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Assessing credit gaps in CESEE based on levels justified by fundamentals – a comparison across different estimation approaches

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ABSTRACT

Relying on a rich panel regression framework, we study the role of different "fundamental" credit determinants in Central, Eastern and Southeastern European (CESEE) EU Member States and compare actual private sector credit-to-GDP ratios to the derived fundamental levels. It turns out that countries featuring positive credit gaps at the start of the global financial crisis (GFC) have managed to adjust their credit ratios downward toward levels justified by fundamentals, but the adjustment is apparently not yet complete in all countries. In addition, negative credit gaps have emerged or widened in most countries that had seen credit levels close to or below the fundamental levels of credit at the start of the GFC. The estimated speed of adjustment implies that at the end of the review period, there was still a rather long way to go for countries with very large credit gaps.

Keywords: private sector credit, fundamental level of credit, bank lending, global financial crisis, financial development, static heterogeneous panel model, panel error correction model.

JEL codes: C33, E44, E51, G01, G21, O16.

Non-technical summary

Strongly rising credit levels in most Central, Eastern and Southeastern European (CESEE) countries before the global financial crisis (GFC) have been widely debated, especially with a view to understanding if this process reflected the emergence of credit bubbles or just represented convergence-related financial deepening. Often, the guiding benchmark used in the assessment has been the deviation of observed credit levels from estimated fundamental or equilibrium levels. Our study complements this strand of literature and provides answers to the question whether private sector credit ratios have successfully been brought back to more sustainable (i.e. fundamental) levels in the CESEE region since the crisis.

There are several ways in which our paper can add value to the existing literature. First, we adopt a more comprehensive definition of credit that includes both domestic and cross-border credit, since cross-border credit is an important source of (corporate) financing in CESEE. Previous work has focused only on domestic bank credit to the private sector. Second, we take into account the role of foreign credit determinants, which has so far been disregarded. Given the high openness of the region in terms of trade and banking and given the potential role of global supply push factors in determining credit (Bruno and Shin, 2015), we add foreign variables to our set of credit determinants. Third, we account for panel heterogeneity, which has not convincingly been attempted so far, apart from the application of several candidate models for estimating fundamental credit levels. Moreover, we also account for a complementary dynamic panel model which allows us to disentangle the short- and long-term effects of each credit determinant and to study the speed of adjustment of actual credit levels to fundamental levels. Previous papers have usually relied on a similar static panel approach using a fixed effect estimator but have not accounted for cross-sectional dependence, possible endogeneity bias and heterogeneity across the sample countries. We provide a full spectrum of results dealing with these key econometric issues to avoid biased statistical inference. Moreover, we analyze the role of different possible fundamentals and provide an extensive set of robustness checks, thereby contributing to the literature in this aspect as well.

Our analysis reveals that countries which experienced overshooting before and/or during the GFC have indeed been able to bring total private sector credit levels back toward fundamental levels. In a few cases, the adjustment has not yet been accomplished, though. On the other hand, several countries shifted toward undershooting during the post-GFC deleveraging episode, often with widening negative credit gaps in recent years. As several of these countries had already been quite close to fundamental levels up to the GFC, post-GFC deleveraging was apparently also driven by other factors, such as the specific composition of credit (featuring e.g. high shares of foreign currency-denominated loans in some cases). Finally, the dynamic panel analysis reveals that the speed of disequilibrium adjustment is rather moderate: it will take about six years on average across the region to halve existing credit gaps. This speed of adjustment would imply that at the end of the review period there was still a rather long way to go for countries with very large credit gaps.

1. INTRODUCTION

Before the 2008–09 global financial crisis (GFC), a number of papers started to address the question whether rapidly rising credit levels in most Central, Eastern and Southeastern European (CESEE) countries reflected the emergence of credit bubbles rather than convergence-related financial deepening (Boissay et al., 2005; Cottarelli et al., 2005; Duenwald et al., 2005; Égert et al., 2006; Kiss et al., 2006; to name only a few). After the rapid credit expansion before the GFC, a period of slowing or negative credit growth rates followed, before credit growth recovered or accelerated more recently (for a more detailed descriptive analysis, see Comunale et al., 2018). Deviations of observed credit levels from long-run equilibrium levels continued to be of interest for economists and policymakers also after the start of the GFC (e.g. Zumer et al., 2009; Geršl and Seidler, 2012; Geršl and Seidler, 2015; IMF, 2015). So far, work on this issue has focused on domestic bank credit to the private sector, while direct cross-border credit and foreign credit determinants have been largely disregarded.

At the core of deriving equilibrium credit levels is the establishment of a relationship between credit and the level of economic development (usually measured by GDP per capita at purchasing power standards) that also takes into account other fundamental factors. The key question is whether credit-to-GDP ratios are found to be consistent with macroeconomic and financial fundamentals, meaning – ceteris paribus – that countries with a higher income level should have a higher degree of financial deepening.

As the year 2008 constituted a watershed year for credit developments in CESEE, let us shed some light on CESEE countries' credit levels at that time: Have credit-to-GDP ratios reached or exceeded their fundamental or equilibrium levels according to the literature at the onset of the GFC? Zumer et al. (2009) provided estimates of equilibrium credit ratios and pointed out that up to the first quarter of 2009, all CESEE countries reached the estimated equilibrium private sector credit-to-GDP range. Looking at the mid-point of the range, one could still detect undershooting tendencies, however, most clearly in the Czech Republic, Poland and Slovakia. The largest upward deviations of actual credit ratios at that time were found in Estonia, Latvia, Bulgaria and Croatia. This assessment (without Croatia in the sample) was largely confirmed by Geršl and Seidler (2012), who also concluded that the credit level in Slovenia was excessive. One could expect particularly countries that saw overshooting to adjust downward to a more solid relationship between credit ratios and GDP per capita in a crisis-driven deleveraging period.

Indeed, in most CESEE countries, private sector credit ratios declined in the observation period, while GDP per capita levels increased thanks to the economic recovery in recent years (see chart 1). Interestingly, credit ratios increased in only three countries – the Czech Republic, Poland and Slovakia – over the period of interest. Against this background and depending on the position of each individual country at the start of the GFC, i.e. below or above the level justified by fundamentals, three research questions arise: Have countries with credit levels below their fundamental level seen a widening of the gap resulting in an even more pronounced undershooting? Have countries with credit levels above their fundamental level seen a downward adjustment toward the fundamental levels and in how far is this process complete? And finally, does our approach yield any signs of overshooting in countries in which credit levels have been rising recently?

[Chart 1 about here]

In addition to assessing credit levels, we also report whether credit *growth* rates have moved toward fundamentally justified rates, whether they appear still too low after the deleveraging period or whether they may already be too high in countries that have seen a more dynamic credit recovery. There are several papers that have already examined short- and long-run determinants of credit growth and/or have come up with estimates of fundamental credit growth rates in CESEE (e.g. Eller et al., 2010; Stojanović and Stojanović, 2015; Jovanovic et al., 2017). At the same time, this stream of literature has switched from the previously dominating out-of-sample to an in-sample approach, arguing that the transition-specific undershooting of the early 1990s might have already been washed out given longer available time series.[5] It is worth noting that fundamentals-driven growth rates of the credit-to-GDP ratio are more difficult to interpret for policymakers, and our results thus focus primarily on fundamental levels. However, we acknowledge also the strand of literature looking at credit growth rates and augment the respective setups by including foreign variables in an econometrically sound way. In addition to that, the dynamic setup provides us with some speed-of-adjustment outcomes, which can be very informative for the static model.

The contribution of our paper to the existing literature is threefold. First, when we look at our main variable of interest – private sector credit –, we do not only include domestic credit but also direct cross-border credit. Direct cross-border credit has emerged as an important (corporate) funding source in CESEE.[6] While early work examining the role of direct cross-border credit found support for a complementary effect of domestic credit and direct cross-border credit (Puhr et al., 2009), more recent papers emphasized the substitution effect (Bussière et al., 2017; Temesvary, 2018) from a lender perspective. In the watershed year 2008, about one-fifth of the total private sector credit stock consisted of direct cross-border credit across the eleven CESEE EU Member States (CESEE-11) on average. While such a composition of credit is not a unique CESEE phenomenon, heterogeneity among countries turns out to be considerable as the share of direct cross-border credit ranged from just 12% of GDP in Slovakia to more than about 30% in Bulgaria and 35% in Croatia (see also chart 2).

[Chart 2 about here]

Second, in terms of credit determinants, we also include foreign explanatory variables besides domestic ones. There are several economic rationales for including them. Foreign variables control for the strong openness of the region with regard to trade and banking (Fadejeva et al., 2017) and the likely importance of global supply push factors in determining credit (Bruno and Shin, 2015). In addition, foreign variables should matter for deriving fundamental credit values as we also take cross-border credit into account. Lastly, they also need to be included from an econometric perspective, i.e. to correct for cross-sectional dependence and thus to avoid biased statistical inference. To the best of our knowledge, related papers have not yet tested for cross-sectional dependence and asked whether foreign factors can influence fundamental credit levels. For this purpose, we look at different foreign variables and study the impact of foreign factors relative to domestic factors.

Third, we opt for a rich panel regression framework as our econometric methodology, which encompasses a variety of tests to identify which estimator suits the investigated data best. Compared to fundamental benchmarks often derived in a country-specific context (e.g. filtering approaches that resort to the time series properties of the credit-to-GDP ratio in a particular country, see Drehmann and Yetman, 2018), the panel

[5] Recall that the out-of-sample approach (as pioneered by Égert et al., 2006) requires long-run parameter homogeneity between benchmark and CESEE countries and a stable structural relationship in the benchmark countries over time.
[6] Another financing source, at least for corporates, could be bond financing. Our data capture bonds held by the domestic banking sector and bonds held by foreign investors, but not bonds held by the domestic nonbank sector. However, according to financial accounts data, bond financing is not yet considerably relevant in the CESEE countries under review.

framework is not as susceptible to “inflated” long-term trends[7] but allows for more degrees of freedom in the estimations and for studying different adjustment paths across (comparable) countries based on the same framework (Geršl and Seidler, 2015). We investigate both a static and a complementary dynamic panel model. The former is used to calculate credit levels determined by fundamentals. The latter allows us to disentangle the short- and long-term effects of each credit determinant and to study the speed of adjustment of actual credit levels to fundamental levels. Previous papers have usually relied on a similar static panel approach using a fixed effect estimator but have not accounted for cross-sectional dependence, possible endogeneity bias and heterogeneity across the sample countries. We provide a full spectrum of results dealing with these key econometric issues to avoid biased statistical inference. Moreover, we analyze the role of different possible fundamentals and provide an extensive set of robustness checks, also in this way contributing to the literature.

The remainder of the paper is structured as follows: Section 2 describes the details of the dataset used in the estimations. Section 3 implements pre-estimation diagnostic tests to decide which econometric setup fits the investigated dataset best. Section 4 presents the details of the econometric framework and explains how we are coming up with credit levels determined by fundamentals. Section 5 presents the estimation results, discusses the importance of different credit determinants and shows the gaps between actual and fundamental credit levels. Section 6 summarizes and concludes.

2. VARIABLE SELECTION AND DATA CHARACTERISTICS

Table A1 in the annex gives a detailed overview of data sources and definitions, while table A2 provides the summary statistics for our core set of variables. Our main variable of interest is the total private sector credit-to-GDP ratio[8]. While previous work focused only on domestic bank credit to the private sector, we adopt a more comprehensive definition of credit that includes both domestic and cross-border credit. Direct cross-border credit has emerged as an important (corporate) funding source in CESEE and constitutes a close substitute for domestic bank credit, which is why we included corresponding data in our calculations. In line with Comunale et al. (2018), we approximate cross-border credit using international investment position (IIP) data, more specifically data on the external debt of the nonbank private sector, excluding intercompany loans and trade credits.[9] Domestic credit refers to domestic banks’ credit to the resident nonbank private sector and is obtained from national central banks, while IIP data is drawn from national central banks’ and IMF statistics. In the remainder of this study, we will refer to the aggregate of these two debt components as “total credit”, although this term differs from the even wider definition of total credit introduced by the BIS (see BIS, 2018).

For the estimations we apply an in-sample approach, so our sample covers the CESEE-11 (Bulgaria, Czech Republic, Estonia, Croatia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia)[10] and our data set contains quarterly observations from mid-1990s until end-2016. But given that data for cross-border credit

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[7] The extraordinary pre-GFC credit boom period, together with comparatively short time series, is still likely leading to upward-biased long-term trends of credit series in CESEE countries.
[8] When calculating the ratio, we use GDP on an annual basis, i.e. the four quarter moving sums, and hence seasonality is not an issue.
[9] Even though intercompany loans are quite sizeable in the investigated CESEE countries, we prefer a narrow definition of cross-border credit as, among others, intercompany loans capture both debt and equity instruments. Moreover, narrow and broad definitions of cross-border credit show a rather similar degree of variation over time. In a robustness check we used the broader classification and the results remained qualitatively unchanged (available upon request).
[10] Data series for EU (potential) candidate countries as well as for Russia and Ukraine have also been accessed but are in most cases too incomplete for the sake of our analysis.

is in a few countries only available since the late 1990s or early 2000s, we run our estimations based on an unbalanced panel.

When it comes to selecting specific determinants of private sector credit in CESEE, we could derive them from theoretical models. However, we have not been able to find a comprehensive theoretical framework studying the determinants of total private sector credit. For the determinants of credit to households, instead, a life-cycle general equilibrium model has been provided by Rubaszek and Serwa (2014). They include as determinants the lending-to-deposit spread, individual income uncertainty and persistence, GDP per capita or disposable income per capita, the real interest rate, the unemployment rate, and a house price index. A corresponding empirical investigation in the case of CESEE countries is, however, still restricted by relatively short time series, especially for household loans.[11] Therefore, we include as a first group domestic variables which have been frequently used in already existing investigations (e.g. more recently in Buncic and Melecky, 2014, or Alessi and Detken, 2018): GDP per capita[12], domestic banks' credit to the general government (% of GDP), the producer price index (PPI) inflation rate, the lending rate and the interest rate spread (lending over deposit rate)[13]. Égert et al. (2006) give an elaborated overview of arguments for this kind of variable selection.

As a second group of credit determinants, we add foreign variables as already motivated in the introduction. In the baseline, we account on the one hand for the role of the global real business cycle, proxied by the seasonally adjusted global GDP.[14] On the other hand, we pay attention to spillovers from credit cycles in the most important trading partners, calculated as the trade-weighted average of trading partners' total private sector credit-to-GDP ratios. Trade weights are from the European Commission Price and Competitiveness database. We do not use financial weights for three main reasons: First, they would be very much correlated with our credit series; second, there is no consensus on the best way to compute such weights (see Kearns and Patel, 2016). Third, for the latter reason, the computation of different types of financial weights for CESEE countries would require a separate paper to be correctly done, especially at a quarterly frequency, given that these types of weights are not provided in any public database. In a robustness check we also replace these regressors with the volatility index (VIX) of the Chicago Board Options Exchange (CBOE) and a trade-weighted measure of GDP growth.[15] These alternative variables are also less prone to multicollinearity issues (see annex tables A5-A6 compared to tables A3-A4 for the setup with baseline global factors). We decided, however, to keep in the baseline world GDP and credit spillovers, rather than this alternative setup, for two reasons. Firstly, we are investigating credit variables and the main channel through which we allow for cross-border spillovers is in the measure of credit flows. Having a country-specific variable as exposure to financial conditions abroad becomes crucial. Moreover, the inclusion of global GDP as a common factor indicates a global cycle which covers also possible global trade developments. Secondly, in an econometric sense, in the dynamic factor model literature (see Pesaran and Tosetti, 2011, among others), the most common way to deal with weak cross-sectional dependence is imposing directly the country-specific averages of the dependent

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[11] Respective preliminary results for household loans (available upon request) are very much in line with the results presented further below for total private sector credit.
[12] GDP per capita expressed in PPS (USD based) is drawn from the IMF World Economic Outlook database. The data is available only on a yearly basis and, hence, we interpolated the data linearly from annual to quarterly frequency.
[13] Deposit and lending rates are obtained from the IMF International Financial Statistics. Gaps in the data series are either filled by applying interpolation by using short-term (for deposit rates) and long-term (for lending rates) interest rates from the same data source or by making use of interest rate data provided by national central banks.
[14] This is the sum of the nominal GDP of 42 countries in USD million from IMF International Financial Statistics.
[15] Similarly, the VIX and weighted averages of credit have been used in Cerutti et al. (2019) to account for the importance of a "global financial cycle" for credit and capital flows. Alessi and Detken (2018) also include the VIX and a measure of global credit to analyze possible early warning indicators for banking crises.

variable as controls. At the end it is also good to recall that the resulting fundamental levels and gaps are very much alike between the two specifications.

3. PRE-ESTIMATION DIAGNOSTIC TESTS

To apply the best possible estimator and setup given our dataset, we perform in a first step various regular diagnostic tests. We test for cross-sectional dependence (CSD),[16] non-stationarity and cointegration. We start applying the test of Pesaran (2004) for cross-sectional independence, which is strongly rejected for the equation without the external variables. Pesaran's test statistic is reduced when our proxies for global factors and spillovers are added to the model (table 1 – baseline specification), which we can see as a contribution in correcting for CSD (see section 5).

[Table 1 about here]

Hence, we found that the panel experiences CSD. Therefore, in order to properly test for the presence of unit roots, we use a second-generation panel unit root test by Pesaran (2007). The null hypothesis assumes that all series across countries are non-stationary. Our panel cannot reject non-stationarity for some of the series (including the dependent variable) or even it does fully accept the null of non-stationarity in some cases (as for global GDP or the interest rate spread).

[Table 2 about here]

Lastly, we apply the cointegration test by Pedroni (2004),[17] which allows performing it in the case of heterogeneous panels, i.e. the cointegrating vector and short-term dynamics can be different from country to country. The test's null hypothesis is no cointegration. We can always reject no cointegration at 5% in the group mean statistics for the setup with external variables (our baseline) and at 10% in the one without them.

[Table 3 about here]

4. ECONOMETRIC FRAMEWORK

4.1. The static model

Based on the pre-estimation diagnostic tests presented in the previous section, we implement a static panel framework that allows for cointegration, heterogeneous coefficients and CSD. We would like to keep as much heterogeneity as possible in order to account for the specific characteristics of the countries, not only in the fixed effects but also in the slope coefficients, which will be crucial in our calculation of fundamental values. Given that, the best possible choice for the estimator in this case (as shown in Pedroni, 2001) is the Group Mean-Fully Modified OLS (GM-FMOLS), whose characteristics are fully described below. In addition, foreign variables (global factors and cross-country credit spillovers) are included to correct for CSD. Not correcting for CSD yields misleading inference and biased estimates (Pesaran and Tosetti, 2011).

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[16] This is when the idiosyncratic errors are cross-sectionally correlated.

[17] As reported by Wagner and Hlouskova (2010), the Pedroni test applying the Augmented Dickey Fuller principle performs best; all the other tests (Westerlund's included) have very low power in many circumstances. The authors conclude that in a situation where the null hypothesis of no cointegration is important, the Pedroni test is the best choice. For a small panel, Pedroni (2004) noted that group RHO-stat could be better because less distortive and more conservative than the other possible alternatives.

The FMOLS is a semi-parametric correction of the OLS estimator which eliminates the second-order bias induced by the endogeneity of the regressors (Phillips and Hansen, 1990). In our panel we applied the group mean (GM) version of this estimator to keep as much heterogeneity as possible and to correct for cointegration.[18] This is built as an (unweighted) average of the within-FMOLS estimator over the cross-sectional dimension: $\hat{\beta}_{gm-fmols} = \left(\frac{1}{N}\right) * \sum_{i=1}^{N} \hat{\beta}_{fmols,i}$. The structure follows a cointegrated system as explained by Pedroni (2000, 2001):[19]

$$y_{it} = \alpha_i + x'_{it}\beta + u_{it} \tag{1}$$

$$x_{it} = x_{i,t-1} + \varepsilon_{it} \tag{2}$$

where α_i are the fixed effects, x_{it} is a k x 1 vector of cointegrated regressors (in our case all the possible fundamentals of the credit ratios), β is a k x 1 vector of slope parameters and the vector error process $(u_{it}, \varepsilon'_{it})$' is stationary. Its asymptotic covariance matrix Ω_i can be further decomposed:

$$\Omega_i \equiv \begin{bmatrix} \Omega_{u_i} & \Omega_{u\varepsilon_i} \\ \Omega_{\varepsilon u_i} & \Omega_{\varepsilon_i} \end{bmatrix} = \Omega_i^0 + \Gamma_i + \Gamma'_i \tag{3}$$

where Ω_{u_i} and Ω_{ε_i} are the long-run covariance of u_{it} and ε_{it}; $\Omega_{\varepsilon u_i}$ gives the covariance between u_{it} and ε_{it} and captures the endogenous feedback effect between the dependent variable y_{it} of which u_{it} is the error term and the regressors x_{it}, whose error term is represented by vector ε_{it}. Eventually, Ω_i^0 is the covariance matrix at time t and $\Gamma_i = \begin{bmatrix} \Gamma_{u_i} & \Gamma_{u\varepsilon_i} \\ \Gamma_{\varepsilon u_i} & \Gamma_{\varepsilon_i} \end{bmatrix}$ is a weighted sum of auto-covariances. Accordingly, the GM-FMOLS is an estimator that eliminates this endogeneity bias between the dependent variable and regressors in the following way:

$$\hat{\beta}_{gm-fmols} = \left(\frac{1}{N}\right) \sum_{i=1}^{N} [\sum_{t=1}^{T} (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)']^{-1} (\sum_{t=1}^{T} (x_{it} - \bar{x}_i) y_{it}^* - T\hat{\gamma}_i), \tag{4}$$

where $y_{it}^* = (y_{it} - \bar{y}_i) - {\hat{\Omega}_{\varepsilon u_i}}/{\hat{\Omega}_{\varepsilon_i}} \Delta x_{it}$ and $\hat{\gamma}_i = \hat{\Gamma}_{\varepsilon u_i} + \hat{\Omega}^0_{\varepsilon u_i} - {\hat{\Omega}_{\varepsilon u_i}}/{\hat{\Omega}_{\varepsilon_i}} (\hat{\Gamma}_{\varepsilon_i} + \hat{\Omega}^0_{\varepsilon_i})$ and $\bar{x}_i$ and $\bar{y}_i$ are the cross-sectional simple averages. Therefore y_{it}^* are the y_{it} adjusted for the covariance between error terms and x_{it}; $T\hat{\gamma}_i$ is the adjustment for the constant (Roudet et al., 2007).

As a robustness check, we estimate the credit levels determined by fundamentals by using the regular fixed effects (FE) estimator with Driscoll-Kraay correction[20] or, as alternative to the latter, the introduction of global factors and spillovers.[21] In order to check for the importance of having heterogeneous coefficients, we also perform a further check by using the Mean Group (MG) estimator as in Pesaran and Smith (1995), instead of the GM-FMOLS, with and without external variables. The MG, however, does not correct for possible cointegration.

As a result, the equations for the external variables-augmented model will be estimated with GM-FMOLS as the preferred method. The specific equation, coming from the cointegrated systems, is as the following:[22]

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[18] For a more detailed discussion of this estimator and its properties see the appendix in Comunale (2017).
[19] A similar cointegrated approach has been applied for the calculation of equilibria and misalignments in Comunale (2017) for the REER, again following Pedroni (2000).
[20] Driscoll-Kraay correction also provides robust standard errors.
[21] The Driscoll-Kraay correction has only implications for the significance of coefficients, it does, however, not fully eliminate CSD as it does not explicitly account for the role of possible other factors which imply CSD.
[22] The number of lags has been selected based on the Schwarz's Bayesian information criterion (SBIC). Including a second lag gives very robust results for all the used static panel estimators (FE, MG or GM-FMOLS).

$$\left(\frac{credit}{GDP}\right)_{i,t} = \beta_{1i}X_{i,t-1} + \beta_{2i}G_{t-1} + \beta_{3i}S_{i,t-1} + \mu_i + \varepsilon_{i,t} \quad (5)$$

where $\beta = (\beta_{1i}, \beta_{2i}, \beta_{3i})'$ is the cointegrating vector of slope parameters. X is a vector of cointegrated series consisting of the domestic (CESEE countries') fundamentals described in section 2. Furthermore, we add two foreign variables (also as cointegrated regressors): G is the common global factor taken as the seasonally adjusted global GDP and S is the country-specific, time-varying variable for spillovers in total credit. Lastly, μ_i is the country-fixed effect or the constant.[23] The error terms $\varepsilon_{i,t}$ are not assumed to be cross-sectionally independent.[24]

4.2. The dynamic model

We find a strong persistence in the dependent variable (table 2), suggesting the use of a lagged dependent variable (and so to have a dynamic panel setup) which, however, is quite hard to defend to be a fundamental determinant. Moreover, it would likely "absorb" the importance of the other regressors. This is also the rationale behind a similar approach looking at the real effective exchange rate (REER) or current account equilibria and misalignments. Both the REER and current accounts are highly persistent too. Respective IMF and ECB assessments and related published papers used the lagged dependent variables in levels in a static setup (IMF: Lee et al., 2008, Ricci et al., 2013, Mano et al., 2019 and ECB: Fidora et al., 2017).[25] If we chose to have a dynamic model, we would end up with fundamental growth rates, rather than levels, because of the econometric characteristics of our variables (see below). And these growth rates of the credit-to-GDP ratio are more difficult to interpret for policymakers. Nevertheless, we want to compare our setup that accounts also for foreign variables to that strand of literature looking at equilibrium credit growth rates. In addition, the dynamic setup provides us with the speed-of-adjustment result, which can be very informative for the static model.

As mentioned above, if the dynamic setup is used, the autoregressive distributed lag (ARDL) model, which would have levels of the dependent variable on both sides, cannot be estimated as such. This is due to some econometric characteristics of our variables, such as unit roots and cointegration (see the test results in section 3). For the dynamic setup, in a panel regression model with lagged endogenous variables, the FE estimator has been proven to be inconsistent for finite T (Nickell, 1981). The bias in the dynamic FE estimator is only almost negligible in the case of large enough T (Roodman, 2006). We have an unbalanced panel with data from 1995Q1 in the best case, implying that T could be not large enough. Furthermore, we may also have a problem of endogeneity between the dependent variable and its lag and among explanatory variables such as between government credit and interest rates. The solution to this issue is usually found in IV-GMM estimators. However, the moment conditions of the GMM estimators are only valid if there is no serial correlation in the idiosyncratic errors (i.e. no CSD) and the slope coefficients are invariant across the individuals (i.e. homogeneous coefficients). In addition, IV-GMM cannot disentangle the effects in the short and long run. One possible way to deal with these issues is to reparametrize the ARDL into an error correction model (see below). Doing so, credit in differences is taken as dependent variable, but in this case the

[23] The constant is an unweighted average of country-specific constants in the GM-FMOLS or the MG, which replace the country fixed-effects in the FE estimations. Some country-specific dummies cannot be included in the GM-FMOLS or the MG because of perfect collinearity.

[24] Normally the errors are taken as i.i.d. across i and t. In our case for each i, the errors are independently and identically distributed (i.i.d.) error terms but we do not assume independence anymore for all t. That opens the possibility of having cross-sectionally correlated idiosyncratic errors (due to common factors or cross-country spillovers). The assumption of stationarity remains, as well as zero mean and variance σ^2. We also assume that underlying error processes are symmetrically distributed. For a deeper understanding of the (weak and strong) cross-sectional dependence and the error structure, see Pesaran (2004).

[25] If a dynamic-like framework is reported, this is analyzed only for the robustness of the coefficients. This setup is not used for the calculation of equilibria/fundamental variables. See for instance Lee et al. (2008), which however keeps the coefficients homogeneous and does not correct the panel for the presence of unit roots, cointegration or cross-sectional dependence.

determinants of growth rates are studied from that point on and not those of the levels anymore. Given that motivation, we perform at this point the proper reparameterization from an ARDL (equation 6) to an ECM (equation 7). This is also applied in Comunale (2017) and Jovanovic et al. (2017). Note that he latter do not correct for CSD, while the former does.

The number of lags has again been selected based on the Schwarz's Bayesian information criterion (SBIC). This method has been proven giving more accurate outcomes for quarterly data series also in case of small samples for PECMs (Ivanov and Kilian, 2005). We implemented this criterion country-by-country. The resulting number of lags for all the countries is one and so we applied in our setups only one lag for the overall panel. This also keeps higher degrees of freedom for the estimations.[26,27]

Recalling an A(R)DL(1,1) model for the baseline:

$$\left(\frac{credit}{GDP}\right)_{i,t} = \alpha_i + \beta_i \left(\frac{credit}{GDP}\right)_{i,t-1} + \zeta_{1i} X_{i,t} + \zeta_{2i} X_{2i,t-1} + \lambda_{1i} G_t + \lambda_{2i} G_{t-1} + \eta_{1i} S_{1i,t} + \eta_{2i} S_{2i,t-1} + \varepsilon_{i,t} \quad (6)$$

we take the first difference of $[\left(\frac{credit}{GDP}\right)_{i,t} - \left(\frac{credit}{GDP}\right)_{i,t-1}]$ as dependent variable ($\Delta \left(\frac{credit}{GDP}\right)_{i,t}$) and we use the equation for $\left(\frac{credit}{GDP}\right)_{i,t-1}$ in the expression above on the right-hand side as well. Reshuffling the terms, we obtain the PECM as the following:

$$\Delta \left(\frac{credit}{GDP}\right)_{i,t} = \phi_i \left(\left(\frac{credit}{GDP}\right)_{i,t-1} - \theta_{0i} - \theta_{1i} X_{i,t-1} - \theta_{2i} G_{t-1} - \theta_{3i} S_{i,t-1} \right) + \zeta_{1i} \Delta X_{i,t} + \lambda_{1i} \Delta G_t + \eta_{1i} \Delta S_{i,t} + \mu_i + \varepsilon_{i,t} \quad (7)$$

where ϕ_i is basically $(\beta_i - 1)$, i.e. the error-correcting speed of adjustment term. This parameter is expected to be significantly negative and signals that the variables show a return to a long-run equilibrium (Blackburne and Frank, 2007). Moreover θ_{0i} is $(\alpha_i/(1-\alpha_i))$, θ_{1i} is $(\zeta_{1i} + \zeta_{2i})/(1-\alpha_i)$, θ_{2i} is $(\lambda_{1i} + \lambda_{2i})/(1-\alpha_i)$ and θ_{3i} is $(\eta_{1i} + \eta_{2i})/(1-\alpha_i)$. The vector $\theta_{.i}$ basically contains the long-run relationships between the variables. In the short run the coefficients are ζ_{1i}, λ_{1i} and η_{1i}.

The regressors and global factors and spillovers are as described in the static setup. In this case, the estimators we can use are the Mean Group (MG) of Pesaran and Smith (1995) as well as the Dynamic Fixed Effects (DFE) and the Pooled Mean Group (PMG) estimators of Pesaran, Shin and Smith (1999). In the MG case, all the coefficients in the short and long run are heterogeneous across individuals and then averaged. In the DFE, they are taken as homogeneous but the constant. The PMG estimator allows only the short-run coefficients to be heterogeneous (it has been applied for instance in Geršl and Seidler, 2015; Stojanović and Stojanović, 2015 and Jovanovic et al., 2017). We believe that in case of CESEE countries, both short- and long-term coefficients may be different across countries, so in theory the MG estimator should be preferred. We used a Hausman test as in Blackburne and Frank (2007) in the setup without external variables and found that the difference in coefficients between the MG and DFE estimators is not systematic.[28] Moreover, in some specifications with more regressors (including our baseline with external variables) we could not compute the MG or the PMG estimators given the limited number of observations. For these reasons, we apply the DFE estimator as our first choice for the dynamic setup.

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[26] The Akaike (AIC) selection criterion also confirms that only one lag should be used.
[27] Only in a robustness check we use an annual lag (i.e. the fourth lag). This corresponds to the year-on-year differences for the PECM in the short-run relationship.
[28] Excluding external variables, the calculated Hausman statistic is distributed as a chi(2) and the probability is Prob>chi2=1.000, so the null hypothesis of unsystematic differences in coefficients between the DFE and MG estimators cannot be rejected.

As stressed in section 3, adding our proxies for global factors and credit spillovers already contributes in correcting for CSD. To fully correct for CSD it would be necessary to account for all the possible cross-country spillovers, which would substantially reduce our degrees of freedom. Another possible way to correct fully for CSD in the dynamic setup is applying a dynamic factor model. However, first of all, in this case we would have the dependent variable in levels and not in first differences as in the ECM and, second, we are not able to calculate the equilibria in the dynamic factor model setup. This is because the global factors (correcting for strong CSD) and spillovers (for weak CSD) are taken there as "unobserved" factors. This means that either we don't have a concrete observed variable from which we can build the equilibria (see Eberhardt and Teal, 2010 or Eberhardt, 2012 for the Augmented Mean Group (AMG) estimator) or these factors are treated as a nuisance as in the case of the Common Correlated Effects Mean Group (CCEMG) estimator (Pesaran and Tosetti, 2011). However, the CCEMG takes the spillovers variables just as controls without an explicit economic underpinning, while in our case spillovers and global factors are deemed as important explanatory variables in analyzing credit developments. Moreover, the spillovers as built in Pesaran and Tosetti (2011) are the weighted averages for every variable there included; in that case we could still have an issue with a relatively small T panel.[29]

4.3. Constructing credit levels and growth rates determined by fundamentals

In this subsection we describe step by step how fundamentals-based credit levels are calculated. The main description concerns the levels, but the same structure applies for the growth rates as well.

We mainly follow the approach by the IMF in the Consultative Group on Exchange Rate Issues (CGER) and this is normally used in calculating equilibria for the REER (Ricci et al., 2013; Comunale, 2017), the current account (Lee et al., 2008; Comunale, 2018) and credit growth (Jovanovic et al., 2017).[30]

We firstly estimate the coefficients concerning the fundamentals of the credit-to-GDP ratios (see section 2) to have the fundamentally-determined values.[31] These are then calculated as the sum of the estimated coefficients from the equations multiplied by the correspondent HP-filtered values of the fundamentals $\tilde{F}_{i,t}^{HP}$.[32] Fundamental determinants of credit may themselves be subject to short-run shocks, potentially creating in certain periods an incorrect impression that actual credit is overshooting, although a widening gap is actually due to lower fundamental levels of credit which are of short-run nature due to adverse shocks. Using actual data and not filtered series would leave only the residuals and this measure of equilibrium is very much dependent on if and how much the determinants are themselves misaligned. This has been stressed in the literature on "BEER"-like methods, see Comunale (2017) reporting Schnatz (2011) and Clark and MacDonald (1999, 2004). The filtering of the fundamental variables takes into account their possible misalignments leaving only the permanent part of them. Hence, we use a filter to obtain smoothed series for the economic fundamentals to generate these long-run trend equilibrium values. We apply here a one-sided HP filter to

[29] For details on the different approaches, i.e. CCEMG by Pesaran and Tosetti (2011) and AMG as in Eberhardt (2012), see the online appendix of Comunale (2017).
[30] We decided to apply the CGER methodology instead of the new External Balance Assessment, EBA (Phillips et al., 2013). This is because the EBA methodology include some desirable (albeit ad-hoc for each country) values for the policy variables. Hence, the resulting values would be driven by subjective valuations of these variables, which may in some cases and countries seriously complicate the analysis.
[31] In the CGER (and related approaches) the coefficients used to build the fundamentally-determined measures are *not* based on already HP-filtered values in equation 5 for the fundamentals. The idea is to have the actual series of fundamentals speaking in the coefficients (so also all the cross-countries differences will fully emerge), then to take for each time and for each country the filtered series to get the fundamental levels. Basically, you have an analysis of the determinants of actual series (informative by its own) and then you build the norms.
[32] The comparison between using HP-filtered values and when other filtering techniques are applied has been shown in Comunale (2017) for the REER case. The results are very robust in that case.

extract long-term trends from credit determinants.[33] We prefer to use filtered values instead of projected values (as it is normally done in the case of current account equilibria, for instance) for two main reasons. First, we do not have projections for all the variables included, as for the global factors for example. Secondly, the projected values, especially in this region, are often widely updated and revised as time progresses and may signal expectations rather than long-run values of the fundamentals. This is the method applied for the REER in the IMF's CGER.

Therefore, by using this methodology, we have country-specific time-varying measures. Recalling the coefficients from equation (7), the vector $\theta_{.i}$ contains the long-run relationships between the variables.

$$\left(\frac{credit}{GDP}\right)_{i,t}^{fund.} = \hat{\beta}_i' \tilde{F}_{i,t}^{HP} = \sum_j^J \hat{\beta}_i \tilde{F}_{i,t}^{HP} \tag{8}$$

In the equation above, $\hat{\beta}_i'$ represents any coefficient in the static equation 5, which here for simplicity might refer to global or spillover effects as well (the complete set of fundamental factors are then added to vector F, i.e. for X, G and S in equation 7). Very similarly, we can calculate the fundamental levels in first differences (i.e. quarter-on-quarter values). Then these values are transformed into year-on-year differences. The products of coefficients and filtered factors (J=7 in the baseline) are then added together over time for each country.

$$\Delta\left(\frac{credit}{GDP}\right)_{i,t}^{fund.} = \widehat{\theta_{.\imath}}^{LR'}{}_i\tilde{F}_{i,t}^{HP} - \widehat{\theta_{.\imath}}^{LR'}{}_i\tilde{F}_{i,t-4}^{HP} = \sum_j^J \widehat{\theta_{.\imath}\beta}^{LR}{}_i\tilde{F}_{i,t}^{HP} - \sum_j^J \widehat{\theta_{.\imath}}^{LR}{}_i\tilde{F}_{i,t-4}^{HP} \tag{9}$$

4.4. Calculation of differences in credit ratios and determinants contribution

We also computed the country-specific contribution of each factor between 2000 and 2007 and then from 2008 to 2016 to changes in the credit ratios (see equations (10) and (11)).

$$\Delta\left(\frac{Credit}{GDP}\right)_i^{2007q4-2000q1} = \left(\frac{Credit}{GDP}\right)_i^{2007q4} - \left(\frac{Credit}{GDP}\right)_i^{2000q1} \tag{10}$$

$$\Delta\left(\frac{Credit}{GDP}\right)_i^{2016q4-2008q1} = \left(\frac{Credit}{GDP}\right)_i^{2016q4} - \left(\frac{Credit}{GDP}\right)_i^{2008q1} \tag{11}$$

The contributions of different explanatory variables are calculated as follows:

$$\Delta F_i^{2007q4-2000q1} * \beta_i \tag{12}$$

$$\Delta F_i^{2016q4-2008q1} * \beta_i \tag{13}$$

Where $\Delta F_i^{2007q4-2000q1} = F_i^{2007q4} - F_i^{2000q1}$ and $\Delta F_i^{2016q4-2008q1} = F_i^{2016q4} - F_i^{2008q1}$. F represents all the fundamental determinants (i.e. both domestic and foreign ones), constant not included, and β_i are the coefficients from the preferred static model (GM-FMOLS) as in equation (5). Given that the available time series for CESEE economies are still limited and this affects the degrees of freedom, we cannot perform the equation separately for the two subperiods. However, we use the coefficients for the whole set of data. This should reflect a more medium-to-long-run perspective of the role of the fundamentals, in line with our objective.

[33] The smoothing parameter lambda is set to 1,600 (see Hodrick and Prescott, 1997) as normally suggested for quarterly frequency data.

5. ESTIMATION RESULTS

Based on the modeling framework described in the previous sections, we present now the main results. On the one hand, we focus on the role of different credit determinants, backed by a broad robustness analysis. On the other hand, we illustrate the resulting fundamental credit levels and discuss the deviation of actual levels from this benchmark. Results are always shown for total private sector credit.[34]

5.1. Importance of different variables in explaining credit levels

Static panel estimation results for total private sector credit in the 11 CESEE EU countries based on estimates of equation (5) are shown in table 4. Column 1 shows the estimates using the baseline GM-FMOLS estimator. Evidently, an increase in the credit-to-GDP ratio in a given quarter is associated with larger GDP per capita levels, higher lending rates, a lower interest rate spread, higher global GDP as well as more intense credit dynamics abroad in the preceding quarter. The inflation rate and government credit do not have a statistically significant impact.

A few results deserve some more discussion. First, the large positive coefficient for GDP per capita (often very close to 1, in a few cases even larger than 1) suggests an economically very significant income elasticity of credit, which is not so much surprising for catching-up economies: a doubling of GDP per capita would be associated with a credit-to-GDP ratio which also doubles or even more than doubles. Second, the positive sign of the coefficient for the lending rate corroborates existing empirical evidence (see the discussion in Eller et al., 2010) and likely reflects the stable positive correlation of credit dynamics and interest rates over the past two decades in the region: credit growth was large in a period with comparatively high interest rates (before the GFC), while after the GFC subdued lending coincides with a low interest rate environment (as also pointed out in Zumer et al., 2009). Third, the result for the interest rate spread variable would suggest that the larger the lending rate compared to the deposit rate, the smaller the credit-to-GDP ratio. In pre-GFC studies (e.g. Égert et al., 2006) this variable was included to account for financial liberalization and/or bank profitability, whereby a higher spread was assumed to signal easier funding of banks' credit supply. However, since the GFC, with deposit rates gradually approaching zero levels, the spread variable has widened considerably and now apparently captures something else than originally intended, e.g. the low post-GFC interest environment, nonstandard monetary policies or just deleveraging. With this different interpretation in mind we retain the spread variable in our baseline set of fundamentals (also endorsed by its robust impact across a variety of specifications).

Chart 3 offers another view for the importance of different credit determinants over time, i.e. the country-specific contribution of the change in credit determinants to changes in actual credit ratios, calculated separately for two different subperiods (before/after the GFC; for the detailed calculations see section 4.4). As already suggested by the sizable coefficient in table 4, we can see that GDP per capita explains a lion's share of the variation in credit ratios (this is in line with the literature, see for instance Jovanovic et al., 2017). This is especially true for the pre-GFC period. In the post-GFC period, the interest spread – in line with the interpretation offered in the previous paragraph – becomes very important, in several cases even more important than GDP per capita, and has clearly contributed to the downward adjustment of credit ratios. Moreover, the lending rate has a negative contribution in chart 3 especially in the post-GFC period (consistent

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[34] These results are compared to the results based only on domestic credit in Comunale et al. (2018).

with the overall decline of the lending rate during this period and the positive coefficient in table 4). Finally, the (positive) contribution of foreign variables to changes in credit ratios is rather modest compared to that of the just mentioned domestic variables and it does not considerably change over time.[35] However, this does not imply that the inclusion of foreign variables is meaningless. Recall that they correct for CSD in the estimations and ensure that the estimated coefficients used for the calculation of fundamental levels are not biased.

[Table 4 about here]

[Chart 3 about here]

5.1.1. Comparison of results across different eligible estimators

Taking properly into account cross-country heterogeneity and correcting for cointegration (as we try to do by applying the GM-FMOLS estimator) can obviously influence the coefficients and improve their accuracy. Comparing the estimation results based on the preferred GM-FMOLS estimator with those based on the two alternatives (see the last two columns in table 4), the size and statistical significance of the estimated coefficients does only in a few cases change considerably across the specifications. Most notably, the lending rate does not any longer have a statistically significant impact in the case of the MG estimator; the same holds true for global GDP in the case of both alternatives. Another noteworthy difference comes from the fact that the coefficient of GDP per capita increases relatively strongly when we use the FE estimator – the most widely used alternative in the literature.

Recall that the GM-FMOLS and MG estimators are very similar in their construction. The only difference is that the former uses FMOLS coefficients and then averages them, while the MG does the same with OLS. If the modification of the OLS (corrected into an FMOLS) due to cointegration is limited, coefficients estimated by GM-FMOLS and MG may be similar in magnitude. On the other hand, the statistical significance of the coefficients may also be affected depending on the method and the correction applied (as shown in table 4 indeed). The FE estimator instead simply takes the countries (and therefore the coefficients) as homogeneous and does not apply any modification for cointegration of any kind.

5.1.2. Impact of different sets of credit determinants

As stressed in section 2, we rely for the selection of credit determinants on already existing empirical investigations and augment the set of usually used domestic variables with some meaningful external variables. To provide a sense of robustness of our selection of credit determinants in the baseline, we compare it with a series of alternative specifications[36] in table 5.

Let us focus in a first step on what happens if the set of external credit determinants is modified. If we use *alternative external variables*, i.e. as a global risk indicator the VIX and as a measure for cross-country spillovers a trade-weighted average of real GDP growth in the main trading partners (column 3), we can notice that the estimated coefficients for the external variables are still positive but for the VIX the size of the

[35] Eller et al. (2016) found that global factors have become more important in the post-crisis period when it comes to explaining the volatility of gross capital inflows in CESEE (including also Russia and Turkey). The authors interpret this finding with a likely increased role of unconventional monetary policies in the US (driving the global co-movement of financial variables). In our panel, however, we do not find this asymmetry and it is probably because controlling for spreads and lending rates (and government credit) we already cover several important policy changes after the crisis in the CESEE EU Member States. In addition, in the way our credit spillover measure is calculated, the US is not as important in the overall magnitude because the trade weights for the US are not much larger than for other partners (we do not include Russia and Turkey).

[36] Note that the pre-estimation diagnostic tests have been conducted also for these alternative specifications and are available upon request. Most importantly, the evidence found for the baseline (existence of cross-sectional dependence, non-stationarity and cointegration) is again confirmed in these alternative specifications.

coefficient is smaller than for global GDP in the baseline.[37] If we use the VIX together with GDP (level) spillovers (column 4) instead, both variables do not exert any statistically significant impact anymore. The fact that credit spillovers have a stronger and more robust impact than GDP (growth) spillovers could point to a more important role of financial rather than real cross-border spillovers in determining credit dynamics in CESEE economies. No matter whether we ignore external variables (column 2) or whether we use the just discussed alternative definitions of external variables (columns 3-4), all of these specifications have in common that the impact of domestic variables does not change incisively compared to the baseline – with the exception that the coefficient for GDP per capita gets considerably larger and government credit turns positive (even though it is sometimes only weakly statistically significant).

Next, we replace the interest rate spread with another variable proxy for *deleveraging*, i.e. banks' leverage ratio (bank assets over equity) as defined in Bologna et al. (2014). In line with the discussion at the beginning of section 5.1, a shrinking leverage ratio is associated with lower credit ratios (column 5). Other regressors remain largely robust, except for the inflation rate that turns positive and government credit that gets a statistically significant negative impact; also, the coefficient for credit spillovers increases considerably. It should be noted that we could face an endogeneity issue when using the leverage ratio (even though regressors enter with a lag of one quarter) as it contains bank assets and thus also credit in the numerator. This is another reason for keeping the interest rate spread in the baseline.[38]

Even though we focus in this paper on long-run fundamental drivers of credit, also *credit supply factors* could be of relevance. Eller et al. (2010) compare the role of credit demand and credit supply factors in CESEE. Along these lines, we include bank equity as credit supply factor in column 6. It is positively related to credit – in line with the expectation that more loans can be extended as soon as more funds are available within the country. The impact of other determinants remains largely unchanged, apart from global GDP which is not any longer statistically significant. To cover additional supply of loans by acquiring funds from abroad, we included in another robustness check net foreign liabilities of the banking sector (as a share of GDP) as explanatory variable. It is also positively related to credit, but the size of the coefficient is rather small and a decisive impact on fundamental credit levels is thus not expected; other regressors remain largely robust (results not reported here, but available upon request).

Finally, to capture the extraordinary turnaround of credit developments in the course of the GFC, we include in column 7 a *crisis dummy* for the immediate GFC period (2008q4-2009q3). It shows – consistent with crisis-driven deleveraging – the expected negative sign, while other baseline results remain largely robust.[39]

To sum up, across a variety of specifications with alternative credit determinants, the baseline results for GDP per capita, interest rates and credit spillovers remain very robust in the sense that statistical significance and signs of the estimated coefficients do not considerably change (even though the size of the estimated

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[37] We cannot fully compare the size of the coefficient for credit spillovers with that of the GDP growth spillover measure (as the latter is not in logs). In any case, the latter resulted to be not significant.

[38] If we did not include neither the interest rate spread nor the leverage ratio, the coefficient of the lending rate would increase significantly, while the effect of global GDP would be a way smaller in magnitude. At the same time, the inflation rate would turn positive. However, as indicated by chart 2, if we ignored the interest rate spread, we would apparently miss a key variable explaining credit dynamics in the region.

[39] To control for other common shocks over time, we could also include time-fixed effects. However, they can only be used as a robustness check for the setup without the common, time-varying global factor (global GDP). Moreover, time-fixed effects cannot be used to compute fundamental credit levels.

coefficients varies somewhat). On the other hand, global GDP loses statistical significance in some instances and government credit and inflation are unstable across most of the specifications.[40]

[Table 5 about here]

5.2. Identified gaps between actual and fundamental levels of credit

Considering the largely robust impact of the chosen determinants as identified in the previous subsection, we calculate the credit levels determined by fundamentals for the period 1998–2016 in line with equation (8). Chart 4 compares these levels of credit that are in line with fundamentals with actual credit levels.

Focusing on the fundamental levels based on the benchmark GM-FMOLS estimator, several interesting results emerge. First, all the countries that recorded large positive credit gaps in the pre-GFC boom years and/or during the GFC have experienced corrections back to fundamental levels in recent years. Nevertheless, there are considerable cross-country differences. While Estonia and Latvia have been able to bring formerly overshooting credit levels more or less fully back to fundamental levels, adjustment in Bulgaria[41] and Croatia is not yet complete. Although overshooting gaps have narrowed in these two countries they are still quite sizable, amounting to about 30% of GDP at the end of 2016. Another case is Slovenia where considerably positive credit gaps opened up in the wake of the GFC but were closed again as a result of the adjustment undertaken in the course of the Slovenian banking crisis in 2012–2013.

Second, there are several countries with undershooting credit levels, i.e. negative credit gaps. Total credit ratios in Hungary, Lithuania, Poland and Romania had been rather close to fundamental levels until the GFC, but the deleveraging episode right after the GFC led to negative credit gaps, reaching about 30% (in the case of Romania even 37%) of GDP until the end of 2016. Poland is a bit different insofar as actual credit ratios have not declined since the GFC but mostly experienced a sideward movement, while fundamental levels increased, thus widening the negative gap. The Czech Republic and Slovakia, in contrast, recorded negative credit gaps already considerably before the GFC, in fact ever since they had implemented adjustments after their banking crises in the late 1990s and early 2000s. In both countries the undershooting gaps widened in the course of the GFC, and while they have remained very persistent in the Czech Republic, some recent closing can be observed in Slovakia.[42]

Chart 4 also shows that fundamental credit levels based on the three different estimators are relatively similar (in line with estimated coefficients of largely similar size discussed in section 5.1.1): those based on GM-FMOLS and MG are nearly identical,[43] while FE-based fundamental credit levels differ in a few cases – yielding in most of the countries somewhat smaller credit gaps.

[Chart 4 about here]

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[40] Note that, when calculating in the subsequent section the fundamental levels of credit, we take in line with the IMF-CGER approach all the estimated coefficients from the baseline specification on board, i.e. also those which are not statistically significant (but show, at the same time, a small close-to-zero coefficient).
[41] The downward sloping fundamental credit level at the end of the sample in Bulgaria is basically due to a strong increase in the (HP-filtered) interest rate spread series during this period. Compared to other countries in the region, lending rates in Bulgaria have remained at elevated levels until the end of the review period.
[42] Interestingly, if we were to ignore cross-border credit, i.e. if we looked only at domestic credit as it is typically done in related papers, we would observe clearly smaller credit gap overshoots (see Comunale et al., 2018). In Bulgaria for instance, the credit gaps for domestic credit would be about two-thirds lower than the figure for total credit at the end of 2016, and in Croatia they would be about three-quarters lower. Likewise, we find smaller and more short-lived overshoots for Estonia and Latvia around the GFC. For countries with negative credit gaps, in contrast, the gap size remains broadly unchanged.
[43] The correction in the GM-FMOLS affects the magnitudes of the coefficients and constant just a little, while the significance of them changes more often (see table 4).

To illustrate the impact of changes in the set of credit determinants on credit gaps, we show in chart 5 how fundamental credit levels evolve if we ignore external variables (dashed green line), reflecting the specification from column 2 in table 5. When ignoring external variables, fundamental credit levels are, on average over the review period, considerably larger than in the baseline in the Czech Republic, Hungary, Slovakia and Slovenia (increasing the gaps with regard to actual credit levels) while considerably smaller in Estonia and Romania. Larger fundamental credit levels come a bit as a surprise given that we estimated a positive impact of external variables in table 5. There are two possible explanations. On the one hand, the HP-filtered values for country-specific external variables (i.e. the credit spillovers) can be negative for a specific country in a given period (e.g. in the Baltics and Bulgaria at the beginning of the sample). On the other hand, and probably more importantly, excluding variables changes the coefficients of other regressors (especially GDP per capita and the constant term). Fundamental credit levels based on alternative specifications of external variables are very much like the ones without external variables, which reflects the economically rather unimportant impact of these alternative external variables featuring real (GDP) spillovers (results are available upon request).

[Chart 5 about here]

Finally, to check whether the way we have filtered country-specific fundamentals could make a difference for the credit gap assessments, we have applied the band pass filter of Christiano and Fitzgerald (2003, CF) as an alternative to the one-sided HP filter. We opt for the CF filter, mainly because it has been increasingly applied to capture business and financial cycles in the literature (see Rünstler et al., 2018, for an up-to-date exercise for the euro area).[44] Chart A1 in the annex shows that in our case there is practically no difference in fundamental credit levels across these two different statistical filtering techniques, confirming the robustness of our findings.

5.3. Dynamic panel estimation results and speed of adjustment

Fundamentally driven growth rates of the credit-to-GDP ratio are more difficult to interpret for policymakers and our work focuses therefore on the fundamental levels. However, the dynamic setup provides us with the speed-of-adjustment result, which can be very informative for the static model, too, and including foreign variables as regressors can help us drawing a comparison with the previous literature on that matter.

Table A7 in the annex shows the estimation results for the dynamic model. It can be seen that stronger growth in the credit-to-GDP ratio is associated in the long run with larger GDP per capita levels and a lower interest rate spread, corroborating the static evidence. However, in contrast to the static results, global GDP and government credit have now a negative impact – the former only in the long run, the latter both in the short and long run. Thus, an increase in government credit volumes is apparently associated with a reduction of private sector credit growth, which could likely reflect some relevant crowding-out effects. Global GDP, on the other hand, could also capture a long-term trend that coincides with very dynamic credit growth in the region before the GFC and subdued lending thereafter and thus produces the negative correlation in the long-run relationship. Interestingly, when including global GDP, the positive coefficient of domestic GDP per capita gets significantly larger in the long run, but, at the same time, this effect is also counterbalanced by the negative impact of global GDP. Including external variables or not does not considerably change the impact of

[44] We use the optimal asymmetric band pass filter from Christiano and Fitzgerald (2003), assuming a unit root with drift. The frequency band of the filter, defining the upper and lower boundary of the cycle lengths to be extracted, is set at 8-80 quarters as in Rünstler et al. (2018).

other domestic variables (see column 2). In an additional check we use year-on-year instead of quarter-on-quarter differences for the dependent variable and for the regressors in the short-run relationship (together with an annual lag for the levels of the regressors in the long-run relation – see column 3). The results remain very much comparable to the baseline, except for the inflation rate that is now positively associated with credit growth in both the short and long run and credit spillovers with a positive impact in the short run.

It should be recalled at this stage that due to different equations in the static and dynamic setup, a one-to-one comparison of estimated coefficients and derived fundamental credit developments is not really possible. However, what we find very useful is the implication of the estimated *error correction term* for the speed of adjustment of actual credit levels back to fundamental levels. It is significantly negative, which mirrors the finding of cointegration between the investigated variables and indicates that adjustment toward a long-run equilibrium takes place. With a size of about 0.03, the speed of disequilibrium adjustment is rather moderate: it will take about six years (24 quarters) *on average* across the region to halve existing credit gaps.[45] This speed of adjustment would imply still a rather long way to go for countries with considerably large credit gaps at the end of the review period. However, as the example of Latvia 2010-2014 shows, more intense adjustment episodes are apparently also feasible for specific countries.

As pointed out in section 4.3, the dynamic panel estimation results can also be used to derive fundamental growth rates of the credit-to-GDP ratio that can be compared with actual figures. Our respective, still somewhat preliminary, results are summarized in chart A2 in the annex. It can be seen that fundamental (year-on-year) growth of the credit ratio went in most countries through a long u-shaped cycle, with the marked contraction in the wake of the GFC and the expansion beforehand and the recovery thereafter.[46] The most recent figures (end-2016) show that actual and fundamental credit growth do only in a few countries differ significantly from each other (namely in Bulgaria with actual growth rates being considerably larger and in Latvia, Romania and Slovenia with actual rates being considerably smaller than fundamental rates). As pointed out before, the level-based credit gap results cannot straightforwardly be compared to those for fundamental growth rates. But how should we interpret a case with overshooting according to the levels while actual credit growth is in line with fundamental growth (e.g. in Croatia)? The latter implies that fundamental and actual credit ratios are growing at the same rate. If the aim is to reach the fundamental level, it should actually grow less. It needs to be decided if the final goal is the level (as in the case of countercyclical capital buffers, for instance) or growth, for other policy reasons.

6. SUMMARY AND CONCLUDING REMARKS

This paper adopts a comprehensive approach to studying the role of different “fundamental” credit determinants in CESEE EU Member States and to assessing the corresponding credit gaps based on levels justified by fundamentals. We calculate fundamental credit levels by using a two-step procedure. First, we estimate the coefficients of the determinants of credit-to-GDP ratios, making use of panel data estimators that account for heterogeneous coefficients, cointegration and cross-sectional dependence. Second, we attach these estimated coefficients to the trend components of the investigated determinants to derive fundamental credit levels.

[45] Based on $\ln(0.97)\times 24 \approx \ln(0.5)$.
[46] The implausibly large swings in Bulgaria and Slovenia are mainly driven by the interest spread variable.

Taking into account a broad measure of credit to the nonbank private sector (including both domestic and direct cross-border credit), we show that GDP per capita is by far the most important and a very robust driver of credit growth in the region. Among other domestic determinants, lending rates and bank-related credit supply factors turn out to be important, too. We also include external factors which may have impacted credit ratios over time. The chosen external variables matter indeed; in particular, spillovers from credit dynamics in the most important trading partners have a considerable and robust impact.

The ensuing credit gap analysis reveals that countries which experienced overshooting before and/or during the GFC have been able to bring actual credit levels back toward fundamentals-based levels. In a few countries, though, adjustment has not yet been accomplished; in Bulgaria and Croatia, e.g., we see clearly positive credit gaps at the end of the review period. On the other hand, several countries shifted toward undershooting during the post-GFC deleveraging episode, often with widening negative credit gaps. As several of these countries had already been quite close to fundamental levels up to the GFC, post-GFC deleveraging was apparently also driven by other factors, such as the specific composition of credit (featuring e.g. high shares of foreign currency-denominated loans in some cases). Comunale et al. (2018) provides some thoughts on what our results could imply for policymakers.

There are several areas of related research which could be expanded in the future. First, it may be worth examining more closely which (bank or country) characteristics explain the variation in credit gaps and the deviation from fundamental credit levels across countries. In turn, the gaps themselves could also be tested regarding their strength in predicting periods of macrofinancial stress or future deleveraging (in the vein of Drehmann and Yetman, 2018, or Geršl and Seidler, 2015). Second, running our exercise for different components of credit might bring about valuable insights, given experiences with credit overhangs in specific sectors in CESEE. The benchmark specification could be adapted to examine the determinants of sector-specific lending in line with theoretical suggestions (such as those of Rubaszek and Serwa, 2014, for determinants of household loans). However, when relying on panel data for CESEE countries, such attempts are still restricted by relatively short sectoral time series in some countries. Moreover, a growing research stream has been addressing risks related to household credit in CESEE based on micro-level data (e.g. Beckmann and Stix, 2019). Third, future research might extend the sample to emerging and advanced economies outside the CESEE region. Including advanced economies outside CESEE – e.g. Western European economies – would bring about the benefit of longer time series capturing more than one financial cycle and the possibility to derive useful benchmarks for converging CESEE countries. Yet, even though we investigate a panel model that allows for heterogeneous coefficients, focusing on a set of comparable countries is important as the preferred estimators are based on (unweighted) means of country-specific coefficients.

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Appendix: Tables

Table 1: Pesaran's test of Cross-Sectional Independence

Setup	Test	Pr.
Baseline	5.220	0.0000
Without global factors and spillovers	10.356	0.0000

Note: Dependent variable is (log) of total credit over GDP. The baseline is the setup with 7 regressors, namely (in logs): GDP per capita, government credit over GDP, lending rate, interest rate spread, the seasonally adjusted global GDP, the spillovers in total credit and PPI inflation rate (the latter is not in logs). The null is cross-sectional INDEPENDENCE.

Table 2: Stationarity test: second generation t-test by Pesaran (2007) for unit roots in heterogeneous panels with cross-section dependence (CIPS)

- Without logs

Variable	Z [t-bar]	P-value
Credit/GDP	2.344	0.990(**)
Credit/GDP (augmented by 1 lag)	-0.012	0.495(*)
GDP per capita	-2.298	0.011
Government credit/GDP	0.483	0.685(*)
PPI inflation	-5.544	0.000
Lending rate	-9.101	0.000
Interest rate spread	2.634	0.996(**)
Global GDP	16.000	1.000(**)
Credit spillovers	-1.226	0.110

Note: Dependent variable is total credit over GDP. The baseline is the setup with 7 regressors, namely: GDP per capita, government credit over GDP lending rate, interest rate spread, the seasonally adjusted global GDP, the spillovers in total credit and PPI inflation rate. The null hypothesis assumes that all series are non-stationary (**). We cannot reject or accept the null (*) at 15%. This t-test is also based on Augmented Dickey-Fuller statistics as IPS (2003) but it is augmented with the cross-section averages of lagged levels and first-differences of the individual series (CADF statistics)

- In logs

Variable	Z [t-bar]	P-value
Log Credit/GDP	1.700	0.955(*)
Log Credit/GDP (augmented by 1 lag)	0.817	0.793(*)
Log GDP per capita	-2.298	0.011
Log Government credit/GDP	-1.234	0.109
PPI inflation	-5.544	0.000
Log lending rate	-3.492	0.000
Log interest rate spread	0.752	0.774(*)
Log global GDP	16.000	1.000 (**)
Log credit spillovers	-1.408	0.080

Note: Dependent variable is (log) of total credit over GDP. The baseline is the setup with 7 regressors, namely (in logs): GDP per capita, government credit over GDP lending rate, interest rate spread, the seasonally adjusted global GDP, the spillovers in total credit and PPI inflation rate (the latter is not in logs). Null hypothesis assumes that all series are non-stationary (**). We cannot reject or accept the null (*) at 15%. This t-test is also based on Augmented Dickey-Fuller statistics as IPS (2003) but it is augmented with the cross-section averages of lagged levels and first differences of the individual series (CADF statistics)

Table 3: Pedroni's test for cointegration

Setup	Panel group RHO-stat
Baseline	2.80
Without global factors and spillovers	2.04

Note: Dependent variable is (log) of total credit over GDP. The baseline is the setup with 7 regressors, namely (in logs): GDP per capita, government credit over GDP lending rate, interest rate spread, the seasonally adjusted global GDP, the spillovers in total credit and PPI inflation rate (the latter is not in logs). We applied one lag (no trend). All reported values are distributed N(0,1) under null of no cointegration. For a small panel (as here) Pedroni (2004) noted that group RHO-stat is better because less distortive and more conservative. In our case (N = 11), we can apply 2-tail t-stat (Rho-stat is distributed approximately as Student's t distribution with n − 2 degrees of freedom under the null hypothesis): 10% with rejection of the null if it is higher than 1.860; 5% rejection if higher than 2.306; 1% rejection if higher than 3.355.

Table 4: Static panel estimation results – Baseline vs. alternative estimators

	baseline: GM-FMOLS	MG	FE
	(1)	(2)	(3)
VARIABLES	Credit/GDP	Credit/GDP	Credit/GDP
GDP per capita	0.918***	0.879***	1.452***
	[0.084]	[0.289]	[0.157]
Domestic general government credit/GDP	-0.041	-0.018	0.018
	[0.020]	[0.081]	[0.036]
PPI inflation rate	-0.022	0.112	0.351**
	[0.130]	[0.344]	[0.139]
Lending rate	0.064***	0.077	0.230***
	[0.030]	[0.058]	[0.034]
Interest rate spread	-0.172***	-0.155***	-0.113***
	[0.010]	[0.046]	[0.024]
Global GDP	0.313***	0.298	-0.135
	[0.080]	[0.196]	[0.100]
Credit spillovers	0.842***	0.915**	0.949***
	[0.110]	[0.379]	[0.342]
Constant	-14.790***	-14.141***	-13.093***
	[0.740]	[2.107]	[1.009]
Observations	819	811	811
Number of countries	11	11	11

Source: Authors' calculations.
Note: Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. GM-FMOLS = Group Mean-Fully Modified OLS estimator. MG = Mean Group estimator as in Pesaran and Smith (1995). FE = fixed effects estimator with Driscoll-Kraay correction. All values in logs except for the PPI inflation rate. All regressors enter with a lag of one quarter.

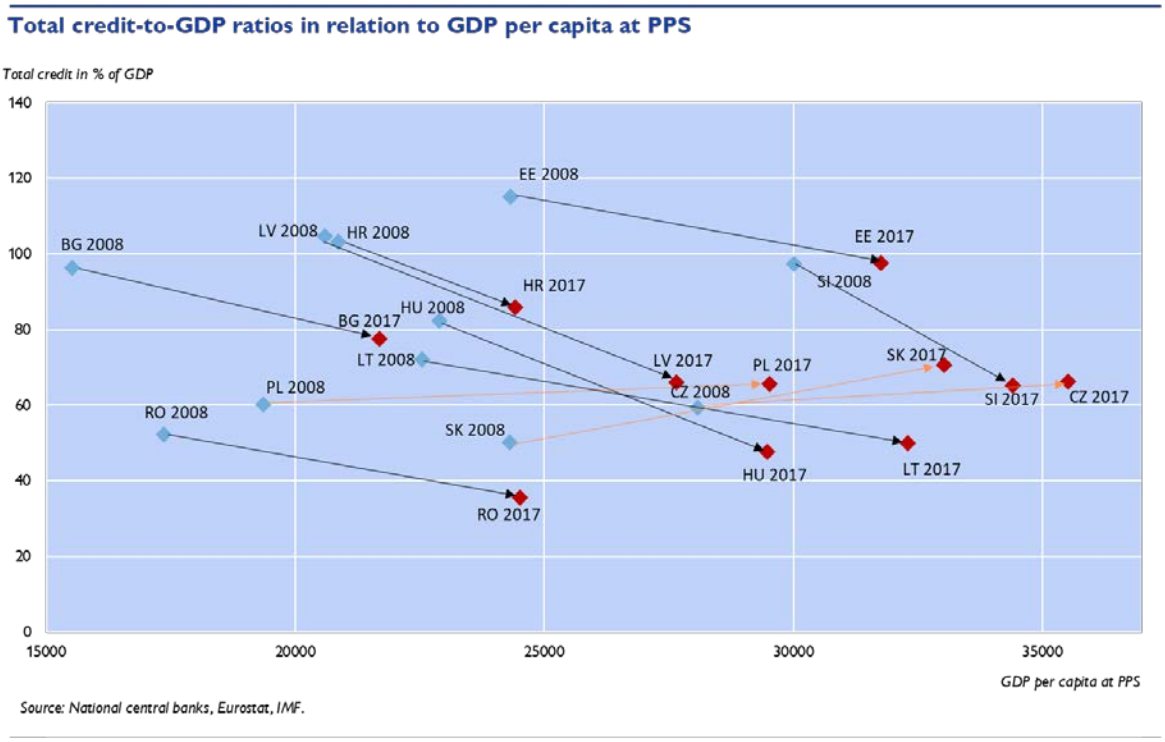
Table 5: Static panel estimation results – Baseline vs. alternative credit determinants

	baseline	without external variables	with alternative external variables (1)	with alternative external variables (2)	with leverage ratio	with equity	with crisis dummy
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Credit/GDP	Credit/GDP	Credit/GDP	Credit/GDP	Credit/GDP	Credit/GDP	Credit/GDP
GDP per capita	0.918***	1.383***	1.388***	1.364***	0.599***	0.859***	1.014***
	[0.084]	[0.036]	[0.133]	[0.055]	[0.077]	[0.336]	[0.080]
Domestic general government credit/GDP	-0.041	0.028*	0.029***	0.035*	-0.079**	-0.007*	-0.045***
	[0.020]	[0.020]	[0.050]	[0.020]	[0.020]	[0.060]	[0.020]
PPI inflation rate	-0.022	-0.244	-0.297	-0.105*	0.269**	0.115**	-0.266*
	[0.130]	[0.140]	[0.820]	[0.140]	[0.090]	[0.090]	[0.140]
Lending rate	0.064***	0.023***	0.074***	0.124***	0.200***	0.050***	0.150***
	[0.030]	[0.040]	[0.040]	[0.030]	[0.020]	[0.020]	[0.020]
Interest rate spread	-0.172***	-0.204***	-0.186***	-0.166***		-0.144***	-0.174***
	[0.010]	[0.020]	[0.020]	[0.020]		[0.010]	[0.010]
Leverage ratio					0.339***		
					[0.030]		
Bank equity						0.134***	
						[0.030]	
Global GDP	0.313***				0.371***	-0.050	0.245***
	[0.080]				[0.060]	[0.060]	[0.070]
Credit spillovers	0.842***				1.328***	0.470***	0.877***
	[0.110]				[0.120]	[0.120]	[0.100]
VIX			0.024**	0.012			
			[0.060]	[0.020]			
GDP growth spillovers			0.001*				
			[0.001]				
GDP spillovers				-0.011			
				[0.060]			
Crisis dummy							-0.045***
							[0.020]
Constant	-14.790***	-13.810***	-11.720***	-13.670***	-13.970***	-9.140***	-14.810***
	[0.740]	[0.040]	[0.380]	[0.570]	[0.580]	[0.760]	[0.720]
Observations	819	811	819	819	775	819	820
Number of countries	11	11	11	11	11	11	11

Source: Authors' calculations.
Note: Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. GM-FMOLS estimator is applied. All values in logs except for the PPI inflation rate, GDP growth spillovers and the crisis dummy. All regressors enter with a lag of one quarter.

Appendix: Charts

Chart 1: Total private sector credit-to-GDP ratios in relation to GDP per capita at PPS



Note: Total credit captures both domestic and direct cross-border credit available for the resident nonbank private sector.

Chart 2: Domestic and direct cross-border credit to the nonbank private sector

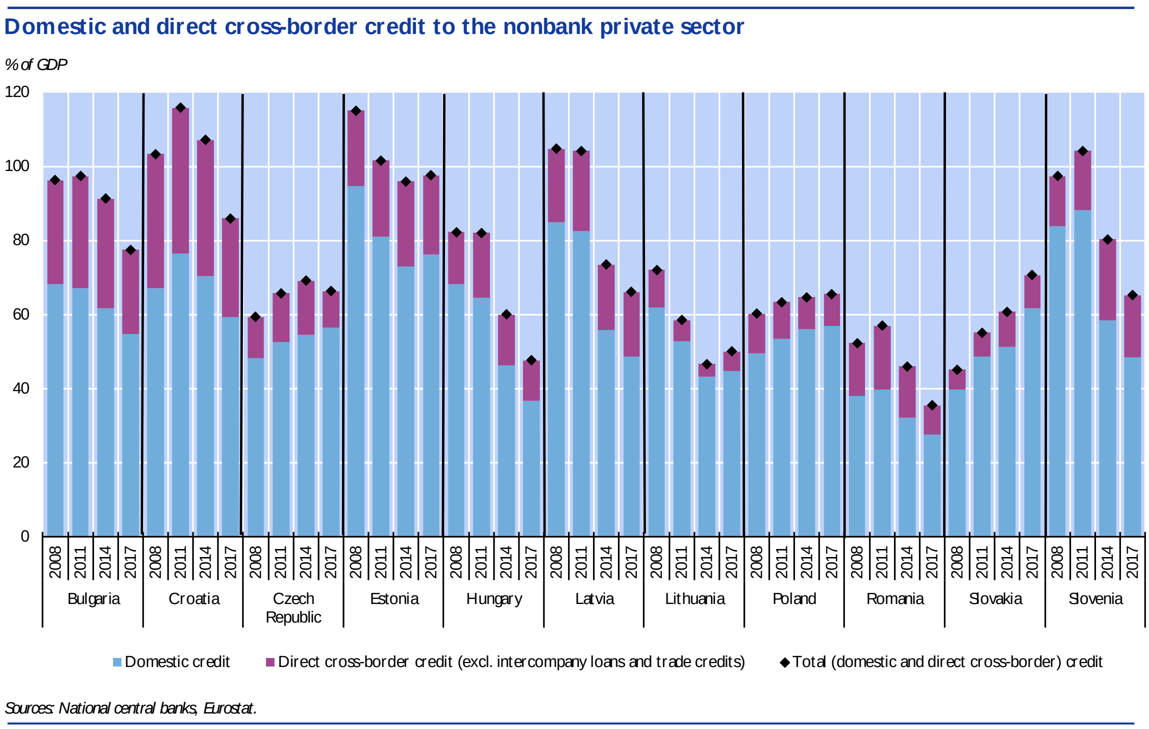
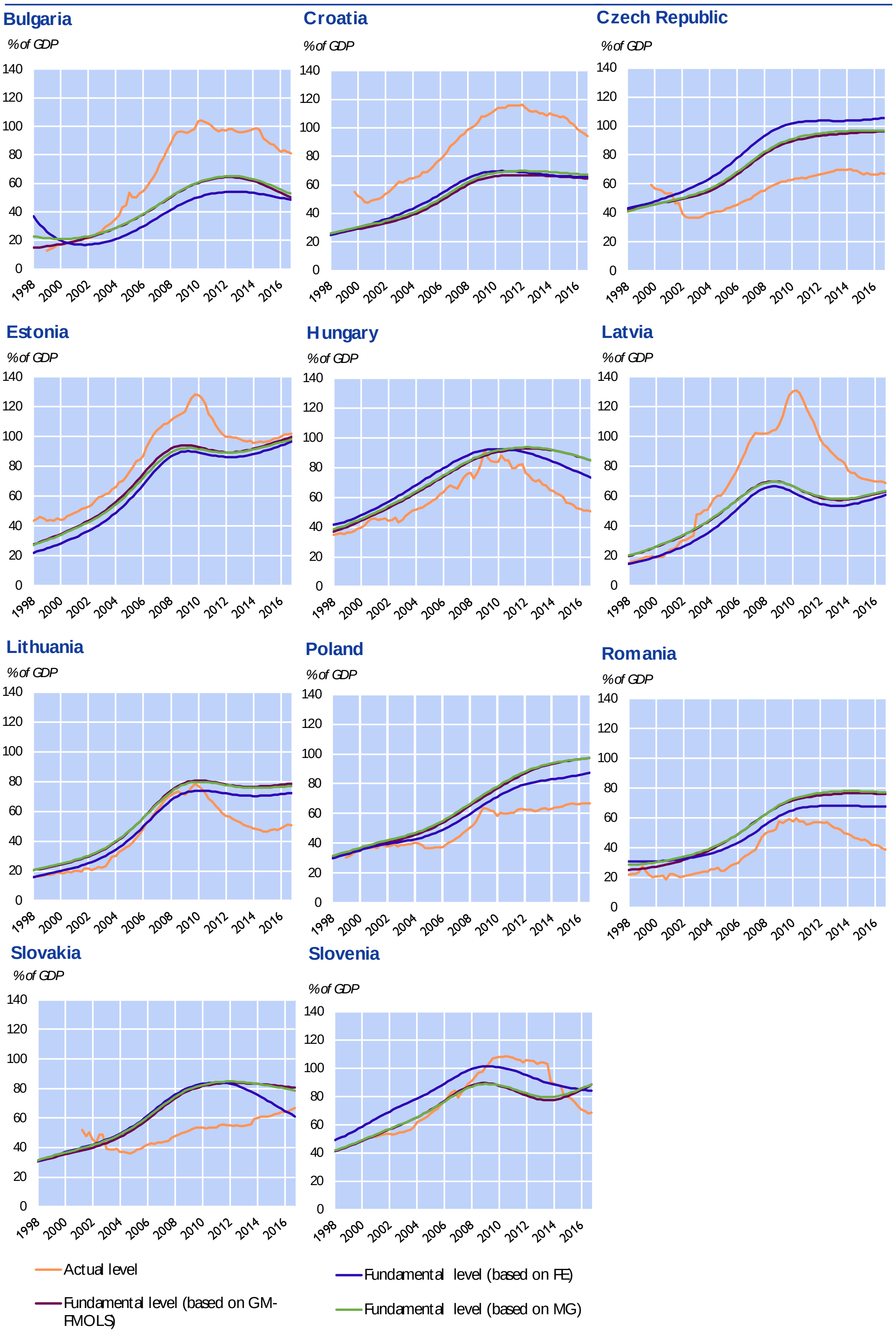


Chart 3: Contribution of change in determinants to changes in actual credit

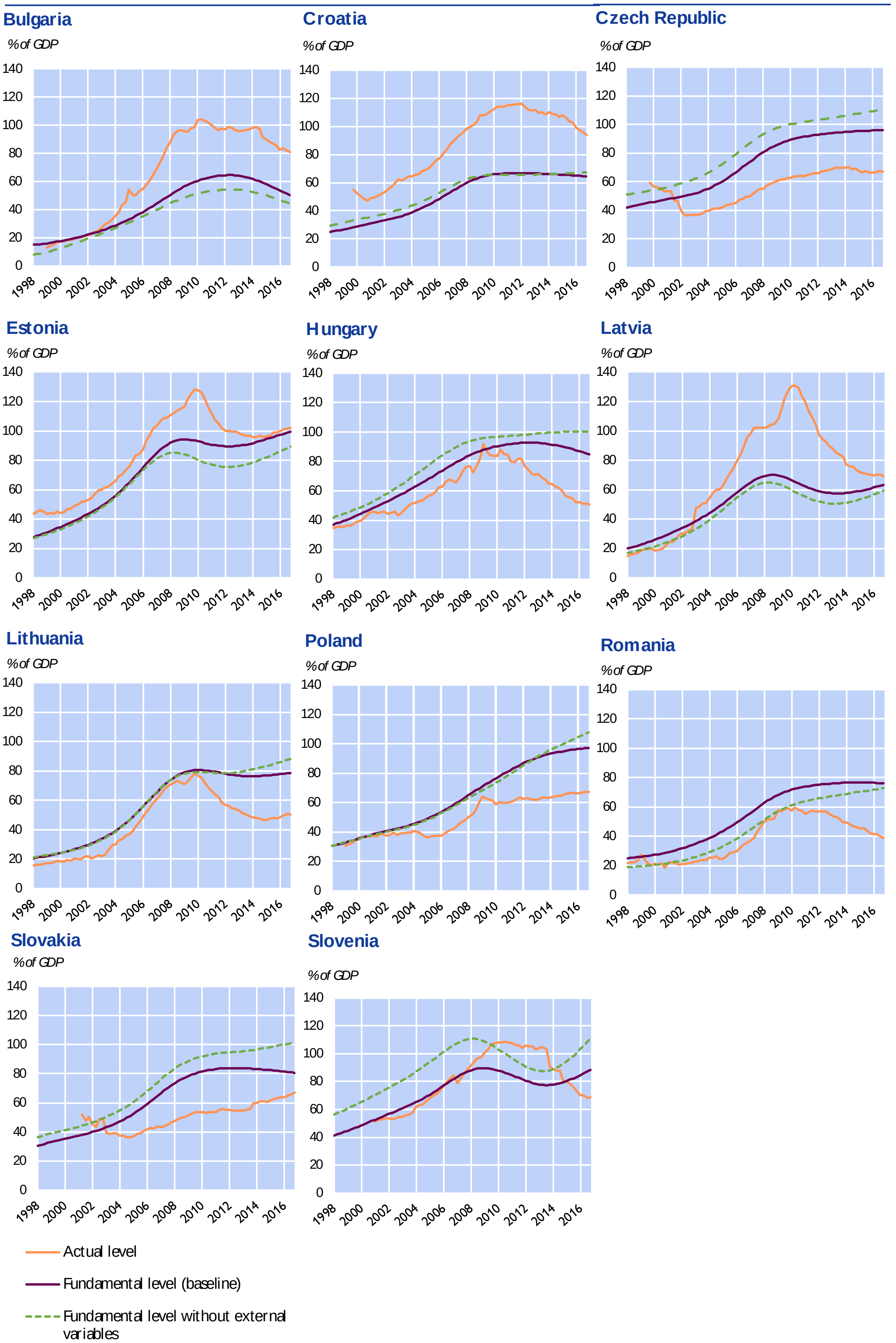
Note: The bars show the % of variation in credit ratios in a particular subperiod which is due to (or can be explained by) the different determinants. Unexplained parts are due to the variation of residuals.

Chart 4: Evolution of private sector credit in comparison to fundamentals-based levels – impact of different estimators



Source: National central banks, IMF, authors' calculations.

Chart 5: Evolution of private sector credit in comparison to fundamentals-based levels – impact of external credit determinants



Source: National central banks, IMF, authors' caclulations.

Annex

Table A1: Description of the variables

Variables	Description	Source
Domestic private sector credit	Domestic banks' credit to resident nonmonetary financial institutions (non-MFIs), excluding the general government, in local currency (LC) million, end of period	National Central Banks
Direct cross-border credit	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).	National Central Banks and IMF, Macrobond for exchange rates
Domestic general government credit	Domestic banks' credit to the general government, in local currency (LC) million, end of period	National Central Banks
Nominal GDP	Nominal GDP in LC million used for calculating credit ratios	Eurostat
GDP per capita	GDP per capita in thousands of purchasing-power-parity U.S. dollars. Available only on a yearly basis and thus we interpolated the time series linearly to quarterly frequency	IMF World Economic Outlook Database
PPI inflation rate	Year-on-year percentage change of the producer price index (PPI, 2010=100)	IMF International Financial Statistics
Lending rate	Other depository corporations rate that usually meets the short- and medium-term financing needs of the private sector. Gaps filled with interpolation using dynamics of long-term interest rates and data from national sources.	IMF International Financial Statistics
Deposit rate	Rates offered to resident customers for demand, time, or savings deposits. Gaps filled with interpolation using dynamics of short-term interest rates and data from national sources.	IMF International Financial Statistics
Interest rate spread	Ratio of lending rate over deposit rate in %	Authors' calculation
Global GDP	Sum of the nominal GDP of 42 countries in million USD. Seasonally adjusted.	Authors' calculation from IMF International Financial Statistics
Credit spillovers	Trade weighted (weights from EU Commission, Price and Competitiveness database) measure of 42 partners' private sector credit, % of GDP (BIS).	Authors' calculation from EU Commission and Bank for International Settlements
Robustness checks variables		
VIX	United States, CBOE, S&P 500 Volatility Index	Macrobond
GDP (growth) spillovers	Trade weighted (weights from EU Commission, Price and Competitiveness database) measure of 42 partners' GDP (growth)	Authors' calculation from EU Commission and IMF International Financial Statistics
Leverage ratio	Total assets over capital & reserves of the banking sector	National Central Banks and IMF
Bank equity	Capital and reserves of the banking sector	National Central Banks and IMF
Crisis dummy	Dummy is one for 2008Q4-2009Q3, zero otherwise	Authors' calculation

Table A2: Summary statistics

Variable	Obs	Mean	SD	Min	Max
Credit/GDP	769	63.512	26.708	12.845	131.194
GDP per capita	792	19218.210	6232.227	6933.645	33529.160
Domestic general government credit/GDP	792	10.190	6.517	0.707	32.256
PPI inflation rate	792	0.038	0.077	-0.219	0.636
Lending rate	792	9.298	7.361	0.426	72.200
Interest rate spread	792	4.894	6.653	1.073	61.857
Global GDP	792	11000000	3203506	6551283	15700000
Credit spillovers	792	120.66	10.91	89.48	148.26

Table A3: Correlation matrix for the setup with the baseline global factors (credit spillovers and global GDP) at t

Obs=769	GDP per capita	Dom. gen. gov. credit/GDP	PPI inflation rate	Lending rate	Interest rate spread	Global GDP	Credit spillovers
GDP per capita	1						
Dom. gen. gov. credit/GDP	0.392	1					
PPI inflation rate	-0.430	-0.253	1				
Lending rate	-0.671	-0.250	0.557	1			
Interest rate spread	0.389	0.099	-0.305	-0.402	1		
Global GDP	0.795	0.287	-0.331	-0.530	0.492	1	
Credit spillovers	0.717	0.188	-0.340	-0.455	0.216	0.745	1

Table A4: Correlation matrix for the setup with the baseline global factors (credit spillovers and global GDP) at t-1

Obs=769	GDP per capita	Dom. gen. gov. credit/GDP	PPI inflation rate	Lending rate	Interest rate spread	Global GDP	Credit spillovers
GDP per capita	1						
Dom. gen. gov. credit/GDP	0.393	1					
PPI inflation rate	-0.417	-0.242	1				
Lending rate	-0.673	-0.247	0.557	1			
Interest rate spread	0.382	0.097	-0.301	-0.400	1		
Global GDP	0.796	0.286	-0.320	-0.536	0.488	1	
Credit spillovers	0.723	0.195	-0.312	-0.476	0.218	0.745	1

Table A5: Correlation matrix for the setup with the alternative global factors (VIX and GDP spillovers) at t

Obs=769	GDP per capita	Dom. gen. gov. credit/GDP	PPI inflation rate	Lending rate	Interest rate spread	VIX	GDP spillovers
GDP per capita	1						
Dom. gen. gov. credit/GDP	0.392	1					
PPI inflation rate	-0.430	-0.253	1				
Lending rate	-0.671	-0.250	0.557	1			
Interest rate spread	0.389	0.099	-0.305	-0.402	1		
VIX	-0.234	-0.076	0.087	0.321	-0.294	1	
GDP spillovers	-0.156	-0.136	0.215	0.111	-0.247	-0.150	1

Table A6: Correlation matrix for the setup with the alternative global factors (VIX and GDP spillovers) at t-1

Obs=769	GDP per capita	Dom. gen. gov. credit/GDP	PPI inflation rate	Lending rate	Interest rate spread	VIX	GDP spillovers
GDP per capita	1						
Dom. gen. gov. credit/GDP	0.393	1					
PPI inflation rate	-0.417	-0.242	1				
Lending rate	-0.673	-0.247	0.557	1			
Interest rate spread	0.382	0.097	-0.301	-0.400	1		
VIX	-0.240	-0.076	0.080	0.323	-0.288	1	
GDP spillovers	-0.146	-0.134	0.213	0.101	-0.243	-0.156	1

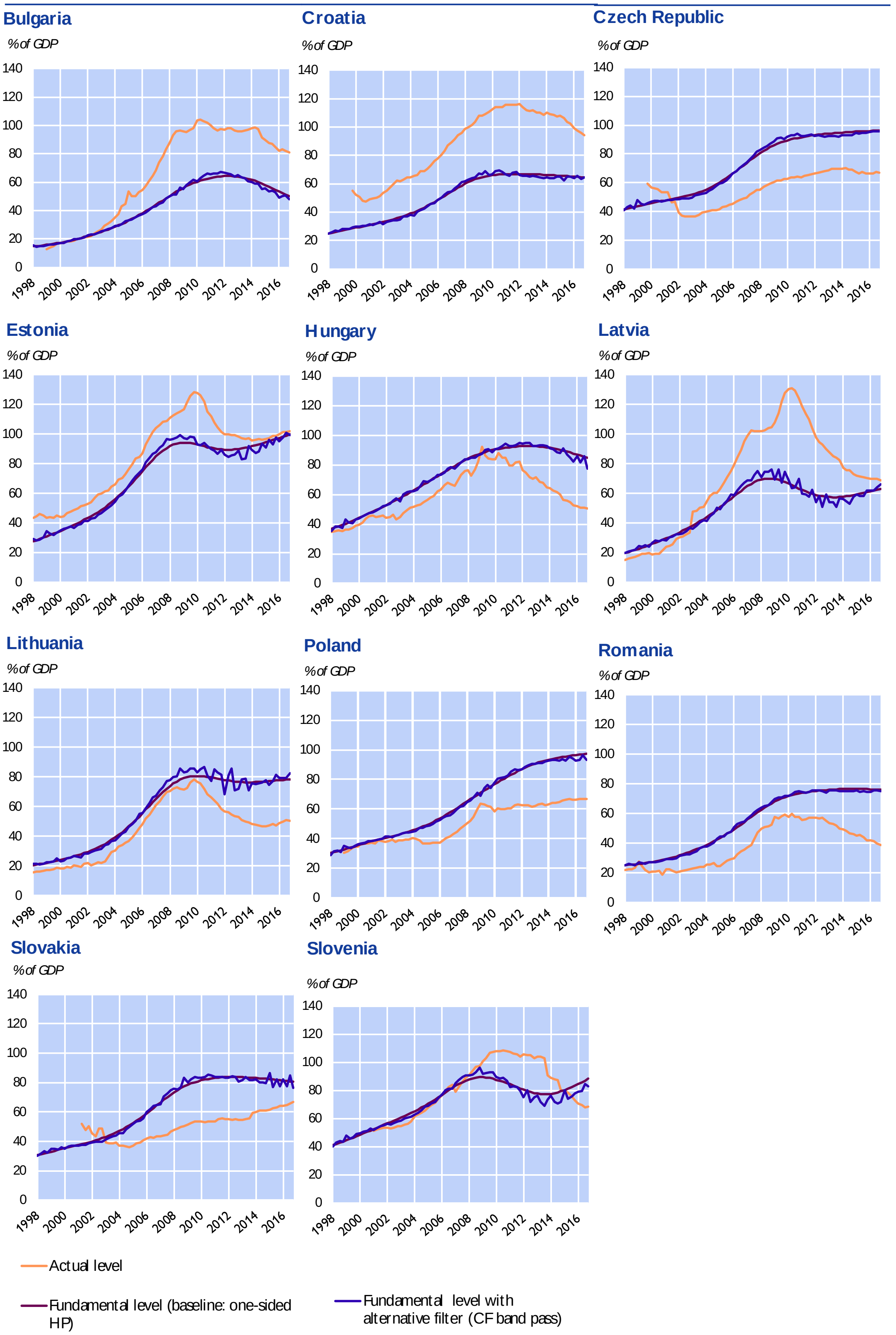
Table A7: Dynamic panel estimation results

VARIABLES	(1) baseline	(2) without external variables	(3) yoy differences	(1) baseline	(2) without external variables	(3) yoy differences
	short-run (differences)			**long-run (lag-levels)**		
Error correction term	-0.0271***	-0.0310***	-0.186***			
	(0.00625)	(0.00603)	(0.0167)			
GDP per capita	-14.20*	-8.354	-19.72***	190.2***	74.78***	124.3***
	(8.425)	(8.122)	(6.390)	(46.02)	(11.22)	(15.29)
Domestic general government credit/GDP	-0.201**	-0.238***	-0.398***	-3.017***	-4.709***	-1.660***
	(0.0904)	(0.0904)	(0.117)	(1.127)	(1.189)	(0.404)
PPI inflation rate	1.256	1.326	12.57***	-41.04	-40.23	86.20***
	(2.281)	(2.263)	(3.824)	(58.63)	(51.09)	(29.44)
Lending rate	0.0195	0.0577	0.0934	0.266	0.392	-0.447
	(0.0451)	(0.0564)	(0.0780)	(0.751)	(0.666)	(0.371)
Interest rate spread	-0.00312	0.00576	-0.159***	-3.831***	-3.887***	-2.483***
	(0.0231)	(0.0305)	(0.0375)	(0.942)	(0.798)	(0.290)
Global GDP	0.820		1.472	-129.8***		-73.75***
	(3.262)		(3.790)	(43.43)		(14.70)
Credit spillovers	0.0488		14.34**	-0.485		22.55
	(0.0359)		(5.695)	(0.508)		(22.08)
Constant	11.66	-18.17***	14.74			
	(8.175)	(4.813)	(23.48)			
Observations	800	800	767	800	800	767
Number of countries	11	11	11	11	11	11

Source: Authors' calculations.

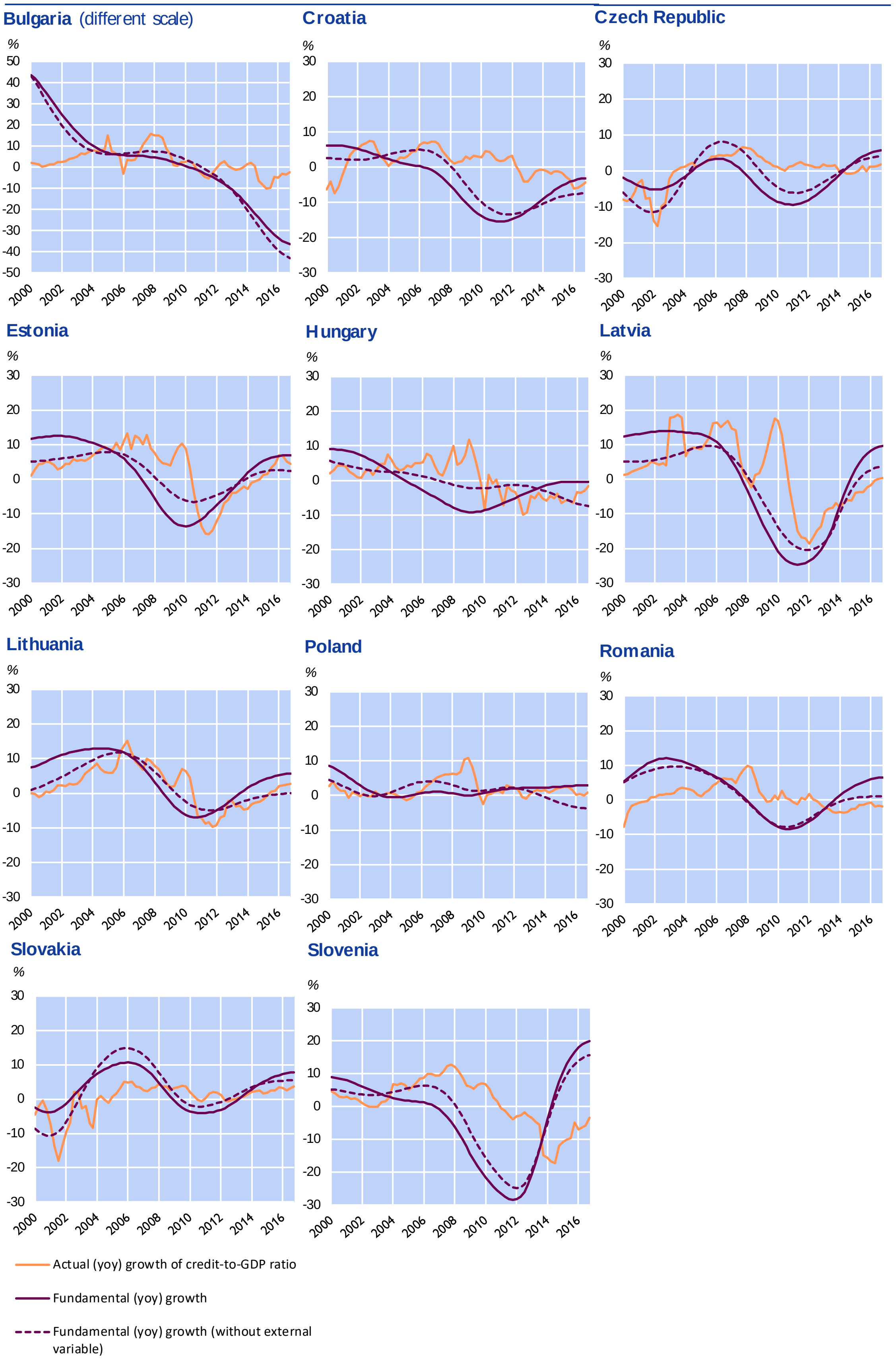
Note: Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. DFE estimator is applied. Only GDP per capita in logs. Dependent variable is credit/GDP in first (q-o-q) differences in columns (1) and (2) and y-o-y differences in column (3). In the short-run the regressors are in first differences in columns (1) and (2) and in column (3) they are in y-o-y differences. In the long-run specification the regressors are in levels, one lag is applied in columns (1) and (2) while in column (3) only the fourth lag is considered.

Chart A1: Evolution of private sector credit in comparison to fundamentals-based levels – impact of different filtering of fundamentals



Source: National central banks, IMF, authors' calculations.

Chart A2: Evolution of actual in comparison to fundamentals-based credit-to-GDP growth rates – based on dynamic model



Source: National central banks, IMF, authors' calculations.