Private Sector Credit in CESEE: Long-Run Relationships and Short-Run Dynamics

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This paper provides an analysis of the long- and short-run determinants of domestic bank lending to the private sector in eleven Central, Eastern and Southeastern European (CESEE) countries. We identify regime shifts for the observation period of 1997 to 2009, and the resulting subperiods are characterized by a different impact of the credit growth determinants. Estimating a credit demand equation as the long-term relation, we find – for most countries – a cointegration relationship with economic activity. We then examine the short-run dynamics by applying both a linear and a nonlinear (Markov-switching) error correction model. While there is a significant correlation between credit growth and supply factors, namely bank deposits and banks' equity, its impact differs across the subperiods. Identified regime switches in the short-run relation are driven primarily by differences in the credit supply factors rather than by the adjustment toward the credit equilibrium as the error correction coefficients show only slight cross-regime differences. In terms of regime switching, we distinguish between two groups of countries: those with one dominant regime, which is only briefly interrupted by a second one, and those with two equally pronounced regimes. In the latter group, a marked switch occurred just before or when the global crisis hit the CESEE region in the latter part of 2008. This regime shift is associated with a decreased correlation between deposit and credit growth.

JEL classification: C3, E4, E5
Keywords: Bank lending to the private sector, transition economies, credit dynamics, Markov-switching error correction model

1 Introduction

Analyzing credit growth in Central, Eastern, and Southeastern Europe (CESEE) has become very popular in the past few years, especially during the period of rapid credit expansion that was observed in most countries of this region before they were hit by the global crisis in the latter part of 2008. In this paper, we add to this literature by studying the long-run (demand-side) *and* short-run (supply-side) determinants of domestic private sector credit developments in eleven CESEE countries (CESEE-11[3]) from January 1997 to April 2009.

Based on the notion that lending evolves in the long run in line with macroeconomic fundamentals (behavioral definition of equilibrium credit levels; for a respective literature overview, see section 2), we test for a cointegration relation between credit levels and demand-side macroeconomic determinants. To examine the short-run credit dynamics, we apply both a linear and a nonlinear error correction model.

We contribute to, and go beyond, the existing literature by (1) conducting our analysis not only for total domestic private sector credit, but in several cases also separately for lending to firms and to households to get more information on how

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[3] *The ten CESEE countries that joined the EU in 2004 and 2007, respectively, and Croatia. In the following, CEE-5 refers to the Czech Republic, Hungary, Poland, Slovakia and Slovenia, SEE-3 to Bulgaria, Croatia and Romania and "Baltic countries" to Estonia, Latvia and Lithuania.*

credit dynamics are determined depending on different target groups, (2) including in the error correction equation new supply-side explanatory variables that are expected to be directly linked to credit dynamics in the short run, and (3) examining whether short-run determinants show a nonlinear behavior over time (i.e. whether their impact differs across particular subperiods). To capture these nonlinearities, which can be interpreted as frictions in the adjustment of credit toward its equilibrium, we apply a Markov-switching error correction model (MS-ECM).

The MS-ECM relies on the idea that there is a cointegration relation, albeit not during each specific subperiod (or "regime" in the diction of this methodology). This approach reveals subperiod-specific particularities in the examined relationships. For instance, it is of interest whether we can separate episodes with adjustment toward the credit equilibrium (stable regime) from episodes where a departure of credit from the underlying macroeconomic fundamentals is not corrected (unstable regime). Moreover, regime switches that separate such subperiods are endogenously identified from the sample data for each country. A particular regime switch can obviously be expected for the current global crisis that resulted in sharply decelerating credit growth rates in the countries under review (see chart 1 in section 4).

The paper is structured as follows: Section 2 gives an overview of related research. Section 3 introduces our methodological setting with a special focus on the Markov-switching error correction model. Section 4 provides descriptive statistics for the evolvement and structure of credit markets in the CESEE-11 as from 1996. The estimation results are described in section 5, and section 6 is a summary. Basic data issues and a description of the variables are covered in the annex.

2 Literature Overview

In this section, we distinguish three strands of related literature: we refer to (1) the existing evidence for the (predominantly long-run) drivers of credit development, (2) the evidence for "excessive" credit growth in terms of a deviation of credit from its equilibrium in CESEE countries and (3) related applications of the Markov-switching methodology.

2.1 Findings on Long-Run Determinants of Credit Development

Real GDP as well as the short- and long-run real interest rates are commonly used as explanatory variables for estimating the long-run determinants of credit developments (see e.g. Calza, Gartner and Sousa, 2003, or Brzoza-Brzezina, 2005). Alternative specifications may include PPP-based GDP per capita instead of real GDP, other interest rates, such as the nominal lending interest rate, or additional variables like government credit, inflation, house prices and financial sector liberalization (as e.g. in Backé, Égert and Zumer, 2006). The latter variables incorporate both the demand for and the supply of credit. Demand for credit in CESEE countries has been driven by the expectation of increased income and growth. Supply of credit, on the other hand, has grown due to the entry of foreign banks and their funding support to CESEE subsidiaries. In addition, new banking products became more broadly available (with households emerging as a new market segment in the mid- to late 1990s), which went hand in hand with higher competition. Most of the previous research shows, however, that in the long run bank lending is mainly driven by demand (see Bernanke and Blinder, 1988; Fase, 1995; Calza, Gartner and Sousa, 2003; Frömmel and Schmidt, 2006).

Using the cointegration methodology for data from the euro area, Calza, Gartner and Sousa (2003) find that, in the long run, real loans are positively related to real GDP and negatively related to real short- and long-term interest rates. Backé, Égert and Zumer (2006) apply a dynamic panel cointegration framework and find that from 1996 to 2004, the private credit-to-GDP ratio was associated positively with GDP per capita (yet not always significant for the CEE-5 and the Baltic countries) and financial market liberalization. The findings for the nominal lending rate (negative sign in the CEE-5 and the Baltic countries; positive sign in the SEE-3), for PPI inflation (negative sign in the SEE-3; inconclusive for the CEE-5 and the Baltics), and for government credit (negative sign for the CEE-5 and the Baltics; inconclusive for the SEE-3) are rather mixed. Kraft (2007) examines the determinants of bank lending to households (the ratio of household loans to GDP being the dependent variable) in a panel of 23 transition countries, and shows that GDP per capita has a strong positive influence, whereas CPI inflation inhibits household lending and has a negative sign.

2.2 Findings on Deviations of Credit from Its Equilibrium in CESEE

Although there is no general measure of "excessive" credit growth, the literature tends to define a credit boom as a period of significant deviation of the observed credit level from its long-run equilibrium that is in turn determined by the macroeconomic fundamentals as discussed in the previous subsection. The most recent related investigation is that of Zumer, Égert and Backé (2009), who applied an out-of-sample approach and estimated the cointegration equation (similar to equation (1) below) for a panel of 14 small OECD benchmark countries. They used the estimated coefficients (country-specific intercepts and panel-wide slope coefficients) together with realized values for the fundamentals from the CESEE countries to calculate fitted values for the credit-to-GDP ratio in CESEE: $\hat{Y}_{CESEE} = \hat{\kappa}_{i,OECD} + \hat{\beta}'_{OECD} X_{CESEE}$. This fit defines the equilibrium credit levels. Evidence for overshooting credit levels is given if there is a clear indication that observed credit-to-GDP ratios deviated from the fitted equilibrium levels, i.e. $Y_{CESEE} - \hat{Y}_{CESEE} > 0, \forall \hat{\kappa}_{i,OECD}$. Applying this conception, they found that in the first quarter of 2009, domestic private sector credit levels were rather high in Estonia, Latvia, Bulgaria, and Croatia given the underlying fundamentals (to a somewhat lesser extent also in Lithuania and Hungary), which indicates that private sector credit had possibly grown beyond the equilibrium path in these countries.

Earlier papers came to similar conclusions, though the country-specific assessments and the methodological approaches differed. Boissay, Calvo-Gonzalez and Koźluk (2005) estimated the elasticity of credit with regard to three main macroeconomic determinants: GDP growth, the interest rate, and the gap between the observed and the equilibrium credit-to-GDP ratio. From these elasticities they derived estimates of expected credit growth and considered credit growth to be excessive if the observed values were significantly higher than the expected ones. Accordingly, they found evidence for excessive credit growth in Bulgaria, Latvia and – to a lesser extent – in Lithuania, Estonia, Hungary and Croatia. Kiss, Nagy and Vonnák (2006) define a credit boom as follows: Either (1) the observed credit growth exceeds the one implied by the long-run equilibrium relationship on the basis of macroeconomic fundamentals, or (2) the observed credit growth rate is higher than the speed of adjustment to the credit equilibrium in the error correction model (i.e. $\Delta\log(c_t) > \hat{b}_1$ when referring to equation (2) below). They detected excessive credit growth only for Estonia and Latvia.

Policy challenges of and responses to lending booms were widely discussed in Kraft and Jankov (2004) for Croatia, in Duenwald, Gueorguiev and Schaechter (2005) for Bulgaria, Romania and Ukraine, or in Backé, Égert and Walko (2007) for the whole European emerging market region. Hilbers, Ötker-Robe and Pazarbasioglu (2007) elaborated how prudential and supervisory policies could be used in strengthening the resistance of the financial system to adverse consequences of rapid credit expansion in CESEE.

2.3 Related Markov-Switching Applications

For first applications of switching error correction models, one can go back to Hall, Psaradakis and Sola (1997), who use them to identify periods in which real house prices differ from what is implied by economic fundamentals in the U.K. Markov-switching models have only recently been used in the analysis of bank lending. For instance, Frömmel and Schmidt (2006) look for overshooting bank lending (related to stock market bubbles) in countries of the euro area. Kaufmann and Valderrama (2008) use a Markov-switching VAR model to investigate differences between bank lending in Germany and the U.K. Their model is not based on error correction, however.

Frömmel and Karagyozova (2008), whose method is closest to our analysis, examine the relation between bank lending and asset prices in Bulgaria, using a Markov-switching error correction model to control for regime changes. They find a positive relationship between real estate prices and banks' lending to households. Moreover, they find evidence for the existence of regime switches linked to administrative measures for curbing credit expansion. In line with their methodology, they take a different view on the stability of credit growth: They no longer look at "excessive" growth in terms of the distance to equilibrium, but instead examine the adjustment process toward equilibrium levels (i.e. the error correction coefficients). A regime is then interpreted as unstable if cointegration between credit growth and its determinants is not given for particular subperiods, which does not necessarily coincide with the error exceeding a particular threshold.

Regime switches in credit equations are usually interpreted as a deviation from equilibrium (e.g. Psaradakis, Sola and Spagnolo, 2004). Their model does not require the deviation to be of any sign, however. It may thus model both lending restrictions, such as a credit crunch, and lending booms. Furthermore, the use of the MS-ECM model for credit equations can be derived from theoretical models, based on the interaction between banks and borrowers. This interaction has been analyzed in theoretical studies, e.g. in Kiyotaki and Moore (1997) or in Chen (2001), where the borrower's net worth serves as collateral for lending. This net worth is highly affected by the value of the borrower's assets and expectations about their future evolution. Consequently, if the price of assets rises (falls), the borrower's capacity for lending will rise (fall), too. Other models that explicitly lead to switches between different equilibria in the credit market are presented by Scheinkman and Weiss (1986) or Azariadis and Smith (1998). The latter is based on constraints in borrowing and asymmetric information and leads to transitions between a Walrasian regime and a regime of credit rationing with slowing economic activity, falling interest rates and binding credit constraints. Linking theoretical models and empirical studies of credit markets, this model thus serves as a theoretical foundation for using the MS-ECM.

3 The Empirical Model

In the analysis of credit volume, it has become common to apply the cointegration approach (see the previous section), since the credit volume itself and most of its determinants empirically turn out to be integrated of order one. However, while in econometric analysis it is often assumed that the adjustment of the credit volume toward its equilibrium is linear, this need not necessarily be the case in reality. First, there may be periods during which unusual events cause credit markets to be temporarily in a disequilibrium. Second, determinants of credit growth may be subject to shifts, i.e. the impact of economic variables may change over time. Accordingly, the Markov-switching error correction model applied in this paper allows the coefficients to switch between different regimes.

Psaradakis, Sola and Spagnolo (2004) suggest proceeding in two steps: checking the long-term, equilibrium-defining relation for cointegration and then investigating the short-term dynamics for Markov-switching. As a result, one may find a stable long-term equation, but more complex dynamics in the short run. In our setting, we follow this two-step procedure and use a credit demand equation as the long-term relation, which is common in the empirical literature (Pazarbasioglu, 1997; Ghosh and Ghosh, 1999; Barajas and Steiner, 2002; Calza, Gartner and Sousa, 2003):

$$\log(c_t) = a_0 + \underbrace{a_1}_{(+)} \log(IP_t) + \underbrace{a_2}_{(-)} LR_t + \underbrace{a_3}_{(-)} \pi_t^{CPI} + \varepsilon_t, \tag{1}$$

where the dependent variable is the logarithm of the real (CPI-deflated) domestic private credit stock c_t (in the empirical analysis we differentiate between total domestic private sector credits, firm credits, and household credits), a_0 is a constant, IP_t represents real industrial production (proxy of economic activity, as we work with monthly data), LR_t denotes the (nominal) lending rate, and π_t^{CPI} is the CPI-based inflation rate (year-on-year changes). For details on the data, see section 4 and the annex.

The signs below the coefficients indicate the theoretically predicted sign. Higher economic activity is expected to increase the demand for loans and thus credit volumes should expand ($a_1>0$). A higher lending rate, in turn, is expected to reduce the demand for credit, as debt servicing costs increase ($a_2<0$). The expected negative correlation of inflation and credit demand ($a_3>0$) may be attributed to two reasons (in line with Kiss, Nagy and Vonnák, 2006): First, once inflation has exceeded a certain threshold, it is associated with greater inflation volatility that can significantly hinder the functioning of financial markets through increased uncertainty. Second, if nominal rates are high, and even if the real interest rate is low, private agents can primarily get loans with shorter duration, which, in turn, limits the maximum lending volume.

If the variables from equation (1) are cointegrated, one may model the short-run dynamics as an error correction equation:

$$\Delta\log(c_t) = b_0 + b_1\varepsilon_{t-1} + b_2'\Delta Z_t + b_3\Delta\log(c_{t-1}) + u_t, \tag{2}$$

with $\Delta\log(c_t)$ the real credit growth rate (month-on-month changes), ε_{t-1} the error term from the long-run equation (1), b_1 the error correction coefficient governing the speed of adjustment to the long-term equation, and Z_t a set of possible explanatory variables. We also include a lagged dependent variable to account for potential inertia in the credit dynamics.[4]

In the vector Z_t of short-term determinants, we include four groups of variables. First, banks' domestic liabilities (equity and deposits) account for the source of funds available for lending within the country. As soon as more funds are available, more loans can be extended, and thus we expect a positive sign for this variable. Second, the banks' net external position (external assets minus external liabilities) covers additional supply of loans by acquiring funds from abroad (positive correlation with credit growth). Yet, this position also comprises net foreign assets as a substitute for lending to domestic customers (negative relation; thus the concrete sign of this variable is ambiguous ex ante). Third, we include the interest spread between lending and deposit rates to account for the effects of banking competition on credit growth. Signaling profitability, a considerable positive spread acts as an incentive for new banks to enter the market. Lending can be expected to accelerate owing to such new entrants. At the same time, competition among banks increases, which results in a narrowing spread. At that point, the question arises whether – at the lower end of the spread – banks still increase lending in pursuit of market share or rather scale back lending (in which case a positive sign can be expected for this variable). Fourth, we include variables taking external exposure and credit risk into account (industrial production in the euro area as well as exchange rate volatility of the local currency vis-à-vis the euro, as the share of euro-denominated loans is relatively high in a number of CESEE countries).

While equation (2) is based on the assumption that the adjustment process to the equilibrium is regime-invariant, we drop this assumption in the MS-ECM framework and let the coefficients switch according to unobservable states. Thus, there is no single error correction equation and, in the case of a first-order Markov process with two states,[5] equation (2) evolves to:

$$\Delta\log(c_t) = b_{01} + b_{11}\varepsilon_{t-1} + b_{21}'\Delta Z_t + b_{31}\Delta\log(c_{t-1}) + u_t\,,\ \text{if}\ s_t = 1, \tag{3a}$$
$$\Delta\log(c_t) = b_{02} + b_{12}\varepsilon_{t-1} + b_{22}'\Delta Z_t + b_{32}\Delta\log(c_{t-1}) + u_t\,,\ \text{if}\ s_t = 2, \tag{3b}$$

where the short-term equation is conditional on the unobservable regime variable s_t. The coefficients b_{k,s_t}, where k=1,...,3 (i.e. three different groups of explanatory variables) and s_t=1,2 (i.e. two different states), may now take different values conditional on s_t. The regime variable follows a two-regime Markov chain process and is characterized by the following transition probabilities p_{ij} for moving from regime i to regime j

[4] *Note that we do not include lagged differences of the explanatory variables of equation (1) as we presume their impact to be mainly a long-run demand-side one. Moreover, residual graphs do not really hint at missing lagged variables. Since we already have a highly nonlinear model with short sample periods, we prefer not increasing the number of variables to be able to execute the quasi-maximum likelihood estimation in the MS-ECM.*

[5] *The MS-ECM could also be extended to a model with more than two regimes. However, the model then becomes highly nonlinear, which causes problems for the estimation (in our case quasi-maximum likelihood). Furthermore, models with more than two regimes do not necessarily perform much better (see Gallo and Rossi, 2006). Note further that the setting of the model includes the existence of one single switch, i.e. an absorbing state, as a special case. Thus, the model is a very flexible one in terms of the possible cases included.*

$$\begin{aligned} p_{11} &= P\left(s_t = 1 \mid s_{t-1} = 1\right),\; p_{12} = 1 - p_{11} = P\left(s_t = 2 \mid s_{t-1} = 1\right), \\ p_{22} &= P\left(s_t = 2 \mid s_{t-1} = 2\right), p_{21} = 1 - p_{22} = P\left(s_t = 1 \mid s_{t-1} = 2\right). \end{aligned} \tag{4}$$

Thus our model extends the standard (linear) error correction model by allowing the parameters in the error correction equation to depend on the stochastic outcome (s_t) of the unobserved Markov process. The main advantages of this approach are the ability to capture different kinds of adjustment processes including temporary nonstationarity, periods of differing short-term variables, and the estimation of the regime switches from the sample data. Consequently, it is not necessary to make a priori assumptions about the exact occurrence of regime changes.

To assess the stability of the adjustment toward equilibrium and respective regime-specific deviations, we need the following characterizations: a stable (or corrective) regime i is given by $b_{1i}<0$ (a significantly negative error correction coefficient), as in this case any departure of credit from the underlying macroeconomic fundamentals is corrected by a change in credit growth. In turn, an unstable (or noncorrective) regime is defined by $b_{1i}\geq 0$, whereby $b_{1i}>0$ marks an explosive deviation and $b_{1i}=0$ indicates a very sluggish or constant and persistent deviation from the credit equilibrium in the case of temporary over- or undershooting of credit levels. As Psaradakis, Sola and Spagnolo (2004) pointed out, it is no contradiction that one finds cointegration in the long run (indicated by $b_1<0$ in equation (2)), whereas locally the connection between the variables may get temporarily lost as if cointegration had been "switched off" and there was no disequilibrium adjustment in particular regimes. However, the model is flexible enough to cover situations where the variables in both regimes are cointegrated, where both regimes have different adjustment speeds, or where additional short-run determinants show a regime-dependent impact (even if the adjustment speed does not change at all).

The MS-ECM is estimated by quasi-maximum likelihood, based on Kim and Nelson (1999). From the estimation procedure we directly receive the ex ante probabilities $P(s_t= i|\Phi_{t-1})$ and the filter probabilities $P(s_t= i|\Phi_t)$. These are the probabilities of being in a particular regime at time t based on all the information available up to time t–1 or up to time t, respectively, i.e. $F_t = \{c_1,..,c_t; Z_1,..,Z_t\}$ for the variables from equation (3). For an ex post analysis, however, it is more appropriate to rely on the smoothed probability $P(s_t= i|\Phi_T)$, where Φ_T is the set of all the information available up to time T, i.e. for the whole sample period with $\Phi_T = \{c_1,..,c_T; Z_1,..,Z_T\}$. The smoothed probability requires an additional filter algorithm for the estimation procedure. Alternative algorithms have been proposed in the literature; we use the one by Kim (1994), which is easy to implement and commonly used in the literature. For a detailed description of the smoothing algorithm, see Kim and Nelson (1999).

One could also think of using alternative empirical approaches to model credit growth, e.g. by letting the long-term equation change instead of the adjustment process or by introducing a time trend into the long-term equation that captures the deepening of the financial market. The first approach could be justified by financial sector reforms that resulted in new equilibria, which could also be captured by including dummy variables (see our robustness checks in section 5.3). In contrast, a time trend would represent a more gradual evolution of the financial sector. However, the residuals of equation (1) do not give any reason to include a time trend in the model.

4 Descriptive Statistics: Evolvement of Credit Stocks and Credit Growth

This section describes our basic variable of interest – the evolvement and composition of credit stocks and credit growth in the CESEE-11 since 1996 (which we compare with the euro area). Basic data issues and a description of other variables are covered in the annex (see table A1).

Chart 1 depicts, for each country, domestic private sector credit stocks (dark blue area) and cross-border credit stocks (orange area) as a percentage of GDP. Whenever disaggregate information was available, be it for the whole observation period or for particular subperiods, we distinguished domestic private credit by households (red area) and by firms (light blue area). Moreover, we also show the year-on-year real growth rate of domestic private credit (black line).

After some disruptions due to country-specific crises in the 1990s, most CESEE-11 countries experienced a strong and smooth expansion of private sector loans until late 2007/early 2008. Nevertheless, as a result of the global economic crisis, credit growth rates decelerated sharply; in the Baltic countries, the year-on-year change of domestic private credit turned even negative in real terms in the first quarter of 2009.

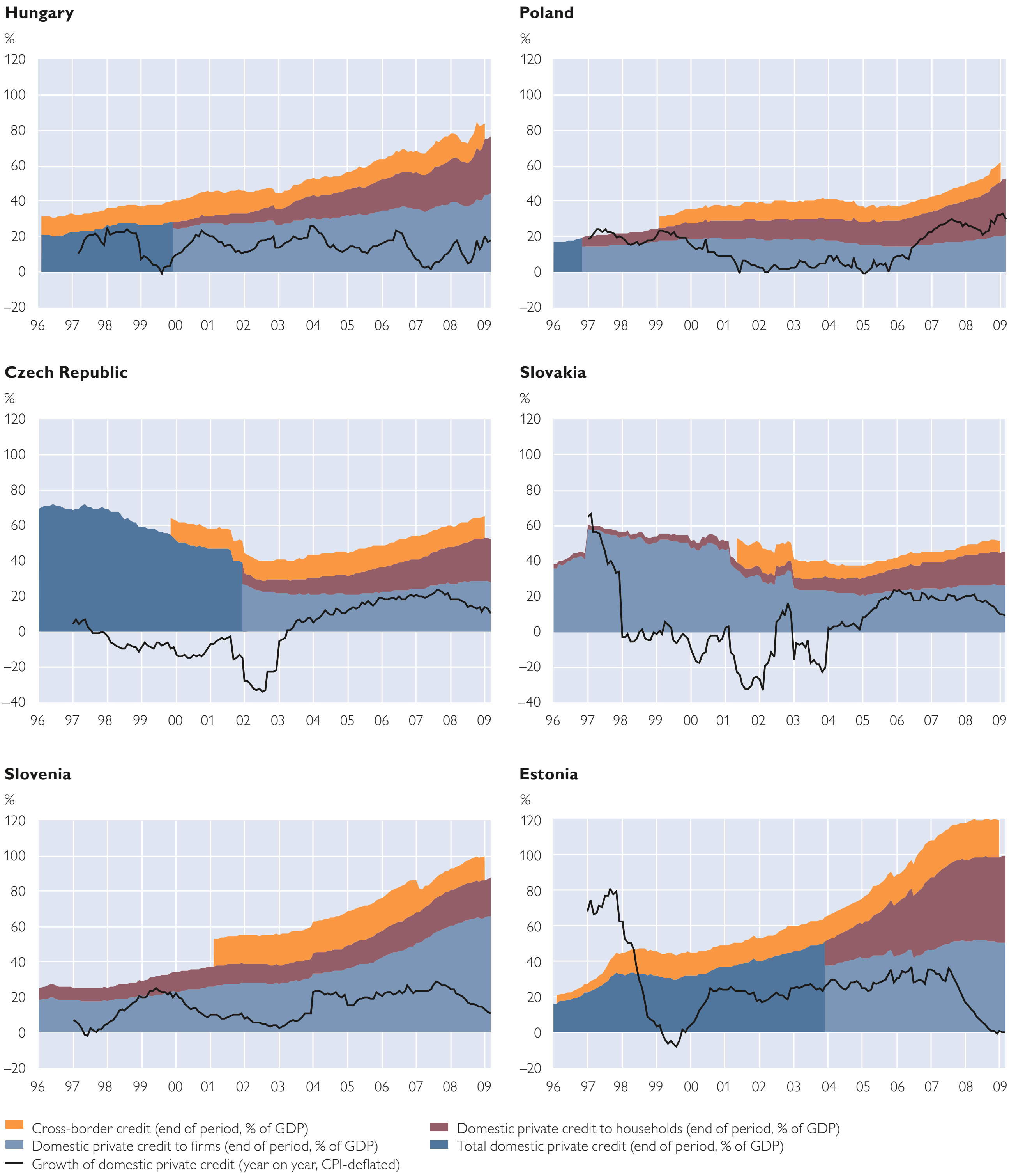
In terms of the evolvement of domestic private sector credit over time, we can distinguish three groups of countries. First, the Czech Republic and Slovakia already disposed of considerably high credit stocks in the mid-1990s (around 60% of GDP). However, credit stocks shrank remarkably as a consequence of bank restructuring in the late 1990s and early 2000s. As a case in point, Slovakia recorded real average change of –20% in 2001 and the Czech Republic –28% in 2002. Credit stocks have still not reached the degree of financial intermediation observed earlier (the high values registered in the Czech Republic and Slovakia in the mid- and late 1990s have to be interpreted with caution as they were "inflated" by a comparatively high share of nonperforming loans; see Eller and Haiss, 2003). Second, Poland and Hungary were characterized by real credit growth rates of more than 20% already in the late 1990s but have experienced a comparatively moderate and steady expansion of credit since then. Third, Slovenia, Bulgaria, Romania, and especially the Baltic countries went through a brisk increase of credit stocks as a percentage of GDP starting with 2000–2003. From January 2003 until December 2007, the average (year-on-year) real credit growth rate was 19% in Slovenia, 28% in Estonia, 35% in Bulgaria, 38% in Romania, 40% in Latvia, and 44% in Lithuania.

Croatia is a special case, where the expansion of domestic credit was comparable with Hungary or the Czech Republic (at least since 2003), but at the same time the share of cross-border credits increased strongly and reached more than 40% of GDP in December 2008. In the CESEE-11, this is by far the highest share of cross-border credits, followed by 30% in Bulgaria, and around 22% in Estonia and Latvia.

Given these different patterns of financial development, we expect that also the dates for the regime shifts in the MS-ECM will differ across countries (see chart 2). Generally speaking, a regime shift can be expected when the country

Chart 1

Stock and Growth Rates of Domestic Private Sector Credit Compared with Cross-Border Credit (1996–2009)

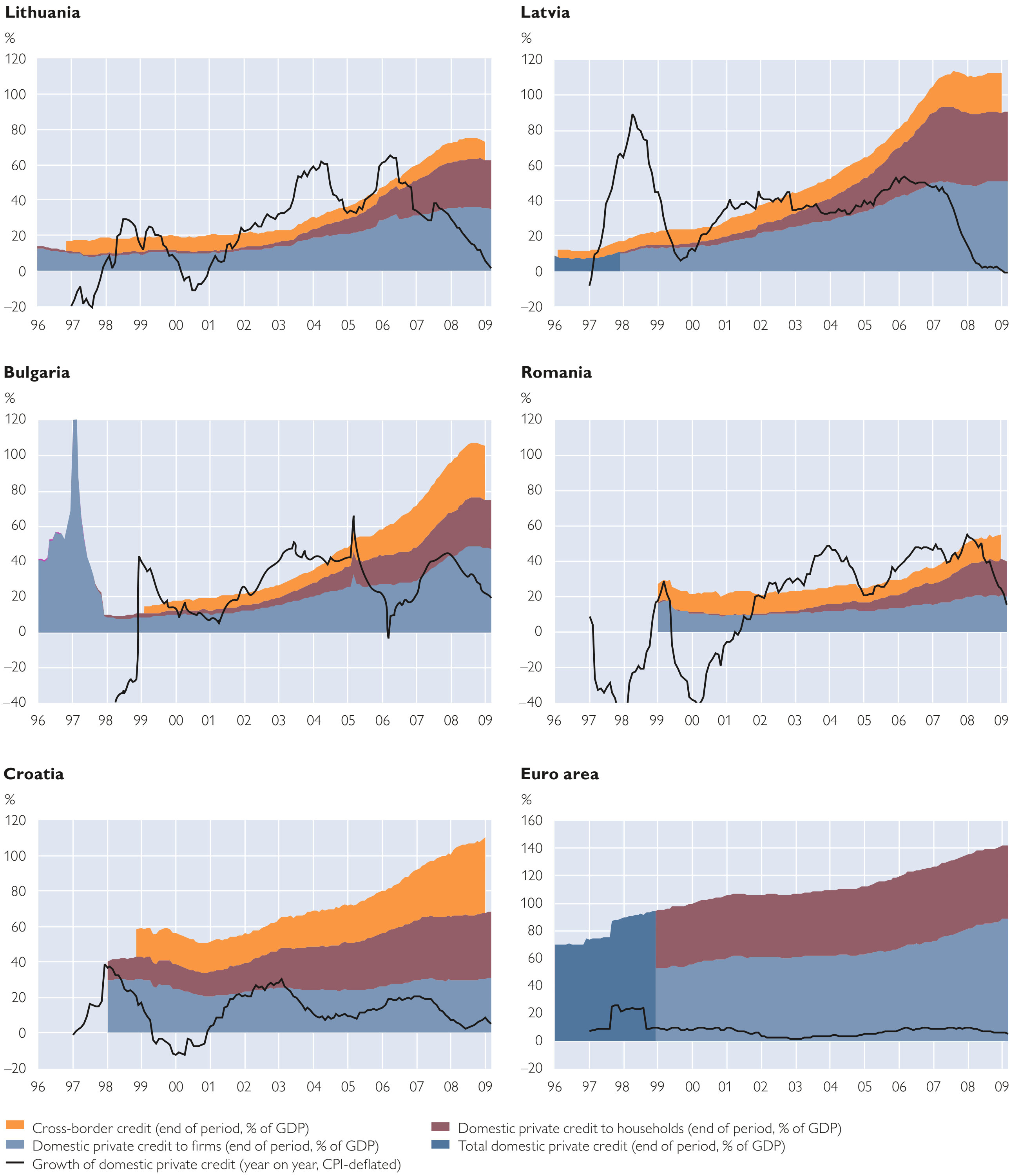


Source: Authors' calculations based on the IMF (1996), NCBs (1997–2003) and the ECB (2004 onward).

Note: End-of-month credit stocks are presented as shares of nominal GDP (in local currency), whereby a rolling 12-month GDP, which was previously linearly interpolated from quarterly to monthly frequency, is used. The (real) growth rate of domestic private credit is calculated as the year-on-year percentage change, deflated by the CPI-based inflation rate. Cross-border credits are approximated by external debt of the nonbank private sector, excluding intercompany loans and trade credits (liabilities). They were only available on a quarterly basis (not available at all for the euro area) and thus we interpolated the end-of-quarter stocks linearly to monthly frequency (this type of interpolation should be straightforward as credit stocks evolve quite moderately over time). For further details, see table A1.

Chart 1 continued

Stock and Growth Rates of Domestic Private Sector Credit Compared with Cross-Border Credit (1996–2009)



Source: Authors' calculations based on the IMF (1996), NCBs (1997–2003) and the ECB (2004 onward).

Note: End-of-month credit stocks are presented as shares of nominal GDP (in local currency), whereby a rolling 12-month GDP, which was previously linearly interpolated from quarterly to monthly frequency, is used. The (real) growth rate of domestic private credit is calculated as the year-on-year percentage change, deflated by the CPI-based inflation rate. Cross-border credits are approximated by external debt of the nonbank private sector, excluding intercompany loans and trade credits (liabilities). They were only available on a quarterly basis (not available at all for the euro area) and thus we interpolated the end-of-quarter stocks linearly to monthly frequency (this type of interpolation should be straightforward as credit stocks evolve quite moderately over time). For further details, see table A1.

under examination experienced pronounced changes in the pattern of credit growth (e.g. in the Czech Republic and Slovakia in 2001–2002 or in the Baltic countries after mid-2007) or in the shape of GDP growth (e.g. in some of the CESEE-11 countries in the wake of the 1998 Russian financial crisis or during the most recent crisis situation).

Besides the overall expansion of domestic private sector credit, the share of household credit increased considerably over time in all the CESEE-11 countries (especially in the Baltic countries and Croatia). The bulk of new lending is attributable to housing loans, which already account for more than 50% of total household loans (see Walko, 2008).

Even though the degree of financial intermediation has been on the rise over the last decade, there is still a considerable catching-up potential vis-à-vis the euro area. The latter's share of domestic private sector credit in GDP lies just above 140% (see the last panel of chart 1). Only Estonia[6] has reached a respective share of nearly 100%, while on the other end, Romania (40%) and Slovakia (45%) clearly lag behind.

A final aspect that we want to address here is the currency decomposition of domestic private sector credits. In line with deepening integration of the CESEE-11 into European financial markets, the massive entry of foreign banks[7] and the prospects of joining the euro area in the foreseeable future, the share of foreign currency loans in total domestic private sector loans has risen steadily in most of the countries. Nevertheless, there is still a great deal of cross-country heterogeneity in the region. In August 2008 (i.e. just before these shares were distorted in a few countries due to crisis-related depreciations of the local currencies), we can distinguish three groups of countries (based on data from national central banks and the ECB): Estonia and Latvia with a very high foreign currency loan share of about 85%; Romania, Bulgaria, Hungary, Croatia and Lithuania with a medium share ranging between 55% and 63%; and finally, countries with relatively small shares: Poland (26%), Slovakia (19%; this share fell to nearly 1% after the introduction of the euro in January 2009), the Czech Republic (9%) and Slovenia (7%; before euro adoption in January 2007, the share was 64% and had risen substantially in the period immediately before euro adoption). In most of these countries, the euro accounts for a clear majority of total foreign currency loans to the nonbank private sector. Notable exceptions are Hungary and Poland, where the Swiss franc predominates foreign currency loans to households.

5 Results and Interpretation

5.1 Long-Run Evolution of Credit Aggregates: Cointegration Relation

To identify the long-run determinants of the credit volume, we estimate equation (1) from section 3; the results are presented in table 1. Since unit root tests on the

[6] *However, if we also include cross-border credits, the share of total private sector credit lies clearly above 100% of GDP not only in Estonia, but also in Latvia, Bulgaria and Croatia (in Slovenia at 100%).*

[7] *According to the EBRD structural change indicators (see EBRD, 2009), the share of banks with foreign ownership exceeding 50% at year-end in total bank sector assets amounted to a CESEE-11 average of 81% in 2008. The individual CESEE-11 figures range from 31% (Slovenia) to 99% (Slovakia).*

data indicate the presence of unit roots in levels (see table A2),[8] we can test for cointegration. The statistics for Johansen's cointegration test show evidence for at least one cointegration relation between credit volume, industrial production, interest rates and inflation rates in all cases but Slovakia, and partly also Hungary and Croatia.[9,10]

All countries show a positive and robust correlation of industrial production and credit volume. The comparatively large coefficients, with the impact being much stronger for household credits than for firm credits, highlight an economically meaningful relationship between credit levels and economic activity in the CESEE-11. As in Kiss, Nagy and Vonnák (2006) or Backé, Égert and Zumer (2006), inflation mostly shows the expected negative correlation with lending. This is particularly the case for Estonia, the SEE-3 and most of the CEE-5. In contrast, the lending rate does not show the expected negative sign in most of the countries. The counterintuitively positive and in some cases even significant sign, however, corroborates existing empirical evidence (Backé, Égert and Zumer, 2006, for Southeastern European transition and non-European emerging market economies; Fair, 2004; for some countries also Boissay, Calvo-Gonzalez and Koźluk, 2005). A possible reason for the positive correlation between credit and interest rates could also be reverse causality: While higher interest rates are expected to decrease the demand for credit, there could also be a reversed impact, namely that a stronger demand for credit by the private sector creates more incentives for banks to increase lending rates in order to maximize their profits. If the causality really ran in the opposite direction, we would have the problem – as some of our regressors are endogenous – that ordinary least squares (OLS) estimation would deliver biased and inconsistent estimates.

We are also aware of another potential source of bias in equation (1): Backé, Égert and Zumer (2006) emphasize that the estimates in the long-run equation could be upward biased because of initial undershooting in the case of transition countries (i.e. these countries started with lower credit-to-GDP ratios than countries with the same level of development given their repressed financial system under communism). Backé, Égert and Zumer (2006) thus use the estimated long-run coefficients for nontransition benchmark economies and realized values for the transition countries to properly fit equilibrium credit-to-GDP levels (out-of-sample approach).

We did not explicitly test for endogeneity of the regressors, but there are some reasons not to go more deeply into the mentioned sources of biased coefficients in

[8] *A unit root in levels is clearly the case for the credit aggregates and industrial production, while the results point to a certain degree of stationarity of the lending and the inflation rate. This is, however, in line with existing empirical evidence (Crespo Cuaresma et al., 2009) and with the expectation that the price level is integrated of order one. In our cointegration analysis, we include all variables, because – although it is less common to use stationary and nonstationary data in the same analysis – Johansen and Juselius (1992) recommend this approach if the fit can be improved.*

[9] *This may be due to the well-known lack of power of the Johansen test in small samples, but also to strong deviations from the equilibrium at the beginning (initial undershooting) and at the end (the global economic crisis 2008–2009) in our sample. Furthermore, the inclusion of country-specific dummies for economic crises and extraordinary data outliers improve the cointegration evidence. The results are not presented here, but available on request.*

[10] *If the trace- and the maximum eigenvalue-based assessment of the number of cointegration relations differ from each other, we rely on the trace-based assessment as Monte Carlo simulations by Lütkepohl, Saikkonen and Trenkler (2001) show that the power performance of the trace test is superior in small samples.*

Table 1

Cointegration Relation

Country	Dependent variable: $\log(c_t)$						Selected (5% level) number of cointegrating relations	
	c_t	$\log(IP_t)$	LR_t	π_t^{CPI}	Adj. R^2	Sample	Trace	Max-Eig
CEE-5								
Czech Republic	Total	0.753*** (0.000)	0.063*** (0.000)	0.022 (0.146)	0.48	1997M01–2009M04	4	1
	Firms	1.227*** (0.000)	0.204*** (0.000)	–0.006 (0.567)	0.68	2002M01–2009M04	1	1
	Households	2.807*** (0.000)	–0.049 (0.702)	0.013 (0.592)	0.75	2002M01–2009M04	3	1
Hungary	Total	2.146*** (0.000)	0.062*** (0.001)	–0.044*** (0.002)	0.94	1997M01–2009M04	0	0
	Firms	1.415*** (0.000)	0.035*** (0.007)	–0.042*** (0.000)	0.92	2000M01–2009M04	0	0
	Households	4.186*** (0.000)	0.111*** (0.000)	–0.147*** (0.000)	0.93	2000M01–2009M04	1	1
Poland	Total	1.643*** (0.000)	0.019*** (0.000)	–0.028*** (0.000)	0.87	1997M01–2009M04	2	2
	Firms	0.774*** (0.000)	0.020*** (0.000)	–0.031*** (0.000)	0.65	1997M01–2009M04	2	1
	Households	2.511*** (0.000)	0.017*** (0.006)	–0.031*** (0.000)	0.93	1997M01–2009M04	2	1
Slovakia	Total	1.198*** (0.000)	0.058*** (0.000)	–0.006 (0.382)	0.52	1997M01–2008M11	0	0
	Firms	0.428 (0.129)	0.058*** (0.000)	–0.006 (0.473)	0.68	1997M01–2008M11	0	0
	Households	3.581*** (0.000)	0.003 (0.753)	0.006 (0.398)	0.95	1997M01–2008M11	0	0
Slovenia	Total	2.195*** (0.000)	–0.058*** (0.000)	0.008 (0.573)	0.88	1997M01–2009M04	1	1
	Firms	2.378*** (0.000)	–0.057*** (0.000)	0.004 (0.794)	0.89	1997M01–2009M04	2	1
	Households	1.755*** (0.000)	–0.058*** (0.000)	0.019 (0.178)	0.87	1997M01–2009M04	1	1
Baltic countries								
Estonia	Total	2.791*** (0.000)	0.051** (0.033)	–0.014 (0.484)	0.92	1998M01–2009M04	2	2
	Firms	1.440*** (0.000)	0.119*** (0.000)	–0.018* (0.097)	0.87	2004M01–2009M04	1	0
	Households	4.008*** (0.000)	0.302*** (0.000)	–0.073** (0.015)	0.84	2004M01–2009M04	4	1
Latvia	Total	6.150*** (0.000)	0.012 (0.741)	–0.008 (0.818)	0.78	1997M01–2009M04	1	0
	Firms	3.849*** (0.000)	0.010 (0.711)	0.037*** (0.006)	0.84	1998M01–2009M04	1	0
	Households	7.049*** (0.000)	0.002 (0.974)	0.065*** (0.009)	0.84	1998M01–2009M04	3	3
Lithuania	Total	3.741*** (0.000)	0.036 (0.189)	0.027 (0.242)	0.92	1998M01–2009M04	2	1
	Firms	3.043*** (0.000)	0.023 (0.295)	0.019 (0.330)	0.92	1998M01–2009M04	2	1
	Households	6.018*** (0.000)	0.062 (0.179)	0.036 (0.333)	0.91	1998M01–2009M04	2	2

Source: Authors' estimations.

*Note: Coefficients are estimated with OLS. The p-values in parentheses (for the null hypothesis of a coefficient being equal to zero) are based on Newey-West heteroskedasticity and autocorrelation consistent standard errors. The asterisks *, **, *** indicate significance at the 10%, 5% and 1% level, respectively. All regressions contain a constant (not reported). Trace (Max-Eig) indicates the cointegration test assessment based on the trace statistic (the maximum eigenvalue statistic). We refer to a specification where we do not allow for a deterministic trend in the data, but include an intercept in the cointegration equation (in line with the specification in equation (1)). Significance stems from critical values based on MacKinnon, Haug and Michelis (1999).*

Table 1 continued

Cointegration Relation

Country	Dependent variable: $\log(c_t)$						Selected (5% level) number of cointegrating relations	
	c_t	$\log(IP_t)$	LR_t	π_t^{CPI}	Adj. R^2	Sample	Trace	Max-Eig
SEE-3								
Bulgaria	Total	3.109*** (0.000)	–0.033 (0.251)	–0.003*** (0.000)	0.89	1997M12–2009M04	1	1
	Firms	2.681*** (0.000)	–0.031 (0.233)	–0.002*** (0.000)	0.87	1997M12–2009M04	1	0
	Households	4.193*** (0.000)	–0.046 (0.201)	–0.005*** (0.000)	0.91	1997M12–2009M04	1	1
Romania	Total	4.039*** (0.000)	–0.004 (0.447)	–0.002 (0.174)	0.72	1997M01–2009M04	3	3
	Firms	2.333*** (0.000)	–0.0009 (0.807)	–0.006*** (0.000)	0.71	1997M01–2009M04	4	4
	Households	7.024*** (0.000)	–0.020** (0.026)	–0.012*** (0.000)	0.85	1997M01–2009M04	3	3
Croatia	Total	3.578*** (0.000)	–0.022 (0.143)	–0.286*** (0.000)	0.95	1997M01–2009M03	1	0
	Firms	2.606*** (0.000)	–0.003 (0.817)	–0.276*** (0.000)	0.94	1997M01–2009M03	0	0
	Households	4.725*** (0.000)	–0.069*** (0.004)	–0.305*** (0.000)	0.94	1997M01–2009M03	1	0

Source: Authors' estimations.

*Note: Coefficients are estimated with OLS. The p-values in parentheses (for the null hypothesis of a coefficient being equal to zero) are based on Newey-West heteroskedasticity and autocorrelation consistent standard errors. The asterisks *, **, *** indicate significance at the 10%, 5% and 1% level, respectively. All regressions contain a constant (not reported). Trace (Max-Eig) indicates the cointegration test assessment based on the trace statistic (the maximum eigenvalue statistic). We refer to a specification where we do not allow for a deterministic trend in the data, but include an intercept in the cointegration equation (in line with the specification in equation (1)). Significance stems from critical values based on MacKinnon, Haug and Michelis (1999).*

our analysis: First, the coefficients – particularly for industrial production – are large enough such that even after bias correction there should still be a non-negligible positive correlation with credit. Second, as the cointegrating vector is superconsistently estimated by OLS, conventional residual-based cointegration tests constructed under the assumption of linear adjustment toward equilibrium will still be valid and can be expected to be able to detect the presence of an equilibrium relationship (see Psaradakis, Sola and Spagnolo, 2004) – the basic prerequisite for our subsequent error correction analysis. Third and finally, also the out-of-sample approach used by Backé, Égert and Zumer (2006) has some challenges, such as the necessity that there is long-run parameter homogeneity between benchmark and transition countries and a stable structural relationship in the benchmark countries over time.

5.2 Short-Run Determinants of Credit Developments: Error Correction Model

In this subsection, we focus on the determinants of short-run private sector credit dynamics, arguing that changes in supply-side variables are directly correlated with credit growth. We do this by estimating the error correction equations (2) and (3a), (3b) for the linear and nonlinear case, respectively.

5.2.1 Evidence from the Linear Error Correction Model

The estimation results for the linear error correction model (i.e. for the whole sample period without subperiod-specific differences that are elaborated in section 5.2.2) are given in table 2. The error correction coefficient is in most of the cases significantly negative, which confirms the finding of cointegration between the variables of equation (1) and indicates that in most countries there is an adjustment toward the credit equilibrium in the long run. However, there are also a few countries with an error correction term that is not statistically different from zero (such as the Czech Republic, Slovakia, Lithuania, and Croatia). In these countries there is thus either a very sluggish disequilibrium adjustment (that can be explained with frictions and transaction costs in the credit market; see Calza, Manrique and Sousa (2006) for respective euro area evidence) or a constant and persistent deviation from the credit equilibrium.

We find that bank deposit and equity growth explains a major part of the variation in credit growth rates. Romania is the only exception, showing a significantly negative relation between the growth rate of aggregate and corporate credit and equity growth. However, in the case of Romania this seems to be offset by a much more pronounced positive relation with the changes in deposits. The latter finding is also corroborated by the other countries, where the coefficient for deposit growth is in the majority of cases large and highly significant (e.g. in Poland a 1% increase of bank deposit growth is associated with an increase of total domestic private sector credit growth by 0.67%).

In contrast, changes in the net external position provide – in line with its theoretical inconclusiveness discussed before – only low explanatory power (i.e. very small coefficients), although there is mostly a negative relation (less pronounced in the CEE-5, but more so in the Baltic countries and the SEE-3). The remaining variables (interest spread, exchange rate volatility, output in the euro area and lagged credit volume) do not show a clear pattern. For the Baltic countries there seems to be weak evidence for a positive correlation with industrial production in the euro area. A positive relation with lagged credit growth can be unambiguously detected only for some credit aggregates in the Czech Republic, Hungary, the Baltic countries and Romania.

Table 2

Linear Error Correction Model

Dependent variable: $\Delta\log(c_t)$

Country	c_t	ε_{t-1}	Δlog (equity)	Δlog (depos)	Δlog (extpos)	Δ(spread)	er_vola	Δlog (IP_EA)	$\Delta\log(c_{t-1})$	Adj. R^2	Sample
CEE-5											
Czech Republic	Total	–0.011	0.514***	–0.007	0.0004***	0.024*	0.024	–0.087	0.177**	0.39	1997M02–2009M03
		(0.243)	(0.000)	(0.966)	(0.002)	(0.065)	(0.347)	(0.468)	(0.030)		
	Firms	–0.017	0.509***	0.113	0.033	0.005	–0.025	–0.113	0.345***	0.32	2002M03–2009M03
		(0.203)	(0.002)	(0.577)	(0.132)	(0.069)	(0.376)	(0.163)	(0.008)		
	Households	0.005	0.166***	0.181*	–0.005	0.017*	–0.083***	0.057	–0.144	0.39	2002M03–2009M03
		(0.231)	(0.003)	(0.070)	(0.687)	(0.060)	(0.000)	(0.168)	(0.225)		
Hungary	Total	–0.002	–0.022	0.103	–0.029	–0.001	0.055***	0.103	0.149	0.09	1997M02–2009M03
		(0.865)	(0.617)	(0.495)	(0.191)	(0.762)	(0.007)	(0.213)	(0.201)		
	Firms	–0.036**	0.187**	0.322**	–0.025	0.005	0.04	0.069	0.226***	0.16	2000M03–2009M03
		(0.022)	(0.042)	(0.015)	(0.286)	(0.316)	(0.100)	(0.481)	(0.005)		
	Households	–0.012	0.127	0.280**	–0.025	0.001	0.049**	0.027	0.25	0.14	2000M03–2009M04
		(0.286)	(0.251)	(0.015)	(0.287)	(0.702)	(0.010)	(0.796)	(0.294)		
Poland	Total	–0.012*	0.049	0.676***	–0.0003	0.001	0.024**	–0.087	0.036	0.41	1997M02–2009M03
		(0.099)	(0.440)	(0.000)	(0.113)	(0.635)	(0.031)	(0.399)	(0.688)		
	Firms	–0.016**	0.202***	0.226***	–0.0003	0.005*	0.007	–0.195***	0.273***	0.31	1997M02–2009M03
		(0.015)	(0.000)	(0.002)	(0.134)	(0.087)	(0.211)	(0.006)	(0.000)		
	Households	–0.013	–0.149	1.178***	–0.0003	–0.002	0.042**	0.079	–0.167**	0.45	1997M02–2009M03
		(0.183)	(0.315)	(0.000)	(0.594)	(0.616)	(0.010)	(0.639)	(0.041)		
Slovakia	Total	–0.027	–0.137	0.174	–0.0007	0.002		0.009	0.016	0.00	1997M02–2008M11
		(0.183)	(0.584)	(0.395)	(0.357)	(0.306)		(0.966)	(0.794)		
	Firms	–0.036	–0.165	0.137	–0.0005	0.002		0.011	0.002	0.00	1997M02–2008M11
		(0.134)	(0.572)	(0.546)	(0.512)	(0.308)		(0.961)	(0.975)		
	Households	0.005	0.013	0.257**	–0.007	0.001		0.02	0.229*	0.13	1997M02–2008M11
		(0.373)	(0.516)	(0.021)	(0.479)	(0.107)		(0.738)	(0.069)		
Slovenia	Total	–0.014**	0.049	0.043	0.001	–0.005**		–0.030	0.176*	0.09	1997M02–2009M03
		(0.019)	(0.756)	(0.711)	(0.161)	(0.024)		(0.703)	(0.064)		
	Firms	–0.012**	0.06	–0.034	0.001*	0.005**		–0.069	0.017	0.03	1997M02–2009M03
		(0.026)	(0.708)	(0.765)	(0.073)	(0.025)		(0.464)	(0.882)		
	Households	–0.028**	–0.005	0.143	0.001	–0.002		0.016	0.146	0.05	1997M02–2009M03
		(0.025)	(0.973)	(0.356)	(0.155)	(0.407)		(0.881)	(0.155)		
Baltic countries											
Estonia	Total	–0.016**	0.089***	0.132**	–0.0003**	0.000		0.238***	0.21	0.20	1998M02–2009M03
		(0.026)	(0.001)	(0.035)	(0.024)	(0.909)		(0.001)	(0.112)		
	Firms	–0.081*	0.227**	0.199	–0.001***	0.010*		0.553***	–0.089	0.13	2004M03–2009M03
		(0.094)	(0.031)	(0.151)	(0.000)	(0.061)		(0.000)	(0.325)		
	Households	–0.0007	0.133**	0.235***	–0.0007***	0.001		0.141	0.676***	0.79	2004M03–2009M03
		(0.894)	(0.010)	(0.001)	(0.000)	(0.538)		(0.117)	(0.000)		
Latvia	Total	–0.013***	–0.003	0.459***	–0.001*	–0.0004		–0.094	0.167	0.48	1997M02–2009M03
		(0.000)	(0.401)	(0.000)	(0.050)	(0.372)		(0.219)	(0.119)		
	Firms	–0.017***	–0.004	0.406***	–0.001	–0.0009		–0.129	0.16	0.30	1998M03–2009M03
		(0.000)	(0.151)	(0.000)	(0.123)	(0.170)		(0.122)	(0.217)		
	Households	–0.006**	–0.008	0.439***	–0.0002	–0.0005		0.158*	0.392***	0.51	1998M03–2009M03
		(0.022)	(0.247)	(0.000)	(0.837)	(0.583)		(0.088)	(0.002)		
Lithuania	Total	–0.007	0.219***	0.405***	–0.001*	–0.0001		0.168*	0.287***	0.33	1998M02–2009M03
		(0.347)	(0.007)	(0.000)	(0.065)	(0.944)		(0.086)	(0.001)		
	Firms	–0.016	0.235**	0.453***	–0.002**	–0.0001		0.157	0.148	0.25	1998M02–2009M03
		(0.162)	(0.013)	(0.000)	(0.010)	(0.965)		(0.132)	(0.104)		
	Households	–0.012	0.141	0.121	0.001	–0.003		0.391**	0.433***	0.23	1998M02–2009M03
		(0.114)	(0.181)	(0.463)	(0.749)	(0.572)		(0.030)	(0.000)		

Source: Authors' estimations.

*Note: Coefficients are estimated with OLS. The p-values in parentheses (for the null hypothesis of a coefficient being equal to zero) are based on Newey-West heteroskedasticity and autocorrelation consistent standard errors. The asterisks *, **, *** indicate significance at the 10%, 5% and 1% level, respectively. All regressions contain a constant (not reported).*

Table 2 continued

Linear Error Correction Model

Country	c_t	Dependent variable: $\Delta\log(c_t)$									
		ε_{t-1}	Δlog (equity)	Δlog (depos)	Δlog (extpos)	Δ(spread)	er_vola	Δlog (IP_EA)	$\Delta\log(c_{t-1})$	Adj. R^2	Sample
SEE-3											
Bulgaria	Total	–0.016**	–0.032	0.796***	–0.0009*	–0.0006		–0.028	–0.053**	0.52	1998M01–2009M03
		(0.015)	(0.389)	(0.000)	(0.075)	(0.654)		(0.84)	(0.015)		
	Firms	–0.008	–0.061	0.964***	–0.001*	–0.001		–0.033	–0.054*	0.49	1998M01–2009M03
		(0.306)	(0.161)	(0.000)	(0.072)	(0.515)		(0.832)	(0.050)		
	Households	–0.015**	0.197***	0.229	–0.003	0.001		0.028	0.552***	0.72	1998M01–2009M03
		(0.022)	(0.000)	(0.120)	(0.345)	(0.154)		(0.806)	(0.000)		
Romania	Total	–0.018**	–0.071***	0.752***	–0.001***	–0.004**	0.095**	–0.035	0.373***	0.52	1997M06–2009M03
		(0.017)	(0.004)	(0.000)	(0.001)	(0.046)	(0.017)	(0.800)	(0.000)		
	Firms	–0.038	–0.093***	0.151	–0.001	–0.001	0.06	–0.172	–0.093	0.00	1997M06–2009M03
		(0.112)	(0.006)	(0.819)	(0.434)	(0.740)	(0.242)	(0.371)	(0.345)		
	Households	–0.014***	0.01	0.372***	–0.0005	0.001	0.023	0.025	0.636***	0.56	1997M06–2009M03
		(0.000)	(0.542)	(0.009)	(0.452)	(0.610)	(0.486)	(0.889)	(0.000)		
Croatia	Total	–0.0005	0.392***	0.609***	–0.0002	–0.0007	–0.021	–0.062	0.002	0.99	1997M03–2009M03
		(0.952)	(0.000)	(0.000)	(0.408)	(0.266)	(0.934)	(0.462)	(0.640)		
	Firms	–0.0004	0.460***	0.546***	–0.0003	–0.0007	–0.076	–0.073	0.003	0.99	1997M03–2009M03
		(0.968)	(0.000)	(0.000)	(0.247)	(0.449)	(0.756)	(0.476)	(0.516)		
	Households	–0.009	0.257**	0.737***	–0.0003	–0.001	0.024	0.002	0.004	0.99	1997M03–2009M03
		(0.417)	(0.039)	(0.000)	(0.398)	(0.206)	(0.919)	(0.977)	(0.616)		

Source: Authors' estimations.
*Note: Coefficients are estimated with OLS. The p-values in parentheses (for the null hypothesis of a coefficient being equal to zero) are based on Newey-West heteroskedasticity and autocorrelation consistent standard errors. The asterisks *, **, *** indicate significance at the 10%, 5% and 1% level, respectively. All regressions contain a constant (not reported).*

5.2.2 Evidence from the Markov-Switching Error Correction Model

Let us now turn to the Markov-switching error correction model that relaxes the assumption of a time-invariant short-run relation.[11] The series for firm and household credits are shorter for some countries (the Czech Republic, Hungary and Estonia), which poses challenges to the estimation of the highly nonlinear MS-ECM and leads to less pronounced regime switches in these cases. Therefore, and for the sake of brevity, we do not present MS-ECM results for the disaggregate series (available from the authors on request). The MS-ECM results for total domestic private sector credit are presented in table 3.

The overall picture that equity and deposit growth are the most important explanatory variables of total domestic private sector credit growth is confirmed for all countries. However, their impact differs significantly across the two identified regimes in most of the countries (see the Wald tests in table A3), which suggests that the main short-run determinants of credit growth do not have the same (i.e. linear) impact over the whole sample period.

There are only slight differences between the error correction coefficients of the respective regimes, which points to a broadly regime-independent adjustment process. Table A3 shows that the error correction terms differ significantly across

[11] *We do not formally test for Markov-switching, i.e. k=1 versus k=2. The reason is that testing in a Markov-switching framework is highly nontrivial and requires a grid search over all combinations of the transition probabilities, and the critical values from the literature (see Garcia, 1998) do not apply to our particular model. However, looking at the clear results of the Wald tests (see table A3), which are often used as a heuristic approach (see e.g. Dewachter, 2001), we feel sufficiently confident about the existence of regime switches in our sample.*

the two regimes in Romania, Lithuania and Slovakia only. In Romania, both adjustment coefficients are negative, but there is a faster disequilibrium adjustment in regime 1. In Lithuania, the regime switches are broadly correlated with ups and downs of the business cycle (see table 4 and a broader discussion below). During downturns, credit corrects toward the equilibrium, which is not the case during booms.[12] In Slovakia, regime 1 (early 2001, late 2002 and early 2003) coincides with the aforementioned period of bank restructuring and shows a correction of credit toward its equilibrium, while the long-lasting regime 2 can be classified as a noncorrecting one[13] (in line with the overall lack of finding a cointegration relation for this country). This evidence for Slovakia and Lithuania highlights that, for the direct linkage between policy measures and the correction of over- or undershooting credit levels, the type of policy measure (in the case of Slovakia bank restructuring) as well as the business cycle position of a country are important.

The existence of only slight differences in the error correction coefficients together with the fact that in most of the countries there is at least one Z_t variable that has a significantly different impact across the two regimes (in most cases banks' equity or deposits, see again table A3) indicates that the switches are driven primarily by the short-run supply factors rather than by the adjustment process itself.

[12] *One might wonder why we were not able to find a similar behavior in the other two Baltic countries. First, the Wald tests in table A3 do not indicate a significant cross-regime difference of adjustment coefficients in Estonia and Latvia (where regime shifts are apparently driven by the short-run supply factors). Second, compared with Lithuania, credit growth rates in Latvia and Estonia were clearly higher (reaching about 80% year on year in real terms; Lithuania: only about 30%, see chart 1) before the spillover of the Russian financial crisis in the late 1990s. This might change the impact of determinants in the regimes coinciding with economic boom periods.*

[13] *A closer inspection of the residuals of the long-term equation reveals that there was not really a need for correction in Slovakia, as the actual credit level only rarely departed from the level fitted on the basis of the underlying macroeconomic fundamentals.*

Table 3

Markov-Switching Error Correction Model

Country	Regime	ε_{t-1}	Δlog (equity)	Δlog (depos)	Δlog (extpos)	Δ(spread)	er_vola	Δlog (IP_EA)	$\Delta\log(c_{t-1})$	Transformed probability	Sample
	Dependent variable: $\Delta\log(c_t)$, with c_t representing total domestic private sector credit										
CEE-5											
Czech Republic	Regime 1	0.013	0.381**	0.279	0.010	0.009	–0.075	–0.018	0.120	0.993	1997M02–
		(0.279)	(0.015)	(0.175)	(0.368)	(0.373)	(0.141)	(0.392)	(0.332)		2009M03
	Regime 2	0.018	0.468***	–0.083	0.000	0.020**	0.259	–0.213	–0.077	0.993	
		(0.119)	(0.000)	(0.305)	(0.278)	(0.016)	(0.132)	(0.211)	(0.215)		
Hungary	Regime 1	0.012	0.648***	–0.827**	0.028**	0.012	0.123***	0.474**	–0.284**	0.743	1997M02–
		(0.324)	(0.004)	(0.048)	(0.034)	(0.148)	(0.000)	(0.011)	(0.017)		2009M03
	Regime 2	0.012	–0.074**	0.129*	–0.068***	–0.002	0.034**	–0.007	0.440***	0.945	
		(0.178)	(0.010)	(0.069)	(0.000)	(0.327)	(0.031)	(0.398)	(0.000)		
Poland	Regime 1	–0.010	0.094	0.822***	–0.008	0.000	0.021	0.203*	–0.026	0.950	1997M02–
		(0.283)	(0.250)	(0.000)	(0.146)	(0.397)	(0.342)	(0.060)	(0.371)		2009M03
	Regime 2	–0.018	–0.017	0.168	0.000	–0.001	0.019	–0.301***	–0.260	0.942	
		(0.107)	(0.395)	(0.159)	(0.267)	(0.395)	(0.117)	(0.002)	(0.220)		
Slovakia	Regime 1	–0.272***	–1.325***	–0.667	0.043***	0.082***		–0.533	–0.318**	0.769	1999M01–
		(0.000)	(0.000)	(0.179)	(0.005)	(0.000)		(0.256)	(0.013)		2008M11
	Regime 2	–0.014	0.166***	0.355***	–0.001	0.003*		0.172	0.280***	0.976	
		(0.206)	(0.000)	(0.002)	(0.331)	(0.061)		(0.201)	(0.000)		
Slovenia	Regime 1	–0.135*	–0.571***	0.248	–0.046	–0.072***		0.540	–0.008	0.766	1997M12–
		(0.075)	(0.000)	(0.306)	(0.246)	(0.002)		(0.146)	(0.398)		2008M11
	Regime 2	–0.014**	0.227***	0.154**	0.002	–0.004*		0.069	0.184**	0.982	
		(0.028)	(0.000)	(0.012)	(0.125)	(0.057)		(0.188)	(0.022)		
Baltic countries											
Estonia	Regime 1	–0.020	0.154**	0.024	0.000	0.000		0.206*	–0.129	0.983	1998M02–
		(0.164)	(0.020)	(0.373)	(0.169)	(0.363)		(0.076)	(0.144)		2009M03
	Regime 2	0.002	0.117**	0.209**	0.000	0.001		0.107	0.419	0.983	
		(0.387)	(0.015)	(0.039)	(0.397)	(0.193)		(0.316)	(0.120)		
Latvia	Regime 1	–0.010	–0.003	0.320**	0.001	0.000		0.094	0.379***	0.949	1997M02–
		(0.111)	(0.376)	(0.011)	(0.366)	(0.398)		(0.309)	(0.006)		2009M03
	Regime 2	–0.014***	–0.005	0.416***	–0.002	0.000		–0.308*	–0.064	0.958	
		(0.001)	(0.380)	(0.002)	(0.121)	(0.388)		(0.063)	(0.342)		
Lithuania	Regime 1	–0.040***	–0.077	0.113	0.000	0.000		0.082	–0.033	0.902	1998M02–
		(0.001)	(0.367)	(0.307)	(0.391)	(0.398)		(0.363)	(0.395)		2009M03
	Regime 2	0.004	0.308***	0.377***	–0.001	–0.005		–0.085	0.190**	0.950	
		(0.351)	(0.000)	(0.001)	(0.334)	(0.164)		(0.364)	(0.043)		
SEE-3											
Bulgaria	Regime 1	–0.038**	–0.089*	0.403***	0.000	–0.001		0.373**	0.117	0.912	1998M01–
		(0.016)	(0.051)	(0.000)	(0.270)	(0.353)		(0.050)	(0.120)		2009M03
	Regime 2	–0.022***	–0.027	1.125***	0.000	0.001		–0.088	–0.081***	0.927	
		(0.001)	(0.288)	(0.000)	(0.396)	(0.239)		(0.299)	(0.000)		
Romania	Regime 1	–0.086***	–0.109***	–0.895***	0.050	–0.010***	1.356***	0.942	–0.066	0.674	1997M06–
		(0.000)	(0.000)	(0.005)	(0.167)	(0.000)	(0.000)	(0.216)	(0.296)		2009M03
	Regime 2	–0.006*	–0.018	0.515***	–0.001**	–0.001	0.047**	0.104	0.355***	0.969	
		(0.099)	(0.259)	(0.000)	(0.050)	(0.330)	(0.025)	(0.234)	(0.000)		
Croatia	Regime 1	–0.001	0.289***	0.715***	0.000	0.000	0.105	0.026	0.003	0.963	1997M03–
		(0.392)	(0.000)	(0.000)	(0.217)	(0.395)	(0.366)	(0.382)	(0.315)		2009M03
	Regime 2	0.029	0.549***	0.043	0.047***	–0.007***	3.915***	–1.297***	0.026	0.636	
		(0.226)	(0.000)	(0.371)	(0.000)	(0.005)	(0.000)	(0.000)	(0.322)		

Source: Authors' estimations.

*Note: Coefficients are estimated with quasi-maximum likelihood. p-values for the null hypothesis of a coefficient being equal to zero are in parentheses. The asterisks *, **, *** indicate significance at the 10%, 5% and 1% level, respectively. The transformed probability represents the transition probability p_{ii} for staying in regime i if the country is already there. All regressions contain a constant (not reported).*

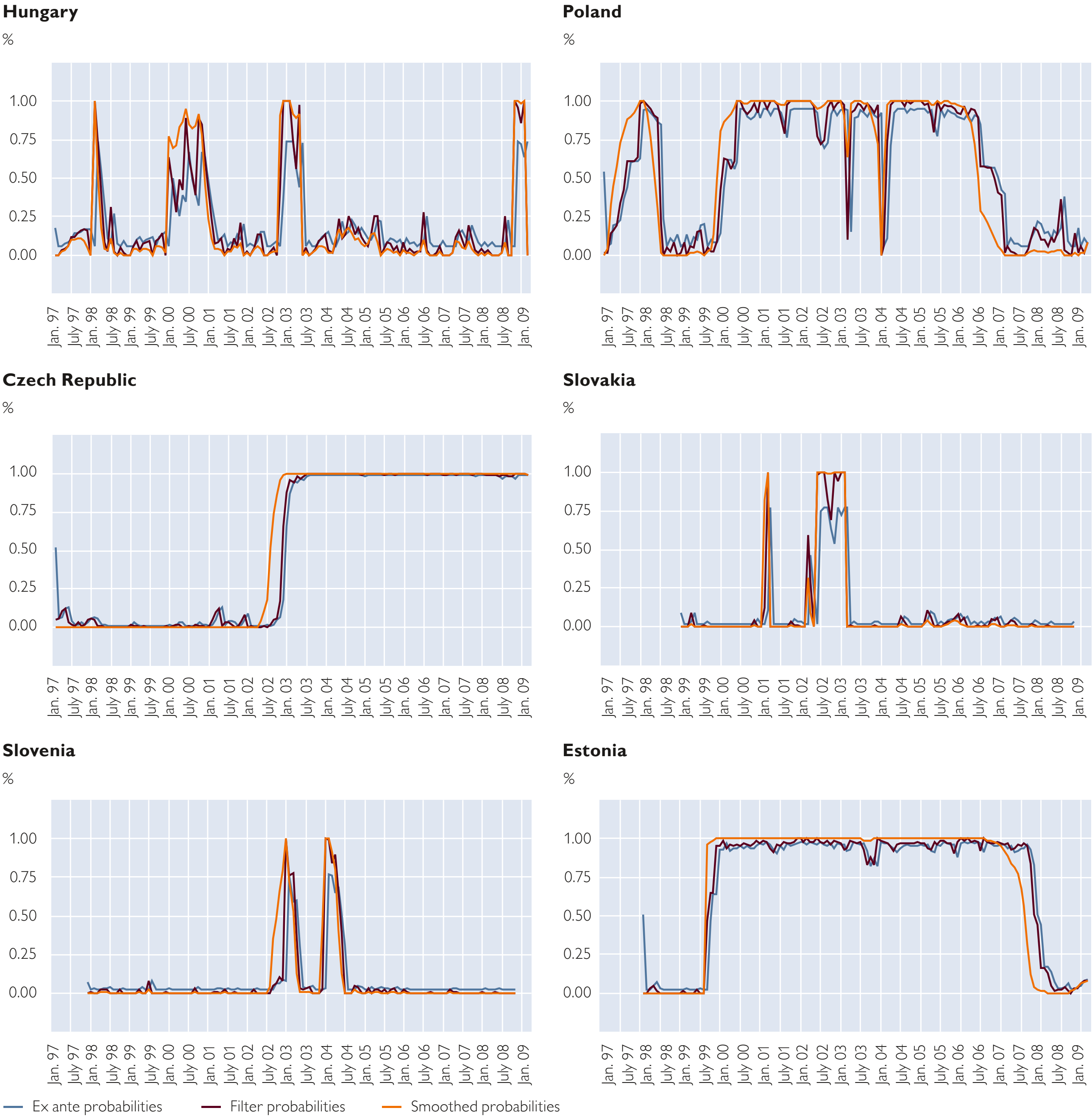
From the MS-ECM estimation we directly get the regime-switching probabilities. Chart 2 shows, for each country, the probability of being in regime 1 (*prob=1*) or regime 2 (*prob=0*) at time t. In terms of regime-switching behavior, we can divide the countries into two groups: While the first group shows clear and long-lasting regime switches (Poland, the Czech Republic, the Baltic countries and Bulgaria), the second group mainly stays in one regime with only short switches (Croatia, Romania and Slovenia, to a lesser extent Hungary and Slovakia). This is also reflected in the transition probabilities p_{ii} for staying in regime i if the country is already there (last column in table 3). While mostly exceeding 90%, the probabilities are generally low for the second group of countries in one of the regimes, with Croatia accounting for the minimum value of 64% in regime 2.

For the first group of countries with long swings in the error correction equation, i.e. p_{ii} is above 90% for both regimes, we find at least one regime for which bank equity and/or deposits show a very pronounced positive relation with credit growth. However, the dates of observed regime switches vary from country to country and show no common pattern. This means that the switches are likely to be due to country-specific rather than global determinants. Nevertheless, just before and during the current global crisis, all countries in this group except for the Czech Republic show a regime switch. This shift, which occurs between early 2007 (Poland) and late 2008 (Lithuania), invariably shows a weakened relation between credit growth on the one hand and bank equity or deposit growth on the other hand. The coefficient thus becomes insignificant or the coefficient remains significantly positive, but gets smaller. The only exception is Bulgaria, which shows a positive credit-deposit relation in both regimes and moves toward the larger coefficient. For Estonia, we observe the same behavior found in the other countries of the first group for equity, but not for deposits.

Most countries with only short-lived regime swings (Croatia, Romania, Slovakia and Slovenia) have one characteristic in common: The regime in which they stay most of the time shows a textbook-like positive relation with deposits, whereas the short-lived regime is characterized by significant impacts of the external position with both a negative and a positive sign depending on the country under review. One may thus argue that the short-run dynamics of these countries were from time to time affected by external determinants.

Chart 2

Regime Switching Probabilities from the MS-ECM for Real Domestic Private Sector Credit Growth

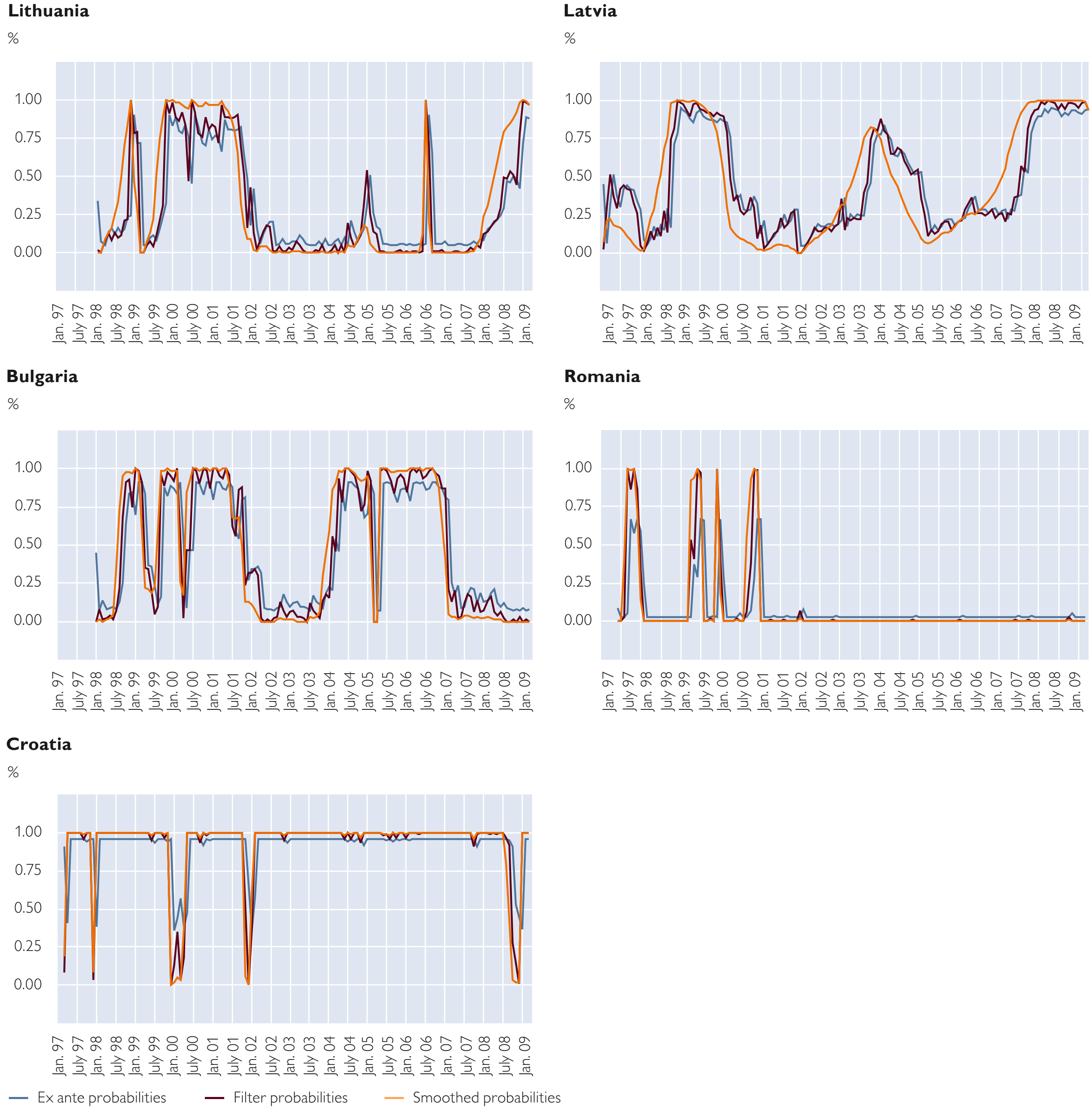


Source: Authors' estimations.

Note: We show the time-varying probability of being in regime 1 as reported in table 3 at time t, based on all the available information up to time t–1 (ex ante probabilities), up to time t (filter probabilities) and up to time T, i.e. as an ex post analysis for the whole sample period (smoothed probabilities).

Chart 2 continued

Regime Switching Probabilities from the MS-ECM for Real Domestic Private Sector Credit Growth



Source: Authors' estimations.

Note: We show the time-varying probability of being in regime 1 as reported in table 3 at time t, based on all the available information up to time t−1 (ex ante probabilities), up to time t (filter probabilities) and up to time T, i.e. as an ex post analysis for the whole sample period (smoothed probabilities).

Regime-specific descriptive statistics for real GDP growth and real domestic private sector credit growth (table 4) provide more information about the macro factors that underlie the two different regimes in each country. It is evident that in the three Baltic countries and in the Czech Republic the two regimes clearly coincide with the respective business cycle position of the country: One regime represents a boom period with high GDP and credit growth, while the other regime represents more of a crisis period with relatively poor economic performance, higher economic volatility and relatively low – if not negative – credit growth. In the other countries, the regime differences appear to be less business cycle-dependent.

Table 4

Regime-Specific Descriptive Statistics for GDP Growth and Credit Growth

		Real GDP growth in %		Real credit growth in %	
		Average	SD	Average	SD
Countries with two equally pronounced regimes					
Czech Republic	Regime 1	4.4	2.6	11.4	11.3
	Regime 2	1.3	1.9	–9.7	9.2
Poland	Regime 1	4.0	2.4	7.8	6.4
	Regime 2	5.2	2.0	22.8	5.2
Estonia	Regime 1	8.3	2.1	24.5	7.3
	Regime 2	0.6	7.0	11.8	16.9
Latvia	Regime 1	3.0	7.3	24.8	19.8
	Regime 2	8.7	3.5	41.8	15.7
Lithuania	Regime 1	1.5	5.5	7.6	10.0
	Regime 2	7.9	2.3	36.6	14.6
Bulgaria	Regime 1	4.9	2.3	19.8	18.1
	Regime 2	4.8	2.5	25.2	26.6
Countries with mainly one regime and only short switches					
Hungary	Regime 1	2.6	4.3	16.8	3.8
	Regime 2	3.8	1.4	14.3	6.2
Slovakia	Regime 1	4.3	2.5	1.5	11.2
	Regime 2	4.9	4.2	3.0	16.0
Slovenia	Regime 1	3.6	0.9	11.5	9.6
	Regime 2	4.1	2.6	15.3	7.6
Romania	Regime 1	n.a.	n.a.	–18.3	21.9
	Regime 2	n.a.	n.a.	20.3	27.3
Croatia	Regime 1	4.6	4.7	13.8	10.2
	Regime 2	5.8	8.5	5.3	16.7

Source: Eurostat, IMF, NCBs, ECB, authors' calculations.

Note: Averages and standard deviations (SD) are calculated for the year-on-year percentage change of quarterly GDP at market prices and for the year-on-year percentage change of CPI-deflated monthly domestic private sector credit stocks. These statistics are calculated separately for regime 1 and regime 2 as indicated by the smoothed probability depicted in chart 2 (as soon as it is larger than 0.5, we classify the related subperiod as regime 1).

5.3 Robustness Checks

Finally, we performed various robustness checks, whose results are not presented here but are available from the authors on request. In particular, we checked various alternative specifications of the long-term equation. First, we replaced in equation (1) the interest rate with alternative ones, namely real interest rates and different maturities. This had almost no effect on the results; the observed positive relation between credit volume and the interest rate, in particular, remained stable.

Second, we included cross-border credits in our analysis, since they account for a substantial share of total credit volume in some of the CESEE-11 countries (especially in Croatia and Bulgaria, but also in Estonia and Latvia; see section 4). Their inclusion did not substantially affect the sign and size of coefficients in the cointegration equation, however. Since our proxy for cross-border credits is only available on a quarterly basis for households and firms combined (and thus, in contrast to other variables, interpolation would be necessary), we decided to work exclusively with the domestic private sector credit stock in the estimations.

Third, we included government credit as an additional variable in the cointegration equation to account for potential crowding-out effects. Again, there was no impact on the estimation results.

Fourth and finally, we constructed a dummy[14] that captures substantial reform progress in the financial sector based on the EBRD transition indicator for banking reform and interest rate liberalization. We included it in the cointegration equation to account for long-run structural conditions that are most likely to have determined the evolvement of credit volumes over time (in contrast to short-run competition effects approximated by the interest spread in the credit growth equation). There is a strong and positive correlation with credit volume in nearly all of the CESEE-11, which indicates that credit expansion in CESEE had also been based on better-functioning financial institutions. The effect on the other coefficients in the long-term equation and on the residuals to be used in the ECM is, however, only marginal.

6 Summary

In this paper, we analyze the determinants of domestic private sector credit developments in eleven CESEE countries, namely the CESEE EU Member States and Croatia, from January 1997 to April 2009. Our multidimensional approach (distinction between supply- and demand-side determinants, separate analysis of lending to firms and to households, identification of subperiods with a different impact of credit growth determinants) contributes to the existing literature since studies researching determinants of credit developments at this level of disaggregation are still rare (see Aisen and Franken, 2010). The finance and growth literature showed that countries with more developed financial systems tend to record stronger growth than countries with less developed systems (see e.g. Rajan and Zingales, 1998). Thus, it is crucial to learn more about the long-run driving forces of credit developments in order to assess the catching-up potential of the examined CESEE countries. Moreover, analyzing the variables that determine credit growth in the short run and especially their varying impact over time is important to assess financial sector risks and macrofinancial stability in the CESEE region.

We find long-term equations that are in line with our expectations. In most countries, there exists at least one cointegration relationship. The most significant long-term determinant of domestic bank lending to the private sector is economic activity (especially pronounced for household credits). Inflation shows the expected negative relation to lending for most countries, whereas the lending rate

[14] *Based on the EBRD transition indicator for banking reform and interest rate liberalization (see EBRD, 2009), the dummy was constructed as follows: 0 if the transition indicator's score was smaller than 3.33 and 1 if it was larger than or equal to 3.33. Note that 3 marks "substantial progress in establishment of bank solvency and of a framework for prudential supervision and regulation; full interest rate liberalisation with little preferential access to cheap refinancing; significant lending to private enterprises and significant presence of private banks" and 4 stands for "significant movement of banking laws and regulations towards BIS standards; well-functioning banking competition and effective prudential supervision; significant term lending to private enterprises; substantial financial deepening." As the transition indicators are only available at an annual frequency, a change in the dummy starts in July of the respective year.*

displays in some cases a counterintuitively positive sign, which is, however, in line with the existing empirical evidence. In the short run, credit supply factors like bank deposits and banks' equity explain a major part of the variation in credit growth rates.

Applying a Markov-switching error correction model, we provide a model that is more plausible than a simple linear error correction model as it relaxes the assumption of a time-invariant credit growth relation. We present the following findings: First, deposits and equity remain the main short-run determinants of credit growth; yet, the strength of their impact differs substantially across the identified subperiods ("regimes" in the diction of the Markov-switching error correction model). This finding is important for financial stability analysis as it should – in the assessment of short-run credit developments – focus also on bank-related credit supply variables and their apparently changing impact over time. Second, as the error correction coefficients differ significantly across the identified regimes only in a few countries, the regime switches are mostly driven by differences in the short-run credit supply factors rather than by the adjustment to the credit equilibrium. Third, for a few countries, the linear model suggests that there is either a very slow or no correction toward the credit equilibrium if the credit level departs from its underlying macroeconomic fundamentals. The Markov-switching error correction model, in contrast, reveals that, in some of these countries, correction does take place in particular subperiods and is correlated with bank restructuring or low growth phases. Fourth, the subperiods separated by the regime shifts differ across the countries under review. We nevertheless identify two groups of countries: those with one dominant regime that is only temporarily interrupted by a second, short-lived one and those with two equally pronounced regimes leading to long-lasting regime switches. While the majority of regime switches seems to be country-specific rather than determined by the global environment, we find for most of the countries in the latter group a marked regime switch just before or during the current global crisis. This switch pushed the way credit growth was determined back to a regime that had already been observed earlier (in most cases, before the economic boom period from 2000 to 2007) and that is characterized by a weaker relation of deposit growth and credit growth.

Based on this evidence, future research could further explore country-specific reasons for the detected regime switches. This could shed light on the effectiveness of policy measures that were implemented to curb rapid credit growth in the period up to 2007–2008[15] and that have been used to sustain lending during the more recent crisis situation.

[15] *Such as the tightening of capital adequacy requirements, of minimum reserve requirements, or of foreign exposure regulations; particularly in Croatia, Bulgaria, Romania, and Poland, and, to a more limited extent, in the Baltic countries.*

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Annex: Data Issues and Description of Variables

For our analysis we use data with monthly frequency (from January 1997 to April 2009) that are real-valued, seasonally adjusted and denominated in local currency. Those variables that are only available in nominal terms are deflated by using the all-items HICP index (2005=100). All series are seasonally detrended by applying the Census X12 method (also used by Eurostat to de-seasonalize EU series). Table A1 provides detailed definitions and sources of the variables used in the analysis.

Table A1

Description of Variables

Variables	Description	Source
Credit variables		
Total domestic private sector credits	Credit to resident nonmonetary financial institutions (non-MFIs), excluding the general government, in local currency (LC) million, end of period	IMF (1993–1996), NCBs (1997–2003), ECB (2004 onward)
Domestic firm credits	Domestic credit to resident enterprises (nonfinancial corporations and other financial intermediaries) in LC million, end of period	
Domestic household credits	Domestic credit to resident households and nonprofit institutions serving households in LC million, end of period	
Cross-border credits to the private sector	Calculated as external debt of the nonbank private sector, excluding intercompany loans and trade credits (liabilities); in EUR million, end of period (conversion to LC million by using the end-of-period exchange rate). Available only on a quarterly basis, and thus we interpolated them linearly to monthly frequency	NCBs and IMF (International Investment Position)
Long-run (demand-side) determinants		
Industrial production (IP)	Real industrial production (excl. construction), gross volume index (wiiw). For the Baltic countries and the euro area (IP_EA), we use working day adjusted data from Eurostat	wiiw, Eurostat
Lending rate (LR)	Weighted average rate charged by non-MFIs on short-term loans to the private nonfinancial sector; the counterparties, maturites and weightings vary slightly from country to country	IMF International Financial Statistics (Datastream)
Inflation rate (π^{CPI})	Year-on-year percentage change of the all-items HICP (index, 2005=100)	Eurostat
Short-run (supply-side) determinants		
Bank equity (equity)	Banks' capital and reserves in LC million, end of period	IMF (1993–1996), NCBs (1997–2003), ECB (2004 onward)
Domestic bank deposits of households and firms (depos)	Deposits of residents, excluding the general government, in LC million, end of period. For the Czech Republic, Hungary, Latvia and Slovakia, we used deposits of resident non-MFIs excluding the central government (longer time series available)	
Banks' net external position (extpos)	External assets minus external liabilities, LC million, end of period	
Lending-deposit rate (spread)	Spread between lending rate (see above) and deposit rate (weighted average rate offered by non-MFIs on deposits of the private nonfinancial sector), in percentage points	IMF International Financial Statistics (Datastream)
Exchange rate volatility (er_vola)	Monthly variation of daily nominal exchange rates from their monthly mean in percent, as measured by the coefficient of variation	WM/Reuters (Datastream)

Source: Compiled by authors.

Table A2

Unit Root Properties of Variables Used in the Cointegration Relation

Country	Test	$\log(c_t^{TOTAL})$	$\log(c_t^{FIRMS})$	$\log(c_t^{HOUSEHOLDS})$	$\log(IP_t)$	LR_t	π_t^{CPI}
Czech Republic	ADF	I(1)	TS	I(1)	I(1)	I(1)	I(0)
	PP	I(1)	TS	I(1)	I(1)	I(1)	I(1)
Hungary	ADF	I(1)	TS	I(1)	I(1)	I(0)	I(1)
	PP	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)
Poland	ADF	I(1)	I(1)	I(1)	I(1)	I(1)	I(0)
	PP	I(1)	I(1)	I(1)	TS	I(1)	I(0)
Slovakia	ADF	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
	PP	I(1)	I(1)	I(1)	TS	I(1)	I(1)
Slovenia	ADF	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)
	PP	I(1)	I(1)	I(1)	TS	I(1)	I(1)
Estonia	ADF	TS	I(1)	I(2)	I(1)	I(1)	I(0)
	PP	I(1)	I(1)	I(2)	I(1)	I(1)	I(1)
Latvia	ADF	I(1)	I(1)	I(2)	I(1)	I(1)	I(0)
	PP	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)
Lithuania	ADF	I(1)	I(1)	I(1)	TS	I(0)	I(0)
	PP	I(1)	I(1)	I(1)	TS	I(0)	I(0)
Bulgaria	ADF	TS	TS	TS	I(1)	I(0)	I(0)
	PP	TS	TS	I(1)	I(1)	I(0)	I(0)
Romania	ADF	I(1)	I(1)	I(1)	I(1)	TS	I(0)
	PP	I(1)	I(1)	I(1)	I(1)	I(1)	I(1)
Croatia	ADF	I(1)	I(1)	I(1)	I(1)	I(0)	I(1)
	PP	I(1)	I(1)	I(1)	TS	I(0)	I(1)

Source: Authors' estimations.

Note: Based on the Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) unit root tests, we show whether a series used in equation (1) has no, one or two unit root(s), i.e. is integrated of order zero – I(0), of order one – I(1), or of order two – I(2). „TS" indicates that the series is trend-stationary, i.e. the hypothesis of a nonstable series is rejected as soon as a deterministic trend is included in the test equation in levels. The detailed test output is available from the authors on request.

Table A3

Wald Tests for Differences in Coefficients across Regimes

Country	ε_{t-1}	Δlog (equity)	Δlog (depos)	Δlog (extpos)	Δ(spread)	er_vola	Δlog (IP_EA)	$\Delta\log(c_{t-1})$
Czech Republic	0.09	0.31	2.17	0.15	0.00	3.37	1.02	8.40**
Hungary	0.00	11.46***	5.46*	32.64***	0.00	10.13**	12.51***	68.97***
Poland	0.22	0.46	20.58***	1.89	0.00	0.00	28.99***	0.97
Slovakia	12.88***	146.16***	3.61	8.98**	0.02		1.45	17.88***
Slovenia	2.67	31.74***	0.07	1.03	0.04		1.52	2.11
Estonia	1.58	0.24	2.48	0.72	0.00		0.27	3.46
Latvia	0.14	0.02	0.25	1.20	0.00		3.89*	6.45*
Lithuania	10.31**	5.79*	2.07	0.02	0.00		0.38	0.75
Bulgaria	1.01	1.32	43.77***	0.39	0.00		4.43*	6.47*
Romania	30.20***	14.04***	20.79***	1.82	0.00	29.29***	63.47***	47.20***
Croatia	1.17	3.84*	32.09***	15.78***	0.04	12.89***	21.11***	0.33

Source: Authors' estimations.

*Note: This table shows whether there are significant differences in the coefficients in equation (3a) and equation (3b), i.e. the Wald test statistics for rejecting the null hypothesis of $b_{k1}=b_{k2}$, where k represents the different explanatory variables. The asterisks *, **, *** indicate significance at the 10%, 5% and 1% level, respectively. The results for the constant are not reported.*