The Role of Credit in Great Moderation: a Multivariate GARCH Approach

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THE ROLE OF CREDIT IN THE GREAT MODERATION: A MULTIVARIATE GARCH APPROACH

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Abstract

During the Great Moderation, financial innovation in the U.S. increased the size and scope of credit flows supporting the growth of wealth. We hypothesize that spending out of wealth came to finance a wider range of GDP components such that it smoothed GDP. Both these trends combined would be consistent with a decrease in the volatility of output. We suggest testable implications in terms of both growth of credit and output and volatility of growth. In a multivariate GARCH framework, we test this view for home mortgages and residential investment. We observe unidirectional causality in variance from total output, residential investment and non-residential output to mortgage lending before, but not during the Great Moderation. 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

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1. Introduction

A substantial literature addresses the dramatic decline in macroeconomic volatility between the mid-1980s and the start of the 2008 financial crisis[1], in the U.S. economy as well as in other countries.[2] A variety of causes for this decline have been suggested.[3] In this paper we explore whether easier credit conditions gave firms and households more discretion in the use of credit, thereby smoothing output volatility. Following the Kocherlakota (2000) argument that credit constraints can create cycles, we extend this to the logically equivalent argument that looser credit policies can create stability.

Several recent studies suggest this hypothesis. Gambetti et al. (2008) find that the Great Moderation saw a change 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. Giannone et al. (2010) find that the decline in the volatility of GDP growth since the mid 1980s is not due to a decline in the volatility of exogenous shocks, but rather a change in their propagation mechanism, which points to the role of financial intermediation. Dynan et al. (2006) show that that, while aggregate economic activity has become less volatile over time, individual households appear to have faced more volatile economic circumstances. The explanation is in

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[1] The end data of 2008 follows e.g. Barnett and Chauvet (forthcoming) and Bean (2011).

[2] Kim and Nelson (1999) and 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. 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.

[3] Authors have variously located the causes in 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; Primiceri, 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.'

declining covariation between households. They also show that the response of household spending to negative shocks fell more during the Great Moderation than the response to positive shocks, and note that this is consistent with financial innovation having diminished the extent of liquidity constraints.

The channel we explore is a wealth effect of looser credit conditions on consumption (e.g. though home equity withdrawal) or investment (e.g. through share buybacks). Whatever the form, the common denominator is that credit flows support the build-up of wealth (in real estate, stocks, bonds and the like), which increases options for discretionary consumption and investment, which may be used to smooth output. In this respect, the present paper differs from analyses that study credit flows which support not wealth but economic activity, such as industrial production (e.g. Larrain 2006).

A methodological innovation is that we study both credit growth rates and the volatility of credit growth rates as potential explanations for reduced GDP growth and its volatility, respectively (as also Bean, 2011 recommends). The reason is that credit flows supporting wealth growth (such as mortgages) may or may not coincide in time with credit flows that finance the spending out of wealth (such as home equity withdrawal) which may smooth GDP. In that case, the causal response of total mortgage credit growth (both for residential investment and as home equity withdrawal) to previous output growth may or may not increase, which means that testable implications cannot be derived in first moments (growth rates). However, the volatility (the second moment) of credit growth will change such that its causal link (if any) to activity and output growth volatility weakens. In the next section we detail this argument. In sum, we hypothesize that credit flows that supported wealth growth and supported increased spending out of wealth contributed to the smoothing of GDP during the Great Moderation. The testable implications that we examine are that the causal linkages between either the growth rates of credit and output, or the volatilities of credit and output were weaker during the Great Moderation than before the Great Moderation. We take the conditional variances as a measure for volatility and study a particular credit flow (mortgages) and its causality-in-variance with the output components that it traditionally supports (residential investment), with other GDP components and with total GDP.

In a multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework, we test this hypothesis for the U.S. over two periods, 1954-1978 (before the Great

Moderation) and 1984-2008 (during the Great Moderation). Previewing the findings, we find that unidirectional causality in variance from residential investment to home mortgage lending existed before, but not during the Great Moderation. We also test the auxiliary hypotheses on causality-in-variance between the volatilities of mortgages, total GDP and GDP other than residential investment, with similar findings. These findings are consistent with the hypothesis that mortgage lending increased wealth, which induced spending that reduced GDP volatility.

The paper proceeds as follows. In the next section we explain the argument in detail. Section 3 explores relevant literature and section 4 develops the methodology. Section 5 presents the data and estimation results and test outcomes. Section 6 concludes with a summing up and discussion.

2. Argument and Testable Implications

The overriding trend that motivates this analysis is the growth in US bank credit flows that increased wealth, by flowing into the finance and real estate sectors. The stock of outstanding bank loans relative to GDP quadrupled from 1952 to 2011, with most of that growth occurring during the Great Moderation, and with credit flows to the finance and property sectors accounting for most of the increase. According to *Bureau of Economics and Statistics* (BEA) data, the combined stock of these credit categories rose from 30% of GDP in 1952 (the start of the data series) to 81% of GDP in 1984, which translates to a modest annualized growth rate of the GDP share of 1.8%. But by 2008, bank credit to the finance and real estate sectors had increased to 260% of GDP, implying an annualized growth rate of 3.0% over 1984-2008.[4] In comparison, bank credit outstanding to the real sector (that is, credit to nonfinancial business, to government and nonmortgage credit to households) rose from 87% of GDP in 1952 to 99% in 1984 and to only 143% of GDP in 2008 (Figure 1). In the U.S., credit stocks that supported wealth build-up increased much faster than credit stocks that supported activity, and most of that process occurred during the Great Moderation.

[Figure 1 HERE]

[4] Bank credit to the finance and real estate sectors was computed as the sum of BEA quarterly time series from the flow of fund Z tables "total mortgage liabilities of the domestic nonfinancial sectors" (FL38316500) and "financial business credit market instrument liabilities" (FL794104005).

On the macro level, this may smooth GDP fluctuations since “credit demand appears to contain a significant countercyclical component, which arises from the desire of households and firms to smooth the impact of cyclical variations in income on spending or production” (Bernanke and Gertler (1995:44). The magnitudes of price changes and of participation in asset markets in the US Great Moderation were certainly large enough for a macro level impact on GDP smoothing.[5] But to rigorously test for the causality between the volatility of credit flows into wealth markets and the volatility of GDP, we need to pinpoint how these flows may increase wealth and then help reduce output volatility. To simplify, we discuss the mechanism in the context of real estate markets where home purchases are 100% debt financed, mortgages are all for existing (rather than newly built) homes, and real estate owners spend a constant proportion of their wealth through home equity withdrawal.

Consider a situation where new entrants to the real estate market take up mortgage credit (C1) for residential investment (RI), so that house prices rise. Owners of real estate see their wealth increase since trade in a small fraction of the real estate stock bids up the prices of the entire real estate stock. In response they borrow through home equity withdrawal (C2) for spending that would not otherwise have occurred. Growth in C2 may occur either simultaneous to or later than C1 growth, as the wealth effect takes time to materialise. Total, observed mortgage credit take-up is C = C1 + C2. Thus, credit flows C1 that support wealth growth are the basis for discretionary spending financed by further credit flows C2, such that (we hypothesize) this smoothes GDP.

There are two testable implications. To the extent that borrowers can shift over time mortgage-financed residential investment (to the amount RI=C1) as well as spending out of mortgage-financed wealth (C2) such that its growth becomes countercyclical to the growth in other GDP components, this will smooth total GDP. (This would fit in, of course, with the greater flexibility that resulted from financial liberalization during the Great Moderation era.) So instead of mortgage borrowing and residential investment driven by fundamentals - proxied by output growth other than growth in residential investment, or (GDP-RI) -, the causation between

[5] 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). Adding in other asset markets, the magnitudes seem sufficiently large that the distribution of these gains over time will matter to the volatility of GDP.

C and (GDP-RI) will weaken. Another implication is that, to the extent that mortgages C do not finance residential investment RI, the causation between C and RI will weaken. Third, to show that our analysis is relevant to GDP volatility itself (rather than only to its components (GDP-RI) and RI), we also test for the causality between C and GDP. We do this in three separate analyses so as to avoid endogeneity concerns.

Importantly, the GDP smoothing effect of credit may or may not be signalled by weaker causation in terms of growth rates, but will show in any case in terms of their volatilities. To see this, consider causation between (GDP-RI) and C. If growth in C2 is not contemporaneous to growth in C1, then the growth rate of C=C1+C2 will change such that its causal link (if any) to the growth of (GDP-RI) weakens. But if growth in C2 coincides in time with growth in C1 such that it smoothes GDP – which may well be the case - then the result will just be a stronger causal response of C growth to previous (GDP-RI) growth. Thus, the impact of these credit flows on the causality between mortgages and output volatility is ambiguous. Similar arguments apply to the causality between C and RI and between C and GDP itself. Therefore we test all three causality patterns both in mean growth rates and in the variance of growth rates. Causality in ***variance*** between C and GDP components will weaken in both of the above scenarios, if GDP smoothing occurs. If C2 mortgage flows are to impact output volatility, then either or both of the amplitude and the distribution of peaks and troughs in the growth rate of mortgage credit (i.e. its variance over time) will change relative to the GDP variance over time. An additional reason to test in variances is that it allows for potential interaction of volatilities, which are not captured in the literature to date.

In the empirical work below, we study mortgage credit flows as a *pars pro toto* for all kinds of credit flows that increase wealth (Figure 1). The hypotheses that we will test, then, are: (i) the causality in mean and in variance between mortgage credit growth and growth in output (other than residential investment) was weaker during the Great Moderation than it was before the Great Moderation; (ii) the causality in mean and in variance between mortgage credit growth and growth in residential investment was weaker during the Great Moderation than it was before the Great Moderation; (iii) the causality in mean and in variance between mortgage credit growth and growth output was weaker during the Great Moderation than it was before the Great Moderation.

3. Relevant Literature

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).

Studies that relate specifically to the hypothesis that growth in financial wealth has smoothed GDP growth include Dynan et al. (2006), who show 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. Jermann and Quadrini (2006) develop a general equilibrium model where innovations in financial markets allow for greater financial flexibility and generate a lower volatility of output, together with a higher volatility in the financial structure of firms. Campbell and Hercowitz (2005) note how market innovations following the financial reforms of the early 1980s relaxed collateral constraints (lower down payments and rates of amortization for durable goods purchases) on household borrowing. They model households with heterogeneity of thrift in a calibrated general equilibrium setup to predict that this relaxation of collateral constraints can explain a large fraction of the observed volatility decline in output and other variables.

Den Haan and Sterk (2010) test the relation between mortgage lending and GDP components in the U.S. in a SVAR specification in levels, not variances. They find no evidence of breaks and reject the hypothesis that financial innovation caused the Great Moderation. Davis and Kahn (2008) 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 firm-level volatility in the durable goods sector 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 (co)variance of real output components 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, that would reduce output volatility.[6]

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 and Blinder, 1988; Bernanke, 1993; Bliss and Kaufmann, 2003; Mendicino, 2007). 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; Campbell, 2005), the present emphasis is on the more traditional notion of credit as the prime source of liquidity, enabling agents to finance spending on both wealth instruments and on goods and services (Borio and Lowe, 2004). Caporale and Howells (2001) show how "loans cause deposits and that those deposits cause an expansion of wealth/GDP transactions" – and in the volatility of GDP transactions, we would add. In support, Benk et al. (2005), building on Uhlig (2004), identify credit shocks as candidate shocks that matter in determining the business cycle. This impact of credit extends to volatility: Larrain (2006) finds that the volatility of industrial output is lower in countries with more bank credit. However, our paper is different from most credit-and-GDP analyses in that we focus on credit flows to wealth markets.

4. Methodology

4.1. Modeling Volatility

We estimate a multivariate GARCH model, an extension of the 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

[6] We also note that our work is complementary (rather than rival) to the well established inventory explanation (McConnell and Perez-Quiros, 2000; Kahn et al., 2002; McCarthy and Zakajsek, 2007). Lown and Morgan's (2006) VAR analysis suggests a large impact of weakening of loan standards on declining inventory investment. The widely noted decline in loan standards during the Great Moderation may have led to both declining inventory investment and to more mortgage lending.

correlate positively. In the presence of ARCH effects we proceed with the estimation of a multivariate GARCH model.[7] Of the several possible specifications for multivariate GARCH models we choose an unrestricted bivariate VAR-BEKK model (Engle and Kroner, 1995), appropriate for the computation of conditional variances and covariances between variables.[8] Below we discuss the VAR-BEKK model in terms of two variables, home mortgages and either real output, residential investment or non residential GDP (part of GDP that does not include residential investment). This implies two conditional mean equations. We select a GARCH (1,1) model for the conditional variance specification because it provides smaller variance than ARCH(1), avoids over-fitting and is usually sufficient to capture volatility clustering (higher-order model are rarely estimated in the academic finance literature; Brooks, 2002:455).[9] We test for bidirectional causality of the mean and conditional variance of home mortgages growth with the mean and conditional variance of output growth, residential investment and non residential GDP. The conditional mean equation is a VAR model specified as:

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

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, residential investment or non residential GDP, respectively. The parameter vector of the mean equation (1) is defined by $\boldsymbol{\mu} = (\mu_1, \mu_2)$ and the autoregressive term Γ_i. 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:

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

[7] 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 matrices for ARCH and GARCH coefficients. 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).

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

[9] Several ARCH(p) and GARCH(p,q) models have been estimated. GARCH(1,1) and ARCH(1) were mostly supported by the data but GARCH(1,1) gives the smallest variance.

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:

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

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/non residential 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:

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

where m is the number of conditional mean equations and ε_t is the m vector of mean equation residuals.[10]

4.2. 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) investigating causality in variance between black and parallel currency

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

markets, as well as interest rates and financial sector returns, respectively. 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.[11]

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, growth in residential investment and non residential GDP growth both in means and in variances (equation (2)).[12] In terms of this model, the CDGM hypothesis is that causality-in-variance from output growth to mortgage growth, and from mortgage growth to growth in residential investment are both weaker or absent during the Great Moderation, relative to the years before the Great Moderation.

5. Data and Estimation Results

We employ quarterly data for the U.S. over two subperiods, 1954Q3-1978Q4 (before the Great Moderation) and 1984Q1-2008Q1 (during the Great Moderation). Studying two samples is preferable to using a structural-break approach to one sample over 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. The choice of sample cut-off years is motivated by the work of Boivin and Giannoni

[11] 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.

[12] 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.

(2006). They report that there is no robust breakpoint at which the Great Moderation would have started; the literature uses any year between the late 1970s and 1984 at the latest. The data construction follows Den Haan and Sterk (2010), where this periodization is also used.[13] We calculated the logarithms of home mortgages (MORT), real GDP (RGDP), residential investment (RINV) and GDP other than residential investment (NRGDP), which are all stationary in their first differences (I(1)).[14]

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 1 reports descriptive statistics for the variables (mean, standard deviation, skewness and kurtosis) and values of the ARCH-LM statistic for the two subsamples.

[Table 1 HERE]

The 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 and non residential GDP 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, residential investment and non residential output. Furthermore, the kurtosis (or "peakedness") statistic for the distribution of mortgages growth shows more deviations from the normal distribution in the first subsample than in the second. 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.

We estimate the unrestricted BEKK model (equations (1)-(3)) where the system of conditional mean equations consists of are VAR(p) models ($p = 1,...,4$).[15] In each subsample, we

[13] We thank Wouter den Haan for making these data available, at http://www.wouterdenhaan.com/data.htm#papers.
[14] 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.
[15] EViews 6 has been used for the estimation of the models.

estimate the model with the growth rates of (i) home mortgages and real output, (ii) home mortgages and residential investment, and (iii) home mortgages and non residential output. 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(3)-BEKK model for all three sets of variables in first subperiod, and a VAR(2)-BEKK for the three sets in the second subperiod. Table 2 reports the estimated conditional variances with associated log-likelihood and SIC values, and numbers of observations.

[Table 2 HERE]

The results of the first part of Table 2 (the conditional mean equations) indicate that the growth rate of home mortgages is affected by its first lagged value and the third lagged value of output growth (γ_{11} and z_{12}, respectively) over 1954Q3-1978Q4. For the same period output growth is affected only by its first lagged value (γ_{22}). During 1984Q1-2008Q1, the growth rates of home mortgages and output are influenced only by their own lagged values. The significance of the cross terms ($\gamma_{12}, \gamma_{21}, \theta_{12}, \theta_{21}, z_{12}, z_{21}$ for the first period and $\gamma_{12}, \gamma_{21}, \theta_{12}, \theta_{21}$ for the second) reveals the occurrence of spillovers in means. In the second set of variables, we find that before the Great Moderation only home mortgages growth is influenced by its first and third lagged values (γ_{11} and z_{11}, respectively) as well as by the lagged value of residential investment growth (γ_{12}). Therefore, there are spillovers in mean from residential investment growth to the growth of home mortgages.

During the Great Moderation none of the cross terms is statistically significant, only the lagged values of the variables themselves. In the third set of variables, the growth rate of home mortgages is affected by its first and third lagged values (γ_{11} and z_{11}, respectively) and by the third lagged value of non residential output growth (z_{12}). This indicates the existence of spillovers in mean during 1954Q3-1978Q4. On the contrary, non-residential GDP growth is affected only by the lagged value of home mortgage growth (z_{21}), supporting the occurrence of bidirectional spillovers in mean. Spillovers in mean are not detected during 1984Q1-2008Q1.

Now consider the conditional variance results in the second part of Table 2. 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 decrease 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 and non residential GDP growth to home mortgage growth in the first subperiod (coefficient value α_{21} = -0.3046 and 0.2202, respectively). We also detect volatility spillovers in both directions between home mortgage growth and residential investment growth (14.38% and 4.13%, respectively). In contrast, during the Great Moderation none of these volatility spillovers can be detected.

In order to test causality in mean we test for joint significance of the cross terms in conditional mean equations. Table 3 reports the results.

[Table 3 HERE]

Before the Great Moderation, we observe causality in mean between home mortgages growth and (i) growth of residential investment, and (ii) non residential output growth. The causality in mean is unidirectional running from the growth rates of residential investment and non-residential output to home mortgages growth. During the Great Moderation causality in mean of either direction is absent.

In order to test causality in variance 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 the undirectional causality from residential investment growth volatility to the volatility of home mortgages growth. Finally, we detect overall causality in variance between home mortgages growth and growth of non-residential-investment output, based on the unidirectional causality from non-residential-investment output growth volatility to the volatility of home mortgages growth.

We can also see this graphically. Variances of mortgages, output, residential investment and non-residential-investment GDP growth rates moved together during 1954Q3-1978Q4 but not in the second subsample (Figures 2a and 2b). We also observe that that during the Great Moderation the volatilities of growth of all three variables (fig 2b) had decreased considerably relative to pre-Great Moderation years (fig 2a), as expected (note the difference in scale).

[Figure 2a HERE]

[Figure 2b HERE]

Both the causality tests and the graphs support our hypotheses which attribute 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. They are consistent with mortgage (and other) finance increasingly supporting spending that was countercyclical to GDP shocks, so lowering the volatility of GDP.

Finally, we study residual diagnostics for the VAR-unrestricted BEKK models in order to test for remaining autocorrelation and ARCH effects at 1% significance level (Table 5). The Ljung-Box Q-statistic of the standardized residuals for two lag lengths (8 and 12 quarters) is not statistically significant ($p = 0.01$) in all cases revealing no remaining autocorrelation in the series. 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 subperiods under investigation.

[Table 5 HERE]

6. 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. Specifically, we hypothesize that debt-financed GDP smoothing is signaled by weaker causation of mortgage finance with residential investment with total output, and with the difference. We test the hypothesis formally by studying both causality-in-mean and causality-in-variance of home mortgage lending with residential investment, with output other than residential investment, and with total output. We do this in a multivariate GARCH framework for the U.S. over two periods, 1954-1978 (before the Great Moderation) and 1984-2008 (during the Great Moderation). It is significant that we test also in variances, not only in means**.** Testing in variances yields less ambiguous findings relating to our hypothesis and it allows for potential interaction of volatilities.

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 unidirectional causality in variance from total output, residential investment and non-residential output to home mortgage lending existed before, but not during the Great Moderation. All three findings are consistent with the hypothesis that growth in credit which supported growth in financial wealth has smoothed GDP growth, in conjunction with other explanations. We conclude with a discussion of its place in the wider literature and suggestions for future research.

This 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. This 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).

In pursuing additional evidence or falsification of the hypothesis, several lines of inquiry are open. One is to be more specific about the channel from mortgage lending to those countercyclical GDP components. 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.[16] Whatever the precise delineation however, an important part of the channel through which wealth 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 present 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 present 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.

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

TABLES

Table 1: Descriptive Statistics

	Mean	Std dev.	Skewness	Kurtosis	LM-Statistic
1954Q3-1978Q4					
MORT	0.0235	0.0091	0.0887	4.6216	20.4439** (9)
RGDP	0.0094	0.0109	-0.3512	3.5788	33.1762*** (12)
RINV	0.0088	0.0501	-0.1068	3.2299	4.8868* (2)
NRGDP	0.0094	0.0104	-0.4501	4.0110	32.3372*** (10)
1984Q1-2008Q1					
MORT	0.0232	0.0092	0.3121	2.4492	40.1714*** (12)
RGDP	0.0074	0.005	-0.2454	3.2731	3.5213* (1)
RINV	0.0029	0.0284	-0.8581	3.5416	10.3171* (5)
NRGDP	0.0078	0.0049	-0.0101	3.0543	6.9961* (3)

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 2: VAR-BEKK (unrestricted) Estimates

Parameters	Pre-Great Moderation period	During-Great Moderation period	Pre-Great Moderation period	During-Great Moderation period	Pre-Great Moderation period	During-Great Moderation period
	1954Q3-1978Q4	1984Q1-2008Q1	1954Q3-1978Q4	1984Q1-2008Q1	1954Q3-1978Q4	1984Q1-2008Q1
			(a) Conditional Mean Equation			
	VAR(3)	***VAR(2)***	***VAR(3)***	***VAR(2)***	***VAR(3)***	***VAR(2)***
	MORT (y_{1t})-*RGDP* (y_{2t})		*MORT* (y_{1t})-*RINV* (y_{2t})		*MORT* (y_{1t})-*NRGDP* (y_{2t})	
μ_1	0.0028*	0.0051*	0.0018	0.0039**	0.0011	0.0060**
	(0.0014)	(0.0027)	(0.0020)	(0.0019)	(0.0019)	(0.0026)
μ_2	0.0090**	0.0044**	0.0286	0.0064	0.0079*	0.0041*
	(0.0041)	(0.0022)	(0.0248)	(0.0072)	(0.0044)	(0.0021)
γ_{11} (y_{1t-1})	0.9225***	0.4878***	0.7079***	0.4429***	0.8888***	0.4726***
	(0.0946)	(0.1040)	(0.1297)	(0.0938)	(0.0861)	(0.1031)
γ_{12} (y_{2t-1})	0.0119	-0.1282	0.0329**	-0.0147	-0.0240	-0.1550
	(0.0621)	(0.1109)	(0.0161)	(0.0310)	(0.0537)	(0.1112)
γ_{21} (y_{1t-1})	0.2676	0.0368	0.2461	0.1495	0.2686	0.0008
	(0.3871)	(0.0916)	(0.1944)	(0.3199)	(0.4349)	(0.0829)
γ_{22} (y_{2t-1})	0.2164**	0.1016	0.2819	0.6611***	0.1268	0.1128
	(0.1045)	(0.1226)	(0.1787)	(0.1342)	(0.1516)	(0.1227)
θ_{11} (y_{1t-2})	-0.1691	0.3408***	-0.1302	0.3863***	-0.1776	0.3484***
	(0.1512)	(0.1057)	(0.2329)	(0.1009)	(0.1412)	(0.1056)
θ_{12} (y_{2t-2})	0.0571	-0.0468	0.0078	0.0452	0.0502	-0.1106
	(0.0507)	(0.1500)	(0.0140)	(0.0348)	(0.0565)	(0.1490)
θ_{21} (y_{1t-2})	0.1250	-0.0260	-0.1759	-0.3433	0.3573	0.0132
	(0.5953)	(0.0728)	(0.1863)	(0.3532)	(0.5052)	(0.0610)
θ_{22} (y_{2t-2})	0.0397	0.3048**	0.0548	-0.0247	0.0700	0.3333***
	(0.1102)	(0.1228)	(0.1611)	(0.1430)	(0.1108)	(0.1188)
z_{11} (y_{1t-3})	0.1565		0.3144*		0.2884**	
	(0.1027)		(0.1787)		(0.1175)	
z_{12} (y_{2t-3})	-0.1136**		-0.0014		-0.1569***	
	(0.0519)		(0.0128)		(0.0439)	
z_{21} (y_{1t-3})	-0.4741		0.1660		-0.5861**	
	(0.3099)		(0.1494)		(0.2846)	
z_{22} (y_{2t-3})	0.0019		-0.0146		0.0205	
	(0.1242)		(0.1265)		(0.1355)	

Table 2 (continued)

Parameters	Pre-Great Moderation period	During-Great Moderation period	Pre-Great Moderation period	During-Great Moderation Period	Pre-Great Moderation period	During-Great Moderation period
	1954Q3-1978Q4	1984Q1-2008Q1	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})		*MORT* (y_{1t})-*NRGDP* (y_{2t})	
c_{11}	0.0023	-0.0006	0.0002	0.0010	0.0009	-0.0002
	(0.0048)	(0.0021)	(0.0209)	(0.0010)	(0.0021)	(0.0054)
c_{12}	-0.0010	-0.0026	-0.0275	0.0041	0.0051	-0.0039
	(0.0272)	(0.0071)	(3.0544)	(0.0063)	(0.0106)	(0.0848)
c_{22}	-0.0087	0.0031	-0.0004	0.0030	0.0001	0.0004
	(0.0120)	(0.0061)	(18.7561)	(0.0053)	(2.7975)	(7.2326)
a_{11}	-0.0864	0.1202	-0.0300	0.0010	-0.1099	0.0974
	(0.2700)	(0.1384)	(0.3761)	(0.1787)	(0.2760)	(0.1480)
a_{12}	0.0516	0.1170	0.1438*	0.5740	0.9978	0.0585
	(1.2275)	(0.1638)	(0.2643)	(0.5456)	(0.7443)	(0.1658)
a_{21}	-0.3046***	0.1963	0.0413***	0.0661	0.2202***	0.1722
	(0.0552)	(0.2727)	(0.0113)	(0.0556)	(0.0604)	(0.3350)
a_{22}	-0.2317	0.4139	-0.2611	0.3833**	0.3767**	0.4460
	(0.3423)	(0.2673)	(0.3230)	(0.1667)	(0.1792)	(0.2740)
g_{11}	0.0673	0.9642***	0.4642	0.9682***	0.7460***	0.9712***
	(1.5033)	(0.0372)	(0.4846)	(0.0400)	(0.2238)	(0.0262)
g_{12}	0.6503	-0.0421	-0.0249	0.0352	-0.0488	-0.0240
	(2.4225)	(0.2329)	(0.0518)	(0.2316)	(0.4334)	(0.2057)
g_{21}	0.0601	-0.1249	0.0494	-0.0281	-0.1125	-0.0032
	(1.9555)	(0.8319)	(0.0365)	(0.0317)	(0.0875)	(0.8000)
g_{22}	0.3443	-0.0036	0.7047*	0.8639***	0.7075***	0.1248
	(3.2898)	(2.1717)	(0.3678)	(0.0906)	(0.2123)	(2.0529)
Log Likelihood	692.7931	744.9436	568.8949	612.0617	693.3746	749.3083
SIC	-13.6803	-14.5212	-11.0159	-11.7528	-13.6928	-14.6121
N	93	96	93	96	93	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 3: Granger Causality Tests in Mean

	Hypothesis	Pre-Great Moderation	During-Great Moderation
		1954Q3-1978Q4	1984Q1-2008Q1
		Chi-square Statistic	
Model 1	Causality from MORT to RGDP		
	$H_0: \gamma_{21} = \theta_{21} = z_{21} = 0$	5.2255 (0.1560)	0.1761 (0.9157)
	Causality from RGDP to MORT		
	$H_0: \gamma_{12} = \theta_{12} = z_{12} = 0$	5.1447 (0.1615)	1.8352 (0.3995)
Model 2	Causality from MORT to RINV		
	$H_0: \gamma_{21} = \theta_{21} = z_{21} = 0$	4.4951 (0.2127)	1.0004 (0.6064)
	Causality from RINV to MORT		
	$H_0: \gamma_{12} = \theta_{12} = z_{12} = 0$	7.7995 (0.0503)	2.0450 (0.3597)
Model 3	Causality from MORT to NRGDP		
	$H_0: \gamma_{21} = \theta_{21} = z_{21} = 0$	4.7675 (0.1896)	0.0767 (0.9624)
	Causality from NRGDP to MORT		
	$H_0: \gamma_{12} = \theta_{12} = z_{12} = 0$	13.5527 (0.0036)	3.3435 (0.1879)

Notes: Probability values of the corresponding Chi-square statistics are in parentheses. Null hypotheses during the Great Moderation is $H_0: \gamma_{21} = \theta_{21} = 0$ and $H_0: \gamma_{12} = \theta_{12} = 0$ because the conditional mean equations reflect a VAR(2) model.

Table 4: Granger Causality Tests in Variance

	Hypothesis	Pre-Great Moderation	During-Great Moderation
		1954Q3-1978Q4	1984Q1-2008Q1
		Chi-square Statistic	
Model 1	Overall Causality between MORT and RGDP		
	$H_0 : a_{12} = a_{21} = g_{12} = g_{11} = 0$	32.1000 (0.0000)	1.3826 (0.8472)
	Causality from MORT to RGDP		
	$H_0 : a_{12} = g_{12} = 0$	0.0867 (0.9576)	0.5102 (0.7748)
	Causality from RGDP to MORT		
	$H_0 : a_{21} = g_{21} = 0$	30.8342 (0.0000)	0.7381 (0.6914)
Model 2	Overall Causality between MORT and RINV		
	$H_0 : a_{12} = a_{21} = g_{12} = g_{11} = 0$	26.0503 (0.0000)	4.0079 (0.4049)
	Causality from MORT to RINV		
	$H_0 : a_{12} = g_{12} = 0$	3.1418 (0.2079)	1.2396 (0.5381)
	Causality from RINV to MORT		
	$H_0 : a_{21} = g_{21} = 0$	16.4956 (0.0003)	1.4159 (0.4926)
Model 3	Overall Causality between MORT and NRGDP		
	$H_0 : a_{12} = a_{21} = g_{12} = g_{11} = 0$	21.0630 (0.0003)	1.1456 (0.8870)
	Causality from MORT to NRGDP		
	$H_0 : a_{12} = g_{12} = 0$	2.0925 (0.3512)	0.1261 (0.9389)
	Causality from NRGDP to MORT		
	$H_0 : a_{21} = g_{21} = 0$	13.2680 (0.0013)	0.8249 (0.6620)

Notes: Probability values of the corresponding Chi-square statistics are in parentheses.

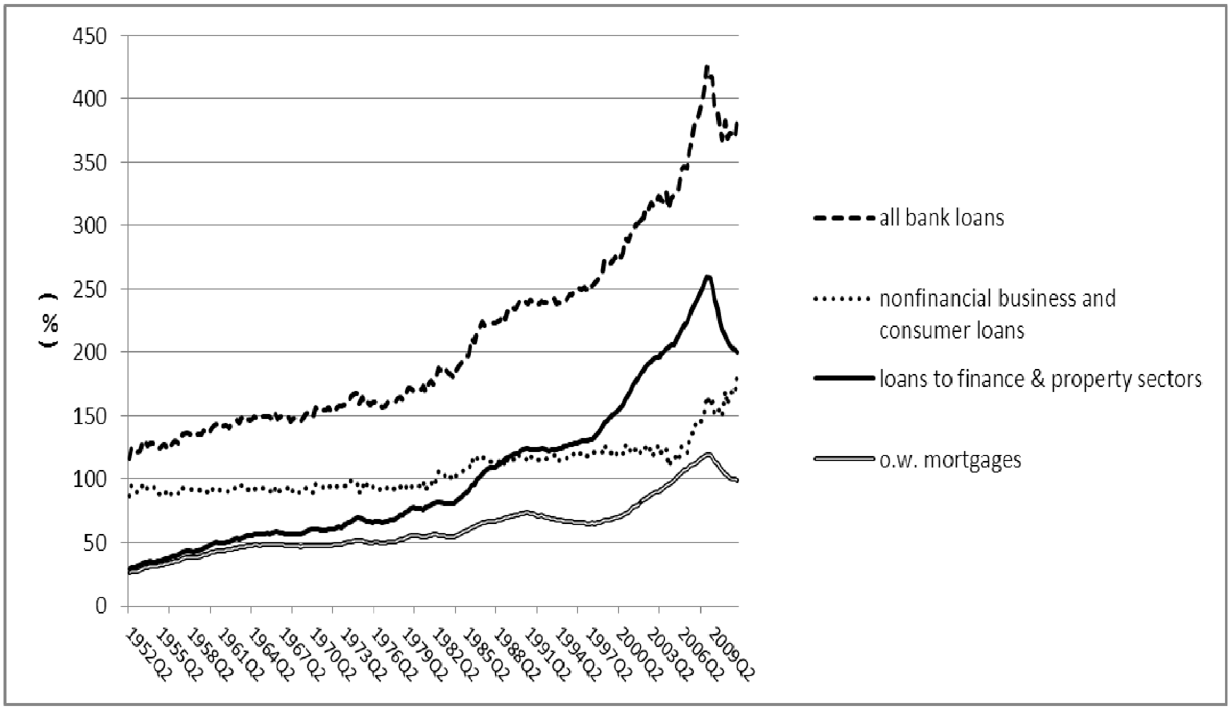
Table 5: Residual diagnostics

	$\varepsilon_{MORT,t}$	$\varepsilon_{RGDP,t}$	$\varepsilon_{RINV,t}$	$\varepsilon_{NRGDP,t}$
1954Q3-1978Q4				
Q(8)	16.286	3.339	5.539	1.315
	[0.038]	[0.911]	[0.699]	[0.995]
$Q^2(8)$	4.323	2.033	8.939	3.537
	[0.827]	[0.980]	[0.348]	[0.896]
Q(12)	20.198	8.305	7.2407	3.403
	[0.063]	[0.761]	[0.841]	[0.992]
$Q^2(12)$	7.902	4.876	12.715	7.679
	[0.793]	[0.962]	[0.390]	[0.810]
1984Q1-2008Q1				
Q(8)	10.498	5.664	8.294	6.654
	[0.232]	[0.685]	[0.405]	[0.574]
$Q^2(8)$	4.017	3.284	9.129	2.586
	[0.856]	[0.915]	[0.332]	[0.958]
Q(12)	12.442	14.451	13.121	13.891
	[0.411]	[0.273]	[0.360	[0.308]
$Q^2(12)$	8.022	8.135	9.966	6.448
	[0.783]	[0.774]	[0.619]	[0.892]

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; Residual diagnostics for $\varepsilon_{MORT,t}$ refer to the system of MORT and RGDP. The diagnostics are similar for the pair of MORT and NRGDP, while in the case of MORT-RINV it is found that $\varepsilon_{MORT,t}$ exhibit remaining autocorrelation.

FIGURES

Figure 1: U.S. bank-credit-to-GDP ratios, 1952Q1 – 2012Q1



Source: Bureau of Economic Analysis, flow of funds data (Z tables).

Figure 2a: Obtained Volatilities of Growth Rate of (a) Mortgages, (b) Real GDP, (c) Real Residential Investment and (d) Non Residential GDP before the Great Moderation (1954Q3-1978Q4)

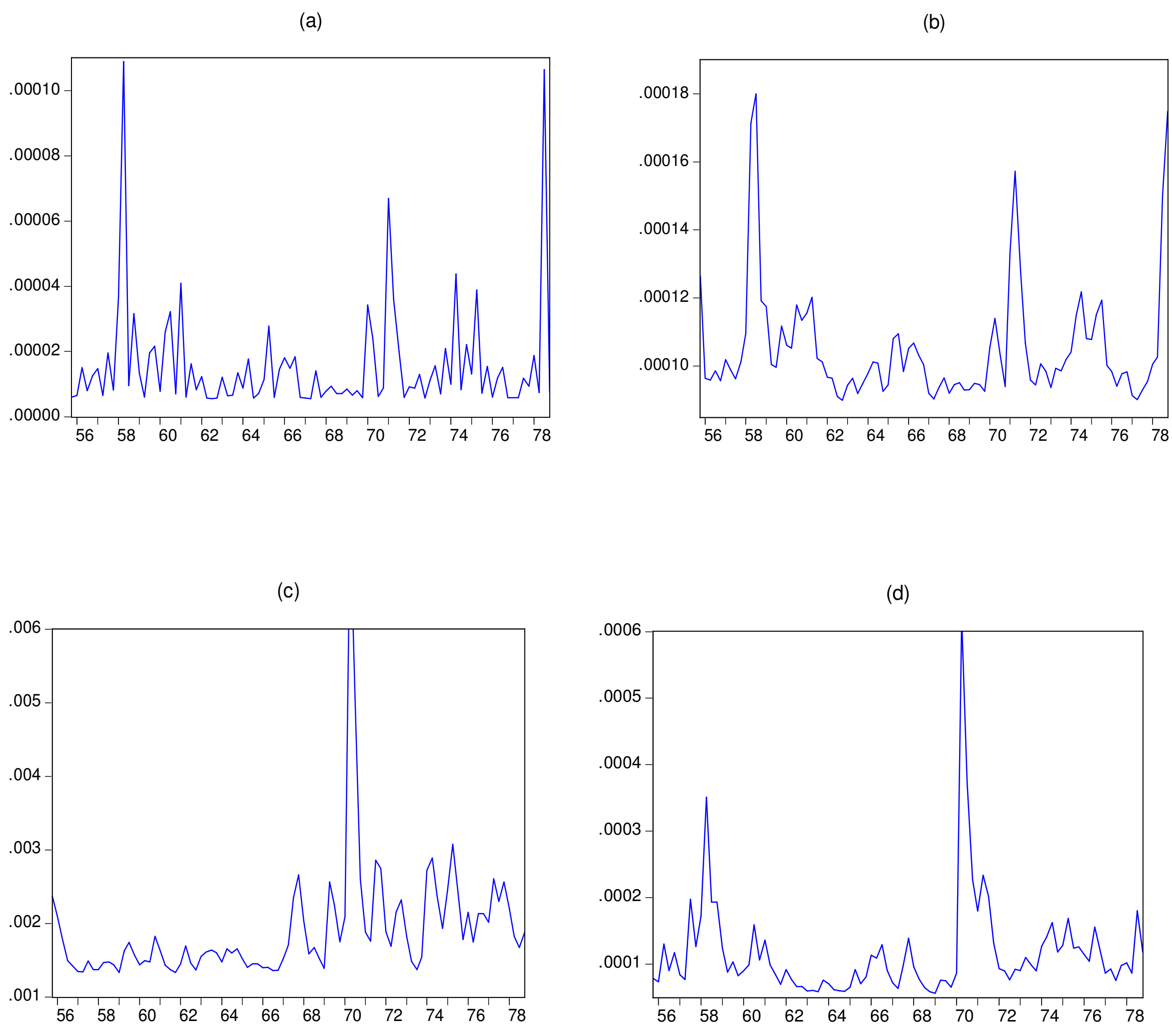
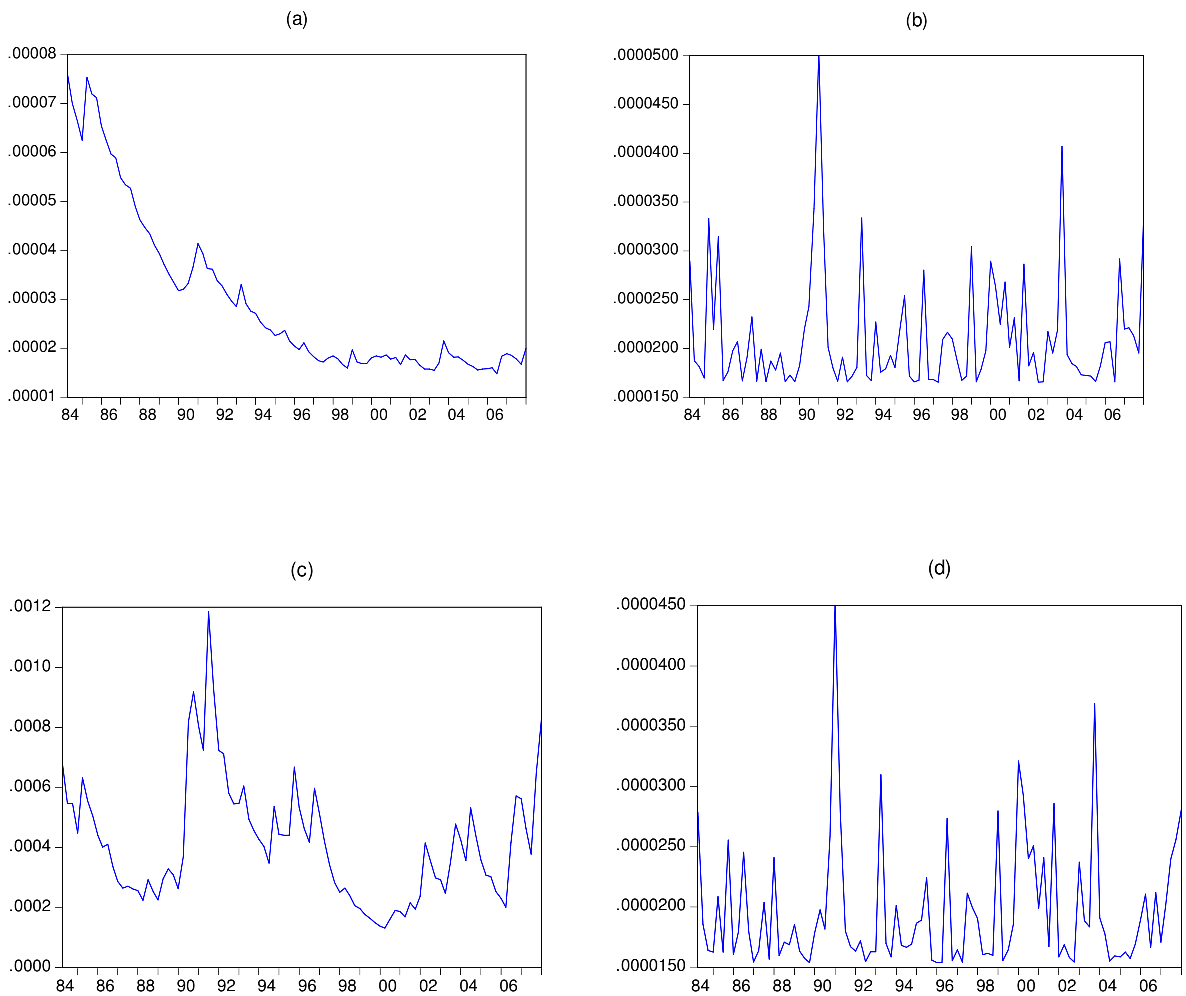


Figure 2b: Obtained Volatilities of Growth Rate of (a) Mortgages, (b) Real GDP, (c) Real Residential Investment and (d) Non Residential GDP during the Great Moderation (1984Q1-2008Q1)



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