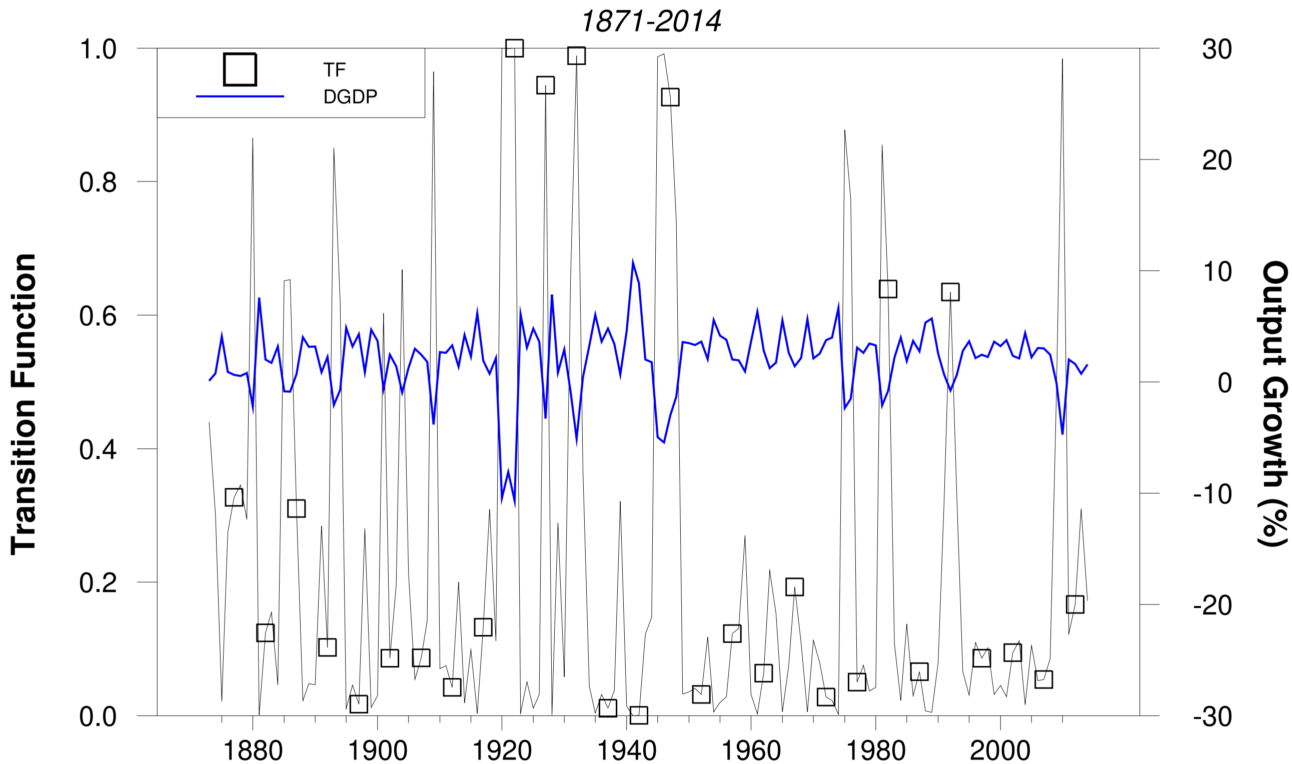

Table 1: England (Britain) GDP at factor cost growth (annual percentages)

Sample	Observations	Mean	Standard deviation	Minimum	Maximum
1270-1499	229	-0.134	6.338	-26.844	19.066
1500-1699	200	0.579	7.862	-29.186	23.991
1700-1869	171	1.322	4.257	-17.065	17.081
1870-2014	144	1.971	3.138	-10.742	10.731

Table 2: GARCH Model for UK output growth: Single Regime

	1270-1499		1500-1699	
Coefficient	Estimate	Standard Error	Estimate	Standard Error
Mean				
ϕ_0	0.072	0.044	0.015	0.009
ϕ_1	-0.432*	0.074	-0.364*	0.067
ϕ_2	-0.419*	0.082	-0.251*	0.082
ψ_0	-1.333	0.785	-0.044	0.162
Conditional Variance				
α_0	0.001	0.001	0.000*	0.000
$\beta_1\sigma^2_{t-1}$	0.708*	0.199	0.978*	0.024
$\alpha_1\epsilon^2_{t-1}$	0.084	0.055	0.015	0.020
LM Test	0.0000		0.0000	

Note: A * represents significance at the 5% level. The final row of the above table reports the P-Value for the LM Test for non-linearity. See Luukkonen *et al.*, (1988) and Teräsvirta (1994).

Table 3: GARCH Model for UK output growth: Single Regime

	1701-1870		**1871-2014**	
Coefficient	Estimate	Standard Error	Estimate	Standard Error
Mean				
ϕ_0	0.043*	0.016	0.023	0.016
ϕ_1	-0.298*	0.080	0.292*	0.101
ϕ_2	-0.174*	0.075		
ψ_0	-0.694	0.487	-0.328	0.597
Conditional Variance				
α_0	0.000	0.000	0.000	0.000
$\beta_1\sigma^2_{t-1}$	0.893*	0.026	0.768*	0.197
$\alpha_1\epsilon^2_{t-1}$	0.004	0.092	0.088	0.080
LM Test	0.0000		0.0000	

Note: A * represents significance at the 5% level. The final row of the above table reports the P-Value for the LM Test for non-linearity. See Luukkonen *et al.*, (1988) and Teräsvirta (1994).

Table 4: EGARCH Model for UK output growth: Single Regime

	1270-1499		**1500-1699**	
Coefficient	Estimate	Standard Error	Estimate	Standard Error
Mean				
ϕ_0	0.078*	0.042	0.004	0.008
ϕ_1	-0.392*	0.075	-0.445*	0.073
ϕ_2	-0.392*	0.091	-0.330*	0.081
ϕ_3	-0.176*	0.085	-0.143*	0.076
ϕ_4	-0.117*	0.070	-0.161*	0.065
ϕ_5	0.001	0.067	-0.001	0.066
ψ_0	-1.454*	0.750	0.150	0.148
Conditional Variance				
α_0	-0.625	0.340	-0.060	0.100
$\beta_1 log(\sigma^2_{t-1})$	0.910*	0.060	0.972*	0.015
$\alpha_1 \mid \frac{\epsilon_{t-1}}{\sigma_{t-1}} \mid$	0.139*	0.065	-0.096*	0.038
$\zeta_1 \frac{\epsilon_{t-1}}{\sigma_{t-1}}$	0.045	0.058	-0.062	0.112
LM Test	0.0000		0.0000	

Note: A * represents significance at the 5% level. The final row of the above table reports the P-Value for the LM Test for non-linearity. See Luukkonen *et al.*, (1988) and Teräsvirta (1994).

Table 5: EGARCH Model for UK output growth: Single Regime

	1701-1870		**1871-2014**	
Coefficient	Estimate	Standard Error	Estimate	Standard Error
Mean				
ϕ_0	0.053*	0.019	0.033	0.021
ϕ_1	-0.312*	0.085	0.261*	0.125
ϕ_2	-0.227*	0.080		
ϕ_3	-0.075	0.088	-0.158*	0.072
ψ_0	-0.937	0.542	1.293	7.452
Conditional Variance				
α_0	-0.356*	0.159	-6.230	4.760
$\beta_1 log(\sigma^2_{t-1})$	0.958*	0.020	0.182	0.662
$\alpha_1 \mid \frac{\epsilon_{t-1}}{\sigma_{t-1}} \mid$	0.071	0.079	0.486*	0.157
$\zeta_1 \frac{\epsilon_{t-1}}{\sigma_{t-1}}$	0.001	0.034	-0.074	0.134
LM Test	0.0000		0.0000	

Note: A * represents significance at the 5% level. The final row of the above table reports the P-Value for the LM Test for non-linearity. See Luukkonen *et al.*, (1988) and Teräsvirta (1994).

Table 6: Regime Switching EGARCH Model for GDP Growth - Two Regimes

	1270-1499		**1500-1699**	
Coefficient	Estimate	Standard Error	Estimate	Standard Error
Mean				
$\phi_{0,L}$	-0.2708	1.6992	-0.9579*	0.4424
$\phi_{0,H}$	1.2135*	0.59489	1.3641*	0.3611
$\phi_{1,L}$	-0.6325*	0.1011	-0.1935*	0.0642
$\phi_{1,N}$	0.1858	0.1198	0.0629	0.0560
$\psi_{1,L}$	-0.8662*	0.3524	-1.4494*	0.3020
$\psi_{1,N}$	-0.1112	0.1726	1.7450*	0.3098
Conditional **Variance**				
$\alpha_{0,L}$	1.6197*	0.3650	0.3363*	0.1669
$\alpha_{0,N}$	0.8967*	0.3017	-0.0798	0.1077
$\beta_{1,L} log(\sigma^2_{t-1})$	0.6195*	0.0699	0.9599*	0.0403
$\beta_{1,N} log(\sigma^2_{t-1})$	0.9526*	0.0846	0.9677*	0.0313
$\alpha_{1,L} \mid \frac{\epsilon_{t-1}}{\sigma_{t-1}} \mid$	1.3993*	0.2665	0.1649*	0.0760
$\alpha_{1,N} \mid \frac{\epsilon_{t-1}}{\sigma_{t-1}} \mid$	1.5418*	0.3734	-0.1319*	0.0408
$\zeta \frac{\epsilon_{t-1}}{\sigma_{t-1}}$	-0.3371*	0.1615	0.6445*	0.1545
γ	24.5958*	4.1238	8.2616*	0.6938
C	-0.4775*	0.1741	0.3508	0.2415
LM Test	0.0000		0.0081	

Note: A * represents significance at the 5% level. The final row of the above table reports the P-Value for the LM Test. The single transition variable model is the null hypothesis for testing for any further non-linearity. See Luukkonen *et al.*, (1988) and Teräsvirta (1994).

Table 7: Regime Switching EGARCH Model for GDP Growth - Two Regimes

	1700-1870		1871-2014	
Coefficient	Estimate	Standard Error	Estimate	Standard Error
Mean				
$\phi_{0,L}$	-3.3932*	0.9239	0.1043	1.9430
$\phi_{0,N}$	5.9822*	0.9045	0.7986	2.6615
$\phi_{1,L}$	0.0310	0.0432	0.0901	0.1736
$\phi_{1,N}$	0.0345	0.0348	0.2063	0.1033
$\psi_{1,L}$	-3.2584*	1.1224	-0.4631	0.9709
$\psi_{1,N}$	4.2969*	1.2928	1.9883	1.8038
Conditional **Variance**				
$\alpha_{0,L}$	0.0516	0.2100	1.0530*	0.3296
$\alpha_{0,N}$	0.1467	0.4342	0.3831*	0.2373
$\beta_{1,L} log(\sigma^2_{t-1})$	0.7885*	0.2113	0.4820*	0.1496
$\beta_{1,N} log(\sigma^2_{t-1})$	-0.0975	0.3170	0.2112	0.2951
$\alpha_{1,L} \mid \frac{\epsilon_{t-1}}{\sigma_{t-1}} \mid$	0.7515*	0.2472	0.5024	0.3716
$\alpha_{1,N} \mid \frac{\epsilon_{t-1}}{\sigma_{t-1}} \mid$	1.2200*	0.5460	0.2197	0.2849
$\zeta \frac{\epsilon_{t-1}}{\sigma_{t-1}}$	-0.6219*	0.1416	0.0700	0.4059
γ	1.2714*	0.0122	13.3632*	2.1217
C	1.7193*	0.3320	2.2737*	0.1374
LM Test	0.3000		0.0311	

Note: A * represents significance at the 5% level. The final row of the above table reports the P-Value for the LM Test. The single transition variable model is the null hypothesis for testing for any further non-linearity. See Luukkonen *et al.*, (1988) and Teräsvirta (1994).

Table 8: Regime Switching EGARCH Model for GDP Growth - Three Regimes

	1272-1499		1500-1699	
Coefficient	Estimate	Standard Error	Estimate	Standard Error
Mean				
$\phi_{0,L}$	-1.0814	0.7696	-1.8676	11.4537
$\phi_{0,M}$	0.0689	1.0720	0.5119	19.9289
$\phi_{0,H}$	2.2698*	0.9324	2.7826	7.5358
$\phi_{1,L}$	-0.0543*	0.0108	-0.0292	0.0392
$\phi_{1,M}$	-0.1223*	0.0740	0.2800*	0.0915
$\phi_{1,H}$	0.0472*	0.0138	-0.0598	0.0916
$\psi_{1,L}$	-3.7989*	0.4577	-7.2287	7.6422
$\psi_{1,M}$	0.1546	1.6580	1.6334	18.668
$\psi_{1,H}$	4.2218*	1.0254	11.0680*	4.3839
Conditional **Variance**				
$\alpha_{0,L}$	2.3839*	0.1909	2.0626*	1.2689
$\alpha_{0,M}$	-2.7327*	1.0781	-2.9497	4.1493
$\alpha_{0,H}$	2.2652*	0.4935	1.4381*	0.0063
$\beta_{1,L} log(\sigma^2_{t-1})$	-0.4630*	0.0926	-0.4152	0.5645
$\beta_{1,M} log(\sigma^2_{t-1})$	0.8229*	0.3387	1.5681	2.2179
$\beta_{1,H} log(\sigma^2_{t-1})$	0.0333	0.1487	0.4269	1.3560
$\alpha_{1,L} \mid \frac{\epsilon_{t-1}}{\sigma_{t-1}} \mid$	0.9101*	0.1242	0.4080	0.8077
$\alpha_{1,M} \mid \frac{\epsilon_{t-1}}{\sigma_{t-1}} \mid$	0.6444	0.5007	-0.0604	2.5228
$\alpha_{1,H} \mid \frac{\epsilon_{t-1}}{\sigma_{t-1}} \mid$	1.4702*	0.2731	1.2902	1.3290
$\zeta \frac{\epsilon_{t-1}}{\sigma_{t-1}}$	-0.2116*	0.0861	0.2933	0.5900
γ_L	2.6427*	0.0498	1.2083*	0.3131
C_L	-1.7092*	0.7501	-1.0617	2.7329
γ_H	1.8468*	0.0964	1.1736*	0.0596
C_H	1.4770*	0.5577	0.9235	7.9913
LM Test	0.4886		0.0703	

Note: A * represents significance at the 5% level. The final row of the above table reports the P-Value for the LM Test. The double transition variable model is the null hypothesis for testing for any further non-linearity. See Luukkonen *et al.*, (1988) and Teräsvirta (1994).

Table 9: Regime Switching EGARCH Model for GDP Growth - Three Regimes

	1700-1870		**1871-2014**	
Coefficient	Estimate	Standard Error	Estimate	Standard Error
Mean				
$\phi_{0,L}$	-0.7779	1.2400	-1.3473	1.7450
$\phi_{0,M}$	0.5554	3.1441	0.6646	2.2972
$\phi_{0,H}$	1.7577	1.2141	3.2696*	1.4364
$\phi_{1,L}$	0.0501	0.0696	0.0138*	0.0003
$\phi_{1,M}$	0.1620	0.3300	0.0731	0.0861
$\phi_{1,H}$	-0.0297*	0.0416	-0.0868*	0.0086
$\psi_{1,L}$	-2.2814*	0.9925	-3.2303*	1.0379
$\psi_{1,M}$	0.7781	4.9525	1.9268	3.2552
$\psi_{1,H}$	3.6671*	1.2023	7.8109*	2.9303
Conditional **Variance**				
$\alpha_{0,L}$	0.5205	0.3251	1.1865*	0.3603
$\alpha_{0,M}$	-1.1947	2.2969	-3.0480*	1.1369
$\alpha_{0,H}$	0.8022*	0.3156	-0.1716	0.6082
$\beta_{1,L}log(\sigma^2_{t-1})$	0.7866*	0.1775	0.0763	0.4928
$\beta_{1,M}log(\sigma^2_{t-1})$	-0.0453	0.9706	0.9185	0.8100
$\beta_{1,H}log(\sigma^2_{t-1})$	0.2868	0.2108	-0.4616	0.3608
$\alpha_{1,L} \mid \frac{\epsilon_{t-1}}{\sigma_{t-1}} \mid$	-0.0599	0.2612	0.6976*	0.2799
$\alpha_{1,M} \mid \frac{\epsilon_{t-1}}{\sigma_{t-1}} \mid$	0.2425	1.5258	0.3494	1.0726
$\alpha_{1,H} \mid \frac{\epsilon_{t-1}}{\sigma_{t-1}} \mid$	1.7744*	0.5002	1.0176	0.8157
$\zeta\frac{\epsilon_{t-1}}{\sigma_{t-1}}$	0.1982	0.1528	0.1091	0.2167
γ_L	3.5079*	1.3624	1.6811*	0.4271
C_L	-0.0566	2.3571	-0.1709	0.5565
γ_H	2.8125*	0.7761	1.5403*	0.4210
C_H	1.9212	2.1691	2.9605*	1.1709
LM Test	0.5906		0.3000	

Note: A * represents significance at the 5% level. The final row of the above table reports the P-Value for the LM Test. The double transition variable model is the null hypothesis for testing for any further non-linearity. See Luukkonen *et al.*, (1988) and Teräsvirta (1994).

Table 10: Summary of the in-mean coefficients (3-regime model)

Sample	$\psi_{1,L}$	$\psi_{1,M}$	$\psi_{1,H}$
1270-1499	(-)*	(+)	(+)*
1500-1699	(-)	(+)	(+)*
1700-1869	(-)*	(+)	(+)*
1870-2014	(-)*	(+)	(+)*

Note: A * represents significance at the 5% level.