Mortgage Lending and the Great moderation: a multivariate GARCH Approach

Bezemer, Dirk J and Grydaki, Maria

University of Groningen

January 2012

MORTGAGE LENDING AND THE GREAT MODERATION:
A MULTIVARIATE GARCH APPROACH

Dirk Bezemer and Maria Grydaki*

Faculty of Economics and Business, University of Groningen, The Netherlands

February 2, 2012

Abstract

Financial innovation during the Great Moderation increased the size and scope of credit flows in the U.S. Credit flows increased both in volume and with regard to the range of activities and investments that was debt-financed. This may have contributed to the reduction in output volatility that was the Great Moderation. We hypothesize that during the Great Moderation (i) growth in mortgage finance partly decoupled from fundamentals as measured by overall output growth and (ii) this allowed mortgages less to finance residential investment and more to finance spending on other GDP components. We document that the start of the Moderation coincided with a surge in bank credit creation (especially mortgage credit), a rise in property income, a rise in the consumption share of GDP, and a change in correlation (from positive to negative) between consumption and non-consumption GDP components (investment, export and government expenditure). In a multivariate GARCH framework, we observe unidirectional causality in variance from total output to mortgage lending before the Great Moderation, which is no longer detectable during the Great Moderation. We also find that bidirectional causality in variance of home mortgage lending and residential investment existed before, but not during the Great Moderation. Both these findings are consistent with a role for credit dynamics in explaining the Great Moderation.

Key Words: great moderation, mortgage credit, multivariate GARCH, causality

JEL codes: E44, C32, C51, C52

* We share equal authorship. E-mail addresses: d.j.bezemer@rug.nl (Dirk Bezemer, corresponding author), m.grydaki@rug.nl (Maria Grydaki). We thank Wouter den Haan, Gerard Kuper and Laura Spierdijk for helpful comments. Thanks also to Wouter den Haan for making the data available and the Institute for New Economic Thinking for financial support. Any errors are ours.

1. Introduction

A substantial literature addresses the dramatic decline in macroeconomic volatility of the U.S. economy between the mid-1980s and the start of the 2007 financial crisis (Kim and Nelson 1999)[1]. Warnock and Warnock (2000) documented strongly declining employment volatility. Blanchard and Simon (2001) noted declines in the standard deviation of quarterly growth and inflation by half and by two thirds, respectively, since 1984. Stock and Watson (2002) found that the standard deviation of U.S. GDP declined from 2.6 - 2.7% in the 1970s and 1980s to 1.5% in the 1990s. Bernanke (2004) drew broad attention to these trends by making it the topic of his 2004 Eastern Economic Association speech. Many countries, particularly the Anglo-Saxon economies, shared this feature. Cechetti and Krause (2006) find that in sixteen out of twenty-five countries they examined, real GDP growth was on average more than fifty per cent less volatile than it was twenty years earlier to their study.

Some writers argue that the greater stability signified that the U.S. economy entered a new phase around 1984. The name ‘Great Moderation’, reminiscent of America’s Great Depression and Great Inflation episodes, conveys this sense of a new era. The novel element is variously thought to be better inventory management (McConnell and Perez-Quiros, 2000; Kahn et al., 2002; McCarthy and Zakajsek, 2007), fundamental labour market changes as the Baby Boomer generation is aging (Jaimovic and Siu, 2009), oil shocks (Nakov and Pescatori, 2010), changes in responses to shocks (Gambetti et al., 2008) or broader factors such as development levels (Acemoglu and Zilibotti, 1997; Easterley et al., 1993), external balances (Fogli and Perri, 2006), the size of the economy (Canning et al., 1998) and lack of strong institutions (Acemoglou et al., 2003). Owyang et al. (2007) find that within U.S. states, the volatility decline was linked to larger nondurable-goods shares, energy consumption, and demographics. Other analysts point to the role of chance and suggest that the volatility decline may well be due to smaller or less frequent shocks to the economy, quite outside the influence of policy makers – or ‘good luck’ (Ahmed et al., 2002; Cogley and Sargent, 2005; Primeceri, 2005; Sims and Zha, 2006; Gambetti et al., 2008). Benati and Surico (2009) show that most analyses, which use Structural Vector Autoregression (SVAR) models, are compatible with both ‘good policy’ and ‘good luck.’

[1] The end data of 2007 follows e.g. Barnett and Chauvet (forthcoming) and Bean (2011).

A number of papers pursue a 'financial sector' explanation of the Great Moderation. These revolve around financial innovations (Dynan et al., 2006; Guerron-Quintana, 2009), financial sector development (Easterly et al., 2000), changing responses to monetary shocks and improvements in monetary policy (Clarida et al., 2000; Bernanke, 2004; Lubik and Schirfheide 2004; Boivin and Giannoni, 2006), and innovations in financial markets and in the dynamics of inflation (Blanchard and Simon, 2001). A common outcome of many of these developments is increased liquidity, though the reasons vary from monetary policy to trade integration to financial stability. For instance, Bean (2011) discusses how the volatilities of both U.S. equities and treasuries had shrunk to very low levels by the mid-2000s, and quotes the Dynan et al. (2006) explanation of how financial innovation smoothed financial variables (such as returns on financial assets). This signalled (correctly or falsely) low risk levels to both banks and real-sector actors, encouraging them to lend and borrow more, respectively.

In the present paper we contribute to this literature. Financial innovation during the Great Moderation increased credit flows in the U.S. both in volume and with regard to the range of activities and investments they financed. We hypothesize that more of economic activity was debt-financed during the Great Moderation than before, and that those debt-financed incomes moved more independently from overall GDP, leading to a reduction in overall output volatility. We refer to this hypothesis as the 'credit-driven Great Moderation hypothesis' (or CDGM hypothesis, for short).

Specifically, we hypothesize that during the Great Moderation (i) growth in mortgage finance partly decoupled from fundamentals as measured by overall output growth and (ii) this allowed mortgage less to finance residential investment and by implication, more to finance spending on other GDP components[2]. Below we document that the start of the Moderation coincided with a surge in bank credit creation (especially mortgage credit), a rise in property income, a rise in the consumption share of GDP, and a change in correlation (from positive to negative) between consumption and non-consumption GDP components (investment, export and government expenditure). In a multivariate Generalized Autoregressive Conditional

[2] Because this can occur in a number of ways, affecting a number of spending categories, we do not specify these 'other' GDP components. They are likely to be a mix of consumption categories which cannot be mapped reliably on durables/nondurables, or some other statistical category. While the number of possible ways in which mortgage lending may have smoothed GDP is large, it is likely that all the channels have rising levels of home equity withdrawal in common. However, no sufficiently long pre-Great Moderation data on home equity withdrawal are available (Greenspan and Kennedy, 2008) so that we cannot apply the before/during analysis conducted in this paper to test for a change in the relation between GDP volatility and home equity withdrawal.

Heteroskedasticity (GARCH) framework, we observe unidirectional causality in variance from total output to mortgage lending before the Great Moderation, which is no longer detectable during the Great Moderation. We also find that bidirectional causality in variance of home mortgage lending and residential investment existed before, but not during the Great Moderation. Both these findings are consistent with a credit-driven Great Moderation, in conjunction with the other explanations discussed above.

Importantly, we test these relations in variances rather than levels. The Great Moderation was a reduction in the variance of output (denoted Y), but also of the financial-sector variables that possibly caused it (Bean, 2011). We therefore study also the variances (not only the levels) of mortgage lending (denoted M) and residential investment (denoted RI). An intuitive way to see the importance of the causality-in-variance approach in this paper is to decompose output into residential investment and other GDP components so that $Y=RI+(Y-RI)$ and $var(Y)=var(RI)+var(Y-RI)+2cov(RI,Y-RI)$. Financial innovation may reduce var(Y) by reducing any one of the three right-hand terms of this expression. A VAR analysis in terms of levels only (e.g. Den Haan and Sterk, 2010) captures the first channel but not the second and third. And since this first channel is the least likely one, it is unsurprising that this method finds no evidence for the financial sector view of the Great Moderation[3]. By testing directly for var(Y), var(M) and var(RI) we capture all three possible channels, including (importantly) their covariances. We do this below in a multivariate GARCH framework.

The remainder of the paper proceeds as follows. In the next section we explore relevant trends in the U.S. economy and locate the argument in the literature. Section 3 develops the methodology and section 4 presents the data as well as the estimation and test results. Section 5 concludes with a summing up and discussion.

[3] Financial innovation may increase the level of credit-supported consumption and production, but there is no particular reason why it would reduce the volatility.

2. Locating the Argument: Empirical Trends and Relevant Literature

2.1. Some Trends

In this section we present and discuss six developments consistent with our hypothesis, and then locate it in the literature (Table 1; all data are taken from the Bureau of Economic Analysis).

[Table 1 HERE]

The average annual volatility of GDP growth nearly halved from 0.0105 in the 1970s and 0.0114 in the 1980s to 0.006 over 1984-2007 – the key feature we attempt to explain, and which is also widely documented in other places (e.g. Bean, 2011). The share of consumption in GDP, which had been virtually stable between 60% and 63% from 1953 to 1981, rose from 64% in 1982 to 70% in 2000-2007. Historically, this was a rapid increase. It implies that the importance of any factors driving consumption (such as mortgage lending) also became more relevant to understanding GDP and its volatility. Shocks to the investment, export and government expenditure components of GDP were increasingly counterbalanced by private consumption movements in opposite direction. The correlation coefficient between the two (in differenced growth rates) was positive (+0.25) in the 1970s but turned negative (-0.36 to -0.40) from the 1980s onwards. Significantly, most of that decline occurred around the start of Great Moderation in the mid-1980s. For most of the Great Moderation years, declines in the combined investment, net export and government expenditures components of GDP were balanced by increases in private consumption.[4] This is consistent with the view that variations in private consumption cushioned negative movements to the other, non-consumption GDP components, reducing the volatility of total output.

The liquidity that facilitated the increase in consumption was provided by increases in the total bank credit stock, which doubled in relative terms from 1.5 times GDP in the 1970s to 3 times GDP in the 2000s. The rise in bank credit creation was largely due to the most important category of credit in the domestic U.S. economy, the stock of mortgage credit. This rose from

[4] As these averages hide great variation, another way to illustrate this difference is to look at the percentage of two-yearly moving-average correlation coefficients that was negative in each decade. This share of observations was 30% in the 1970s, but 77% in the 1980s, 92% in the 1990s and 90% in the 2000s.

just 3% of GDP in the early 1950s to 30% of GDP in 1985 and on to an average 96% in the 2000s. Other credit stocks also increased, especially in the Great Moderation, but more slowly.

This shift in credit flows is linked to the rise in income from property as a share of GDP: from 30% in the 1970s to around 40% in the 1980s, 1990s and 2000s. Again, most of that increase occurred at the start of the 1980s. In the four years 1978-1982, income from property rose from 31% to 42% of GDP. Then it remained at that level, fluctuating between 35% and 45% for the remainder of the Great Moderation. This trend was also evident in the estimated housing wealth effect on consumption. Carroll et al. (2006) estimate that in the U.S. over 1960-2004, the immediate (next-quarter) marginal propensity to consume from a $1 change in housing wealth was about two cents, increasing to around between four and ten cents in the long run. During the Great Moderation, average nominal U.S. house prices more than tripled, so that the housing wealth effect would have induced an increase of consumption of 12 to 30 per cent over the period (in nominal values). To the extent that wealth-induced consumption was countercyclical to other GDP components, this could lead to significant GDP smoothing. These figures are only indicative, but the orders of magnitude are sufficiently large that the distribution of these gains over time will matter to the volatility of GDP.

2.2. Relevant Literature

The CDGM hypothesis fits into the Great Moderation literature. For instance, Gambetti et al. (2008) find changes in the way the private sector responds to supply and real demand shocks, together with changes in the variability of structural shocks. A next step is to research why responses changed; altered availability of credit is one possible reason. Beyond the Great Moderation literature, the present paper also connects to a strand of literature where credit is a key factor in understanding the macroeconomy, especially cyclicality and volatility (Bernanke, 1993; Bernanke and Blinder, 1998; Bliss and Kaufmann, 2003). While most contemporary work on credit and the macroeconomy is in the spirit of the Credit View (Bernanke and Gertler, 1995) or some variety of an accelerator model (Kyotaki and Moore, 1997), the present emphasis is on the more traditional notion of credit as the prime source of liquidity, enabling agents to finance expenditures (as also in Borio and Lowe, 2004). This paper follows the Kocherlakota (2000) argument that credit constraints can create cycles, and extends this to the logically equivalent argument that looser credit policies can create stability. It, thus, also connects to the literature which views business cycles (partly) as credit cycles (Kiyotaki and Moore, 1997; Mendicino, 2007). In support, Benk et al. (2005), building on Uhlig (2004), identify credit shocks as candidate shocks that matter in determining GDP.

We explore linkages between (the volatility of) credit components and GDP components. These linkages are supported by Caporale and Howells (2001) who analyse the interactions between bank loans, bank deposits and total transactions in the economy. They conclude that "loans cause deposits and that those deposits cause an expansion of wealth/GDP transactions" (Caporale and Howells, 2001:555). This paper is also focused on loan volumes rather than interest rates; Lown and Morgan (2006) show that loan volumes – determined largely by credit standards and regulation – dominate loan rates in explaining output and output components. Their work also suggests that the CDGM hypothesis is complementary (rather than rival) to the well established inventory explanation (McConnell and Perez-Quiros, 2000; Kahn et al., 2002; McCarthy and Zakajsek, 2007). The Lown and Morgan (2006) VAR analysis suggests a large impact of weakening of loan on declining inventory investment. This suggests that the widely noted decline in loan standards during the Great Moderation led to both declining inventory investment and to more mortgage lending. Both, in different ways, may have contributed to declining output volatility. Other closely related papers outside the Great Moderation literature are by Campbell (2005), who poses a link between rapid growth and increased volatility in credit flows to financial markets and stability in the real economy. Also, Lorrain (2006) finds that the volatility of industrial output is lower in countries with more bank credit.

Den Haan and Sterk (2010) address another interpretation of the CDGM hypothesis in a test for structural breaks in the relation between mortgage lending and consumption in the U.S. in a SVAR specification – but in levels, not variances. They find no evidence of breaks and reject the hypothesis that financial innovation caused the Great Moderation. Another relevant finding is by Davis and Kahn (2008), who decompose the decline in macro volatility and find that most of it is explained by a combination of changes in firm-level volatility and aggregate volatility – most clearly in the durable goods sector. A surprising finding in their study is that both volatility declines occurred without a decline in the volatility of household consumption, or in the uncertainty of incomes. Davis and Kahn (2008) therefore ascribe the lower durable goods sector firm-level volatility not to financial innovation, but to real-sector supply-side factors including better supply chain management (especially, inventory control) and a shift from employment and production from goods to services. However, both these studies consider the level, but not the variance of real output and its financial-sector determinants. This is where we break new ground. Even if the volatility of household consumption did not decline as Davis and Kahn (2008) report, if its covariance with other GDP components turned form positive to negative (Table 1) that would reduce output volatility.

3. Methodology

3.1. Modeling Volatility

In this section we present our econometric model and approach. To model conditional variances and covariances we estimate a multivariate GARCH model, an extension of a univariate GARCH model (Bollerslev, 1986 based on Engle's (1982) ARCH model). We first test for the existence of ARCH effects or volatility clustering, which is the tendency of large (small) changes (of either sign) to follow large (small) changes and, so that current and past volatility levels tend to correlate positively. In the presence of ARCH effects we proceed with the estimation of a multivariate GARCH model. Of the several possible specifications for multivariate GARCH models[5] we choose an unrestricted bivariate VAR-BEKK model (Engle and Kroner, 1995), appropriate for the computation of conditional variances and covariances between variables[6]. Below we discuss the VAR-BEKK model in terms of two variables, home mortgages and either real output or residential investment. This implies two conditional mean equations. We choose a GARCH (1,1) model for the conditional variance specification because it is more parsimonious than ARCH, avoids over-fitting and is usually sufficient to capture volatility clustering (higher-order model are rarely estimated in the academic finance literature). We test for bidirectional causality of the conditional variance of home mortgages growth with the conditional variance of output growth and of residential investment. Here we go.

[5] A common specification of multivariate GARCH models is the VECH model (Bollerslev et al. 1988), which seems infeasible to be estimated because of the large number of parameters. To solve this, Bollerslev et al. proposed the diagonal VECH, but this does not suit our purposes as it restricts the conditional variance-covariance matrix by assuming diagonal A and B matrices. Other specifications include the Constant Conditional Correlation (CCC) specification (Bollerslev, 1990) and the Dynamic Conditional Correlation (DCC) model (Engle, 2002; Tse and Tsui, 2002). An analytical survey of multivariate GARCH models is in Bauwens et al. (2006).

[6] The acronym BEKK comes from the synthesized work on multivariate ARCH models by Yoshi Baba, Rob Engle, Dennis Kraft and Ken Kroner.

The conditional mean equation is a VAR model specified as:

$$\boldsymbol{Y}_t = \boldsymbol{\mu} + \sum_{i=1}^{p} \Gamma \boldsymbol{Y}_{t-i} + \boldsymbol{\varepsilon}_t, \tag{1}$$

where, $\boldsymbol{Y_t} = (y_{1t}, y_{2t})$, y_1 and y_2 are the growth rates of home mortgages and of either real output or residential investment, respectively. The parameter vector of the mean equation (1) is defined by $\boldsymbol{\mu} = (\mu_1, \mu_2)$ and the autoregressive term $\boldsymbol{\Gamma}$. The residual vector $\boldsymbol{\varepsilon_t} = (\varepsilon_{1,t}, \varepsilon_{2,t})$ is bivariate and normally distributed $\boldsymbol{\varepsilon}_t \mid \boldsymbol{\psi}_{t-1} \sim (0, \boldsymbol{H}_t)$ with its corresponding conditional variance-covariance matrix given by:

$$H_t = \begin{bmatrix} h_{11t} & h_{12t} \\ h_{12t} & h_{22t} \end{bmatrix} \tag{2}$$

The parameter matrices for the variance equation (2) are defined as C_0, which is restricted to be upper triangular, and two unrestricted matrices, A_{11} and G_{11}. Therefore, the second moment takes the following form:

$$H_t = C_0' C_0 + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1}' \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1}' & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \tag{3}$$

Equation (2) models the dynamic process of H_t as a linear function of its own past values H_{t-1} as well as past values of squared innovations $\left(\varepsilon_{1,t-1}^2, \varepsilon_{2,t-1}^2\right)$, allowing for influences from both investment/output and mortgages on the conditional variance. Importantly, this specification allows the conditional variances and covariances of the two series to influence each other. We can in this way test the null hypothesis of no volatility spillover effects in one or both directions. There are two further advantages. The specification requires estimation of only eight parameters for the bivariate system (excluding a constant). And estimating a BEKK model by construction guarantees that the variance-covariance matrix is positive definite.

Assuming a multivariate standard normal distribution of the error terms, the parameters of the multivariate GARCH model are estimated by maximizing the log likelihood function:

$$L_{norm} = -\frac{1}{2}\left[m \log(2\pi) + \log\left(\left|H_t\right|\right) + \varepsilon_t' H_t^{-1} \varepsilon_t\right] \tag{4}$$

where m is the number of conditional mean equations and ε_t is the m vector of mean equation residuals[7].

[7] Laurent and Peters (2002) provide details on the log likelihood functions of multivariate GARCH models.

3.2. Causality-in-Variance Tests

In the literature, testing for causality in variance has been based on the residual cross-correlation function (CCF), as in Cheung and Ng (1996), or by estimating of a multivariate GARCH framework, as in Caporale et al. (2002). The methodology developed by Cheung and Ng (1996) (extended by Hong, 2001) is a two-step procedure where the estimation of univariate GARCH models is followed by computation of CCFs of squared standardized residuals. Applications to the analysis of volatility spillovers include Kanas and Kouretas (2002), Alaganar and Bhar (2003) and Hong (2003). Van Dijk et al. (2005) suggest that the Cheung and Ng (1996) test could provide unreliable inference about the (non-) existence of causality in variance if structural changes have not been accounted for[8].

Caporale et al. (2002) propose an alternative by estimating a multivariate GARCH framework and then testing for the relevant zero restrictions on the conditional variance parameters. By constraining sequentially the matrices A_{11} and G_{11} to be upper triangular and lower triangular, they allow for causality in either direction. We prefer to test for bidirectional causality-in-variance in a one-step procedure with unrestricted matrices A_{11} and G_{11} . This has better power properties and is robust to model misspecification, as Hafner and Herwartz (2004) show. So, we test simultaneously the null hypotheses of no causality-in-variance from y_{1t} to y_{2t}, ($H_0 : a_{12} = g_{12} = 0$) and no causality-in-variance from y_{2t} to y_{1t}, ($H_0 : a_{21} = g_{21} = 0$). Since this test for causality-in-variance would suffer from size distortions when causality-in-mean effects are left unaccounted for, we use the VAR specification of equation (1) to test also for causality in means (as recommended by Pantelidis and Pittis, 2004). In sum, we study the relations between mortgage growth, output growth and growth in residential investment both in means and in variances (equation (2))[9].

[8] Li et al. (2008) examine evidence of the contemporaneous causality-in-variance approach applying the method of Directed Acyclic Graphs (DAGs). See also Glymour and Cooper (1999) and Spirtes et al. (2000) for discussions.

[9] Note that even if we were interested in the conditional mean only, outcomes would still depend on correctly modeling the conditional variance (Hamilton, 2008). In this respect our study is an innovation over other Great Moderation studies, notably the closely related Den Haan and Sterk (2010) paper.

4. Data and Estimation of Volatilities

4.1. Data

We employ quarterly data for the U.S. over two subsamples, 1954Q3-1978Q4 (before the Great Moderation) and 1984Q1-2008Q1 (during the Great Moderation)[10]. The data construction follows Den Haan and Sterk (2010)[11], where this periodization is also argued. We calculated the logarithms of home mortgages (MORT), real GDP (RGDP) and residential investment (RINV), which are all stationary in their first differences (I(1)). [12]

As outlined above in section 3.1, we first examine the presence of ARCH effects (clustered volatility) by conducting the ARCH Lagrange Multiplier (ARCH-LM) test along 1-12 lags (Engle 1982). Table 2 reports descriptive statistics for the variables (mean, standard deviation, skewness, kurtosis and Jarque-Bera statistics) and values of the ARCH-LM statistic for the two subsamples.

[Table 2 HERE]

We see that variables exhibit positive growth rates (differenced logs) on average. The largest is for home mortgages in the first subsample (growing from a low base) and the smallest for residential investment growth in the second subsample. Real output growth and the growth of residential investment (but not mortgage growth) are more volatile before the beginning of the Great Moderation than during the Great Moderation, obviously. The distribution of home mortgages growth exhibits positive skewness with few high values in both subsamples; the opposite holds for real output and residential investment. Furthermore, the kurtosis (or "peakedness") statistic for the distribution of mortgages growth shows more deviations from the

[10] Studying two samples is preferable to using a structural-break approach to one sample 1954Q3-2008Q1. Fang and Miller (2008) show that the time-varying variance of output falls sharply or even disappears once they incorporate a one-time structural break in the unconditional variance of output starting 1982 or 1984.

[11] We thank Wouter den Haan for making these data available, at http://www.wouterdenhaan.com/data.htm#papers.

[12] We apply the following stationarity tests to the logs of the variables: (i) Kwiatkowski–Phillips–Schmidt–Shin (KPSS) (Kwiatkowski et al., 1992), (ii) Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979) and (iii) Phillips and Perron (PP) (Phillips and Perron, 1988). For tests (i) and (iii), the lag length was selected by the kernel-based estimator of the frequency zero spectrum, which is based on a weighted sum of the covariances. For test (ii) the selection of the number of lags in the test equations is according to the Schwartz Information Criterion (SIC). The stationarity is tested at 1%, 5%, 10% significance levels and the time trend has been taken into account in the test equation. The unit root test results are avaialable on request.

normal distribution in the first subsample than in the second. The Jarque-Bera (JB) statistic indicates normality of distributions except for the growth rates of home mortgages and residential investment in first and second subsample, respectively. Finally, the ARCH-LM test shows that there is evidence of ARCH effects in the squares of the growth rates of all variables in both subsamples. Overall, the descriptive statistics support the estimation of GARCH models assuming multivariate normally distributed errors.

4.2. Empirical Results and Residual Diagnostics of the BEKK Model

We then estimate the unrestricted BEKK model (equations (1)-(3)) where the system of conditional mean equations consists of are VAR(p) models ($p = 1,...,4$). In each subsample, we estimate the model with the growth rates of (i) home mortgages and real output, and (ii) home mortgages and residential investment. Model selection is based on residual properties, i.e. no remaining GARCH effects and, if possible, no remaining autocorrelation. We use different sets of starting values for parameter estimation and then select the best model based on the Schwarz Information Criterion (SIC). Taking into account the residual properties of all estimated models, we end up considering a VAR(1)-BEKK model for both sets of variables in first subsample, and a VAR(2)-BEKK for both sets in the second subsample. Table 3 reports the estimated conditional variances with associated log-likelihood and SIC values, and numbers of observations.

[Table 3 HERE]

The results of the first part of Table 3 (the conditional mean equations) indicate that the growth rates of home mortgages and output are affected only by their own lagged values, in both 1954Q3-1978Q4 and 1984Q1-2008Q1. The insignificance of the cross terms (γ_{12}, γ_{21}, θ_{12}, θ_{21}) suggests that there is no interaction between the two variables, and therefore no spillovers in means. Growth rates of home mortgages and of residential investment are both influenced by their own lagged terms, and by lagged values of the other variable. This interaction, and thus the occurrence of spillovers in mean, is absent in the second subsample.

Now consider the conditional variance results in the second part of Table 3. Coefficients α_{12} and α_{21} are indirect effects (spillover effect) while g_{12} and g_{21} are direct effects. For instance, coefficient a_{12} indicates if innovations in mortgage growth in quarter t decreases the conditional variance of output growth in quarter $t+1$. The estimation results do not support this, but we do observe volatility spillovers from output growth to home mortgage growth in the first subsample (coefficient value α_{21} = -0.2071). We also detect volatility spillovers in both directions between home mortgage growth and residential investment growth (7.04% and -4.84% respectively). In contrast, during the Great Moderation none of these volatility spillovers can be detected. Moreover, we detect that before the Great Moderation an increase in the volatility of mortgage growth causes an increase in the volatility of output growth (coefficient value $g12$=0.0911).

In order to test causality in variance (the purpose for which we did the estimations) we need to consider both the indirect and direct effects and compute test statistics. Table 4 reports the test results.

[Table 4 HERE]

Before the Great Moderation, we observe overall causality in variance between home mortgages growth and output growth, based on unidirectional causality from output growth volatility to the volatility of home mortgages growth. In terms of variances, mortgage finance was driven by real-sector fundamentals during 1954Q3-1978Q4. Second, we detect overall causality in variance between home mortgages growth and growth of residential investment, based on their bidirectional causality. Variances of mortgages and residential investment growth rates moved together during 1954Q3-1978Q4. Both these findings are absent in the second subsample.

This is in line with the CDGM hypothesis, which attributes lower output volatility to the partial decoupling of finance from the real sector and of the (volatility of) mortgages from its primary use in supporting residential investment. These conditions would facilitate a trend in which mortgage (and other) finance came to support consumption growth that was countercyclical to GDP shocks (Table 1), so lowering the volatility of GDP. Thus, these findings are supportive of the CDGM hypothesis.

Finally, we study residual diagnostics for the VAR-unrestricted BEKK models in order to test for remaining autocorrelation and ARCH effects (Table 5). The Ljung-Box Q-statistic of the standardized residuals for two lag lengths (8 and 12 quarters) is not statistically significant (p = 0.01) except in the first subsample for the growth rate of home mortgages, which exhibits remaining autocorrelation. We also compute squared standardized residuals and compute the Q-statistic, which is never significant (p=0.01). Hence we cannot reject the null hypothesis of no remaining ARCH effects along the two lag lengths in both subsamples.

[Table 5 HERE]

5. Summary, Discussion and Conclusions

Financial innovation during the Great Moderation increased credit flows both in volume and with regard to the range of activities and investments they could finance. We hypothesize that a larger part of economic activity was debt-financed during the Great Moderation than before, and that those debt-financed incomes moved more independently from other GDP components, leading to a reduction in overall output volatility. We refer to this hypothesis as the 'credit-driven Great Moderation hypothesis' (or CDGM hypothesis, for short).

Specifically, we hypothesize that during the Great Moderation (i) growth in mortgage finance partly decoupled from fundamentals as measured by overall output growth and (ii) this allowed mortgage finance less to finance residential investment and by implication, more to finance spending on other GDP components. We document that the start of the Moderation coincided with a surge in bank credit creation (especially mortgage credit), a rise in property income, a rise in the consumption share of GDP, and a change in correlation (from positive to negative) between consumption and non-consumption GDP components (investment, export and government expenditure).

We test the CDGM hypothesis formally by studying causality-in-variance of home mortgage lending, residential investment and total output, in a multivariate GARCH framework for the U.S. both over two periods, 1954-1978 (before the Great Moderation) and 1984-2008 (during the Great Moderation). It is significant that we test in variances rather than levels since the Great Moderation was about second, not first moments: it was a change in the variance of output but also of the financial-sector variables that possibly caused it (Bean, 2011). Testing in variances allows for potential interaction of volatilities, which are not captured in the literature to date.

We estimate a bivariate unrestricted BEKK model and conduct causality-in-variance tests following Caporale et al. (2002). We observe unidirectional causality in variance from total output to mortgage lending before the Great Moderation, which is no longer detectable during the Great Moderation. We also find that bidirectional causality in variance of home mortgage lending and residential investment existed before, but not during the Great Moderation. Both these findings are consistent with a credit-driven Great Moderation view, in conjunction with other explanations. We conclude with a discussion of its place in the wider literature and suggestions for future research.

The present paper presents the argument that the Great Moderation was (partly) caused by a surge and shift in credit flows. It so provides a basis to connect the Great Moderation to the 'Great Panic' and the 'Great Depression' as in Bean (2011). Empirically, Kemme and Roy (2012) utilize vector error correction models and panel probit and logit models to show that the U.S. mortgage-driven house price boom was a good predictor of the current crisis. The present paper also provides a link between Moderation and Crash: perhaps there was a moderation of volatility partly due to immoderate credit growth.

The paper is consistent with, but different in focus from, other papers that take a 'financial sector view' of the Great Moderation. Increased liquidity is a common outcome of financial innovations (Blanchard and Simon, 2001, Dynan et al., 2005), financial sector development (Easterly et al., 2000) and improvements in monetary policy (Clarida et al., 2000; Bernanke, 2004). The novel contribution of this paper is that it attempts to analyse how this increase combined with a shift in the relation of credit aggregates (mortgage lending) with fundamentals (output growth) on the one hand, and with the financing of output components (residential investment) on the other hand. Methodologically, this paper presents a case for testing these relations in variance, since the Great Moderation is a puzzle about second moments (as also Bean, 2011 stresses). This is a major reason for our different findings from the closely related paper by Den Haan and Sterk (2010). In the present perspective, it is too early to write of 'the myth of financial innovation and the Great Moderation' (Den Haan and Sterk, 2010:707).

In pursuing additional evidence or falsification of the CDGM hypothesis, several lines of inquiry are open. One is to be more specific about the channel from mortgage lending to those countercyclical GDP components. The Table 1 correlations suggests that much of this is consumption in one form or another. But as noted, there is no simple link from changes in the use of mortgage finance to growth in a defined statistical category such as 'durable goods consumption'. Also, including total consumption (the larger part of GDP) in the model poses serious endogeneity problems[13]. Whatever the precise delineation however, the channel through which mortgage growth feeds into growth of consumption (or other spending categories) is plausibly home equity withdrawal. Finding better, and especially longer, time series for home equity withdrawal than are presently available (Greenspan and Kennedy, 2008) is a major challenge, but potentially fruitful.

Second, home mortgages are one instance (though the most important one) of credit flows that supported the price boom in all kinds of assets within the 'Finance, Insurance and Real Estate' category of the U.S. National Income and Product Accounts. Another way therefore of pursuing the CDGM hypothesis is to aggregate all these financial-sector credit flows rather than focusing on one of them. Any credit flows supporting the realization of capital gains which could then be used to smooth consumption is in principle relevant to the CDGM hypothesis. This would include bank credit supporting mortgage products but also those of pension funds, savings institutions, credit unions, funding corporations, exchange traded funds, money market mutual funds, and the like. There is broad agreement on the wealth effects of capital gains in these assets (through e.g. equity withdrawal, asset sales and share buybacks) but no research has been undertaken on the consequences for output volatility during the Great Moderation. Widening the definition of assets on which wealth effects operate might just introduce noise in the analysis (if house wealth really were the major or only relevant asset class), or it might provide a more complete view of wealth effects on output volatility during the Great Moderation. Exploring this is a fruitful avenue for future research.

[13] We thank James Kennedy for drawing our attention to this point.

TABLES

Table 1: Trends in Credit and the Macroeconomy Before and During the U.S. Great Moderation

(decade averages)	*1970s*	*1980s*	*1990s*	*2000s**
Consumption** (% GDP)	62.4	64.3	67.0	69.9
correlation of consumption growth with non-consumption growth (coefficient)**	25.4	-35.8	-35.8	-40.4
total US domestic bank credit stock *** (% GDP)	147.3	186.1	236.7	297.0
bank mortgage credit stock (% GDP)	14.5	29.1	54.9	96.3
Income from property (% GDP)	30.0	41.7	40.5	38.9
Volatility of GDP growth (annual s.d., '000)	10.5	11.4	5.4	6.3

Source: Bureau of Economic Analysis

Note: all decadal figures are unweighted averages calculated from nominal quarterly data.
* The 2000s include the 8 years of 2000 to 2007.
** The ‘non-consumption’ part of GDP comprises investment, export and government expenditures; the ‘consumption’ part includes private consumption. ‘Correlation’ is a two-year moving average of correlations between quarterly observations of differenced growth rates.
*** The total US domestic bank credit stock is the value of all credit market instruments held as liability by the US domestic nonfinancial sector.

Table 2: Descriptive Statistics

	Mean	Std dev.	Skewness	Kurtosis	LM-Statistic	JB
1954Q3-1978Q4						
MORT	0.0235	0.0091	0.0887	4.6216	19.8769* (12)	10.7556
RGDP	0.0094	0.0109	-0.3512	3.5788	33.1762*** (12)	3.3477
RINV	0.0088	0.0501	-0.1068	3.2299	4.8668* (2)	0.3981
1984Q1-2008Q1						
MORT	0.0232	0.0092	0.3121	2.4492	40.1714*** (12)	2.7721
RGDP	0.0074	0.005	-0.2454	3.2731	3.5213* (1)	1.2620
RINV	0.0029	0.0284	-0.8581	3.5416	10.3171* (5)	12.9547

Notes: The variables included refer to the first difference of the logarithm of the initial series. ARCH-LM test has been conducted and the value of LM-Statistic is presented. The numbers in parentheses represent the number of lags used for the ARCH-LM test; ***, * denote rejection of the null hypothesis of no ARCH effects at 1% and 10% significance level, respectively.

Table 3: VAR-BEKK (unrestricted) Estimates

Parameters	Pre-Great Moderation sample	During-Great Moderation sample	Pre-Great Moderation sample	During-Great Moderation sample
	1954Q3-1978Q4	1984Q1-2008Q1	1954Q3-1978Q4	1984Q1-2008Q1
	(a) Conditional Mean Equation			
	VAR(1)	***VAR(2)***	***VAR(1)***	***VAR(2)***
	MORT (y_{1t})*-RGDP* (y_{2t})		*MORT* (y_{1t})*-RINV* (y_{2t})	
μ_1	0.0039***	0.0051*	0.0037**	0.0039**
	(0.0013)	(0.0027)	(0.0014)	(0.0019)
μ_2	0.0074**	0.0044**	0.0343**	0.0064
	(0.0037)	(0.0022)	(0.0150)	(0.0072)
γ_{11} (y_{1t-1})	0.8337***	0.4878***	0.8386***	0.4429***
	(0.0530)	(0.1040)	(0.0573)	(0.0938)
γ_{12} (y_{2t-1})	0.0042	-0.1282	0.0272***	-0.0147
	(0.0448)	(0.1109)	(0.0094)	(0.0310)
γ_{21} (y_{1t-1})	0.0165	0.0368	-1.1905*	0.1495
	(0.1417)	(0.0916)	(0.6309)	(0.3199)
γ_{22} (y_{2t-1})	0.2434**	0.10159	0.4514***	0.6611***
	(0.1025)	(0.1226)	(0.1047)	(0.1342)
θ_{11} (y_{1t-2})		0.3408***		0.3863***
		(0.1057)		(0.1009)
θ_{12} (y_{2t-2})		-0.0468		0.0452
		(0.1500)		(0.0348)
θ_{21} (y_{1t-2})		-0.0260		-0.3433
		(0.0728)		(0.3532)
θ_{22} (y_{2t-2})		0.3048**		-0.0247
		(0.1228)		(0.1430)

Table 3 (continued)

Parameters	Pre-Great Moderation sample	During-Great Moderation sample	Pre-Great Moderation sample	During-Great Moderation sample
	1954Q3-1978Q4	1984Q1-2008Q1	1954Q3-1978Q4	1984Q1-2008Q1
		(b) Conditional Variance Equation		
		BEKK-GARCH(1,1)		
	MORT (y_{1t})-*RGDP* (y_{2t})		*MORT* (y_{1t})-*RINV* (y_{2t})	
c_{11}	0.0013	-0.0006	-0.0028***	0.0010
	(0.0093)	(0.0021)	(0.0004)	(0.0010)
c_{12}	-0.0074	-0.0026	-0.0134	0.0041
	(0.0887)	(0.0071)	(0.0126)	(0.0063)
c_{22}	0.00006	0.0031	0.00001	0.0030
	(9.8149)	(0.0061)	(40.3586)	(0.0053)
a_{11}	-0.5916***	0.1202	-0.2941	0.0010
	(0.1552)	(0.1384)	(0.2101)	(0.1787)
a_{12}	0.4937	0.1170	0.0704***	0.5740
	(0.8419)	(0.1638)	(0.0250)	(0.5456)
a_{21}	-0.2071***	0.1963	-0.0484***	0.0661
	(0.0419)	(0.2727)	(0.0141)	(0.0556)
a_{22}	-0.2313	0.4139	-0.2431	0.5740
	(0.2073)	(0.2673)	(0.1898)	(0.5456)
g_{11}	0.0216	0.9642***	0.0021	0.9682***
	(0.5320)	(0.0372)	(0.2189)	(0.0400)
g_{12}	0.2936	-0.0421	0.0911**	0.0352
	(1.4335)	(0.2329)	(0.0427)	(0.2316)
g_{21}	0.2008	-0.1249	-0.0122	-0.0281
	(0.5614)	(0.8319)	(0.0277)	(0.0317)
g_{22}	0.6332	-0.0036	0.1041	0.8639***
	(1.1407)	(2.1717)	(0.4478)	(0.0906)
Log Likelihood	691.8080	744.9436	574.0287	612.0617
SIC	-13.8977	-14.5212	-11.2700	-11.7528
N	94	96	95	96

Note: Figures and numbers in parentheses reflect the estimates and the corresponding standard errors, respectively; ***, **,* indicate statistical significance at 1%, 5% and 10%, respectively.

Table 4: Granger Causality Tests in Variance

	Hypothesis	Chi-square Statistic	Prob
1954Q3-1978Q4			
	Overall Causality between MORT and RGDP		
	$H_0 : a_{12} = a_{21} = g_{12} = g_{11} = 0$	25.1290	0.0000
	Causality from MORT to RGDP		
	$H_0 : a_{12} = g_{12} = 0$	0.3457	0.8413
	Causality from RGDP to MORT		
	$H_0 : a_{21} = g_{21} = 0$	24.5918	0.0000
	Overall Causality between MORT and RINV		
	$H_0 : a_{12} = a_{21} = g_{12} = g_{11} = 0$	6.02901	0.0000
	Causality from MORT to RINV		
	$H_0 : a_{12} = g_{12} = 0$	9.9533	0.0069
	Causality from RINV to MORT		
	$H_0 : a_{21} = g_{21} = 0$	12.7111	0.0017

Table 4 (continued)

	Hypothesis	Chi-square Statistic	Prob
1984Q1-2008Q1			
	Overall Causality between MORT and RGDP		
	$H_0 : a_{12} = a_{21} = g_{12} = g_{11} = 0$	1.3826	0.8472
	Causality from MORT to RGDP		
	$H_0 : a_{12} = g_{12} = 0$	0.5102	0.7748
	Causality from RGDP to MORT		
	$H_0 : a_{21} = g_{21} = 0$	0.7381	0.6914
	Overall Causality between MORT and RINV		
	$H_0 : a_{12} = a_{21} = g_{12} = g_{11} = 0$	4.0079	0.4049
	Causality from MORT to RINV		
	$H_0 : a_{12} = g_{12} = 0$	1.2396	0.5381
	Causality from RINV to MORT		
	$H_0 : a_{21} = g_{21} = 0$	1.4159	0.4926

Table 5: Residual diagnostics

	$\varepsilon_{MORT,t}$	$\varepsilon_{RGDP,t}$	$\varepsilon_{RINV,t}$
1954Q3-1978Q4			
Q(8)	24.613	3.6047	7.6552
	[0.002]	[0.891]	[0.468]
$Q^2(8)$	3.5104	2.1571	13.574
	[0.898]	[0.976]	[0.094]
Q(12)	40.252	8.305	10.669
	[0.000]	[0.761]	[0.557]
$Q^2(12)$	6.3648	4.8547	18.320
	[0.897]	[0.963]	[0.106]
1984Q1-2008Q1			
Q(8)	15.903	5.4035	9.7428
	[0.044]	[0.714]	[0.284]
$Q^2(8)$	6.2651	8.1651	14.541
	[0.618]	[0.418]	[0.069]
Q(12)	19.324	13.684	13.923
	[0.081]	[0.321]	[0.306]
$Q^2(12)$	12.662	12.479	14.994
	[0.394]	[0.408]	[0.242]

Notes: Probability values are in brackets. *Q(p)* and $Q^2(p)$ are the Ljung-Box test statistic for *p*th order serial correlation for standardized residuals and squared standardized residuals, respectively.

References

Acemoglou, D. and F. Zilibotti (1997), "Was Prometheus Unbound by Chance? Risk, Diversification, and Growth," *Journal of Political Economy* 105: 709-51.

Acemoglou, D., S. Johnson, J. Robinson and Y. Thaicharoen (2003), "Institutional Causes, Macroeconomic Symptoms: Volatility, Crises and Growth," *Journal of Monetary Economics* 50: 49-123.

Ahmed, S., A. Levin and B. Wilson (2002), "Recent U.S. Macroeconomic Stability: Good Luck, Good Policies, or Good Practices?," *International Finance Discussion Papers* 730, Board of Governors of the Federal Reserve System (U.S.).

Alaganar, V. and R. Bhar (2003), "An International Study of Causality-in-Variance: Interest Rate and Financial Sector Returns," *Journal of Economics and Finance* 27: 39-55.

Barnett, W. and M. Chauvet (forthcoming), "The End of the Great Moderation? How Better Monetary Statistics Could Have Signaled the Systemic Risk Precipitating the Financial Crisis," *Journal of Econometrics Annals*.

Bauwens, L., S. Laurent and J. Rombouts (2006), "Multivariate GARCH Models: A Survey," *Journal of Applied Econometrics* 21: 79-109.

Bean, C. (2011), "Joseph Schumpeter Lecture: The Great Moderation, the Great Panic, and the Great Contraction," *Journal of the European Economic Association* 8: 289-325.

Benati, L. and P. Surico (2009), "VAR Analysis and the Great Moderation," *American Economic Review 99*: 1636-52.

Benk, S., M. Gillman and M. Kejak (2005), "Credit Shocks in the Financial Deregulatory Era: Not the Usual Suspects," *Review of Economic Dynamics* 8: 668-87.

Bernanke, B. (1993), "Credit in the Macroeconomy," *Quarterly Review, Federal Reserve Bank of New York* issue Spr: 50-70.

Bernanke, B. (2004), "The Great Moderation," Speech at the meetings of the *Eastern Economic Association*, Washington, D.C., February 20.

Bernanke, B. and M. Gertler (1995), "Inside the Black Box: The Credit Channel of Monetary Policy Transmission," *Journal of Economic Perspectives* 9: 27-48.

Blanchard, O. and J. Simon (2001), "The Long and Large Decline in U.S. Output Volatility," *Brookings Papers on Economic Activity* 1: 135-74.

Bliss, R. and G. Kaufmann (2003), "Bank Procyclicality, Credit Crunches, and Asymmetric Policy Effects: A Unifying Model," *Journal of Applied Finance* 13: 23-31.

Boivin, J., and M. Giannoni (2006), "Has Monetary Policy Become More Effective?," *The Review of Economics and Statistics* 88: 445-62.

Bollerslev, T, R Engle and J Wooldridge (1988), "A Capital Asset Pricing Model with Time Varying Covariances," *Journal of Political Economy* 96: 116-31.

Bollerslev, T. (1986), "Generalized Autoregressive Conditional Heteroskedasticity," *Journal of Econometrics* 31: 307-27.

Bollerslev, T. (1990), "Modelling the Coherence in Short-Run Nominal Exchange Rates: A Multivariate Generalized Arch Model," *The Review of Economics and Statistics* 72: 498-505.

Borio, C. and A. Lowe (2004), "Should Credit Come back from the Wilderness?," *Bank of International Settlements Working Paper* No. 157.

Campbell, S. (2005), "Stock Market Volatility and the Great Moderation," *FEDS WP, 2005-47, Board of Governors of the Federal Reserve System.*

Canning, D., L.A.N. Amaral, Y. Lee, M. Meyer and H.E. Stanley (1998), "Scaling the Volatility of the GDP Growth Rate," *Economics Letters* 60: 335-41.

Caporale, G. and P. Howells (2001), "Money, Credit and Spending: Drawing Causal Inferences," *Scottish Journal of Economics* 48: 547-57.

Caporale, G., N. Pittis and N. Spagnolo (2002), "Testing for Causality-in-Variance: An Application to the East Asian Markets," *International Journal of Finance and Economics* 7: 235-45.

Carroll, C., M. Otsuka and J. Slacalek (2006), "How Large Is the Housing Wealth Effect? A New Approach," *NBER Working Paper* No. 12746.

Cechetti, A. and S. Krause (2006), "Assessing the Sources of Changes in Volatility of Real Growth," *NBER Working Paper* No. 11946.

Cheung, Y. and L. Ng (1996), "A Causality-in-Variance Test and its Application to Financial Market Prices," *Journal of Econometrics* 72: 33-48.

Clarida, R., J. Gali, and M. Gertler (2000), "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory," *The Quarterly Journal of Economics* 115: 147-80.

Cogley, T. and T. Sargent (2005), "Drifts and Volatilities: Monetary Policy and Outcomes in the Post-WWII US", *Review of Economic Dynamics* 8: 262-302.

Davis S. and J. Kahn (2008), "Interpreting the Great Moderation: Changes in the Volatility of Economic Activity at the Macro and Micro Levels," *Journal of Economic Perspectives* 22: 155-80.

Den Haan, W. and V. Sterk (2010), "The Myth of Financial Innovation and the Great Moderation," *The Economic Journal* 121: 707-39.

Dickey, D. and W. Fuller (1979), "Distribution of the Estimators of Autoregressive Time Series with a Unit Root," *Journal of the American Statistical Association* 74: 427-31.

Dijk, D. van, D. Osborn and M. Sensier (2005), "Testing for Causality in Variance in the Presence of Breaks," *Economics Letters* 89: 193-99.

Dynan, K., D. Elmendorf and D. Sichel (2006), "Can Financial Innovation Help to Explain the Reduced Volatility of Economic Activity?," *Journal of Monetary Economics* 53: 123-50.

Easterly, W., M. Kremer, L. Pritchett and L. Summers (1993), "Good Policy or Good Luck? Country Growth Performance and Temporary Shocks," *Journal Of Monetary Economics* 32:459-83.

Easterly, W., R. Islam and J. Stiglitz (2000), "Shaken and Stirred: Explaining Growth Volatility," Paper at the 2000 *Annual World Bank Conference on Development Economics.*

Engle, R. (1982), "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation," *Econometrica* 50: 987-1007.

Engle, R. (2002), "Dynamic Conditional Correlation-A Simple Class of Multivariate GARCH Models," *Journal of Business and Economic Statistics* 20: 339-50.

Engle, R. and K. Kroner (1995), "Multivariate Simultaneous Generalized ARCH," *Econometric Theory* 11: 122-50.

Fang, W. and S. Miller (2008), "The Great Moderation and the Relationship between Output Growth and its Volatility," *Southern Economic Journal* 74: 819-38.

Fogli, A. and F. Perri (2006), “The "Great Moderation" and the US External Imbalance,” *NBER Working Paper* No. 12708.

Gambetti, L., E. Pappa, and F. Canova (2008), “The Structural Dynamics of US Output and Inflation: What Explains the Changes?,” *Journal of Money, Credit, and Banking* 40: 369–88.

Glymour, C. and G. Cooper (1999), *Computation, Causation, and Discovery,* The MIT Press, Cambridge, MA, USA.

Greenspan A. and J. Kennedy (2008), “Sources and Uses of Equity Extracted from Homes.” *Oxford Review of Economic Policy* 24: 120-44.

Guerron-Quintana, P. (2009), “Money Demand Heterogeneity and the Great Moderation,” *Journal of Monetary Economics* 56: 255-66.

Hafner, C. and H. Herwartz (2004), “Testing for Causality in Variance Using Multivariate GARCH Models,” *Working Paper* No. 03.

Hamilton, J. (2008), “Macroeconomics and ARCH,” NBER *Working Paper* No. 14151.

Hong, Y (2003), “Extreme Risk Spillover between Chinese Stock Markets and International Stock Markets,” *Working Paper*.

Hong, Y. (2001), “A Test for Volatility Spillover with Application to Exchange Rates,” *Journal of Econometrics* 103: 183-224.

Jaimovich, N. and H. Siu (2009), “The Young, the Old, and the Restless: Demographics and Business Cycle Volatility,” *American Economic Review* 99: 804–26.

Kahn, J., M. McConnell and G. Perez-Quiros (2002), "On the causes of the increased stability of the U.S. economy," Federal Reserve Bank of New York *Economic Policy Review* 8: 183-202.

Kanas, A. and G. Kouretas (2002), "Mean and Variance Causality between Official and Parallel Currency Markets: Evidence form Four Latin American Countries," *The Financial Review* 37: 137-64.

Kemme, D. and S. Roy (2012), "Did the Recent Housing Boom Signal the Global Financial Crisis?," *Southern Economic Journal* 78: 999-1018.

Kim, C. and C. Nelson (1999), "Has the U.S. Become More Stable? A Bayesian Approach Based on a Markov-Switching Model of the Business Cycle," *Review of Economics and Statistics* 81: 08-16.

Kiyotaki, N. and J. Moore (1997), "Credit Cycles," *Journal of Political Economy* 105: 211-48.

Kocherlakota, N. (2000), "Creating Business Cycles Through Credit Constraints," *Federal Reserve Bank of Minneapolis Quarterly Review* 24: 2-10.

Kwiatkowski, D., P Phillips, P. Schmidt and Y. Shin (1992), "Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root," *Journal of Econometrics* 53: 159-78.

Laurent, S. and J-P Peters (2002), "G@RCH 2.2: An OX Package for Estimating and Forecasting Various ARCH Models," *Journal of Economic Surveys* 16: 447-85.

Li, G., J. Refalo and L. Wu (2008), "Causality-in-Variance and Causality-in-Mean among European Government Bond Markets," *Applied Financial Economics* 18: 1709-20.

Lorrain, B. (2006), "Do Banks Affect the Level and Composition of Industrial Volatility?," *The Journal of Finance* 61: 1897–925.

Lown C. and D. Morgan (2006), “The Credit Cycle and the Business Cycle: New Findings Using the Loan Officer Opinion Survey,” *Journal of Money, Credit, and Banking* 38: 1575-97.

Lubik, T., and F. Schorfheide (2003), “Computing Sunspot Equilibria in Linear Rational Expectations Models,” *Journal of Economic Dynamics and Control* 28: 273-85.

McCarthy, J. and E. Zakrajsek (2007), “Inventory Dynamics and Business Cycles: What Has Changed?,” *Journal of Money, Credit and Banking* 39: 591-613.

McConnell, M. and G. Perez-Quiros (2000), “Output Fluctuations in the United States: What Has Changed since the Early 1980’s,” *American Economic Review* 90: 1464-76.

Mendicino, A. (2007), “Credit Market and Macroeconomic Volatility,” *European Central Bank Working Paper Series* No. 743.

Nakov, A. and A. Pescatori (2010), “Oil and the Great Moderation,” *The Economic Journal* 120: 131-56.

Owyang, M.T., J. Piger and H. Wall (2007), “A State-Level Analysis of the Great Moderation,” *Federal Reserve Bank of St Louis, Working Paper* No. 003B.

Pantelidis, T. and N. Pittis (2004), “Testing for Granger Causality in Variance in the Presence of Causality in Mean,” *Economics Letters* 85: 201-7.

Phillips, P. and P. Perron (1988), “Testing for a Unit Root in Time Series Regression,” *Biometrika Trust* 75: 335-46.

Primiceri, G. (2005), “Time Varying Structural Vector Autoregressions and Monetary Policy,” *The Review of Economic Studies* 72: 821-52.

Sims, C. and T. Zha (2006), "Were There Regime Switches in U.S. Monetary policy?," *American Economic Review* 96: 54-81.

Spirtes, P., C. Glymour and R. Scheines (2000), *Causation, Prediction and Search,* The MIT Press, Cambridge, MA, USA.

Stock, J. and M. Watson, "Has the Business Cycle Changed and Why?," *National Bureau of Economic Research*, Inc., working paper 9127 (2002).

Summers, P. (2005), "What Caused the Great Moderation? Some Cross-Country Evidence," *Federal Reserve Bank of Kansas City Economic Review*, 3rd Quarter.

Tse, Y. and A. Tsui (2002), "A Multivariate GARCH Model with Time-Varying Correlations," *Journal of Business and Economic Statistics* 20: 351-62.

Uhlig, H. (2004), "What Moves GNP?," *Econometric Society 2004 North American Winter Meetings* 636.

Warnock, M. and F. Warnock (2000), "The Declining Volatility of U.S. Employment: Was Arthur Burns Right?," Board of Governors of the Federal Reserve System, *International Finance Discussion Paper* No. 677.