Did Credit Decouple from Output in the Great Moderation?

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ABSTRACT
The U.S. during the 1984-2007 Great Moderation saw unusual macroeconomic stability combined with strong growth in asset prices and in credit relative to output. The distribution of credit shifted towards the financial and real estate sectors. The literature shows that each of these trends increases financial fragility, suggesting that the Great Moderation stability was destabilizing. We explore this interpretation by testing the Allen and Gale (2000) bubble feature that credit growth was driven more by past credit growth and less by output growth. We test this distinguishing between credit to asset markets and credit to the nonfinancial sectors. Results from a VAR model estimated on quarterly data for 1955-2007 suggest that the causal relations of credit aggregates and output differed before the Great Moderation and during the Great Moderation, along the lines we hypothesize. This invites a reinterpretation of the Great Moderation, and may help understand when a credit boom turns into a credit bubble.

Key Words: great moderation, credit, output, VAR, financial fragility

JEL codes: E44, C32, C51, C52

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Did Credit Decouple from Growth in the Great Moderation?

1. Introduction

How does the relation between credit growth and output growth change during a credit boom? Understanding these changes during the boom may help us better understand if and how credit booms precipitate credit crises. In the present paper we focus on this question in an empirical study of the US credit boom that preceded the 2008 crash. The analytical challenge is that credit growth leads to output growth in the short term, but may simultaneously lead to imbalances and crisis in the medium and long term. The first effect has been intensively researched, but the conditions for the second effect are not yet well understood.

Classical credit cycle theories (Wicksell, 1898; Veblen, 1904; Fisher, 1933; Minsky, 1964, 1986) have been applied and extended in contemporary work (Allen and Gale, 2000; Keen, 1995, 2011; Borio, 2012). They describe how the function of credit in the economy changes over the course of a credit boom and in the run up to a bust: from financing low-risk, low-return investment in fixed capital accumulation and productivity improvements, towards financing high-risk, high-return investments in real estate and financial assets and instruments, with increasing leverage and financial fragility. The distribution of the credit stock shifts away from the nonfinancial sectors and towards the financial and real estate sectors. In the process, the link between credit dynamics and output growth becomes looser. At the end of a speculative boom, credit growth is no longer mainly driven by economic fundamentals, but more by its own past dynamics. Another feature of the run up to a boom is that ‘stability is destabilizing’, as Minsky (1978) wrote. Greater-than-usual stability is both caused by more generous credit conditions, and encourages further expansion of credit and leverage.

The US economy during the credit boom that preceded the 2007 Great Crash conformed to each of these features. The ‘Great Moderation’ years 1984-2007 saw both unusual macroeconomic stability, unprecedented expansion of credit, and a shift in the distribution of credit towards the financial and real estate sectors. Based on these observations and the literature, we develop three testable hypotheses on the relation between credit aggregates and

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1 See e.g. Bernanke (2004). Blanchard and Simon (2001) showed that the standard deviation of quarterly growth and inflation in the U.S. declined by half and by two thirds, respectively, since 1984. Stock and Watson (2003), Kim and Nelson (1999) and Warnock and Warnock (2000) also found this, with strongly declining employment volatility. See Cecchetti et al. (2006) for cross country evidence.
growth when financial fragility is increasing. These are (i) a weakening of causality from output growth to growth in credit to the nonfinancial sectors, (ii) a weakening of causality from both output growth and growth in credit to the nonfinancial sectors, to growth in credit to the real estate and financial markets, and (iii) stronger causality in growth in credit to real estate and financial markets to its own future growth. Our argument is different from, but compatible with, a wide range of explanations for the Great Moderation in the literature.²

We test these hypotheses in a VAR framework on quarterly U.S. data during the Great Moderation (1984-2008) and before the Great Moderation (1955-1979), controlling for inflation and for the stance of monetary policy. We motivate our choice of time samples below. We use Granger causality tests, impulse response functions and forecast error variance decomposition, and find that the results are in line with our hypotheses. For instance, during the Great Moderation output growth ceases to cause growth in credit to the nonfinancial sectors. And the percentage of forecast error variance of credit to real estate and financial markets explained by its own past growth rises from 27.5 % before the Great Moderation to a remarkable 85.1% during the Great Moderation. We suggest that these and other changes in the causal relation of credit and output invite a reinterpretation of the Great Moderation, and may help understand when a credit boom turns into a credit bubble.

In the next section we present and discuss the stylized facts of credit and growth in the U.S. from the early 1950s to 2008. We motivate the functional differentiation of the two credit aggregates. In section 3 we develop testable hypotheses. In section 4 we present the methodology, the data and the analysis. Section 5 concludes with a discussion of limitations and possible extensions.

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² This includes labour market changes (Jaimovic and Siu, 2009), oil shocks and responses to shocks (Nakov and Pescatori, 2010, Gambetti et al., 2008), inventory management (McConnell and Perez-Quiros, 2000; Kahn et al., 2002; McCarthy and Zakrajsek, 2007), external balances (Fogli and Perri, 2006), better monetary policies (Bernanke, 2004) and “good luck” (Ahmed et al., 2002; Cogley and Sargent, 2005; Primiceri, 2005; Sims and Zha, 2006; Gambetti et al., 2008; Benati and Surico, 2009).
2. The Functional Differentiation of Credit: Trends in the U.S.

Following King and Levine’s (1993) seminal *Finance and Growth: Schumpeter Might Be Right*, a large empirical literature has established the positive effects on output growth of the growth in credit to the nonfinancial sectors (see Ang (2008) for an overview; also Uhlig, 2004; Benk et al., 2005). This strong relation also holds up in country-level analyses; Caporale and Howells (2001:555) note in their VAR study on the UK that “loans cause deposits and those deposits cause an expansion of transactions” - and thus, in GDP, which is the total value of final-demand transactions. And indeed there is close quantitative correlation between growth in credit to the nonfinancial sectors and output growth.³

However, we should “distinguish between different categories of credit, which perform different economic functions“, as the LSE *The Future of Finance* report (Turner et al, 2010:16) urges. The economy is composed of a real sector where goods and services are produced and traded, and a financial sector which may facilitate real sector growth, but whose primary function is to originate and circulate financial claims rather than goods and services. Since credit flows to financial and real estate markets do not finance transactions in goods and services in the way analysed by Caporale and Howells (2001), they are not included in the usual ‘credit-and-growth’ regressions.

But it is on the markets for mortgages, stocks, bonds and derivative products that financial fragility typically develops, often leading to crisis. Financial fragility is linked especially to the growth of credit to asset markets, of which household mortgage credit growth is an important category (Beck et al., 2012; Japelli and Pagano, 1994; Japelli et al., 2010; Büyükkarabacak and Valev, 2010). Allen and Gale (2000) show theoretically how by simultaneously driving up prices and leverage in a mutually enforcing process, financial fragility is increased by credit to markets for real estate, stock, bonds and many other financial assets and instruments - jointly labelled the ‘finance, insurance and real estate’ sectors, or ‘FIRE’ sectors in the U.S. National Product and Income Accounts. Financial fragility is defined as sensitivity of default rates to income shocks (Japelli et al., 2010), increasing the probability of financial instability (Minsky, 1978). Empirical

³ Federal Reserve statisticians who compile U.S. financial statistics note in their guide to the U.S. flow of funds ‘Z’ tables that “[a]nalysts have found that over long periods of time there has been a fairly close relationship between the growth of debt of the nonfinancial sectors and aggregate economic activity” (Board, 2013:76). Godley and Zezza (2006:3) likewise observed for the U.S. that “the two series have moved together to an extent that is somewhat surprising...”. 

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research by Borio and Lowe (2004) confirms that high FIRE-sector growth coupled with an asset price boom is a good predictor of financial fragility and instability.

In view of the different effects of these two credit categories, in this paper we separately study credit to the nonfinancial sectors and credit to the FIRE sectors. Below we discuss some reasons why growth in credit to the FIRE sectors increases financial fragility. We then show the strong growth in FIRE-sector credit growth in the US during the Great Moderation. This supports our view of the Great Moderation as an era of increasing financial fragility, and motivates the VAR analysis that follows.

It is now well established that above a threshold level, high credit-to-GDP growth slows down growth in the nonfinancial sectors (Arcand et al., 2011; Cecchetti and Kharroubi, 2012). It is also clear that high credit-to-GDP growth precipitates crisis, as Reinhart and Rogoff (2009), Schularick and Taylor (2012) and Jorda et al. (2011) show. The point here is that the rapid increase in the stock of credit relative to GDP that characterizes the U.S. credit boom since the 1980s is overwhelmingly due to credit to the ‘FIRE’ sectors, not to the nonfinancial sectors.

Figure 1 illustrates this. The GDP ratio of credit to the nonfinancial sectors is roughly stable between 80% and 110% over the six decades 1951-2007, with most of the increase due to an upward shift in the mid 1980s. But credit to the FIRE sectors rose from less than one third of GDP in the early 1950s to more than twice the GDP level in 2007, with most of that growth occurring during the Great Moderation. In 1984, the GDP ratio of FIRE-sector credit instruments was still below 100%. After that until the 2008 Crash, it was growing at 4.6% annually on average, compared to only 1.1% for the GDP ratio of nonfinancial sector credit.

A second reason why growth in credit to the FIRE sectors is of special interest is that it increases financial fragility. This because of the opportunities for leveraged investment which real estate and financial markets offer. Research finds that credit to the FIRE sectors combined with rising asset prices is the best predictor of crisis, rather than the growth of a total-credit measure (Borio and Lowe, 2004). Household mortgage credit is a major part of FIRE sector credit (Büyükkarabacak and Valev, 2010). Specifically, Kemme and Roy (2012) find that the U.S. mortgage credit boom was a good predictor of the 2007 crisis.
A final reason to view the Great Moderation in this light is that these were years of macroeconomic tranquillity. Minsky (1978) identified unusual stability as another feature of a destabilizing credit boom. With more stability, agents are encouraged to take more risk, leading to bubbles and busts (Allen and Gale, 2000). Bean (2011) discusses how during the Great Moderation, low volatility in real and financial variables induced more debt-financed investment and risk taking. For all these reasons – the upward shift in credit-to-GDP ratios; the shift in credit growth from nonfinancial to FIRE sector growth; and the onset of stability ending in severe instability – we study the ‘Great Moderation’ years 1984-2007 as a ‘credit boom gone bust’ (Schularick and Taylor, 2012) in contrast to the preceding years in our data set (1955-1979).

3. Testable Hypotheses

We now turn from motivating the functional differentiation of credit and our focus on the Great Moderation, to developing testable hypotheses. The challenge we address is how to distinguish a credit boom leading to a bust from one that is part of the normal financial deepening process. The approach we take is not so much to ask ‘what drives GDP?’ (as in the credit-growth literature; Uhlig, 2004) as ‘what drives credit?’. The question we ask is: How are the causal relations of the two credit aggregates with growth and with each other different in a sustainable growth episode, compared to credit growth with increasing financial fragility? We exploit the fact that we know that the U.S. credit boom since the mid-1980s did lead to a credit crisis (Kemme, 2012) and suggest three testable hypotheses.

If nonfinancial sector credit is allocated such that it increases economic efficiency, it is allocated in response to observed growth opportunities (an assumption also exploited in the literature on international financial flows and growth; Prasad et al., 2007; Rodrik and Subramanian, 2009). By implication, over time we expect nonfinancial sector credit growth to increase in response to increases in GDP growth. This implies Granger causality from output growth to nonfinancial sector credit growth (in addition to the well-established causality from nonfinancial sector credit growth to output growth). Conversely, if the build-up of financial fragility is due to the misallocation of credit, then we expect to see a weakening of this Granger causality between output and credit.
The sequence in a sustainable growth process is that nonfinancial sector financing by banks or markets which leads to growth, then allows for investments in wealth (real estate, stocks and bonds), and the credit flows that finance these investments (such as mortgages). In the process we should observe Granger causality from nonfinancial credit growth to FIRE-sector credit growth, and from GDP growth to FIRE-sector growth. If, on the contrary, financial fragility is building, this implies self-propelled growth in asset markets where capital gains induce more borrowing, with little relation to investment and growth in the nonfinancial sectors. This is the process James Tobin referred to in his 1984 Hirsch Memorial Lecture “On the Efficiency of the Financial System”, when he worried about “financial activities remote from the production of goods and services”. In this case, we expect to see a weakening of Granger causality from GDP growth and nonfinancial credit growth to FIRE-sector credit growth. This indicates that FIRE-sector credit growth is less driven by output growth and its financing, and more by its own dynamics. Our testable hypotheses, then, are (i) a weakening of causality from output growth to growth in credit to the nonfinancial sectors, (ii) a weakening of causality from both output growth, and growth in credit to the nonfinancial sectors to growth in credit to the FIRE sectors, and (iii) stronger causality in growth in credit to real estate and financial markets to its own future growth.\(^4\)

4. Methodology, Data and Analysis

In order to analyze the dynamics and causality of output growth and credit growth, we apply a Vector Autoregressive (VAR) model (Sims 1980), which allows analysis of interdependencies between time series. Since we have no priors on exogeneity or the direction of causation, all

\(^4\) Note that we do not have a hypothesis on the causal relation from nonfinancial-sector credit growth to output growth. Because credit to the nonfinancial sectors is used by nonfinancial firms and households for nonfinancial transactions, this is bound to increase GDP over all stages of a credit cycle. We expect to find Granger causality from nonfinancial sector credit to output growth both before and during the Great Moderation, but this is not a hypothesis that helps us distinguish between sustainable growth and increasing financial fragility. A second point of note is that we also do not hypothesize that credit to the FIRE sector normally causes output growth, but that this causal link weakens during a bubble. FIRE-sector credit consists of loans to support investment in assets, not in goods and services, so there is no reason to expect a direct causal relation to transactions in goods and services, as measured by GDP. At best, debt-financed investment in bonds and stocks may facilitate investment in the nonfinancial sectors, which in turn causes growth. In that sense FIRE-sector credit flows are secondary to the growth process. Beck et al. (2012) show in cross-country regressions that mortgages - the larger part of their household credit measure - indeed has no effect on output growth.
variables are treated as endogenous. Values of a variable may depend on its own lags and on the lags of other variables. The structure of the model is:

$$y_t = A_0 + A_1 y_{t-1} + ... + A_p y_{t-p} + \epsilon_t$$

(1)

where $y_t$ is an $(n \times 1)$ vector with each of the $n$ endogenous variables, $A_0$ an $(n \times 1)$ vector of intercept terms, $A_i$ is an $(n \times n)$ matrices of coefficients with $i=1,...,p$, and $\epsilon_t$ is an $(n \times 1)$ vector of error terms. We discuss the variables included in the model below.

The variables included in the model are the annual growth rates of the logarithm (i) of real GDP (RGDP), (ii) of the real value of the stock of credit instruments in the nonfinancial sectors (RCR), and (iii) of the real value of the stock of credit instrument in the FIRE sectors (RCF). This includes both credit by deposit taking institutions (banks) and other financial institutions, which hold both (securitized) bank loans and other credit assets. Data were obtained from the Bureau of Economic Analysis.\(^5\) We also include two control variables: the annual growth rate of the logarithm of the (overnight) Federal funds rate (FR), and inflation (INF) measured by the real GDP deflator, both provided by the St Louis Fed website. We use quarterly data over two subsamples, 1955Q3-1979Q4 (before the Great Moderation) and 1984Q1-2008Q1 (during the Great Moderation). We follow the convention in the Great Moderation literature, where 1984 is often adopted as the start of the Great Moderation (among others Kim and Nelson, 1999; McConnell and Perez-Quiros, 2000; Kahn et al., 2002; Stock and Watson, 2003), though other years in the early 1980s are also used.\(^6\)

\(^5\) We utilize quarterly data from ‘Z’ tables in the Flow of Funds Accounts. We construct the stock of credit instruments in the nonfinancial sectors as follows. We take series FL384004005.Q, titled ‘domestic nonfinancial sectors credit market instruments’ and subtract mortgage credit (series FL383165005.Q, ‘domestic nonfinancial sectors; total mortgages). We correct for inter-firm trade credit (FL383070005.Q; see Mateut et al. (2006) on the role of trade credit), firm-to-customer consumer credit (FL383066005.Q) and ‘other loans and advances’ (FL383069005.Q). Finally, we subtract net financial investment (including home equity withdrawal; Greenspan and Kennedy, 2008). We construct FIRE sector credit by adding mortgage credit held in the nonfinancial sector (series FL383165005.Q) to domestic financial sector credit market instruments.

\(^6\) Our choice of samples ensures that the first sample is before the Great Moderation, and the second sample is during the Great Moderation. We applied the Chow test for structural breaks over the whole period 1955Q3-2008Q1 and find that any other quarter during 1980Q1-1983Q4 is also a potential breakpoint in output volatility. We also ran robustness analyses to ensure that our findings are not sensitive to using another quarter as the start of the Great Moderation.
All three variables are found to be stationary at their level (I(0)) but INF is found to be I(1) in both subsamples. Table 1 reports descriptive statistics for the variables (absolute mean, standard deviation, skewness and kurtosis) for the two subsamples.

Growth of all variables is positive before the Great Moderation and all variables are more volatile before the Great Moderation than during the Great Moderation, apart from the growth rate of RCR. The distribution of annual growth rates of real output, real credit to nonfinancial sectors and real credit to financial and real estate sectors all exhibit positive skewness with few high values in the first subsample; the opposite holds for the remaining variables. Furthermore, the kurtosis (or “peakedness”) statistics for the distributions of almost all the variables show more deviations from the normal distribution in the first subsample than in the second, apart from the annual growth rate of funds rate for which the inverse case holds.

We estimate a number of reduced-form VAR models for two subsamples using quarterly data, 1955Q3-1979Q4 (before the Great Moderation) and 1984Q1-2008Q1 (during the Great Moderation). We examine whether lags of the annual growth of RCR, RCF and output cause these or other variables. The three endogenous variables are stationary at their level, while the control variables, inflation and interest rate, were once differentiated in order to be stationary. We estimate VAR($p$) models with $p=1,...,12$ and the model selection criterion is the minimum value of Schwarz Information Criterion (SIC). This procedure yields VAR(2) and VAR(1) models for the first and second subsamples, respectively.

After estimating the model, we explore the existence of any causal relationships between the variables in three ways. First, we run Granger causality tests, where a series $x_t$ is said to Granger cause a series $y_t$ if changes in $x_t$ precede changes in $y_t$ so that $x_t$ improves predictions $y_t$, but $y_t$ does not improve predictions of $x_t$ (Granger, 1969). Second, we compute impulse response

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7 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 Schwarz Information Criterion (SIC). The stationarity is tested at 1%, 5%, 10% significance levels and the time trend has not been taken into account in the test equation. The unit root test results are available on request.

8 Although the lag order of the VAR is too short, the dynamic behavior of the variables can be captured sufficiently in the first subsample. We tried also VAR(5) and VAR(11) for the first and second subsample, respectively, indicated by Akaike Information Criterion (AIC) and the results do not change substantially.
functions (IRFs) which quantify the effect of a one standard deviation shock to innovations in the error terms of one variable on current and future values of it and all other variables. An IRF graph so displays the response of any variable over time to a shock in its own or other error terms. Sims (1980) suggests that examining IRFs might be the most effective way to observe the presence (or otherwise) of Granger causality in multivariate frameworks. A third way of characterizing the dynamic behavior of the VAR is to conduct a forecast variance decomposition analysis, as suggested also by Sims (1980). Granger Causality tests are reported in Table 2.

We detect bidirectional causality from the growth of RCR (GLRCR) to growth of RGDP (GLGDP) and vice versa in the first subsample, but unidirectional causality from GLRCR to GLRGDP in the second subsample. This finding is consistent with the hypothesis that the build-up of financial fragility during the Great Moderation was due to the misallocation of credit, indicated by weaker Granger causality from GLRGDP to GLRCR. Second, both GLRCR and GLGDP Granger-caused the growth of RCF (GLRCF) before the Great Moderation. The causality from GLRCR to GLRCF is still significant in the Great Moderation, though with much lower values for the test statistic. Thus, the Granger test results do not clearly support the second hypothesis. But both the impulse response function (IRF) graphs and the forecast error variance decomposition do, as we now show. In addition, they show greater responsiveness of credit to its own lags in the Great Moderation (something we cannot test in a Granger causality framework).

The Figures show results from IRF analyses over 12 periods for the two subsamples. The IRF graphs are all consistent with the Granger causality tests before, but not during the Great Moderation. GLGDP responds positively to a one-standard deviation shock in the growth of GLRCR both before and during the Great Moderation. Reverse causality from GLRCR to GLRCR exists before the Great Moderation, but is absent during the Great Moderation, in line with our first hypothesis. Further, GLRCF responds positively to a one-standard deviation shock in the growth of GLRCR before, but not during the Great Moderation, in line with hypothesis 2.
We also note that during the Great Moderation, FIRE-sector credit growth appears much more self-propelled during the Great Moderation than before. GLRCF responds more strongly and with longer duration to a one-standard deviation shock in its own growth during the Great Moderation.

Finally, also forecast error variance decomposition analysis supports the observations from Granger causality tests. We computed the 12-quarters-ahead forecast error variance decompositions. The percentage of forecast error variance of nonfinancial sector credit growth explained by real output growth was 11.5% before the Great Moderation but only 0.3% during the Great Moderation, in line with our first hypothesis. Second, the percentage of forecast error variance of FIRE-sector credit growth explained by nonfinancial sector credit growth was 66.8% before the Great Moderation, falling to 14.7% during the Great Moderation, in line with our second hypothesis. The percentage caused by GDP growth goes down from 5.7% to 0.3%. In this sense, FIRE-sector credit indeed decoupled from output and especially from the credit flows that finance output. Finally, the percentage of the forecast error variance of FIRE-sector credit growth explained by its own past growth was 27.5% before the Great Moderation, but rising to a remarkable 85.1% during the Great Moderation. FIRE sector credit became mainly driven by itself, by this evidence.

5. Summary, Discussion and Conclusions

The U.S. during the 1984-2007 Great Moderation saw unusual macroeconomic stability combined with strong growth in asset prices and in credit relative to output, with a shift in the distribution of credit towards the financial and real estate sectors. The empirical literature shows that each of these trends increases financial fragility (Borio and Lowe, 2004; Büyükkarabacak and Valev, 2010; Bean, 2011), suggesting that the Great Moderation stability was destabilizing. We explore this interpretation by testing another feature of a credit bubble: that credit growth is driven more by past credit growth and less by output growth (Japelli and Pagano, 1994; Allen and Gale, 2000). Results from a VAR model estimated on quarterly data for 1955-2008 show that before the Great Moderation, output both causes and is caused by credit to the nonfinancial sectors. Credit to asset markets is caused by credit to the nonfinancial sectors. During the Great Moderation and until the 2008 crash, output ceases to cause credit to the nonfinancial sectors,
and credit in asset markets is caused by itself more than by any other variable in the system. We suggest that this change in the causal relation of credit and output invites a reinterpretation of the Great Moderation, and may help understand when a credit boom turns into a credit bubble.
### Table 1: Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std dev.</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>1955Q3-1979Q4</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( RGDP )</td>
<td>0.0764</td>
<td>0.0349</td>
<td>0.1338</td>
<td>3.4540</td>
</tr>
<tr>
<td>( RCR )</td>
<td>0.0764</td>
<td>0.0309</td>
<td>0.6074</td>
<td>4.2750</td>
</tr>
<tr>
<td>( RCF )</td>
<td>0.1059</td>
<td>0.0280</td>
<td>0.3029</td>
<td>2.4826</td>
</tr>
<tr>
<td>( INF )</td>
<td>0.0007</td>
<td>0.0044</td>
<td>-0.2635</td>
<td>4.3228</td>
</tr>
<tr>
<td>( FR )</td>
<td>0.0878</td>
<td>0.4175</td>
<td>-0.4358</td>
<td>3.5891</td>
</tr>
<tr>
<td><strong>1984Q1-2008Q1</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( RGDP )</td>
<td>0.0566</td>
<td>0.0273</td>
<td>-0.6319</td>
<td>3.0708</td>
</tr>
<tr>
<td>( RCR )</td>
<td>0.0683</td>
<td>0.0353</td>
<td>-0.2852</td>
<td>2.7373</td>
</tr>
<tr>
<td>( RCF )</td>
<td>0.1011</td>
<td>0.0290</td>
<td>0.0785</td>
<td>2.5500</td>
</tr>
<tr>
<td>( INF )</td>
<td>-0.0002</td>
<td>0.0023</td>
<td>-0.1862</td>
<td>3.3362</td>
</tr>
<tr>
<td>( FR )</td>
<td>-0.0330</td>
<td>0.3934</td>
<td>-0.0048</td>
<td>4.1800</td>
</tr>
</tbody>
</table>

Note: \( RGDP \) and the credit variables are the annual growth rates of the logarithm of \( RGDP \) and credit stocks, respectively. \( INF \) and \( FR \) are the quarter-on-quarter change in \( INF \) and the log of \( FR \), respectively.
Table 2: Granger Causality Tests

<table>
<thead>
<tr>
<th>Testable Hypotheses</th>
<th>Pre-Great Moderation</th>
<th>During-Great Moderation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Chi-square statistic</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1955Q3-1979Q4</td>
<td>1984Q1-2008Q1</td>
</tr>
<tr>
<td>$RCR$ does not Granger Cause $RGDP$</td>
<td>15.7741 (0.0004)</td>
<td>9.7792 (0.0018)</td>
</tr>
<tr>
<td>$RGDP$ does not Granger Cause $RCR$</td>
<td>12.0705 (0.0024)</td>
<td>0.1453 (0.7031)</td>
</tr>
<tr>
<td>$RGDP$ does not Granger Cause $RCF$</td>
<td>7.0446 (0.0295)</td>
<td>0.0069 (0.9336)</td>
</tr>
<tr>
<td>$RCR$ does not Granger Cause $RCF$</td>
<td>36.1535 (0.0000)</td>
<td>8.2267 (0.0041)</td>
</tr>
<tr>
<td>$RCF$ does not Granger Cause $RCR$</td>
<td>2.7934 (0.2474)</td>
<td>1.2572 (0.2622)</td>
</tr>
</tbody>
</table>

Notes: Probability values of the corresponding Chi-square statistics are in parentheses.
Figure 1: U.S. Stocks of Credit Market Instruments (% GDP)

Source: Bureau of Economic Analysis, flow of funds data (Z tables).
Figure 2: Impulse Responses to shocks before the Great Moderation (1955Q3-1979Q4)

- Response of GLRGDP to GLRGDP
- Response to Cholesky One S.D. Innovations ± 2 S.E.
- Response of GLRGDP to GLRCR
- Response of GLRGDP to GLRCF
- Response of GLRCR to GLRGDP
- Response of GLRCR to GLRCR
- Response of GLRCR to GLRCF
- Response of GLRCF to GLRGDP
- Response of GLRCF to GLRCR
- Response of GLRCF to GLRCF
Figure 3: Impulse Responses to shocks during the Great Moderation (1984Q1-2008Q1)
References


Wicksell, K. (1898), Interest and Prices, New York: Augustus M. Kelley.