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The credit channel in U.S. economic history

Torben W. Hendricks [a], Bernd Kempa [b,*]

[a] Department of Economics, University of Duisburg-Essen, Campus Essen, Germany
[b] Department of Economics, University of Muenster, Universitaetsstr. 14-16, 48143 Muenster, Germany

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Abstract

This paper analyzes the effectiveness of the credit channel as a transmission mechanism of monetary policy in 20th century economic history by applying a Markov-switching model on the default premium of U.S. corporate bond portfolios. Beside the stance of monetary policy and the state of the business cycle, we identify a latent factor accounting for the strength of the credit channel. In particular, the credit channel appears to be active only in periods of financial distress, most notably during the Great Depression and the 1980s Savings and Loan debacle.

JEL classification: C22; E51

Keywords: Markov switching; Monetary policy; Credit channel; Default premium

1. Introduction

There is a strong presumption that credit markets play an important role in the monetary transmission process. In fact, a large and growing literature views the credit channel as the decisive conduit through which monetary policy affects the real economy.[1] In this literature, the financial system is seen as both an accelerator of monetary impulses and as an independent source of non-monetary effects on the business cycle, with the influence of the credit channel becoming particularly obvious in times of severe financial crises, such as during the Great Depression of the early 1930s or in the aftermath of the Savings and Loan debacle of the 1980s. Bernanke

* Corresponding author. Tel.: +251 83 28660; fax: +251 83 22826.
E-mail address: bernd.kempa@uni-muenster.de (B. Kempa).
[1] See Bernanke and Gertler (1995) for an overview.

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(1983) relates the conditions in the financial system of the early 1930s to the severity of the Great Depression in the United States. He provides evidence that the reduced effectiveness of the financial sector during the disruptions of the early 1930s increased the real cost of intermediation, resulting in a credit squeeze which contributed to converting the severe but not unprecedented downturn of 1929–1930 into a protracted depression. In contrast, the Savings and Loan crisis was not primarily triggered by credit rationing, but rather by a steep rise in the moral hazard premium, itself due to a dramatic decline in the market values of assets used as collateral by savings and loan institutions (e.g., Shoven, Smart, & Waldfogel, 1992).

Apart from such severe episodes of financial distress, the evidence of whether the credit channel is active or passive at any given point of time is rather mixed. Although the general existence of a credit channel is uncontroversial, its effectiveness appears to depend on a number of different factors. In particular, the leverage of the credit channel appears to vary throughout and across business cycles (Gertler & Gilchrist, 1994), may be strongly influenced by whether monetary policy is tight or easy (Oliner & Rudebusch, 1996a), and may deteriorate on a secular path as financial innovation increases the substitutability of intermediated and non-intermediated credit (Bernanke & Gertler, 1995).

This paper attempts to identify the credit channel in 20th century U.S. economic history from long time series of output and interest rate data, where we utilize the default premium as the difference between yields on BAA- and AAA-rated corporate bond portfolios as an indicator of the credit channel. We are concerned with assessing the relative importance of the business cycle, the secular component as well as other potential latent factors determining the effectiveness of the credit channel over time. To this end, we employ a Markov-switching model (MSM) in which the parameters of the data generating process (DGP) of the observed time series depend on an unobservable state variable which we associate with a genuine credit channel.

The remainder of the paper is structured as follows: Section 2 provides a brief introduction to the concept of the credit channel, Section 3 contains technical details on our estimation strategy, Section 4 reports on the estimation results and a concluding section summarizes our findings.

2. The credit channel

The credit channel refers to the way in which monetary policy is transmitted onto the real economy through its effect on financial markets. Two variants of the credit channel can be distinguished: a bank lending channel and a broad credit channel. The bank lending channel arises because some borrowers, mainly small- and medium-sized businesses, are dependent on bank credit and are unable to borrow in the securities markets. This in turn is due to the high costs involved in obtaining information about borrowers' creditworthiness. Monetary policy then impacts not only the interest rate on bonds but may also affect the spread between loans and bonds or the quantity of bank loans available (Bernanke & Blinder, 1988; Honda, 2004).

According to the bank lending channel, small firms with weak balance sheets should be more strongly affected by the rising cost of capital than are large firms. In fact, Gertler and Gilchrist (1993, 1994) and Oliner and Rudebusch (1996b) find that tight money leads to a general shift in the availability of all types of finance from small firms to large firms, and Kashyap, Stein, and Wilcox (1996) show that even among large U.S. firms there is considerable disintermediation away from bank finance in such an environment. Similar micro-level evidence in favor of the bank lending channel has been provided for firms (Calomiris, Himmelberg, & Wachtel, 1995; Chatelain, Generale, Hernando, von Kalckreuth, & Vermeulen, 2003a) as well as for banks (Kashyap & Stein, 1995; Kashyap & Stein, 2000; Chatelain et al., 2003b).

Whereas the bank lending channel focuses exclusively on the banking industry as the amplifier of monetary policy impulses, the broad credit channel considers the whole range of financial intermediaries with no special role for the banking sector (e.g., Bernanke, 1993; Bernanke, Gertler, & Gilchrist, 1999; Carlstrom & Fuerst, 2001). The amplification effect of the broad credit channel comes through the role of the external finance premium which drives a wedge between the cost of internal and imperfectly collateralised external finance. This risk premium is due to informational asymmetries and can be regarded as compensation to lenders for the expected cost of monitoring, evaluation and contract enforcement. In models of the broad credit channel, the interest rate in period t faced by firms, R_t^f, typically depends on the policy rate, R_t, and the external finance premium, f_t, which is increasing in the debt-to-equity ratio of the firm, D_t/E_t (compare, e.g., Bean, Larsen, & Nikolov, 2002):

$$R_t^f = R_t + f_t\left(\frac{D_t}{E_t}\right), \quad f' > 0. \tag{1}$$

Beside its direct effect, a rise in the policy rate exerts an indirect impact on the lending rate by affecting firms' debt-to-equity ratio, as equity prices fall and firms' collateral deteriorates. This indirect effect is frequently referred to as the balance sheet channel.

3. An econometric model for the identification of the credit channel

In what follows, we investigate the broad credit channel in long time series of U.S. data. Whereas the general existence of a credit channel is well established for U.S. data, its intensity appears to vary over time in a nonlinear fashion. For example, Bernanke et al. (1999, p. 39) point out that "the dynamics of the [business] cycle are intrinsically nonlinear; more specifically, financial accelerator effects are stronger, the deeper the economy is in recession." In the same vein, De Bondt (2000, pp. 107–108) finds that "the relevance of the bank lending channel and particularly the balance sheet channel may be asymmetric over the business cycle", whereas Bean et al. (2002, p. 18) argue that "the credit channel can work in a highly non-linear fashion, implying significant potential for asymmetries in monetary transmission."

In order to account for such nonlinearities, we allow for discrete shifts in the data generating process by employing a Markov-switching model. In this class of nonlinear models the parameters of the DGP of the observed time series depend on an unobservable state variable which we associate with a genuine credit channel. In particular, we model the default premium as the difference between yields on BAA- and AAA-rated corporate bond portfolios. This default premium, also referred to as the quality spread, measures the impact of monetary policy on the tendency for disintermediation across these two classes of creditors.

The Markov-switching model was pioneered by Hamilton (1989, 1990) and has since developed into one of the most popular non-linear time series models. In this model, the nonlinearities are introduced via discrete shifts among any number of regimes. Here we allow for regime switching between two possible states, one state in which the credit channel is absent, denoted by $S_t = 1$, and another in which it is operative, denoted by $S_t = 2$. The model is estimated without any prior knowledge about possible break points, such that the identification of the two states is solely determined by the data.

The model can be written as follows:

$$\rho_t = c_{S_t} + X_t\beta_{S_t} + u_t, \tag{2}$$

where ρ_t denotes the quality spread in period t, c_{S_t} is a (state-dependent) constant, X_t is a matrix of conditioning information used to predict ρ_t, β_{S_t} is the (state-dependent) vector of coefficients, and u_t is an error term, with $u_t \sim NID(0, \sigma^2_{S_t})$. Any regime shift between the two states represents a structural break in the data. If the timing of these shifts was known in advance, the approach would degenerate into a simple dummy variable model. However, as the states S_t are not directly observable, we make the common assumption that these follow a first-order Markov chain. The underlying process can be described by the following transition probabilities governing the switches between the two states:

$$\begin{aligned} p_{11} &= P(S_t = 1 | S_{t-1} = 1), \\ p_{12} &= P(S_t = 2 | S_{t-1} = 1), \\ p_{21} &= P(S_t = 1 | S_{t-1} = 2), \\ p_{22} &= P(S_t = 2 | S_{t-1} = 2), \end{aligned} \tag{3}$$

such that the probability of being in a particular state at time t depends only on the state the system has been in at time $t-1$. The system may thus prevail in any of the two states for a random period of time, and is replaced by the other state when switching takes place. The attractive feature of this model is that no extraneous information is needed regarding the dates when the system was in each regime.[2] The probability of the system being in a particular regime is solely inferred from the data. Suppose that the density conditional on being in state j, is Gaussian:[3]

$$\eta(\rho_t | \Omega_{t-1}, S_t = j) = \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp\left(\frac{-(\rho_t - c_j - X_t\beta_j)^2}{2\sigma_j^2}\right), \tag{4}$$

for $j = 1, 2$, and Ω_{t-1} denoting information at time $t-1$. Then the log-likelihood function can be written as:

$$\ell(\rho_t | \Omega_{t-1}) = \sum_{t=1}^{T} \ln(\phi(\rho_t | \Omega_{t-1})), \tag{5}$$

where the density $\phi(\rho_t | \Omega_{t-1})$ is the sum of the probability-weighted state densities, $\eta(\cdot)$, of the two states

$$\phi(\rho_t | \Omega_{t-1}) = \sum_{j=1}^{2} \eta(\rho_t | \Omega_{t-1}, S_t = j) P(S_t = j | \Omega_{t-1}). \tag{6}$$

Here $P(S_t = j | \Omega_{t-1})$ denotes the conditional probability of being in state j at time t given information at time $t-1$. The conditional state probabilities are obtained recursively:

$$P(S_t = j | \Omega_{t-1}) = \sum_{k=1}^{2} P(S_t = j | S_{t-1} = k) P(S_{t-1} = k | \Omega_{t-1}), \tag{7}$$

[2] The properties of Markov chains are discussed extensively in Hamilton (1994).

[3] This is not a particularly strong assumption since combinations of normals can accommodate densities with nonzero skewness and fat tails.

Table 1
ADF and Phillips–Perron tests.

	BAA–AAA	TBB	DIP	DIP12
ADF (constant only)	−3.0868**	−4.7000***	−12.1133***	−4.8030***
ADF (constant and trend)	−3.2451*	−4.6874***	−12.4806***	−5.4015***
PP (constant only)	−3.5822***	−4.6883***	−24.9122***	−5.7587***
PP (constant and trend)	−3.8162**	−4.6727***	−24.8708***	−6.0691***

Asterisks refer to level of significance: *10%, **5%, ***1%.

where $P(S_t = j|S_{t-1} = k)$ is the state transition probabilities of Eq. (3). Finally, the conditional state probabilities are updated according to Bayes' rule using the new information about the state of the economy, S_t, contained in the tth observation of the dependent variable, ρ_t:

$$P(S_t = j|\Omega_t) = P(S_t = j|\Omega_{t-1}; \rho_t) = \frac{\eta(\rho_t|S_t = j; \Omega_{t-1})P(S_t = j|\Omega_{t-1})}{\sum_{j=1}^{2}\eta(\rho_t|S_t = j; \Omega_{t-1})P(S_t = j|\Omega_{t-1})}. \quad (8)$$

Eqs. (7) and (8) can be iterated on recursively to derive the state probabilities $P(S_t = j|\Omega_{t-1})$ and to obtain the parameters of the likelihood function. There are various ways of estimating the Markov-switching model (see Hamilton, 1990, or Kim & Nelson, 1999). Here we use the Expectation Maximization (EM) algorithm discussed by Hamilton (1994) and Krolzig (1997), and drawing on the software provided by Krolzig (2004), to perform the iterations.[4]

4. Empirical evidence

We apply the regime-switching approach on the default premium, represented here by the quality spread between yields on Moody's BAA- and AAA-rated U.S. corporate bond portfolios, as the dependent variable. Estimation is performed by means of a Markov-switching model. The vector of conditioning information contains the stance of the Fed's monetary policy, the state of the U.S. business cycle and a latent factor associated most broadly with developments in financial markets. Our Markov-switching model has the format:

$$\rho_t = \begin{cases} c_1 + \alpha_1(TBB_t) + \beta_1(DIP_t) + \gamma_1(DIP12_t) + \varepsilon_{1,t}, & S_t = 1 \\ c_2 + \alpha_2(TBB_t) + \beta_2(DIP_t) + \gamma_2(DIP12_t) + \varepsilon_{2,t}, & S_t = 2 \end{cases}. \quad (9)$$

Here TBB is the spread between the 3-month maturity yield rate of U.S. Treasury Bills and the 10-year Treasury bond rate. TBB is used as an indicator of monetary policy because the long bond is relatively insensitive to short-run variations in monetary tightness or ease (Bernanke & Blinder, 1992). Business cycle conditions are proxied by monthly (DIP) and annual (DIP12) rates of change of the seasonally adjusted industrial production index. All data are obtained from the Federal Reserve System, with the sample consisting of monthly data for the time period 1920(1)–2005(12).

Table 1 reports that all variables are stationary using standard ADF and Phillips–Perron tests. In order to classify the two regimes with respect to the presence or absence of a credit channel, Table 2 reports the regression results for each of the two regimes identified by the Markov-switching

[4] Performing the iteration using data only up to period t results in the filter probability, whereas utilizing the information in the whole data set yields the smoothed probability (Kim, 1994).

Table 2
Estimation results.

	Coefficient	Standard error	t-value
Regime 1			
Constant	0.7311***	0.0250	29.2407
TBB	−0.0043	0.0117	−0.3657
DIP	−0.0119	0.0234	−0.5094
DIP12	−0.0128*	0.0076	−1.6806
σ_1	0.1585		
p_{11}	0.9892		
p_{12}	0.0108		
Regime 2			
Constant	1.6529***	0.0848	19.5010
TBB	0.1226**	0.0530	2.3131
DIP	−0.1771	0.1157	−1.5296
DIP12	−0.1355***	0.0347	−3.8995
σ_2	0.6557		
p_{22}	0.9844		
p_{21}	0.0156		
Log-likelihood (MSM)	−260.1819		
Log-likelihood (linear)	−1014.9327		
LR linearity test	1509.5016***		

Asterisks refer to level of significance: *10%, **5%, ***1%, Newey-West HAC standard errors.

model. As reported in the lower part of the table, the nonlinear model is found to assume a higher maximum of the log-likelihood function than the linear alternative. The likelihood-ratio (LR) test confirms that the MSM fits the data significantly better than a linear model.[5]

The two regimes identified by the model are both highly persistent, evidenced by transition probabilities of remaining in either one of the two regimes, p_{11} and p_{22}, of 98.92% and 98.44%, respectively. The corresponding regime-switching probabilities of exiting Regime 1 and entering Regime 2, p_{12}, and vice versa, p_{21}, are 1.08% and 1.56%. The regime-dependent estimates of the standard deviations of the innovations are denoted by σ_1 and σ_2. As there is some serial correlation in the residuals, we rely on heteroskedasticity and autocorrelation consistent standard errors throughout (Newey & West, 1987). It turns out that the influence of monetary policy has a significant impact on the default premium only in Regime 2. An increase in the U.S. Treasury bill rate relative to the long bond (TBB) leads to a significant rise in the quality spread. The evidence is somewhat less clear-cut with respect to the influence of the business cycle. In both regimes, the monthly growth rates in industrial production (DIP) do not significantly affect the default premium. In contrast, the corresponding annual figures (DIP12) are significantly negative in either regime, implying that positive (negative) output growth is associated with lower (higher) levels of the quality spread. However, the coefficient on the business cycle variable is substantially higher in Regime 2. Taken together, the results thus clearly point towards associating Regime 2 with the credit channel scenario.

Table 3 provides some statistics on the two regimes. Regime 1 is active in 568 months and Regime 2 in 452 months of the sample, which translates into regime probabilities and average

[5] Significance also obtains when the LR test is adjusted for the existence of unidentified nuisance parameters under the alternative, as proposed by Davies (1977, 1987).

Table 3
Regime statistics.

	Regime 1	Regime 2
Number of observations	568	452
Regime probability	0.5569	0.4431
Average regime duration (in months)	81.14	64.57
Cycle dating (smoothed probabilities)	1926:12–1928:11	1921:01–1926:11
	1944:02–1970:07	1928:12–1944:01
	1972:07–1974:09	1970:08–1972:06
	1977:06–1979:04	1974:10–1977:05
	1989:02–1990:08	1979:05–1989:01
	1991:03–2001:11	1990:09–1991:02
	2003:09–2005:12	2001:12–2003:08
Cycle dating (filtered probabilities)	1927:02–1929:01	1921:01–1927:01
	1944:03–1957:11	1929:02–1944:02
	1958:02–1970:08	1957:12–1958:01
	1972:11–1974:10	1970:09–1972:10
	1977:08–1979:06	1974:11–1977:07
	1989:04–1990:09	1979:07–1989:03
	1991:04–2001:12	1990:10–1991:03
	2003:11–2005:12	2002:01–2003:10

regime durations of 55.69% respectively 81.14 months for Regime 1, and 44.31% respectively 64.57 months for Regime 2.[6] The table also lists the exact dates in which either of the regimes has been active. The episodes thus identified vary marginally when the smoothed rather than the filtered probabilities are used (compare footnote 5), where the smoothed probabilities date the onset of the regime switches a few months prior to those identified by the filtered probabilities. Also, the filtered probabilities identify a brief switch into Regime 2 in 1957 which is absent under the smoothed probabilities.

We can now turn to Fig. 1 to visualize along the time axis the relative likelihoods of being in either of the two regimes. In the figure, the regime probabilities are specified separately for Regime 1 (upper panel) and Regime 2 (lower panel). The results show that the model identifies the individual regimes with a very high level of confidence as the probabilities mostly assume values close to 1.0. Due to the high persistence of the individual regimes, there are only very few regime switches over the course of the sample period, and each of the switches can be related to particular historic circumstances surrounding these events. This way we can offer an economic interpretation of the latent factor identified by the regime-switching model.

The system starts out in Regime 2 in the early 1920s until the end of 1926. This period of post World War I depression and recovery is followed by a switch into Regime 1 in which the credit channel is inactive. However, the system quickly reverts back to Regime 2 at the beginning of the downturn of 1929, which eventually triggered the Great Depression of the 1930s. Bernanke (1983) argues that the disruptions of 1930–1933 reduced the effectiveness of the financial sector and induced a severe contraction in the supply of credit. Interestingly, our evidence shows that the credit market effect was not restricted to this period, but extended well beyond the immediate crisis years of the Great Depression throughout the entire 1930s and early 1940s almost until the

[6] Due to the lag structure of the estimation, the regimes are identified for the time period 1921(1)–2005(12), resulting in a total of 1020 observations.

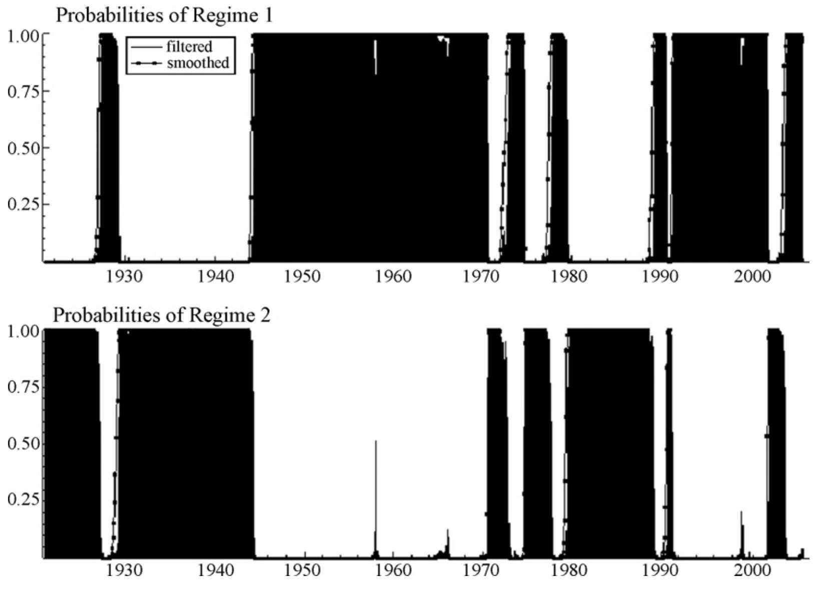

Fig. 1. Regime probabilities.

end of the Second World War. As Friedman and Schwartz (1962, pp. 449–462) report, banks at the time had been very reluctant to extend credit and instead chose to hold safe and liquid assets instead. The combination of lender reluctance and continued debtor insolvency thus hampered the recovery of credit markets for several years after 1933, where the recovery was further impeded by the downturn of 1937–1938 and the onset of the Second World War in 1939.[7]

The system falls back into Regime 1 at the beginning of 1944 and remains in that state throughout the boom years of the 1950s and 1960s, with just a flicker of a regime switch for the filtered probabilities in late 1957 and early 1958 in the wake a mild recession and the concerns over Sputnik, Hungary and Eisenhower's heart attack. The next switch into the credit channel regime takes place in the latter part of the year 1970. This switch occurs in the aftermath of the June 1970 commercial paper default by Penn Central Railroad and coincides with the trough of the U.S. recession of 1970–1971. The Penn-Central default had at the time been the largest ever single bankruptcy in the U.S. and the first default of investment grade bonds, prompting the Federal Reserve to intervene as a lender of last resort (Brimmer, 1989). This particular credit channel episode is overcome by a renewed reversal into Regime 1 towards the end of 1972. The next switch occurs in 1974 and can be associated with the onset of the first oil price shock and the concomitant U.S. recession of 1974–1975. After reverting to Regime 1 in the second half of the 1970s, the next switch into the credit channel regime takes place in 1979 in the wake of the second oil price shock. This period is characterized by the imposition of credit controls by the Carter administration in 1980, a sharp business cycle slowdown and tight money in an attempt to defeat rising inflation. After a brief recovery in 1981, and with inflation still high, the Fed tightened once again, and the U.S. economy experienced the severe 1982 recession. Unlike the two previous

7 The exact timing of the peaks and troughs of the U.S. business cycle is documented by the NBER Business Cycle Expansions and Contractions, available at http://www.nber.org/cycles.html.

credit channel periods, however, this one is not reversed in the wake of the subsequent recovery, but continues to be active right until the end of the 1980s.

During the 1980s, the United States experienced a prolonged bout of distress in financial markets. The Latin American debt crisis, originating with the Mexican debt default of August 1982, plunged a range of private international banks in New York City, which held the bulk of Mexican loans, into severe financial difficulties. As other developing nations struggled to pay the interest on their loans, U.S. banks had to reschedule the debt and reduce additional lending. Only by forcing developing countries to keep up their interest payments, a major banking collapse was averted. However, the difficulties in U.S. financial markets did not abate but were even further aggravated first by the Continental Illinois problem of 1984, and then by the onset of the Savings and Loan debacle, which became the nation's largest-ever financial scandal. The Continental Illinois Bank had been among the largest banks in the U.S. during the period of its de facto failure and rescue by the Federal Deposit Insurance Corporation (FDIC) in 1984. This was the last government rescue of a major bank prior to the "too big to fail" doctrine, initiated several months afterwards (Slovin, Sushka, & Polonchek, 1993). Two years later, the bursting of the U.S. real-estate bubble in 1986 triggered the Savings and Loan crisis, affecting commercial banks, savings banks, and savings and loan associations (S&Ls). In its wake, some 1500 commercial and savings banks and 1200 savings and loan associations failed. In addition, an even larger number of institutions were in precarious financial condition at some time during that period (Kaufman, 1994).

With the resolution of the turmoil in financial markets a short switch to the inactive Regime 1 occurs in 1989, but the "credit crunch" episode of 1990–1991 brings the credit channel briefly back into operation. The "credit crunch" episode was a period of excessive corporate leverage and bank capitalization problems (see Bernanke & Lown, 1991, and Bernanke & Gertler, 1999, p. 41). For the remainder of the 1990s the system reverts to Regime 1 with only an inkling of a switch around the time of the Long-Term Capital Management (LTCM) crisis in 1998. LTCM was a hedge fund company trading in derivative securities. By the end of 1998, LTCM found itself in a crisis situation as it had underestimated the consequences of short-term liquidity problems following the Russian default of the same year. Shortly thereafter, the Federal Reserve Bank of New York had to rescue the company from bankruptcy (Majumder, 2006). The credit channel regime returns once more at the end of 2001 in the wake of the bursting of the internet bubble, the 9/11 terror attacks and the recession of 2001, remains active during the U.S. accounting scandals, before it again tapers off in the middle of 2003.

5. Conclusion and policy implications

This paper has analyzed the effectiveness of the credit channel as a transmission mechanism of monetary policy by applying a Markov-switching model on the default premium of U.S. corporate bond portfolios. We identify two regimes, one in which the credit channel is active and one in which it is passive. The two regimes are found to be highly significant and persistent, and we are able to relate the switches between the regimes to particular episodes throughout 20th century U.S. economic history.

We find that the timing of regime switches and the strength of the financial accelerator are affected not only by the state of the business cycle and the stance of monetary policy, but is also influenced by conditions in financial markets, identified as the latent factor in the regime-switching model. The potency of the credit channel becomes especially obvious in times of severe financial distress, such as the Great Depression of the 1930s as well as the Savings and Loan crisis of the

1980s, and to a lesser extent during the "credit crunch" episode of 1990–1991 and in the aftermath of the bursting of the internet bubble in 2000–2003.

The historical circumstances surrounding the periods for which a credit channel is identified in our Markov-switching model closely conform to a set of common factors associated with having triggered financial crises in the past, as outlined by Mishkin (1991). Such common factors are the onset of a recession, rising interest rate spreads between low and high-quality bonds, or the failure of a big financial institution. As in Mishkin (1991), the timing of the episodes studied here seems to fit an asymmetric information interpretation of financial crises. By increasing the level of uncertainty in financial markets, these factors aggravate adverse selection and agency problems and lead to a fall in aggregate economic activity through a decline in lending and investment. Such adverse selection and agency problems are also at the core of the credit channel mechanism.

We find no evidence of a secular decline in the importance of the credit channel, which the global process of financial liberalization and the deepening of financial markets may have led one to believe. Quite to the contrary, the credit channel re-emerges during the 2001–2003 period after having been dormant throughout most of the 1990s. Rather than reducing informational problems, financial liberalization may have actively contributed to the deterioration of transparency in financial markets in the recent past. In particular, the rapid pace of financial innovation and the invention of ever more sophisticated and opaque financial instruments, the increasing number of unregulated financial actors, and the switch to "originate and distribute" strategies of banks, in which credit risk is securitized and sold on to investors, may all play a part in this process.

Certainly, monetary authorities bear a particular responsibility to act as lender of last resort in environments in which the credit channel is active. At the same time, monetary policy may become a destabilizing device, with policy potentially contributing to financial distress. The preferred policy of overcoming credit channel cycles in the future may thus lie in actively fostering transparency in financial markets.

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