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Equilibrium Credit

The Reference Point for Macroprudential Supervisors

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Abstract

Equilibrium credit is an important concept because it helps identify excessive credit provision. This paper proposes a two-stage approach to determine equilibrium credit. It uses two stages to study changes in the demand for credit due to varying levels of economic, financial and institutional development of a country. Using a panel of high and middle-income countries over the period 1980–2010, this paper provides empirical evidence that the credit-to-GDP ratio is inappropriate to measure equilibrium credit. The reason for this is that such an approach ignores heterogeneity in the parameters that determine equilibrium credit across countries due to different stages of economic development. The main drivers of this heterogeneity are financial depth, access to financial services, use of capital markets, efficiency and funding of domestic banks, central bank independence, the degree of supervisory integration, and experience of a financial crisis. Countries in Europe and Central Asia show a slower adjustment of credit to its long-run equilibrium compared with other regions of the world.

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EQUILIBRIUM CREDIT: THE REFERENCE POINT FOR MACROPRUDENTIAL SUPERVISORS*

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1. Introduction

Excessive credit provision by the financial system was one of the main sources of the $2007 - 2008$ global financial crisis.[1] When credit provision becomes excessive is judged against an unobserved benchmark known as equilibrium credit. One of the most challenging aspects of determining excessive credit provision is the estimation of equilibrium credit.

The Basel III regulatory framework proposed by the Basel Committee on Banking Supervision instructs macroprudential supervisors to estimate equilibrium credit by using the Hodrick-Prescott (HP) filter applied to the ratio of nominal credit to nominal GDP (henceforth, credit-to-GDP ratio).[2] Any *"significant"* deviation of the credit-to-GDP ratio from its HP filtered trend then triggers accumulation of the counter-cyclical capital buffer.[3] Although such an approach could be seen as simple and transparent, its purely statistical nature disregards fundamental changes in equilibrium credit due to economic and financial development. Greater financial deepening and more credit provision can improve access to finance and economic growth (see, among others, Dell'Ariccia *et al.*, 2012, page 5). Excessively restrictive credit, on the other hand, especially in developing economies with increasing credit needs, is likely to result in underinvestment and slow economic growth. Therefore, a structural approach based on economic fundamentals, which accounts for the level of financial development of the economy, seems to be a more appropriate approach to estimate equilibrium credit.

The existing literature has studied equilibrium credit provision by estimating long-run credit demand functions that also allow for short-run dynamics. Typically, the focus has been on modelling credit demand with two different dependent variables. For example, Cottarelli *et al.* (2005), Boissay *et al.* (2005), Kiss and Vadas (2007) and Coudert and Pouvelle (2010) use the credit-to-GDP ratio, while the ratio of nominal credit to the GDP Deflator (henceforth, real credit) is used in, Calza *et al.* (2001), Hofmann (2004), Calza *et al.* (2003), Brzoza-Brzezina (2005), Durkin *et al.* (2009), Coudert and Pouvelle (2010) and Eller *et al.* (2010).

Defining the dependent variable in a credit demand model to be either the credit-to-GDP ratio or real credit imposes strong a priori restrictions on the statistical model that is used, which may not be supported by the empirical data and observed economic behavior. Namely, such restrictions implicitly assume a unit elastic relationship between credit demand and GDP and the GDP deflator. That is, a one-percent increase in GDP

[1]See, for example, Loayza and Ranciere (2006).

[2]See page 13 of BCBS (2010).

[3]See Step 3 on pages $13 - 14$ in BCBS (2010) on how exactly deviations from equilibrium are tied to increases in the capital buffer, risk weighted assets and what the term *"significant"* means in relation to percentage points away from the HP filtered trend. How macroeconomic factors can be incorporated in the risk weighting of assets over different phases of the business cycle is described in Buncic and Melecky (2013).

(or the GDP Deflator) — the number of transactions in the economy (the average price of transactions) — results in a one-percent increase in the demand for credit. Although this assumption might be reasonable for some economies, for many others, particulary developing countries, it will be violated because of the varying levels of credit usage in economic transactions.[4]

The studies by Cottarelli *et al.* (2005) and Égert *et al.* (2006) also consider the effects of changes in development and structural indicators on equilibrium credit demand. They do so by inserting low frequency development and structural indicators into the credit demand equation (the conditional mean equation of credit), together with higher frequency variables that determine credit demand over the business cycle. This approach, however, does not allow for the possibility that the sensitivity of credit to GDP in more credit intensive economies is likely to be higher than in less credit intensive ones. Moreover, especially in time-series panels that include a limited number of countries as in Cottarelli *et al.* (2005), the development and structural indicators, which change only at a very low frequency, fail to identify any material effects of the indicators on equilibrium credit. Further, mixing higher frequency variables such as GDP, prices and interest rates measured on a quarterly basis with low frequency indicators like financial liberalization or public governance, which change typically over a period longer than a business cycle, is likely to result in statistical collinearity between the long-term and short-term indicators when both are measured at quarterly frequency. This collinearity will make it difficult to identify the true effects of the long-term indicators on equilibrium credit and derive any reliable policy recommendation.

The objective of this study is to propose a structural framework to estimate equilibrium credit, which is anchored in the long-run transaction demand for credit by the real economy, and accounts for the effects of economic and financial development on equilibrium credit. The proposed framework consists of two stages. First, we estimate country specific credit demand functions and conduct cross-country poolability tests on the income and price elasticities of credit. This step is implemented using the Mean Group (MG) and Pooled Mean Group (PMG) estimation methods of Pesaran and Smith (1995) and Pesaran *et al.* (1999) and quarterly panel data for high- and middle-income countries over the period $1980 - 2010$.

Second, we model the cross-country variation in the income and price elasticities of credit, as well as the speed of adjustment of credit to its long-run equilibrium, by regressing the country specific coefficients on a set of relevant development indicators. To

[4] As an example, consider the countries of the US and Croatia. Taking the credit-to-GDP ratio as the dependent variable to model credit demand would imply that the use of credit in economic transactions in these economies is the same. This seems hard to rationalise. One would clearly expect that US consumers and businesses use credit much more frequently in their transactions than consumers and businesses in Croatia.

find the set of relevant development indicators, we employ a variable-selection procedure which reduces the number of possible indicators from 42 to about 10. The set of possible development indicators is combined from the FinStats database of Al-Hussainy *et al.* (2010), the Financial Structure database of Beck *et al.* (2000) and various supervisory structure and public governance indicators constructed in Kaufmann *et al.* (2010) and Melecky and Podpiera (2012). By explicitly modelling the variation of the parameters that determine equilibrium credit with our selected set of indicators, we account for the country-specific level of economic, financial and institutional development and are thus able to more precisely detect excessive credit provision.

We provide empirical evidence to suggest that the credit-to-GDP ratio, which restricts the response of credit to GDP and the GDP deflator to unity, is an inappropriate indicator to determine equilibrium credit. Empirical evidence of this is twofold. We first estimate the aggregate cross-country averages of the income and price elasticities of credit within the MG framework and test the unit elasticity hypothesis. This hypothesis is strongly rejected for the income elasticity of credit, and rejected at the 5% level for the price elasticity of credit. The MG estimate of the price elasticity of credit shows substantial variation and is, in fact, not significantly different from zero. We then inspect the cross-country distribution of the income elasticity of credit and find strong evidence of bi-modality. We use the PMG estimation framework to test for cross-country homogeneity of the income and price elasticities and find that this hypothesis is also strongly rejected by the data.

We show further that the cross-country variation in the elasticities is significantly related to the level of development of the countries in our sample. The main development indicators that explain the variation in equilibrium credit elasticities are: financial depth, access to financial services, use of capital markets, efficiency and funding of domestic banks, central bank independence, the degree of supervisory integration, and the experience of a financial crisis. In addition, countries located in Europe and Central Asia show a slower adjustment speed of actual credit to its long-run equilibrium than other countries in our sample.

Based on our findings, we recommend that a structural approach be used to determine equilibrium credit provision to the real economy to avoid any potential negative effects on economic growth in developing countries, due to the implementation of overly restrictive macroprudential policy. The overall objective of our structural estimation of equilibrium credit is to strike a better balance between managing macro-financial risks and facilitating financial development in support of sustained and stable economic growth.

The remainder of the paper is organized as follows. Section 2 discusses the economic motivation behind the proposed empirical approach. Section 3 describes the econometric methodology employed in the paper and the data used in the construction of the different variables of interest. Section 4 presents the empirical results and provides a discussion of the economic significance of the cross-country regression results. Section 5 concludes with a summary of results, policy implications and some directions for future research.

2. Economic motivation and outline of the proposed framework

In economies with developed financial markets credit can finance real as well as financial transactions in the same way that cash currency does in less developed economies. The study by Humphrey *et al.* (2004) provides empirical evidence that the use of credit in financing transactions has increased considerably since the mid 1990s. In the context of traditional money demand models such as, for example, the cash-in-advance model of Lucas and Stokey (1987), this finding implies that the share of credit goods in the economy increases with financial development. There also exist some earlier theories such as Mitchell-Innes's (1914) credit theory of money which postulates that all transactions in an economy can in fact be viewed as credit-based transactions, stressing the important role of credit in a financially developed economy.

A convenient way to think about the concept of equilibrium credit is to form a parallel to the notion of equilibrium money demand. For this purpose, consider the well known Quantity Theory of Money (QTM) relation of Friedman (1956):

$$M \times V = T \times P \tag{1}$$

where M is the quantity of money, V is the velocity of money, T is the volume of real transactions in the economy that requires monetary payments, and P is the average unit price of a transaction. Given the increasing importance of credit based transactions in an economy, the relation in (1) can equivalently be re-stated with credit (CR) replacing money (M), giving

$$CR \times V = T \times P \tag{2}$$

where CR stands for total bank credit to the private sector, or simply credit henceforth.

In empirical studies, it is common to approximate the volume of transactions T in the economy by real GDP. The average unit price of a transaction denoted by P in (2) above can be approximated by the GDP Deflator.[5] For estimation purposes, it is further standard to log-linearize the relation in (2) and explicitly allow the real income and price level elasticities to differ from unity by re-writing the relation in (2) in a general form as:

$$cr_t - (\beta^{gdp} gdp_t + \beta^{def} def_t) = v_t. \tag{3}$$

[5]It is also possible to use other available price measures such as the CPI or PPI. Nonetheless, since the GDP Deflator is consistent with the calculation of real GDP, we prefer to write the representation in terms of the GDP Deflator. From this point onwards, we will also use the GDP Deflator in the notation of the paper.

The terms cr_t, gdp_t, def_t and v_t in (3) are (natural) logarithms of credit, real GDP, the GDP Deflator and credit velocity.[6] The parameters β^{gdp} and β^{def} capture, respectively, the sensitivity (or elasticity) of credit to GDP and credit to the price level. These elasticities are implicitly restricted to unity when the credit-to-GDP ratio is used to determine equilibrium credit in an economy. The credit velocity term v_t in (3) can be driven by a number of different determinants. The most commonly used ones are *"own"* and *"alternative"* returns to investment (see Tobin, 1969).[7]

The considered determinants of velocity in this study are: *(i)* own returns on the cost of credit (the lending rate), *(ii)* alternative returns on deposits (the deposit rate), and *(iii)* alternative returns from purchasing goods or services (the inflation rate), all denominated in local currency. In empirical money demand studies, Arango and Nadiri (1981) and Brissimis and Leventakis (1985), among others, find that the alternative cost of borrowing in foreign currency is an important determinant of money demand in open economies. Since the majority of countries in our sample are open economies, we also include the cost of borrowing in foreign currency, that is, the foreign interest rate adjusted for changes in the nominal exchange rate, as an alternative return measure to proxy international borrowing costs.

One practical issue that we encountered when using both domestic lending as well as deposit rates in the specification of credit velocity in (3) was that for a large number of countries these rates are highly co-linear. Because of this, we specify the empirical credit velocity equation in terms of spreads, using the local currency lending rate as the basis. In our study, the process driving credit velocity thus takes the form:

$$v_t = \beta^{rr} rr_t + \beta^{sprd} sprd_t + \beta^{acb} acb_t \tag{4}$$

with the main determinants of credit velocity in (4) being the real domestic interest rate (rr_t), the lending-deposit rate spread $(sprd_t)$, and the alternative cost of borrowing in foreign currency (acb_t).[8] A priori, we expect that increases in rr_t, $sprd_t$ and acb_t in the relation in (4) should lead to, respectively, a decline in the demand for credit, an increase in savings deposits, and a decline in the demand for credit in foreign currency.

Since the global financial crisis, the credit-to-GDP ratio has become the focal point for macroprudential supervisors when disequilibrium provisions of credit to the real econ-

[6]Note that it should be $-v_t$ on the right-hand side of (3). However, since the sign can be absorbed in the coefficients of the terms in the velocity equation, this has no significance. We therefore do not explicitly write down the negative sign.

[7]We will focus only on the main drivers of credit velocity v_t, as there potentially exist several explanatory variables that could be used. The main reason for this is practicality and data availability. Our objective is thus to condition on a relatively parsimonious set of velocity determinants that will be available for a large number of countries and over a long enough period in our panel data set.

[8]Details regarding the exact construction of these variables are provided in the Data Section.

omy are discussed (see, for example, Basel III, 2011 and the technical documentation in BCBS, 2010). To see how the credit-to-GDP ratio is related to our credit demand specification, we can combine (3) and (4) to relate the disequilibrium provision of credit to the real economy to credit velocity as:

$$\underbrace{cr_t - (\beta^{gdp} gdp_t + \beta^{def} def_t)}_{\text{credit-to-GDP ratio if } \beta^{gdp},\ \beta^{def}=1} = \underbrace{\beta^{rr} rr_t + \beta^{sprd} sprd_t + \beta^{acb} acb_t}_{\text{credit velocity equation}}. \tag{5}$$

The left-hand side of (5) can be viewed as an "*unrestricted*" version of the credit-to-GDP ratio, explicitly allowing the elasticities of credit to GDP and the price level, as measured by the GDP Deflator, to differ from unity. The right-hand side of (5) is a time-varying measure of disequilibrium credit provision to the real economy which captures the excess or the lack of credit supplied to the real economy that is not utilised to satisfy transaction demand. Equation (5) thus postulates that credit in excess of the transaction demand for credit, as shown on the left-hand side of (5), is provided to satisfy the speculative (or portfolio) demand for credit. It is this quantity that affects asset prices by stimulating the formation of asset price bubbles and hence persistent deviations of credit velocity from its long-run steady-state value. Prudential supervisors should therefore focus on managing large departures of credit from its transaction demand component, that is, the left hand side of (5).

The relation in (5) describes a theoretical long-run equilibrium relationship. In order to compute the right-hand side of equation (5), which captures the time-varying disequilibrium credit provision to the real economy, one only needs estimates of β^{gdp} and β^{def} of the left-hand side relation of (5). Nevertheless, as for any statistical estimation problem, one needs to condition on all relevant explanatory variables that influence the dependent variable to obtain consistent estimates of β^{gdp} and β^{def}. In our context, this means that we need to condition on the velocity determinants that appear on the right-hand side of equation (5) as well as on the GDP and price level measures, ie., the gdp_t and def_t variables that appear on the left-hand side. Moreover, it is important to leave β^{gdp} and β^{def} on the left-hand side of (5) unrestricted, since estimates of all other parameters in the velocity equation will be biased if the imposed restrictions are not supported by the data.

Leaving the β^{gdp} and β^{def} parameters in (5) unrestricted is an important generalisation of the credit-to-GDP ratio as it allows us to view any restrictions that are imposed as a testable implication of the model on the data. In the above context, this means that the unity restriction, which is imposed on β^{gdp} and β^{def} when the credit-to-GDP ratio is used to estimate equilibrium credit, can be tested statistically for validity. Given that there exists ample evidence in the empirical literature on money demand that the typical range of parameter estimates of the income elasticity (of money demand) across countries is between $0.25 - 3.5$ (Sriram, 2001, page 360), we also anticipate considerable heterogeneity in the β^{gdp} and β^{def} estimates across countries in our sample. This heterogeneity will reflect the different levels of access to credit and intensity of use in transactions in the economy and therefore is related to the overall level of economic, financial and institutional development of the country.

Once estimates of the unrestricted β^{gdp} and β^{def} parameters are obtained, we will be able to address the following three questions of interest to us. First, assuming that the countries are homogenous with regards to the elasticities of credit to GDP and the price level, can the average $\hat{\beta}^{gdp}$ and $\hat{\beta}^{def}$ coefficients computed as cross-country sample means of the long-run coefficients be validly restricted to unity as the use of the credit-to-GDP ratio assumes for all countries? Second, if this hypothesis is rejected so that the average coefficients cannot be constrained to unity at the aggregate level, can we restrict the coefficients to be homogenous across countries?[9] If this restriction is also rejected by the data, the third question that we are interested in answering is how the cross-country heterogeneity or variation in the $\hat{\beta}^{gdp}$ and $\hat{\beta}^{def}$ coefficients (as well as the speed of adjustment coefficient $\hat{\alpha}$) relates to indicators of economic, financial and institutional development. This last question is addressed by regressing the $\hat{\beta}^{gdp}$, $\hat{\beta}^{def}$ and $\hat{\alpha}$ coefficients on a "*relevant*" set of development indicators. These three questions can be summarized as follows:

(*i*) test the unity restriction on the cross-country average of the long-run parameters

(*ii*) test the cross-country homogeneity of the long-run parameters

(*iii*) determine whether the cross-country heterogeneity can be explained by differences in economic, financial and institutional development.

The last point above is of particular interest to macroprudential supervisors and policymakers, as it enables them to tailor the estimation of equilibrium credit to their country specific circumstances. Such a country specific estimate of equilibrium credit is a conditional measure, which takes into account the level of development of the economy and is contrary to current unconditional measures where the smoothed historical trend from the credit-to-GDP ratio is extracted.

3. Econometric methodology and data

Several methodological approaches to determine equilibrium credit exist in the literature. We initially describe the conceptual framework that we follow and then outline the statistical approach that we implement to estimate the long-run equilibrium parameters β^{gdp}, β^{def} and the speed of adjustment parameter α. Lastly, we describe how these estimates relate to a subset of cross-country development indicators.

[9]This is a weaker restriction than the previous one, as we only require the coefficients to be homogenous across countries but not necessarily equal to unity.

3.1. Notion of equilibrium and econometric approach

3.1.1. Equilibrium as the long-run level

The notion of equilibrium credit adopted in this study is in line with the notion of "*long-run equilibrium*" followed in the economics literature in general as discussed, among others, in Pesaran (1997). That is, we perceive equilibrium credit to be linked conceptually to the economic notion of the "*long run*". Note that the notion of the long-run in the recent econometric literature is frequently associated with the literature on co-integration of individually integrated economic time-series. Although the econometric approach that we follow allows for the existence of a co-integrating relationship between individually integrated variables, integration of the individual series is not a prerequisite. It is thus still possible to formulate an equilibrium relationship between a set of stationary variables. Therefore, there is no need to test for the order of integration of the individual series, which is typically a requirement when wanting to test for the existence of a long-run equilibrium using co-integration techniques.[10]

Given our notion of equilibrium, we specify the econometric model as an Autoregressive Distributed Lag (ARDL) model. To outline briefly how the ARDL model is used to investigate equilibrium relationships, consider the following first order ARDL(1,1) model. For simplicity of exposition, we use a general y_t and x_t notation to denote the dependent "*left hand side*" variable and the regressor "*right hand side*" variables:

$$y_t = k + \rho y_{t-1} + \gamma_0 x_t + \gamma_1 x_{t-1} + \varepsilon_t \tag{6}$$

where ε_t is an unobserved noise process and k is an intercept term. In equilibrium, we have that $y_t = y_{t-1} = y$ and also that $\varepsilon_t = 0$ so that the ARDL(1,1) model in (6) gives the equilibrium relation

$$\begin{aligned} y(1-\rho) &= k + (\gamma_0 + \gamma_1)x \\ y &= (1-\rho)^{-1}k + (1-\rho)^{-1}(\gamma_0 + \gamma_1)x \\ y &= c + \beta x \end{aligned} \tag{7}$$

where $c = (1-\rho)^{-1}k$ and $\beta = (1-\rho)^{-1}(\gamma_0 + \gamma_1)$. The term labelled β in (7) captures the long-run equilibrium relationship between y_t and x_t.

The short-run dynamics, together with the deviations from the long-run equilibrium value and the adjustment back towards it, can be modeled within the ARDL(1,1) framework by re-writing the relation in (6) in its so called equilibrium correction model (ECM) form. Subtracting y_{t-1} from both sides of (6) and adding and subtracting $\gamma_0 x_{t-1}$ on the

[10] Typical cointegration tests that require at least two of the series to be integrated of order 1 are the Engle and Granger (1987) two step estimator or the systems estimator of Johansen (1988, 1991) are used.

right hand side of (6) one obtains:

$$
\begin{aligned}
y_t - y_{t-1} &= k - (1-\rho)y_{t-1} + \gamma_0(x_t - x_{t-1}) + (\gamma_0 + \gamma_1)x_{t-1} + \varepsilon_t \\
\Delta y_t &= k + \alpha y_{t-1} + \gamma_0 \Delta x_t + \delta x_{t-1} + \varepsilon_t
\end{aligned}
\tag{8}
$$

with $\alpha = -(1-\rho)$ and $\delta = (\gamma_0 + \gamma_1)$. In equilibrium, we have again that $y_t = y_{t-1} = y$ and hence $\Delta y_t = 0$ and $\Delta x_t = 0$ so that (8) yields

$$
\begin{aligned}
0 &= k + \alpha y + \delta x \\
y &= c + \beta x
\end{aligned}
\tag{9}
$$

where $\beta = -\delta/\alpha$ and $c = -k/\alpha$, which is equivalent to the result found in (7).

Given these results, the equation in (8) can be re-expressed as

$$
\Delta y_t = k + \alpha(y_{t-1} - \beta x_{t-1}) + \gamma_0 \Delta x_t + \varepsilon_t \tag{10}
$$

where $(y_{t-1} - \beta x_{t-1})$ is the equilibrium error or the error correction term at time period $(t-1)$. The speed of adjustment parameter that captures the rapidness of adjustment towards the long-run equilibrium level is α. The α parameter is required to be less than zero for a stable long-run equilibrium relationship between y_t and x_t to exist (see assumption 2 in Pesaran *et al.*, 1999, page 624 within a panel data setting). In the context of our relation in (6), this means that the term ρ has to be less than unity in absolute value, so that y_t cannot contain a unit-root once we have conditioned upon x_t and its lagged values.[11]

Other approaches of determining deviations of credit from its long-run equilibrium have been used in the literature. One particular approach uses the Hodrick and Prescott (1997) filter (HP filter) to extract the *"smooth"* component from the credit-to-GDP ratio.[12] This method is implemented, among others, in Gourinchas *et al.* (2001), Cottarelli *et al.* (2005) and is also advocated in the Basel III (2011) regulatory framework. The smooth component is then given the interpretation of the equilibrium level of credit relative to GDP and any deviations from this HP filtered trend are taken as indications of credit being above or below the financing needs of the economy.

[11]Notice that the relation in (10) has a linear adjustment term. One could also model the adjustment within a non-linear set-up so that larger deviations are adjusted to at a faster rate, as is done in the empirical literature on real exchange rates (see, for instance, Taylor *et al.*, 2001). Nonetheless, Buncic (2012) has recently shown that non-linearity is often very mild and that little is gained from adopting such a framework. For this reason, we do not consider non-linear adjustments to equilibrium credit.

[12]We will use the terminology of a filter and smoother interchangeable here. Although the HP filter is referred to as a filter, it is in fact a smoother and is a particular type of a smoothing spline that imposes a penalty for roughness which is proportional to the second difference of the time-series. In that respect, the HP filter is akin to a moving average filter, where the trend component is the weighted average of a lags and leads of the series of interest.

The HP filter is a widely used tool in the empirical macroeconomics literature partly because of its computational simplicity and ability to extract the *"smooth"* component of a time-series. Despite these positive features, the use of the HP filter to extract the trend component of a series has several drawbacks. Some of these are well known. For example, because the HP filter is a two-sided weighted moving average filter, the extracted trend can significantly depend not only on the specified smoothing parameter (often denoted by λ), but also on the overall length of the time-series data that are available for computation. Data sets with a much smaller number of time-series observations will produce quite different estimates of the trend given relatively small changes in the smoothing parameter. Also, due to the two-sided nature of the HP filter (and in fact any two-sided filter/smoother), the well known *"end-point bias"* constructs highly unreliable trend estimates for the last two data points in the sample.[13] This is a rather unfortunate fact from the viewpoint of a practitioner or a policy maker, as the last few available data points are the most common ones used to make timely policy decisions.

In the context of the economic notion of long-run equilibrium that was discussed above, the most important deficiency that the use of the HP filter based equilibrium credit definition entails is that it is based on a univariate representation. It provides no information about how credit provision should change in relation to the economic, financial and institutional development of the economy. We see this as a substantial weakness of the HP filtered credit-to-GDP ratio when used to determine equilibrium credit.[14]

3.1.2. First-stage ARDL panel regression

We work with the ARDL specification of the long-run equilibrium in our analysis. Since our main objective is a cross-country comparison of the β and α parameter estimates in the ECM specification, we apply the ARDL model to a cross-country panel of data, using the Mean Group and Pooled Mean Group estimators proposed by Pesaran and Smith (1995) and Pesaran *et al.* (1999).

The Mean Group (MG) estimator considers individual country regressions and constructs an estimator for the entire group by averaging over the coefficients of the individual countries. The Pooled Mean Group (PMG) estimator takes advantage of the possibility that the long-run equilibrium relations across the groups (countries) could be ho-

[13]The standard HP filter uses two leads and lags to extract the trend component from a series, so one would need two future time-series observations to get reliable estimates of the trend in the last time period. Due to this, the technical documentation that accompanies the Basel III (2011) framework actually suggests to use a one-sided lag version of the HP filter (see the middle of page 13 in BCBS, 2010). The standard HP filter imposes initial and terminal conditions to get *"trend"* estimates for the first two and last two observations. For example, for the last observations this means that the trend at time T is computed only from current and two lagged values of the series of interest, with the respective weights suitably adjusted.

[14]There are various other issues when using the HP filter in economic analysis in general, some of which are discussed in more detail in Harvey and Jaeger (1993).

mogenous and restricts all or some of the long-run equilibrium parameters to be the same across the groups. The aggregate short-run dynamics are again arrived at by averaging across the country specific estimates (see also Pesaran *et al.*, 1999, for a general motivation of the Pooled Mean Group estimator).

The empirical ECM form of the ARDL model that we work with is as follows:

$$\Delta cr_{it} = k_i + \alpha_i(cr_{it-1} - \boldsymbol{\beta}_i'\mathbf{x}_{it-1}) + \sum_{p=1}^{P} \pi_{pi}\Delta cr_{it-p} + \sum_{q=0}^{Q} \gamma_{qi}'\Delta\mathbf{x}_{it-q} + \epsilon_{it} \tag{11}$$

where k_i and α_i are the country specific intercept and speed of adjustment parameters, $\boldsymbol{\beta}_i$ is a $(k \times 1)$ parameter vector capturing the country specific long-run equilibrium, ie.,

$$\boldsymbol{\beta}_i = \left(\beta_i^{gdp}\ \beta_i^{def}\ \beta_i^{rr}\ \beta_i^{sprd}\ \beta_i^{acb}\right)' \tag{12}$$

and the $(k \times 1)$ vector $\mathbf{x}_{it}$ contains the variables of interest for country i at time period t, where $\mathbf{x}_{it}$ is defined as:

$$\mathbf{x}_{it} = \left(gdp_{it}\ def_{it}\ rr_{it}\ sprd_{it}\ acb_{it}\right)'. \tag{13}$$

The parameters π_{pi} and γ_{qi} allow for extra dynamics in the dependent variable Δcr_{it} up to lag order P and up to Q extra lags in the vector of explanatory variables, respectively.[15]

Specifications similar to the one given in (11) have been used in previous studies, see, for example, Cottarelli *et al.* (2005) and Égert *et al.* (2006). However, what distinguishes our study from earlier ones is that we do not a priori restrict the parameters attached to GDP and the GDP Deflator to unity. Our view is that using the credit-to-GDP ratio as the dependent variable is overly restrictive and that it is a testable implication of the model on the data that needs to be verified empirically. In empirical money demand studies, for example, the typical range of parameter estimates of the income elasticity (of money demand) across countries is $0.25 - 3.5$ (see, for instance, Sriram, 2001, page 360). Given the use of credit in economic transactions, we also expect the income elasticity of credit to vary considerably across countries.

The approach that we propose leaves the effect of GDP and the GDP Deflator on credit unrestricted by including these variables explicitly in $\mathbf{x}_{it-1}$ in (11). The β_i^{gdp} and β_i^{def} parameters are therefore freely estimated. This enables us to determine how appropriate the unity restrictions are at the aggregate level. More importantly, it further allows us to look at the cross-country variation in the $\hat{\beta}_i^{gdp}$ and $\hat{\beta}_i^{def}$ coefficients to see if there are any fun-

[15] We use standard i and t subscripts to denote the cross section and the time-series dimensions of a variable or a parameter. In the estimation of (11) we also allow for a non-zero intercept term in the short-run dynamics to ensure that ϵ_{it} has a zero mean.

damental differences in their magnitudes. We can then use statistical tests to determine whether the homogeneity assumption and the unity restrictions on the β_i^{gdp} and β_i^{def} parameters across countries, which are imposed when the credit-to-GDP ratio is used on the left hand side of (11), are supported by the data. It is well known that imposing restrictions on a subset of parameters that are not supported by the data leads to substantial distortions in the estimates of the remaining unrestricted parameters.

3.1.3. Second-stage cross-country regression

We are particularly interested in the cross-country variation of the long-run coefficients on real GDP and the GDP Deflator in (11); that is, the variation in the $\hat{\beta}_i^{gdp}$ and $\hat{\beta}_i^{def}$ coefficients and also the speed of adjustment coefficient $\hat{\alpha}_i$ which measures how fast deviations from the long-run equilibrium are eliminated. Once estimates have been computed, we proceed by relating the cross-country variation in $\hat{\beta}_i^{gdp}$, $\hat{\beta}_i^{def}$ and $\hat{\alpha}_i$ to a set of development indicators. These are obtained from various sources, such as the FinStats database of Al-Hussainy *et al.* (2010) and the Financial Structure data set of Beck *et al.* (2000). We also add economic development indicators to this set. No well developed economic theory exists to guide us in the selection of possible drivers of the variation in $\hat{\beta}_i^{gdp}$, $\hat{\beta}_i^{def}$ and $\hat{\alpha}_i$. We therefore also consider traditional scale variables, such as the level of economic development (i.e., GDP per capita) a measure of overall GDP and population to control for an economy's size, and the degree of openness. We further include data on financial sector supervisory structures from Melecky and Podpiera (2012). These contain measures of the degree of integration in prudential supervision, the pursuit and integration of business conduct supervision, and central bank independence. The Kaufmann *et al.* (2010) governance indicators are also included.[16] This yields a total of 42 economic, financial and institutional development indicators.

Our goal here is to relate the cross-country variation in $\hat{\beta}_i^{gdp}$, $\hat{\beta}_i^{def}$ and $\hat{\alpha}_i$ to the level of development of the economy of interest. Once the variation in these coefficients is linked to a set of relevant indicators, we will be able to determine equilibrium credit provision for a specific country based on its development stage, its financing needs, and the capacity of its financial sector to meet these needs. Our proposed framework will therefore enable macroprudential supervisors to gauge current credit provision in the economy against what is needed to maintain a financially stable economic growth path over the medium to long run.

The relationship between the coefficients and the considered development indicators

[16] A description of the explanatory variables that we use is provided in the Data Section.

is estimated using a second stage regression model taking the form:

$$\xi_i = \phi_0^m + \sum_{\ell=1}^{L} \phi_\ell^m z_{\ell i} + \varepsilon_i, \tag{14}$$

where $\xi_i = \{\hat{\beta}_i^{gdp}, \hat{\beta}_i^{def}, \hat{\alpha}\}$ are the coefficients on real GDP, the GDP Deflator and the speed of adjustment term in (11), $\{\phi_j^m\}_{j=0}^{L}$ with $m = \{gdp, def, \alpha\}$ are the corresponding second stage regression parameters that capture the cross-country variation in ξ_i and ε_i is a disturbance term with zero mean and constant variance. The regressors $\{z_{\ell i}\}_{\ell=1}^{L}$ are the economic and financial development indicators listed above. Notice from the relation in (14) that once estimates of ϕ_ℓ are available, it is possible to construct predicted or fitted values of the income and price elasticities of credit, conditional on the economic and financial development of the economy. The advantage here is that the coefficients can be used to give a more tailored determination of equilibrium credit provision based on the historical cross-country evidence of economic and financial development of the countries included in our sample. This will give policy makers a more appropriate measure to gauge if credit provision is in excess of the development needs of the economy, rather than using deviations of credit provision from its HP filtered trend which has no link to credit demand based on real economic transactions.

It is evident from the set of potential regressors that are listed above that this set is rather large compared to the number of cross-country observations that are available. That is, we identify a total of 42 viable explanatory variables, but have only 49 cross-country observations to estimate the regression parameters in (14). Since no economic theory exists to aid in the selection of important regressors and it is not sensible to estimate 42 parameters from 49 observations, we use a statistical approach to determine the best set of explanatory variables in the relation in (14). We implement this in two steps. Firstly, we use a Bayesian model averaging (BMA) procedure to narrow down the number of viable candidate regressors to a subset of around $15 - 20$ variables. We use the posterior inclusion probability (PIP) of a variable as the criterion to guide in the selection of the most likely regressors.[17] Secondly, we use the Lasso penalized regression estimator of Tibshirani (1996) as a variable selection tool to shrink the coefficients of irrelevant or insignificant regressors of the BMA selected subset to zero.[18]

Our main goal here is to find the smallest possible set of relevant financial and economic development indicators. To achieve this goal, we make use of the Lasso's ability

[17]See, for example, Raftery (1995) and Hoeting *et al.* (1999) for an overview on the use of Bayesian model averaging and selection methods in social sciences and Chapter 11 in Koop (2003) for a textbook style treatment.

[18]See also Zou (2006) and Zhao and Yu (2006) on how the Lasso can be used as a consistent variable selector and also Section 3.4 in Chapter 3 of Hastie *et al.* (2009) for a general textbook type treatment of the Lasso estimator.

to shrink small or weakly significant regressors to zero. Because of the shrinkage that the Lasso imposes in the penalized least squares estimation, parameter estimates are intentionally biased. For this reason, once the relevant set of final regressors has been determined with the Lasso procedure, we use the Ordinary Least Squares (OLS) estimator to obtain unbiased estimates of the regression parameters that are not shrunk to 0.

3.2. Data

The source of our data set is the IMF's International Financial Statistics (IFS) database. All data is on a quarterly basis. The maximum possible sample size in the time dimension is from 1980:Q1 to 2010:Q3. The cross sectional dimension of the panel data set, i.e., the number of countries that are included, is 49.[19] The credit variable that we use is defined as total bank credit to the private sector, expressed in local (national) currency units. Since the scale of private sector credit can be very different across the countries, we create a credit index, with the base of the index (where the value of the index is equal to 100) being 2001:Q1. The index version of the credit variable is then log transformed before used in the analysis.

The real GDP data (GDP for short henceforth) and GDP Deflator data are taken from volume measures, and are hence also index measures with different base years. Both, GDP and the GDP Deflator are also log transformed. The lending to deposit rate spread is computed as the lending rate minus the deposit rate. We use Consumer Price Inflation (CPI) data to construct an ex-post measure of the real interest rate. This is done by computing CPI inflation as 100 times the year-on-year inflation rate, ie., as $100 \times (\ln(CPI_{it}) - \ln(CPI_{it-4}))$.[20] The real interest rate is then calculated as the lending rate minus year-on-year inflation. The alternative cost of borrowing variable, which captures the cost of borrowing in foreign currency, is calculated as the country specific lending rate minus the world interest rate minus the year-on-year change in the exchange rate. The exchange rate is defined as the number of local currency units per one US dollar, so that a declining value indicates an appreciation of the respective country's currency against the US dollar. To avoid unnecessary volatility in the exchange rate series, we use quarterly averages rather than end-of-quarter values. For the US, we use (the inverse) of the Trade Weighted Exchange Index of major currencies to get a measure of the exchange rate impact on credit.[21] The world lending rate is approximated by the US dollar lending rate.

[19] We do not provide a separate table that lists the countries included in the panel data set to conserve space, nonetheless, the $x-$axis labels of Figure 2 show explicitly which countries are included in the panel.

[20] We use year-on-year values, rather than annualised quarter-on-quarter values, to reduce the volatility of the inflation series.

[21] This series was obtained from the FRED2 database of the Federal Reserve Bank of St. Louise. The series code is DTWEXM. The series was also aggregated to the quarterly average. We use the inverse to be consistent with the definition of a decreasing value implying an appreciation of the domestic currency for non-US countries in the cross-section.

A few additional comments on the data set that we use and the data transformations that we apply are in order. The set of countries consists of a reasonable mix of developed and emerging market economies with a satisfactory north/south and continental representation. The initial cross-sectional dimension consisted of 65 countries, but due to the lack of largely GDP and GDP Deflator data, it was necessary to exclude countries that did not have GDP related data available for a long enough period.

There were further occasional data gaps that were interpolated with a linear interpolation method to keep the size of the sample as large as possible. These were occasional gaps in the lending and deposit rates of some countries, and very rarely also in the credit series. For EU countries, we have converted the relevant variables and the exchange rate to euro-denominated values prior to the 1^{st} of January 1999, where the official EU conversion rates were used.[22] Although the real GDP data were marked as seasonally adjusted, it became evident from visual inspections of the series that for a handful of countries that were included in the final data set, this was in fact not the case. It was, therefore, necessary to use a seasonal filter to remove the seasonality in those GDP series. The X12-ARIMA seasonal filter of the US Census Bureau was used.[23]

The number of time-series observations of each of the 49 countries that are included in the cross-section ranges from 25 observations for Bulgaria up to 118 observations for France. Evidently, having less than 40 observations for the time-series dimension is far from optimal, nonetheless, we chose to leave as many cross-sections in the final data set as possible. A brief summary of the number of time-series observations of the individual countries is as follows: there are only 5 countries with less than 40 observations, there are 21 countries with 100 observations or more and the remaining countries have between 40 and 92 time-series observations.

The regressor variables intended to capture the cross sectional variation in the GDP, GDP Deflator and speed of adjustment coefficients were taken from the FinStats and Financial Sector Development Indicators of Al-Hussainy *et al.* (2010) and Beck *et al.* (2000). The economic development indicators are GDP per capita as a measure of economic development, the foreign trade to GDP ratio as a measure of an economy's openness (both were obtained from the World Bank Central Database), the Kaufmann *et al.* (2010) overall public governance quality indicator, the degree of integration in prudential, business conduct and overall financial sector supervision of Melecky and Podpiera (2012), a central bank political and economic independence indicator, and an indicator for previous financial crisis experience (also from Melecky and Podpiera, 2012). A list of the final set of economic, financial and institutional development indicators that we used is provided in Table 3.

[22]See http://ec.europa.eu/economy_finance/euro/adoption/conversion/index_en.htm.

[23]Details regarding the computation of the filter are available from the Census Bureau's website available at: http://www.census.gov/srd/www/x12a/.

4. Empirical results

We will initially discuss the estimation results of the ECM parameterisation of the ARDL model in (11). Note that, as discussed in the Data Section, the time-series dimension for some of the countries that we included in the final data set is small. For that reason, we focus on estimating parsimonious models for each country and use the Bayesian Information Criterion (BIC) to determine the appropriate lag order of the ECM in (11). Nonetheless, we ensure that the chosen lag order of the dynamic specification in (11) does not result in any significant serial correlation in the residuals of the fitted models. We initially start with an upper bound of up to three lags in both Q and P in (11) and then reduce the lag order until the BIC was minimized. The chosen lag order for the ECM specification of the ARDL in (11) is $Q = P = 1$.[24]

4.1. Visual overview of the cross-country long-run coefficients

Recall that we are primarily interested in testing whether it is appropriate to restrict the β^{gdp} and β^{def} parameters which determine the long-run equilibrium relation of credit to unity. This is the assumption that is implicitly made when the credit-to-GDP ratio is used as the dependent variable. We therefore initially inspect the distribution of the estimates of the long-run equilibrium parameters, focusing particularly on the $\hat{\beta}^{gdp}$ and $\hat{\beta}^{def}$ coefficients. To gain some intuition, and before formal statistical tests on the poolability of the long-run parameters are implemented, we show histograms and density estimates of $\hat{\beta}^{gdp}$ and $\hat{\beta}^{def}$ in Panels (a) and (c) of Figure 1. In Panel (e) of Figure 1, we also plot the empirical distribution of the speed of adjustment parameter $\hat{\alpha}$ of equation (11). We used a Gaussian Kernel with an optimal bandwidth selected according to the approach of Shimazaki and Shinomoto (2010) for the density estimates. 95% confidence intervals, shown by the dashed line, are based on asymptotic standard errors. The number of bins in the histograms was chosen optimally according to the method described in Shimazaki and Shinomoto (2007).

INSERT FIGURE 1 HERE

The distribution of the $\hat{\beta}^{gdp}$ coefficients plotted in Figure 1 Panel (a) shows visual signs of bi-modality, where the peak of the first mode is at a value of around 2 and that of the second mode at a value of around 4. The density is centered at around 3. This preliminary visual analysis suggests that first, at an aggregate or cross-country average level,

[24]We initially allow the lag order to differ across the individual countries, but found that the BIC would, at times, select a too low lag order for some countries, leading to mild autocorrelation in the residuals. To remove the residual autocorrelation, we decided to fix the lag length to 1 for both Q and P across all countries that were included.

the income elasticity of credit seems to be considerably larger than unity. Second, the bi-modality of the density indicates that substantial heterogeneity in the magnitudes of the income elasticity of credit across countries exist. The restriction that is imposed when the credit-to-GDP ratio is used as the dependent variable when modelling equilibrium credit, thus appears to be rejected by the data.

The distribution of the $\hat{\beta}^{def}$ coefficients plotted in Panel (c) does not show any visual evidence of bi-modality, having a single peak centered at 0. Although this distribution seems to be more inline with the unit elasticity assumption on the GDP Deflator parameter, it is evident that there exists considerable variation and a mild left skew in the distribution. This appears to indicate that the cross-sectional mean may not be statistically different from zero. We will return to this discussion later when formally testing the significance as well as the unity hypothesis on these coefficients.

The estimates of the speed of adjustment parameter $\hat{\alpha}$ displayed in Panel (e) of Figure 1 show less evidence of bi-modality, but a decisive left skew. Skewness in a distribution can come from a variety of sources. If one interprets the left skew as arising from a mixture of three distributions, then one may argue that three modes are visible at values in the -0.05 and -0.10 interval (the main mode), as well as at -0.20 and -0.30. This seems to indicate that some heterogeneity exists in how fast deviations from long-run equilibrium credit are eliminated. A handful of countries have large (in absolute value) estimates of the speed of adjustment parameter, with some being around — or in excess of — 0.4.

The distributions of the $\hat{\beta}^{rr}$, $\hat{\beta}^{sprd}$ and $\hat{\beta}^{acb}$ coefficients that are part of the credit velocity equation in (5) are displayed in Panels (b), (d) and (f) of Figure 1. Recall that we are not *per se* interested in the distributions of these coefficients and show them only for completeness and to contrast them with the bi-modality seen in $\hat{\beta}^{gdp}$. Overall, these three distributions look uni-modal, with the peaks of the densities centered at values marginally below zero. This suggests that, on average, credit responds negatively to increasing values in the lending to deposit rate spread, the real interest rate, as well as the alternative cost of borrowing in foreign currency, when measured at the mode.

The three distributions plotted in the right Panels of Figure 1 show also sizable variability in the $\hat{\beta}^{rr}$, $\hat{\beta}^{sprd}$ and $\hat{\beta}^{acb}$ coefficients around the zero line, which is an indication that the population parameters corresponding to the aggregate coefficients are most likely not significantly different from zero. Notice here also that although the distributions do not look Bell-shaped, they are reasonably symmetric. The $\hat{\beta}^{rr}$ coefficients show signs of fat tails with a high peak at around zero. The $\hat{\beta}^{sprd}$ coefficients, on the other hand, are somewhat positively skewed. Finally, the $\hat{\beta}^{acb}$ coefficients portray a higher than expected frequency of values within the -0.02 to -0.03 interval, indicated by the bump in the left tail of Panel (c).

4.2. Mean Group (MG) and Pooled Mean Group (PMG) estimation results

We now discuss the results of the Mean Group (MG) and Pooled Mean Group (PMG) estimation as well as statistical tests of hypotheses (i) and (ii) raised at the end of Section 2. Since we are primarily interested in the long-run equilibrium relationship between credit and its macroeconomic determinants, we only report the MG and the PMG estimates of the long-run equilibrium parameters $\boldsymbol{\beta}$, as well as the intercept and the speed of adjustment terms c and α, and do not report results related to the short-run dynamics.[25] We use standard asterisk $(^*)$ symbols in Table 1 and Table 2 to denote significant values at the 10% $(^*)$, 5% $(^{**})$ or 1% $(^{***})$ level.

4.2.1. Mean Group estimates

Consider first the results reported in Table 1. The upper part of Table 1 provides the Mean Group estimates of the long-run equilibrium parameters that are computed from the cross-sectional average of each individual country's ARDL regression as $\hat{\boldsymbol{\beta}}_{MG} = N^{-1}\sum_{i=1}^{N}\hat{\boldsymbol{\beta}}_i$. Note that the long-run coefficient on GDP is highly significant, centered at a value of 2.96. Testing the null hypothesis $\mathcal{H}_0: \beta_{MG}^{gdp} = 1$ against the one-sided alternative $\mathcal{H}_1: \beta_{MG}^{gdp} > 1$ yields a $t-$statistic of $(2.96-1)/0.33 \approx 6$. This result, therefore, provides strong statistical evidence against a unity restriction at the aggregate cross-country level that the commonly used credit-to-GDP ratio imposes when employed as the dependent variable in the estimation of equilibrium credit.

INSERT TABLE 1 HERE

The MG estimate of the GDP Deflator coefficient is 0.27 with a $p-$value of 0.19, indicating that it is not statistically different from zero. Testing the null hypothesis $\mathcal{H}_0$: $\beta_{MG}^{def} = 1$ against a one-sided alternative results in a $t-$statistic of $(0.27-1)/0.32 \approx -2.28$, which has a corresponding one-sided $p-$value of 0.01. The statistical evidence against the unit restriction on the GDP Deflator parameter is thus somewhat weaker than for the GDP parameter itself. From a visual inspection of the $\hat{\beta}^{def}$ distribution plotted in Panel (b) of Figure 1 it may seem surprising that the null of unity is rejected at, for instance, a significance level of 5%, given the relatively large dispersion of $\hat{\beta}^{def}$ over the -6 and 5 interval. It should be stressed here again that we are testing the Mean Group estimator, which is

[25]We used a modified version of the specialised GAUSS code of Pesaran *et al.* (1999) for MG and PMG estimation available from http://www.econ.cam.ac.uk/faculty/pesaran/jasa.exe. The complete regression output from the individual country regressions is large and of no particular interest to us, apart from model checking purposes. We thus do not report the full results here, but these are available from the authors upon request.

defined as:

$$\hat{\beta}_{MG}^{def} = N^{-1} \sum_{i=1}^{N} \hat{\beta}_i^{def} \tag{15}$$

with corresponding variance

$$\text{Var}(\hat{\beta}_{MG}^{def}) = [N(N-1)]^{-1} \sum_{i=1}^{N} \left(\hat{\beta}_i^{def} - \hat{\beta}_{MG}^{def}\right)^2. \tag{16}$$

The expression in (16) is simply the variance of the sample mean. With the sample standard deviation of $\hat{\beta}_i^{def}$ being 2.2129, we can thus see that the MG estimator has a standard error of $2.2129/\sqrt{49} = 0.3161$, where $N = 49$ is the number of observations (countries) in the cross-section. This leaves a rather tight interval around the point estimate of 0.27, making the unity restriction statistically unlikely.

The Mean Group estimate of the parameter on the error correction term, shown in the bottom part of Table 1 suggests that, on average, deviations of credit from its long-run equilibrium are eliminated with a fast adjustment speed of around 16% per quarter. This point estimate is significantly different from zero, with a $t-$statistic of -6.94. From the visual inspection of the coefficient's distribution in Panel (e) of Figure 1 we can see that this result appears to be largely driven by the pronounced left skew in the $\hat{\alpha}$ density. As indicated by the mode of the density, the speed of adjustment estimate is in the -0.10 to -0.05 interval for the majority of countries in our sample, suggesting a more reasonable 5% to 10% quarterly adjustment towards the long-run equilibrium level. The MG estimate of the intercept term is also significantly different from zero, with a point estimate of -1.86 and a $t-$ statistic of -6.46.

The Mean Group estimates of the parameters on the real interest rate, the lending to deposit rate spread and the alternative cost of borrowing, which make up the velocity equation in (4), all have the expected negative point estimates, indicating that a decrease in either of the three borrowing costs leads to a decrease in credit demand. Nonetheless, the results reported in Table 1 show that only the coefficient on the alternative cost of borrowing in foreign currency is significantly different from zero at the 5% level. In contrast, the $\hat{\beta}^{rr}$ and $\hat{\beta}^{sprd}$ coefficients have $t-$statistics well below 1 in absolute value, and are statistically insignificant.

4.2.2. Pooled Mean Group Estimates

We now turn more formally to the question whether it is valid to assume that the long-run parameters that determine equilibrium credit are homogenous across the countries in our sample.[26] We investigate this question by estimating the long-run parameters in (11) using the Pooled Mean Group estimator of Pesaran *et al.* (1999), which restricts some (or all) of the long-run parameters in (11) to be the same across all countries. The validity of these restrictions can then be tested with a standard likelihood ratio (LR) test. As our primary interest is in equilibrium credit determined by the β^{gdp} and β^{def} parameters, we only impose the homogeneity restriction on these two parameters, leaving the effect of the real interest rate, the lending to deposit rate spread and the alternative cost of borrowing in foreign currency which make up the velocity equation unrestricted.[27] These estimates are reported in Table 2.

INSERT TABLE 2 HERE

The Pooled Mean Group estimates of the restricted β^{gdp} and β^{def} parameters that are reported in Table 2 are, overall, comparable in size to those of the MG estimator. The PMG parameters are, nonetheless, estimated with much greater precision. The standard errors of the MG estimates are about 2.5 and 5 times larger than those of the PMG estimates. Testing the unity restrictions on the PMG estimates of β^{gdp} and β^{def}, with the smaller standard errors, yields $t-$statistics of $(3.27 - 1)/0.12 = 18.92$ and $(0.2049 - 1)/0.0679 = -11.71$, indicating that the PMG estimates are also statistically different from 1.

Looking over the remaining unrestricted coefficients in Table 2, it is noticeable that the PMG estimates of the three long-run parameters β^{rr}, β^{sprd} and β^{acb} are substantially different from those obtained using the MG estimator. The sign of the coefficient on the real interest rate ($\hat{\beta}^{rr}$) is now positive and statistically different from zero. The influence of the lending to deposit rate spread ($\hat{\beta}^{sprd}$) has increased 50 times and is also statistically significant. The effect of the alternative cost of borrowing in foreign currency has increased about five fold and remains statistically significant at the 5% level. The estimate of the speed of adjustment parameter α under the restricted PMG estimator is now only -0.02, which is about 8 times smaller in absolute magnitude than the MG estimate reported in Table 1. Additionally, there were four instances where the cross-country restrictions imposed on the β^{gdp} and β^{def} parameters by the PMG estimator lead to positive estimates of the speed of adjustment parameter, thus violating assumption 2 of Pesaran *et al.* (1999). The above reported differences in the PMG and MG estimates of the unrestricted long-run

[26] Note that this is a different hypothesis than testing whether the MG estimates are equal to unity. We are interested in determining whether restricting the long-run coefficients to be the same across the countries is sensible and supported by the data.

[27] We have also restricted all the long-run equilibrium parameters, which evidently is a stronger restrictions. The PMG estimates under this scenarios are $4.4825, -0.4160, -0.0098, -0.0034, -0.0142$ for $\beta^{gdp}, \beta^{def}, \beta^{sprd}, \beta^{acb}$ and β^{rr}, respectively. The $LR-$statistic is 1085, with 240 degrees of freedom, so this restriction is strongly rejected by the data. Full results are available from the authors.

parameters and the speed of adjustment parameter are an indication that the homogeneity restrictions of β^{gdp} and β^{def} being the same across our sample of countries appears to be incompatible with the data.

Since the PMG estimator is inconsistent when the restrictions that are imposed on the long-run parameters are not valid, we perform a poolability test to formally assess the validity of the restrictions. This is implemented by means of an LR test. Note that the PMG estimator imposes $(N-1) \times \tilde{R}$ restrictions on the ARDL model, where in our case $N = 49$ and the number of homogeneity restrictions $\tilde{R}$ is equal to 2. The restricted and unrestricted log-likelihood functions of the PMG estimator are 8089.54 and 8359.71, respectively, resulting in an LR test statistic of over 540. One can see that this corresponds to a $p-$value of effectively 0 for a Chi-squared random variable with 96 degrees of freedom.[28] We can conclude, therefore, that the two cross-country homogeneity restrictions on the long-run parameters β^{gdp} and β^{def} are strongly rejected by the data.[29]

4.2.3. Summary of MG and PMG results

With regards to the first two questions or hypotheses that were raised at the end of Section 2, the statistical findings of this section can be summarized as follows. First, we find strong statistical evidence against the hypothesis that the Mean Group estimates of the β^{gdp} and β^{def} parameters are equal to unity. Second, we find considerable heterogeneity in the cross-country distribution of the β^{gdp} estimates. This heterogeneity was initially illustrated by means of a visual inspection of the distribution of the $\hat{\beta}^{gdp}$ coefficients, which showed signs of bimodality. We then formally tested for poolability of the β^{def} and β^{def} parameters using a likelihood ratio test within the PMG estimation framework. This test resulted in a strong rejection of the poolability hypothesis.

Given these findings, we can conclude that no statistical evidence exists to suggest

[28]The LR test statistic is distributed asymptotically as a Chi-squared random variable under the null hypothesis of the restrictions being valid.

[29]We should highlight here that the LR test, as remarked by Pesaran *et al.* (1999), is a fairly stringent test in the sense that we restrict all the parameters across the different countries to be the same. This is the restriction that the credit-to-GDP ratio implicitly imposes and the one that we are objecting to. Pesaran *et al.* (1999) therefore also implement and suggest to use a Hausman (1978) type test to determine whether the difference between the *aggregate* MG and PMG estimates are statistically significant. However, in the current context, such a test is not overly informative, as the bi-modal distribution is centered around 3 which is in the proximity of the PMG estimates. Given the size of the standard errors of the MG estimates and the reasonable proximity of the two GDP Deflator estimates, a Hausman (1978) type test implemented as $(\hat{\underline{\beta}}^{+}_{MG} - \hat{\underline{\beta}}^{+}_{PMG})'[\mathrm{Var}(\hat{\underline{\beta}}^{+}_{MG}) - \mathrm{Var}(\hat{\underline{\beta}}^{+}_{PMG})]^{-1}(\hat{\underline{\beta}}^{+}_{MG} - \hat{\underline{\beta}}^{+}_{PMG})$ where $\hat{\underline{\beta}}^{+} = (\hat{\beta}^{gdp}\ \hat{\beta}^{def})'$, (ie., the vector $\boldsymbol{\beta}$ but including only the GDP and the GDP Deflator terms) yields a test statistic of 2.0675, which with 2 degrees of freedom returns a $p-$value of around 35%. This suggests that the (aggregate) PMG and MG estimates are not statistically different from one another. But this is not the question that we seek to answer. It would seem more natural to see if all the parameter estimates are unaffected by the restrictions imposed by the PMG estimator. This could be done by testing the MG-PMG differences of the full $\hat{\boldsymbol{\beta}}$ vectors. Unfortunately, the standard errors of the PMG estimates are in fact larger for β^{rr}, β^{sprd} and β^{acb} than the MG ones, resulting in a non-positive definite covariance matrix. This prevents us from implementing a test on the full $\hat{\boldsymbol{\beta}}$ vector.

that the restrictions that are implied by the use of the credit-to-GDP ratio are supported by our cross-country panel data. Our view thus is that the use of the credit-to-GDP ratio to determine equilibrium credit, and therefore also to determine excessive credit provision, appears to be inappropriate.

4.3. Linking the cross country variation to country-specific characteristics

As outlined in Section 3.1.3, we use the BMA framework to reduce the large set of 42 potential development indicators to a smaller subset of around $15 - 20$ variables. The criterion for inclusion of a given variable in the subset is its posterior inclusion probability (PIP). We use a PIP threshold value of 25% for a variable to be included in the subset. This value may seem low, nonetheless, the purpose here is to perform a first round of *"pruning"* rather than finding the final model.[30] Our objective is to reduce the set of all potential regressors to a smaller set of highly relevant determinants of the cross-country variation in β^{gdp} and β^{def}. The Lasso is thus used as a variable selection tool.[31]

Note that we follow the same variable selection or reduction procedure to model the cross-country variation in the $\hat{\beta}^{gdp}$ as well as in the $\hat{\beta}^{def}$ and $\hat{\alpha}$ coefficients. To avoid unnecessary repetition and to keep the section as short and informative as possible, we only present the BMA and Lasso regression results for the $\hat{\beta}^{gdp}$ coefficient in this section and provide equivalent results for the $\hat{\beta}^{def}$ and $\hat{\alpha}$ coefficients in the Appendix. Also, we will initially refer to the regressors in the preliminary discussions of the BMA and Lasso estimations in Section 4.3.1 and Section 4.3.2 by their short names listed in the first column of Table 3 and Table 4. Although the short names are not very informative, these are only preliminary discussions to highlight some initial variable exclusion results.[32] We discuss the economic meaning of the regressors and their significance in the context of the final selected models in detail in Section 4.3.3.

[30] Eicher *et al.* (2011) have recently used a PIP value of 50% as the variable inclusion threshold in a growth regression context to determine the *"Number of Effective Regressors"* (see Figure 1 on page 38). One could thus naturally adopt that value here as well or even set the cut-off mark higher. Nonetheless, we do not follow such an approach here and use the Lasso penalized regression estimator instead in a second step to further *"shrink"* small or irrelevant coefficients to zero.

[31] It should be clear that the posterior mean of the BMA procedure under the given priors that we use is analogous to a Ridge regression estimator, which is also a penalised regression estimator like the Lasso, with the penalty function being the sum of squared coefficients rather than the sum of absolute coefficients (see (17) for the objective function of the Lasso). One important difference between the Lasso and the Ridge regression estimator is that the Ridge estimator cannot shrink coefficients to zero, but only to small values to reduce the importance of these variables. This means that all variables are included in the regression, which we want to avoid, given the large number of potential regressors. The advantage of the Lasso is that it shrinks unimportant variables to zero, thereby acting as a variable selector. We should also point out here that the reason why we use the BMA in the first step rather than using the Lasso on the full set of 42 potential regressors is that we ran into numerical problems when implementing the penalised regression procedure using the Matlab lasso function. We therefore found it sensible to reduce the number of potential regressors to a smaller subset first and then proceed with the Lasso.

[32] A more detailed description of these variables is provided in the second column of these tables.

4.3.1. Selecting the subset regressors

We follow the empirical BMA literature and stay within the natural conjugate prior framework for computational simplicity, thereby avoiding the need to use simulation methods to compute marginal likelihoods. We use a Normal (Gaussian) prior for the regression coefficients with a prior mean of 0 and Zellner's g−prior for the variance, so that closed form marginal likelihoods can be computed. That is, for a given model (ie., set of included regressors), we have the prior on the regression parameters being $\phi^{gdp}|\sigma_\varepsilon^2 \sim N(0, \sigma_\varepsilon^2 \, \mathrm{g} \, (Z'Z)^{-1})$, where Z is the $(N \times L)$ design matrix representation of the regressors $z_{\ell i}$ in (14) and g is a prior hyperparameter.[33]

A well known advantage of using the g−prior setup is that only the hyperparameter g needs to be specified by the user. We follow Fernandez *et al.* (2001) and set $\mathrm{g} = \max(N, L^2)$ which in our set-up yields $\mathrm{g} = L^2$. We further use uniform priors on the model probabilities. This choice results in an expected model size of $L/2 = 21$ variables. It is evident that having an expected number of 21 regressors in a cross-sectional regression with 49 observations is still rather unsatisfactory. Nevertheless, the uniform prior was used with the intention to reduce the number of relevant variables to a subset, and not to the final set of relevant development indicators. Our choice of the model prior is thus a conservative one, in the sense that we prefer a medium sized expected model size to one that shrinks the number of variables more aggressively.

As there are $2^{42} > 4.3 \times 10^{12}$ possible (linear) regression models that can be created with 42 potential regressors, we use the Model Composition MCMC (MC^3) algorithm of Madigan and York (1995) to generate draws from model space.[34] We run a chain of 75 million MCMC iterations, where the first 25 million are discarded as burn-in draws. We check the convergence of the (model space) Markov chain by computing the correlation between the model iteration counts and analytic posterior model probabilities for the best 5 000 models. This correlation is well over 99%, indicating that the Markov chain on the model space has converged. The PIPs of the included variables in the BMA procedure, together with a brief description of the 42 variables included, are reported in Table 3. The results are sorted by largest to smallest PIP value, with the dashed horizontal line marking the 25% PIP cut-off value.

INSERT TABLE 3 HERE

The posterior inclusion probabilities reported in Table 3 show that the `prudential1` and `cba_economic` variables have the highest inclusion probabilities with values close to 100%, indicating that these two variables are included in almost every regression model

[33]See Koop, 2003 pages 269 − 273 for more details regarding this set up and a general overview of BMA.
[34]See also Koop, 2003 pages 269 − 273 for more details regarding this algorithm.

that is fitted. Two other important variables in terms of high PIPs are the crisis and the cba_political variables with PIPs of 90% and 87%, respectively. Below the cba_political variable, a noticeable drop in the PIP size of around 20% occurs, with the next three important variables being s02cgp0, s13ifs0, and s01ifs0 with PIP values of 68%, 63% and 60%, respectively. The eca indicator variable has a PIP of only around 54%. Another two noticeable drops in the PIPs follow the eca variable, of around 10% each, where the PIPs drop from 54% to 45% and then further to 34% for the s01ess0 variable. When using a 25% cut-off mark in the PIPs, the governance1 variable is the last variable to be included in the resulting subset of 20 variables. In this subset of 20 variables, there are 12 variables that have PIPs of less than 50% and 8 variables have PIPs of less than 30%.

4.3.2. Shrinking the subset regressors

We employ the Lasso penalized regression estimator of Tibshirani (1996) as a variable selection tool to further reduce the subset of economic, financial and institutional development indicators selected with the 25% PIP cut-off criterion of the BMA procedure. In the context of our cross-sectional regression of $\hat{\beta}_i^{gdp}$ on the BMA reduced subset indicators $z_{\ell i}$, for example, the criterion function for the Lasso is defined as:

$$\hat{\phi}^{gdp}_{Lasso} = \underset{\{\phi^m\}_{\ell=0}^{L^s}}{\arg\min} \left\{ \sum_{i=1}^{N} \left(\hat{\beta}_i^{gdp} - \phi_0^{gdp} - \sum_{\ell=1}^{L^s} \phi_\ell^{gdp} z_{\ell i} \right)^2 + \lambda \sum_{\ell=1}^{L^s} \left| \phi_\ell^{gdp} \right| \right\}, \tag{17}$$

where L^s denotes the number of subset variables selected with the BMA procedure in Section 4.3.1, which is equal to 20 here.

The λ parameter in (17) is a "*tuning*" or "*complexity*" parameter that controls the amount of shrinkage or penalty coming from the $\sum_{\ell=1}^{L^s} |\phi_\ell^{gdp}|$ term. When $\lambda = 0$, the penalty term drops out and the Lasso estimator is equivalent to the OLS estimator. For any non-zero values of λ, shrinkage will be applied to the regression problem, and some coefficients will be shrunk to zero. The larger the value of λ the more aggressive the shrinkage is. We use "$k-$fold" cross-validation to select the value of λ that minimizes the mean squared error (MSE). Since our sample size consists of 49 cross-sectional observations, we use a "k" value of 5 in the cross-validation procedure, which corresponds to around 10% of the sample size.[35] The results of the Lasso penalized regression estimator are reported in Table 4. Since we are primarily interested in determining which coefficients are relevant, ie., not shrunk to zero, we only report the Lasso point estimates, where we use the notation $\Rightarrow 0$ in Table 4 to denote that a coefficient was shrunk to 0.

[35]Note that k is frequently set to values of either 5 or 10 (see Section 7.10 in Hastie *et al.*, 2009 on this and also for more details regarding cross-validation in general).

INSERT TABLE 4 HERE

Table 4 shows that 13 of the total of 20 subset development indicators are shrunk to 0. The variables that are selected by the Lasso are the top five variables in terms of the PIPs obtained from the BMA procedure of Section 4.3.1, namely, the `prudential1`, `cba_economic`, `crisis`, `cba_political`, and `s02cgp0` variables, as well as the `s01ifso` and `eca` variables.[36] We follow the same procedure to determine the most important development indicators for the $\hat{\beta}^{def}$ and $\hat{\alpha}$ coefficients. These results are, without any discussion, reported in the Appendix.

4.3.3. Results of the cross-country regression models

Since the Lasso estimator yields biased parameter estimates due to the penalty that is imposed on the sum of the absolute size of the coefficients to implement the shrinkage, we estimate OLS based cross-country regressions of $\hat{\beta}^{gdp}$, $\hat{\beta}^{def}$ and $\hat{\alpha}$ on their respective subset of selected development indicators.[37] These regression results are reported in Table 5 below. We will initially discuss the overall regression results in terms of fit for all three regressions and then proceed to the discussion of the economic significance and interpretation in Section 4.4. Standard asterisk (*) notation is again used to denote 10% (*), 5% (**) and 1% (***) levels of significance.

INSERT TABLE 5 HERE

Overall, all three regression results reported in Table 5 provide a reasonable cross-sectional fit, with about 45%, 53% and 38% of the variation in $\hat{\beta}^{gdp}$, $\hat{\beta}^{def}$ and $\hat{\alpha}$ explained by their respective regression models. Tests of the overall significance of the models yield $F-$statistics of 4.75, 6.22 and 5.31 with corresponding $p-$values well below 1% in terms of significance. We use the Breusch-Pagan LM test to test for heteroskedasticity in the residuals. The results of this test are reported next to the "BP Heteroskedasticity" entry in Column 2 of Table 5. For all regressions, no statistical evidence of heteroskedasticity is detected. For this reason, we simply report homoskedastic standard errors in Table 5, rather than heteroskedasticity consistent ones.

To provide some visual indication of how well the models fit the $\hat{\beta}^{gdp}$, $\hat{\beta}^{def}$ and $\hat{\alpha}$ series,

[36] It is interesting to observe that the `s01ifso` variable is not shrunk towards 0 by the Lasso estimator despite of its coefficient being rather small in magnitude.

[37] Recall that we used the Lasso as a variable selection tool to get the smallest possible set of "important" regressors. Given that we have found the smallest set of important regressors, we use OLS to obtained unbiased estimates of the parameters.

we plot the actual and fitted series for all three models in the top, middle and bottom Panels of Figure 2. All three models track the actual series quite well, with a reasonably good ability to fit countries that are away from the general centre of the series (see, for example, the fits for Finland, Mexico and Georgia for the $\hat{\beta}^{gdp}$ series, the fits for Finland and the Czech Republic for the $\hat{\beta}^{def}$ series and the fits for Cyprus and Hong Kong for the $\hat{\alpha}$ series). A mildly worse fit is obtained for some of the countries plotted on the right hand side of the Panels in Figure 2. For the $\hat{\beta}^{def}$ series, this concerns Poland, Romania, Georgia and Thailand. For the $\hat{\beta}^{gdp}$ series, this concerns Israel, Egypt and South Korea. For the $\hat{\alpha}$ series, this concerns the fits for Greece, Australia, Israel and Poland. Nevertheless, overall, we judge the fits of the models to be satisfactory.

We also investigate the distributional properties of the $\hat{\beta}^{gdp}$, $\hat{\beta}^{def}$ and $\hat{\alpha}$ regression residuals. Similar to the set-up in Section 4.1, we produce histogram and density plots of the regression residuals. These are shown in Figure 3. Panel (a) of Figure 3 shows the residuals from the $\hat{\beta}^{gdp}$ regression. The bi-modality in the distribution of the $\hat{\beta}^{gdp}$ coefficient disappears and the distribution takes on a more "Normal" looking shape once we condition on the relevant subset cross-country development indicators for $\hat{\beta}^{gdp}$. The skewness and kurtosis values are 0.1573 and 2.8265, respectively, yielding a Jarque-Bera test statistic of 0.2582, with a corresponding Monte Carlo simulated $p-$value in excess of 0.50.[38] The Jarque-Bera test for Normality thus fails to reject the null hypothesis of the data matching the skewness and kurtosis of a Normal distribution.[39]

INSERT FIGURE 3 HERE

The plot in Panel (b) of Figure 3 shows the empirical distribution of the residuals from the cross-country regression of $\hat{\beta}^{def}$ on its relevant indicators. Recall that the distribution of $\hat{\beta}^{def}$ plotted in Panel (c) of Figure 1 showed signs of substantial kurtosis and mild skewness. By conditioning the $\hat{\beta}^{def}$ coefficient on its relevant development indicators, the kurtosis and also the skewness in the distribution are noticeably diminished. Skewness and kurtosis values are -0.5204 and 3.6797, respectively, yielding a Jarque-Bera test statistic of 3.0904, with a corresponding Monte Carlo simulated $p-$value of 0.1032. The statistical evidence in favour of the $\hat{\beta}^{def}$ regression residuals being Normally distributed is thus somewhat weaker than for the $\hat{\beta}^{gdp}$ regression residuals.

The distribution of the residuals from the $\hat{\alpha}$ regression on its relevant indicators is

[38] We use the Matlab function jbtest which relies on Monte Carlo simulation to compute the $p-$values of the Jarque-Bera test due to the well known oversensitivity of the asymptotic Chi-squared approximation in small samples.

[39] This is evidently a weak test of Normality as it only tests the 3^{rd} and 4^{th} moments of a series. Nonetheless, the intention here is solely to provide some indication that the distribution of the residuals is much better behaved in terms of shape than the original distribution of the $\hat{\beta}^{gdp}$ series.

shown in Panel (c) of Figure 3. Comparing this distribution to that of the $\hat{\alpha}$ one plotted in Panel (e) of Figure 1, we see that conditioning on the relevant subset development indicators reduces some of the obvious left skew in the $\hat{\alpha}$ distribution. Nevertheless, the conditioning has a considerably weaker effect on the $\hat{\alpha}$ residuals than it had on the $\hat{\beta}^{gdp}$ and $\hat{\beta}^{def}$ residuals, as the distribution still shows some evidence of left skewness and excess kurtosis. This is also reflected in the skewness and kurtosis statistics, which are -1.2086 and 4.7730, respectively, yielding a Jarque-Bera test statistic of 18.3479, with a corresponding Monte Carlo simulated $p-$value of 0.0043. The null hypothesis of Normality of the $\hat{\alpha}$ regression residuals is hence rejected.

4.4. Discussion of the cross-country regression results

Having evaluated the overall statistical fit of the $\hat{\beta}^{gdp}$, $\hat{\beta}^{def}$ and $\hat{\alpha}$ regressions on their relevant development indicators, we now discuss in detail the economic relevance of the variables that determine the cross-country variation in the $\hat{\beta}^{gdp}$, $\hat{\beta}^{def}$ and $\hat{\alpha}$ coefficients. To facilitate this discussion, consider again the regression results that are reported in Table 5.

4.4.1. GDP regression

The Private Credit to GDP ratio (`s01ifs0`), which is a measure of an economy's financial depth, has a positive impact on the income elasticity of credit ($\hat{\beta}^{gdp}$).[40] This suggests that, as a country's financial system develops, it becomes more responsive (sensitive) to changing credit needs in the economy ($\hat{\beta}^{gdp}$ increases).

The effect of the Number of Branches per $100,000$ Adults (`s02cgp0`) on the income elasticity of credit is -4. This is an interesting result. In an economy where customers rely on face-to-face interactions with bank staff, the Number of Branches variable measures the access to finance, where a higher number suggests that easier access to finance is available. Nonetheless, with the advent of internet based banking and credit availability, a decrease in the income elasticity of credit with an increasing number of branches may in fact capture the effect of financial development of the economy. Many advanced economies experienced a reduction in the number of bank branches over the last $10-15$ years due to the goal of financial institutions to reduce staffing costs. Furthermore, the popularity of and demand for internet banking has increased substantially. Alternatively, the negative effect of the Number of Branches on the income elasticity of credit can be explained by portfolio diversification where agents replace credit with other financial services to increase diversity in their financial portfolios. Such a strategy is often pursued in an effort to manage risks more effectively by using market insurance and investment diversification instead of credit to reduce the risk of potential portfolio losses (see also

[40] Note here that Private Credit to GDP is measured in %, thus at a base value of 100. This means that an increase of 50% in the ratio, ie., from 100 to 150, results in an increase in $\hat{\beta}^{gdp}$ from 3.21 to 4.815.

Ehrlich and Becker, 1972 for additional details).

Greater Integration of Prudential Supervision (prudential1) increases the flexibility of the financial system to respond promptly to changes in credit demand in the economy. This is due to the effect that Greater Integration of Prudential Supervision has on increasing competition by creating a more harmonised and transparent regulatory framework across different financial sub-sectors. Both, Central Bank Economic and Political Independence (cba_political and cba_economic) have a positive impact on the income elasticity of credit. This result follows from the general tendency of many independent central banks to respond either directly or indirectly to developments in GDP as well as credit. GDP (or its deviation from potential) and credit are now commonly part of the reaction function of a central bank (see Cúrdia and Woodford, 2010 and Christiano *et al.*, 2007).[41]

The Financial Crisis Experience dummy (crisis) affects the income elasticity of credit negatively. Countries that have experienced a financial crisis in the past have a roughly 50% lower income elasticity of credit than the Mean Group estimate across all countries, which is around 3. This indicates that economies with crises experience are more conservative in increasing credit demand and supply when economic activity is expanding. Also, it is likely that some of our sample countries that have experienced a financial crisis in the past may have undergone periods where credit was failing much faster than GDP, irrespective of the credit requirements of the economy.

The estimated positive coefficient on the Europe and Central Asia (ECA) region dummy (eca) suggests a higher income elasticity of credit for ECA countries. We explain this finding by the large capital inflows into ECA countries preceding the $2007-2008$ global financial crisis and subsequent larger outflows once the crisis hit. However, the ECA dummy coefficient is estimated rather imprecisely, indicating that considerable variation exists across the ECA countries in terms of a higher average $\hat{\beta}^{gdp}$ relative to non-ECA countries.

4.4.2. GDP Deflator regression

The price elasticity of credit ($\hat{\beta}^{def}$) is positively related to the Number of Branches per $100,000$ Adults (s02cgp0). This suggests that easier access to credit enables the private sector to adjust credit demand to changes in the average price of a transaction more easily. Outstanding Domestic Private Debt Securities (s01bis0), on the other hand, decrease the price elasticity of credit. This result can arise as private agents in more developed domestic debt markets may rely less on credit and can easily substitute credit by issuing debt in the domestic capital market. The Cost to Income Ratio (s05bsk0), which measures the cost effectiveness of banks, has a positive effect on the price elasticity of credit. This indicates that a more efficient financial system has greater flexibility in responding to

[41]See also Cho and Moreno (2006) and Buncic and Melecky (2008) for examples of monetary policy reactions functions in a small New Keynesian model for the US and a small open economy version for Australia.

changing credit demand as the average price level in the economy varies.

Integration of Prudential Supervision (`prudential1`) as well as Central Bank Political and Economic Independence (`cba_political` and `cba_economic`) have negative coefficients, suggesting that an increase in either one of these three indicators leads to a reduction in the price elasticity of credit.[42] All three indicators measure how independent monetary policy and, in many cases, macroprudential policy are from political pressures and industry lobbies. As outlined earlier, many independent central banks now have explicit targets for GDP, inflation as well as credit growth. Any increasing measure of central bank independence (together with prudential supervision) can thus be taken as an indication of conservatism on the sensitivity of aggregate price changes to credit and vice versa.

From the coefficient on the Financial Crisis Experience dummy (`crisis`) it is interesting to see that the experience of financial crises increases the price elasticity of credit. There could be two reasons for this result. First, from an empirical perspective, countries may have experienced periods of deflation during crisis times due to a negative wealth effect on prices. Second, from a moral hazard perspective, if excessive risk taking that leads to a financial crisis is not adequately punished, then otherwise conservative agents may pursue an active strategy to take on more risky investments, resulting in inflated asset prices. This is then reflected in an overall increase in the price elasticity of credit.

4.4.3. Speed of adjustment regression

The speed of adjustment of credit toward its long-run equilibrium ($\hat{\alpha}$) increases with the Number of Branches per $100,000$ Adults (`s02cgp`). This positive relation suggests that greater access to financial services results in faster adjustment speeds, thus keeping credit closer to its long-run equilibrium value. This positive relation can arise as agents can afford to hold less precautionary credit to finance unexpected transactions. The Gross Portfolio Equity Assets to GDP ratio (`s12ifs0`), which measures the share of portfolio equity assets (claims on non-residents), has a positive effect on the speed of adjustment to credit equilibrium. A possible explanation of this effect is that countries and their agents that have the capacity to make investments abroad are able to better monitor over- or under-supply of credit and respond to it, instead of lending domestically through banks or capital markets.

The impact of the Consolidated Foreign Claims to GDP ratio (`s05bis0`) on the speed of adjustment of credit to its equilibrium is negative. This could stem from the lower abil-

[42]Notice here that the parameter estimates of the two central bank independence measures are -4.82 and -4.85, respectively. It may thus seem that the similarity of the two coefficients is driven by high collinearity in these two measures. This is, however, not the case here, as the sample correlation between the series is only 0.22. These two variable therefore measure different parts of Cental Bank independence and its impact on $\hat{\beta}^{def}$.

ity of countries with larger capital inflows to manage credit provision in their economy. Central Bank Political Independence (`cba_political`) has a positive effect on the speed of adjustment. Central banks often have the mandate to foster financial stability in addition to their primary objective of price stability and full employment. Greater Central Bank independence can thus lead to a more timely and appropriate response of the Central Bank to excessive credit growth, using either standard monetary or macroprudential tools. The estimated negative coefficient on the Europe and Central Asia (ECA) region dummy (`eca`) suggests that ECA countries have been less successful in achieving timely and speedy adjustments of credit to its equilibrium.

4.4.4. Correlation between $\hat{\beta}^{gdp}$ and $\hat{\beta}^{def}$

The results reported in Table 5 show that the economic and financial development indicators that affect both $\hat{\beta}^{gdp}$ and $\hat{\beta}^{def}$ appear to do so consistently with opposite signs. This appears to indicate that the $\hat{\beta}^{gdp}$ and $\hat{\beta}^{def}$ coefficients are negatively correlated. This is indeed the case here. The correlation between $\hat{\beta}^{gdp}$ and $\hat{\beta}^{def}$ is -0.81, with a highly significant $t-$statistic of -9.50. This is an interesting result that has not been observed or tested in previous cross-country panel studies of credit demand. Note that this is a robust result in the sense that it is not driven by outliers in our sample data. To corroborate this point, we show a scatter plot of $\hat{\beta}^{gdp}$ and $\hat{\beta}^{def}$ in Figure 4, with superimposed linear regression and non-parametric Kernel regression fits.[43] The two regression lines are consistent with a significant correlation coefficient estimate of -0.81 and overlap reasonably well for the 49 cross-sectional observations in our sample.

Recall that the $\hat{\beta}^{gdp}$ and $\hat{\beta}^{def}$ are the income and price elasticities estimated from the empirical ECM form of the ARDL model in (11) within the Mean Group estimation framework of Pesaran and Smith (1995). That is, each of the cross-country coefficients $\hat{\beta}^{gdp}$ and $\hat{\beta}^{def}$ are obtained from separate ARDL regressions on each individual country. Due to this, it should be clear that the obtained negative correlation cannot be the result of a restriction or a model structure that is imposed on the data. Our conjecture is that frequent or large supply side shocks could be the cause of the negative correlation between $\hat{\beta}^{gdp}$ and $\hat{\beta}^{def}$. Both GDP and the price level are affected in opposite directions, which could be due to the credit stock being a more stable process than GDP and or the GDP Deflator.

5. Conclusion

This paper carried out a cross-country estimation of equilibrium credit. It utilized the framework of long-run transaction demand for credit, in which parameters of the equi-

[43]The Nadaraya-Watson Kernel regression estimator was used together with the simple plug-in (rule of thumb) bandwidth of Silverman (1986) (see, for example, Pagan and Ullah, 1999, Chapter 3 for the computational details).

librium credit relation vary with the level of economic, financial, and institutional development. It provided empirical evidence that using the credit-to-GDP ratio to gauge equilibrium credit is inappropriate. This is because such an approach ignores heterogeneity (cross-country variation) in the parameters that determine long-run equilibrium credit. The main development indicators driving the variation in the country-specific parameters of equilibrium credit as a country develops are: financial depth, access to financial services, use of capital markets, efficiency and funding of domestic banks, central bank independence, the degree of supervisory integration, and the experience of a financial crisis. In addition, countries from the Europe and Central Asia region show a much slower adjustment of credit to its equilibrium than other countries in our sample.

Our findings have important policy implications. We acknowledge that simplicity and country specificity present a tradeoff in the design of an indicator to assess and monitor sustainable provision of credit to the economy. A simple indicator can be preferred as long as it is not too simplistic. Our results show that the proposal of Basel III to use the HP filtered credit-to-GDP ratio to gauge equilibrium credit could be too simplistic because it disregards important country specificities, that is, how equilibrium credit changes with financial, economic and institutional development. We provide empirical evidence that shows that country specificities are important and need to be accounted for when equilibrium credit is estimated, especially for developing countries.

Developed countries might be more concerned about financial stability rather than financial development as nearly everyone can access finance in normal times. Developing countries, on the other hand, have much to lose if they focus too intensely on financial stability and severely restrict credit provision to the real economy. Over restrictive credit provision can hinder financial development and be in the way of more general economic development.

Concerns by developing countries might have been voiced too little when international policy makers were deliberating appropriate indicators to assess sustainable credit provision and monitor credit cycles in response to the $2007 - 2008$ global financial crisis. This paper provides a structural framework that policymakers in developing countries can use to argue against the rigid implementation of the HP filtered credit-to-GDP ratio as a measure of equilibrium credit in their country. Moreover, this paper's framework and results enable policymakers in developing countries to measure equilibrium credit tailored to their countries' level of development and thus strikes a balance between financial development and stability.

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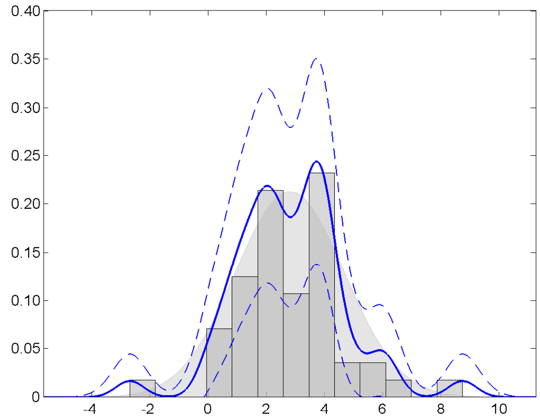
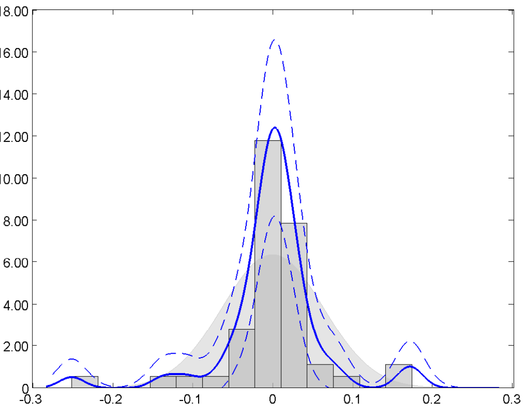
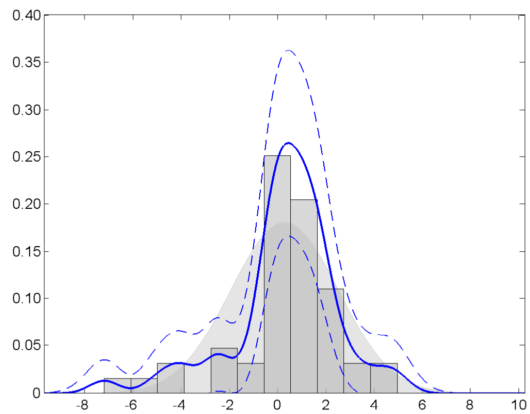


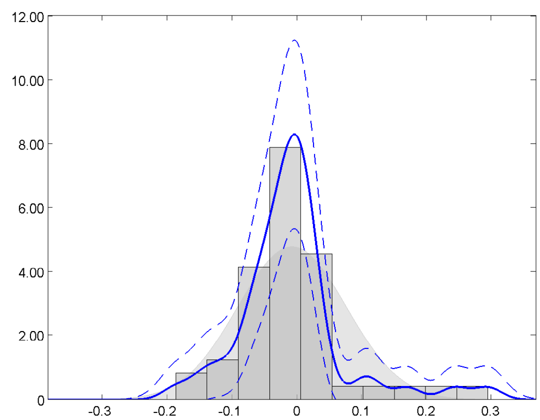
(a) Distribution of $\hat{\beta}^{gdp}$



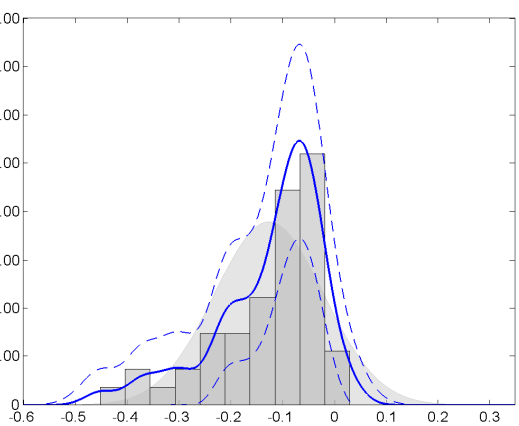
(b) Distribution of $\hat{\beta}^{rr}$



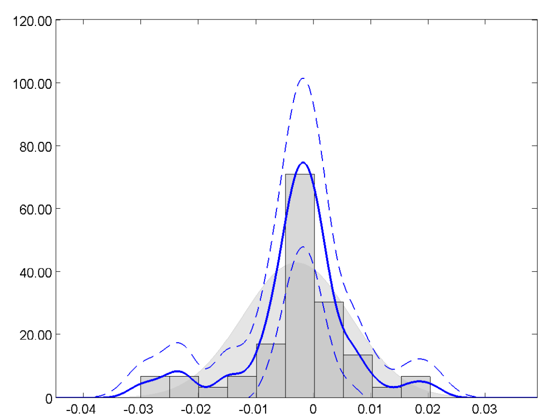
(c) Distribution of $\hat{\beta}^{def}$



(d) Distribution of $\hat{\beta}^{sprd}$



(e) Distribution of $\hat{\alpha}$



(f) Distribution of $\hat{\beta}^{acb}$

Figure 1: Histograms and densities of the coefficients $\hat{\beta}^{gdp}$, $\hat{\beta}^{def}$ and the speed of adjustment $\hat{\alpha}$ are in the left column and $\hat{\beta}^{rr}$, $\hat{\beta}^{sprd}$ and $\hat{\beta}^{acb}$ are in the right column. 95% (asymptotic) confidence intervals are denoted by the (blue) dashed line. A normal density, centered and scaled at the sample mean and standard deviation, is plotted in light gray in the background. Optimal smoothing bandwidth and histogram bin size were selected using the approaches of Shimazaki and Shinomoto (2010, 2007), respectively.

Table 1: Mean Group estimation results

Parameter on Variable:	Estimate	Std. error	$t-$statistic	$p-$value	95% CI
GDP	2.9613^{***}	0.3260	9.0833	0.0000	[2.3223, 3.6002]
GDP Deflator	0.2744	0.3161	0.8681	0.1927	[−0.3452, 0.8940]
Real interest rate	−0.0005	0.0090	−0.0528	0.4790	[−0.0181, 0.0171]
Lending to deposit spread	−0.0072	0.0120	−0.5998	0.2743	[−0.0308, 0.0164]
Alternative cost of borrowing	-0.0029^{**}	0.0013	−2.2184	0.0133	[−0.0056, −0.0003]
Error correction term	-0.1631^{***}	0.0235	−6.9381	0.0000	[−0.2092, −0.1170]
Intercept term	-1.8644^{***}	0.2887	−6.4573	0.0000	[−2.4304, −1.2985]

Notes: This table shows the MG estimates of the long-run equilibrium parameters, and the error correction and the intercept terms in the top and bottom parts of the table, respectively. Estimates are computed as the arithmetic averages over the N countries that are included in the estimation. Standard errors (Std. error) are computed as the sample standard deviation divided by $\sqrt{N}$ (see Pesaran and Smith, 1995 for more details). The column with the heading $p-$values reports one sided probability values under a standard normal distribution. The asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The full estimation results for each country are available upon request.

Table 2: Pooled Mean Group estimation results

Parameter on Variable:	Estimate	Std. error	$t-$statistic	$p-$value	95% CI
GDP (R)	3.2672^{***}	0.1201	27.2110	0.0000	[3.0318, 3.5026]
GDP Deflator (R)	0.2049^{***}	0.0679	3.0170	0.0013	[0.0718, 0.3380]
Real interest rate	0.1488^{***}	0.0408	3.6476	0.0001	[0.0688, 0.2288]
Lending to deposit spread	-0.3387^{***}	0.0913	−3.7110	0.0001	[−0.5176, −0.1598]
Alternative cost of borrowing	-0.0140^{**}	0.0078	−1.7986	0.0360	[−0.0293, 0.0013]
Error correction term	-0.0238^{***}	0.0056	−4.2416	0.0000	[−0.0348, −0.0128]
Intercept term	-0.2424^{***}	0.0554	−4.3722	0.0000	[−0.3510, −0.1338]
Unrestricted log-likelihood:	8359.71		Restricted log-likelihood:		8089.54

Notes: This table shows the PMG estimates of the long-run equilibrium parameters and the error correction and the intercept terms in the top and bottom parts of the table, respectively. Only the GDP and GDP Deflator parameters are restricted to be the same across the groups (countries). This is denoted by (R) in the table above. All other parameters are left unrestricted. These estimates were computed using the system Maximum Likelihood Estimator of Pesaran *et al.* (1999). The column with the heading $p-$values reports one sided probability values under a standard normal distribution. The asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The full estimation results for each country are available upon request.

Table 3: Posterior Inclusion Probabilities for $\hat{\beta}^{gdp}$ from BMA regressions

Variable name	Description	PIP
`prudential1`	Integration of prudential supervision	0.9953
`cba_economic`	Central bank economic independence	0.9927
`crisis`	Financial crisis experience (0,1 dummy variable)	0.9025
`cba_political`	Central bank political independence	0.8675
`s02cgp0`	Number of Branches per 100,000 Adults, Commercial Banks$^{(1)}$	0.6809
`s13ifs0`	Gross Portfolio Debt Assets/GDP (%)	0.6254
`s01ifs0`	Private Credit/GDP (%)	0.6007
`s14ifs0`	Gross Portfolio Equity Liabilities/GDP (%)	0.5603
`eca`	Europe and Central Asia (ECA) region dummy	0.5363
`s03bis0`	Outstanding International Private Debt Securities/GDP (%)	0.4549
`s01ess0`	Percent of Firms With Line of Credit, All Firms (%)	0.3351
`s12ifs0`	Gross Portfolio Equity Assets/GDP (%)	0.3045
`s01wfe0`	Percent Market Capitalization of Top 10 Largest Companies (%)	0.3026
`s01wdi0`	Stock Market Turnover Ratio (%)	0.2980
`s02fsi0`	Bank Capital to Assets (%)	0.2748
`gdp_ppp`	GDP per Capita PPP adjusted	0.2712
`s01axc0`	Insurance Premiums (Life)/GDP (%)	0.2637
`s02bis0`	Outstanding Domestic Public Debt Securities/GDP (%)	0.2621
`s01bis0`	Outstanding Domestic Private Debt Securities/GDP (%)	0.2609
`governance1`	Kaufmann *et al.* (2010) overall governance indicator	0.2577
`s05wdi0`	Number of Listed Companies$^{(1)}$	0.2196
`s03ifs0`	Credit to Government and SOEs/GDP (%)	0.2191
`s04fsi0`	Provisions to NPLs (%)	0.2150
`s01fsi0`	Regulatory Capital to Risk-Weighted Assets (%)	0.1900
`s05bis0`	Consolidated Foreign Claims of BIS-Reporting Banks/GDP (%)	0.1435
`tradepgdp`	Openness (imports plus exports over GDP)	0.1390
`s08bsk0`	3 Bank Asset Concentration (%)	0.1318
`s01_s03`	Private Credit/Number of Listed Companies (%)	0.1299
`s06bsk0`	Return on Assets (%)	0.1224
`s10bsk0`	Liquid Assets / Deposits and Short Term Funding (%)	0.1119
`s02ess0`	Percent of Firms With Line of Credit, Small Firms (%)	0.1112
`s01nbf0`	Pension Fund Assets/GDP (%)	0.1078
`s04bis0`	Outstanding International Public Debt Securities/GDP (%)	0.0924
`s03bsk0`	Non-Interest Income / Total income (%)	0.0885
`dist_crisis`	Cumulative number of crises experienced by a country	0.0144
`s05bsk0`	Cost to Income Ratio (%)	0.0139
`s09ifs0`	Private Credit to Deposits (%)	0.0132
`s15ifs0`	Gross Portfolio Debt Liabilities/GDP (%)	0.0130
`s02nbf0`	Mutual Fund Assets/GDP (%)	0.0122
`s07bsk0`	Return on Equity (%)	0.0112
`s03fsi0`	NPLs to Total Gross Loans (%)	0.0111
`s02axc0`	Insurance Premiums (Non-Life)/GDP (%)	0.0020

Notes: This table shows the Posterior inclusion probabilities (PIPs) of the 42 possible economic, financial and institutional development indicators for $\hat{\beta}^{gdp}$ computed from a Bayesian model averaging procedure, where a Zellner g−prior was used for the specification of the hyperparameter g in the variance prior of $\varphi^{gdp}|\sigma_\epsilon$. The MC^3 algorithm of Madigan and York (1995) was used to generate draws from the model space. A chain with 75 million MCMC draws was run, where the first 25 million were discarded as a burn-in sample. The dashed line in the table above marks the cut off value at PIP = 25%.
$^{(1)}$denotes values that have been log transformed.

Table 4: Lasso penalised regression estimates of ϕ^{gdp}

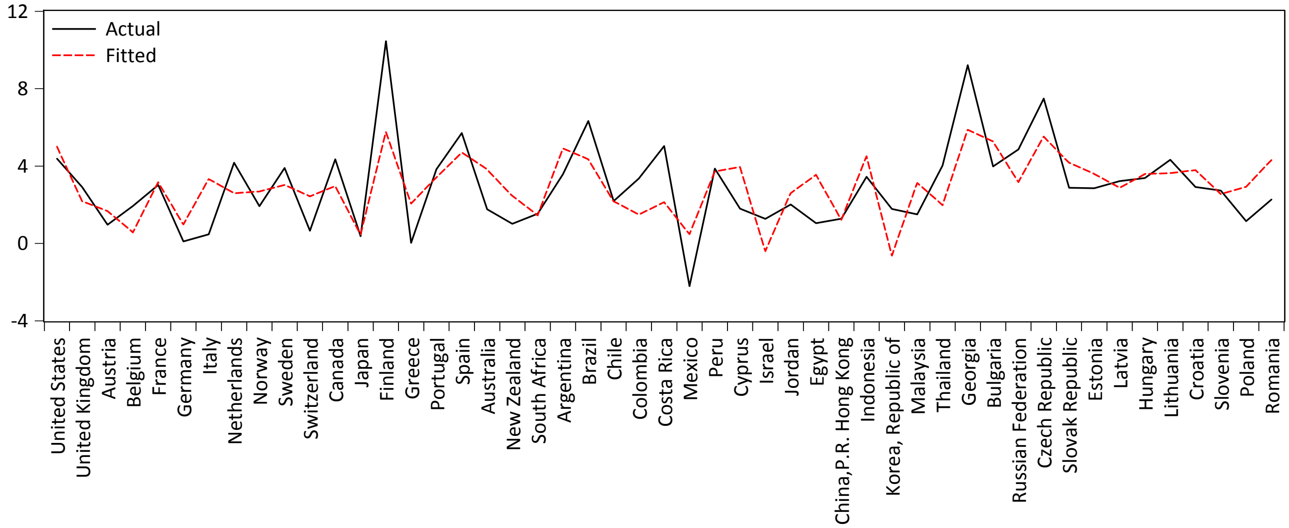
Variable name	Description	Lasso estimate of ϕ^{gdp}
`prudential1`	Integration of prudential supervision	1.2064
`cba_economic`	Central bank economic independence	4.5758
`crisis`	Financial crisis experience (0,1 dummy variable)	-1.4273
`cba_political`	Central bank political independence	2.0995
`s02cgp0`	Number of Branches per 100,000 Adults, Commercial Banks$^{(1)}$	-1.3186
`s13ifs0`	Gross Portfolio Debt Assets/GDP (%)	$\Rightarrow 0$
`s01ifs0`	Private Credit/GDP (%)	0.0059
`s14ifs0`	Gross Portfolio Equity Liabilities/GDP (%)	$\Rightarrow 0$
`eca`	Europe and Central Asia (ECA) region dummy	0.7137
`s03bis0`	Outstanding International Private Debt Securities/GDP (%)	$\Rightarrow 0$
`s01ess0`	Percent of Firms With Line of Credit, All Firms (%)	$\Rightarrow 0$
`s12ifs0`	Gross Portfolio Equity Assets/GDP (%)	$\Rightarrow 0$
`s01wfe0`	Percent Market Capitalization of Top 10 Largest Companies (%)	$\Rightarrow 0$
`s01wdi0`	Stock Market Turnover Ratio (%)	$\Rightarrow 0$
`s02fsi0`	Bank Capital to Assets (%)	$\Rightarrow 0$
`gdp_ppp`	GDP per Capita PPP adjusted	$\Rightarrow 0$
`s01axc0`	Insurance Premiums (Life)/GDP (%)	$\Rightarrow 0$
`s02bis0`	Outstanding Domestic Public Debt Securities/GDP (%)	$\Rightarrow 0$
`s01bis0`	Outstanding Domestic Private Debt Securities/GDP (%)	$\Rightarrow 0$
`governance1`	Kaufmann *et al.* (2010) overall governance indicator	$\Rightarrow 0$

Notes: This table shows the Lasso penalised regression estimates of ϕ^{gdp}. These were computed with a mean squared error (MSE) cross-validated complexity parameter λ. Coefficients that are shrunk towards zero by the Lasso estimator are denoted by $\Rightarrow 0$.
$^{(1)}$denotes values that have been log transformed.

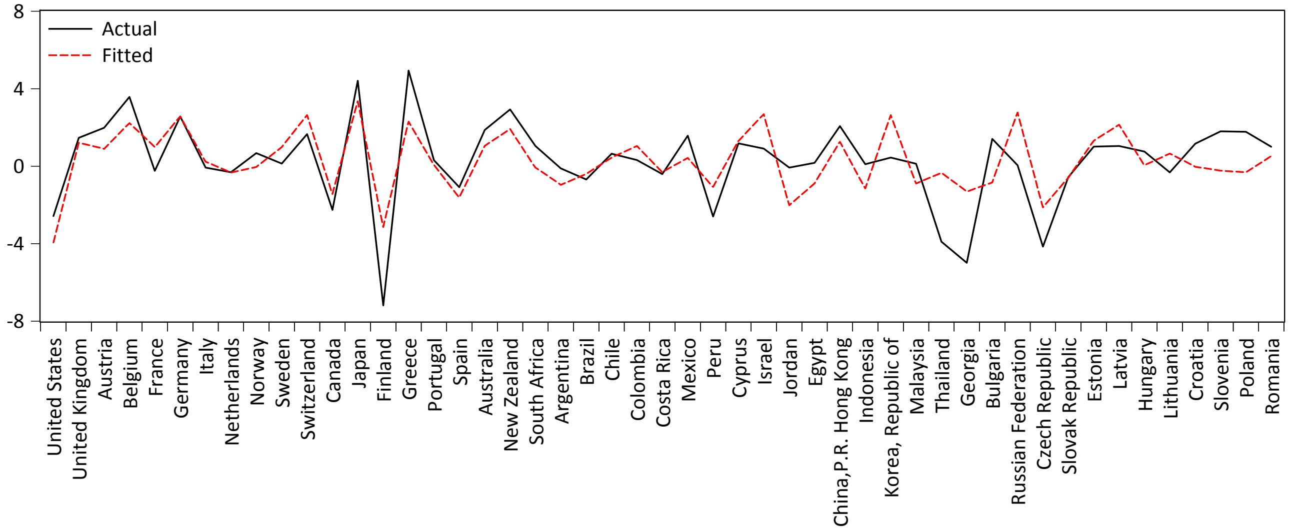
Table 5: OLS cross-country regressions

Explanatory Variables		Dependent Variable		
Variable name	Description of Variables	$\hat{\beta}^{gdp}$	$\hat{\beta}^{def}$	$\hat{\alpha}$
`s01ifs0` (std. error) [$p-$value]	Private Credit/GDP (%)	0.0321*** (0.0116) [0.0087]	—	—
`s02cgp0` (std. error) [$p-$value]	Number of Branches per 100,000 Adults(1)	−3.9798*** (1.0599) [0.0005]	3.8461*** (0.7451) [0.0000]	0.2672** (0.1028) [0.0128]
`s05bsk0` (std. error) [$p-$value]	Cost to Income Ratio (%)	—	0.1981*** (0.0627) [0.0031]	—
`s01bis0` (std. error) [$p-$value]	Outstanding Domestic Private Debt Securities/GDP (%)	—	−0.0353*** (0.0110) [0.0034]	—
`s12ifs0` (std. error) [$p-$value]	Gross Portfolio Equity Assets/GDP (%)	—	—	0.0047** (0.0018) [0.0107]
`s05bis0` (std. error) [$p-$value]	Consolidated Foreign Claims of BIS-Reporting Banks/GDP (%)	—	—	−0.0079*** (0.0019) [0.0003]
`prudential1` (std. error) [$p-$value]	Integration of Prudential Supervision	1.5539*** (0.4373) [0.0010]	−1.0809*** (0.3731) [0.0060]	—
`cba_political` (std. error) [$p-$value]	Central Bank Political Independence	2.1719* (1.1178) [0.0589]	−4.8218*** (1.1342) [0.0001]	0.1656** (0.0756) [0.0341]
`cba_economic` (std. error) [$p-$value]	Central Bank Economic Independence	6.6749*** (2.0999) [0.0028]	−4.8525** (1.8145) [0.0107]	—
`crisis` (std. error) [$p-$value]	Financial Crisis Experience (0,1 dummy variable)	−1.6136** (0.7781) [0.0444]	2.6972*** (0.6634) [0.0002]	—
`eca` (std. error) [$p-$value]	Europe and Central Asia (ECA) region dummy	1.0292 (0.9379) [0.2789]	—	−0.1496*** (0.0450) [0.0004]
`Constant` (std. error) [$p-$value]	Intercept term	18.56*** (6.1237) [0.0042]	−13.21*** (4.3810) [0.004]	−0.6877*** (0.2261) [0.0040]
	Log-Likelihood	−94.89	−90.21	31.17
	R-squared {Adjusted R^2}	0.4479 {0.3536}	0.5150 {0.4322}	0.3817 {0.3099}
	$F-$statistic [$p-$value]	4.7518*** [0.0006]	6.2200*** [0.0001]	5.3104*** [0.0007]
	BP Heteroskedasticity [$p-$value]	5.8273 [0.5600]	9.2212 [0.2376]	6.5441 [0.2568]

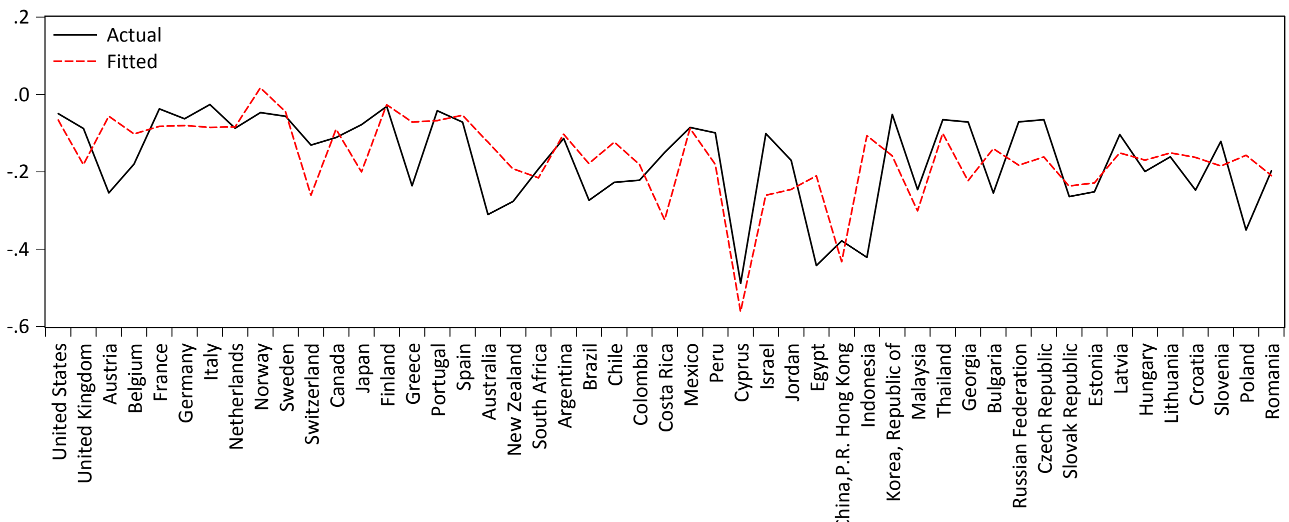
Notes: This table shows the OLS regression estimates of the ϕ^{gdp}, ϕ^{def} and ϕ^{α} parameters from the regressions of $\hat{\beta}^{gdp}$, $\hat{\beta}^{def}$ and $\hat{\alpha}$ on their respective relevant subset economic, financial and institutional development indicators selected from the BMA and Lasso procedures. Standard errors (denoted by std. error in parenthesis below estimates) are homoskedastic standard errors. One sided probability values (denoted by $p-$value) are reported in square brackets below the estimates and the standard errors. Values in the bottom part of the table show standard regression goodness-of-fit and mis-specification indicators. The entry next to BP Heteroskedasticity is the Breusch-Pagan test for heteroskedasticity. The asterisks ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
(1) denotes values that have been log transformed.



(a) Actual and fitted values of $\hat{\beta}^{gdp}$

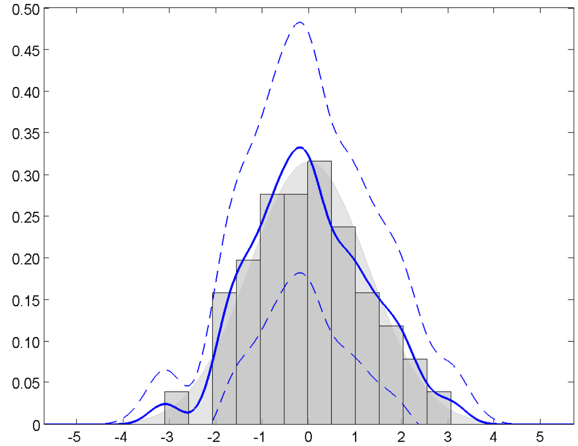


(b) Actual and fitted values of $\hat{\beta}^{def}$

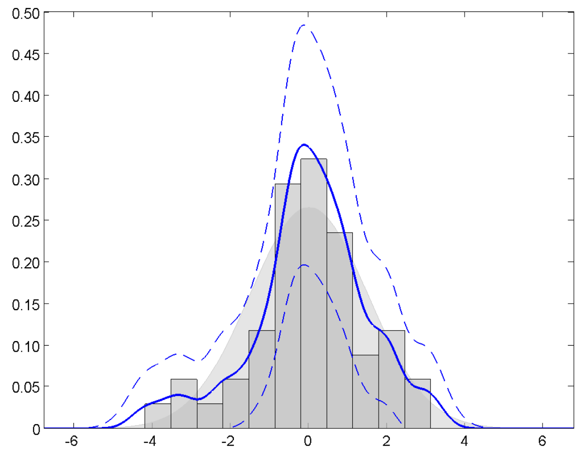


(c) Actual and fitted values of $\hat{\alpha}$

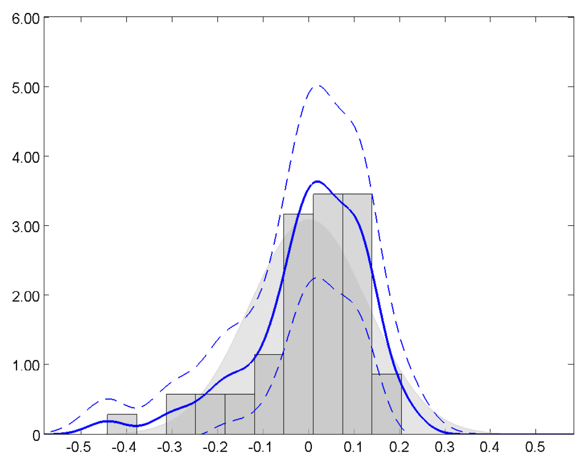
Figure 2: This figure shows the actual (blue solid line) and fitted (dashed red line) values of $\hat{\beta}^{gdp}$, $\hat{\beta}^{def}$ and $\hat{\alpha}$ from the regressions on their respective relevant subset economic, financial and institutional development indicators as reported in Table 5. The cross-countries that are included in the regressions are shown on the $x-$axis labels of the plots.



(a) Distribution of $\hat{\beta}^{gdp}$ residuals



(b) Distribution of $\hat{\beta}^{def}$ residuals



(c) Distribution of $\hat{\alpha}$ residuals

Figure 3: Histograms and density estimates of the residuals from the $\hat{\beta}^{gdp}$, $\hat{\beta}^{def}$ and $\hat{\alpha}$ regressions on their respective relevant subset economic, financial and institutional development indicators as reported in Table 5. 95% (asymptotic) confidence intervals are denoted by the (blue) dashed line. A normal density is plotted in light gray in the background. Optimal smoothing bandwidth and histogram bin size were selected using the approaches of Shimazaki and Shinomoto (2010, 2007), respectively.

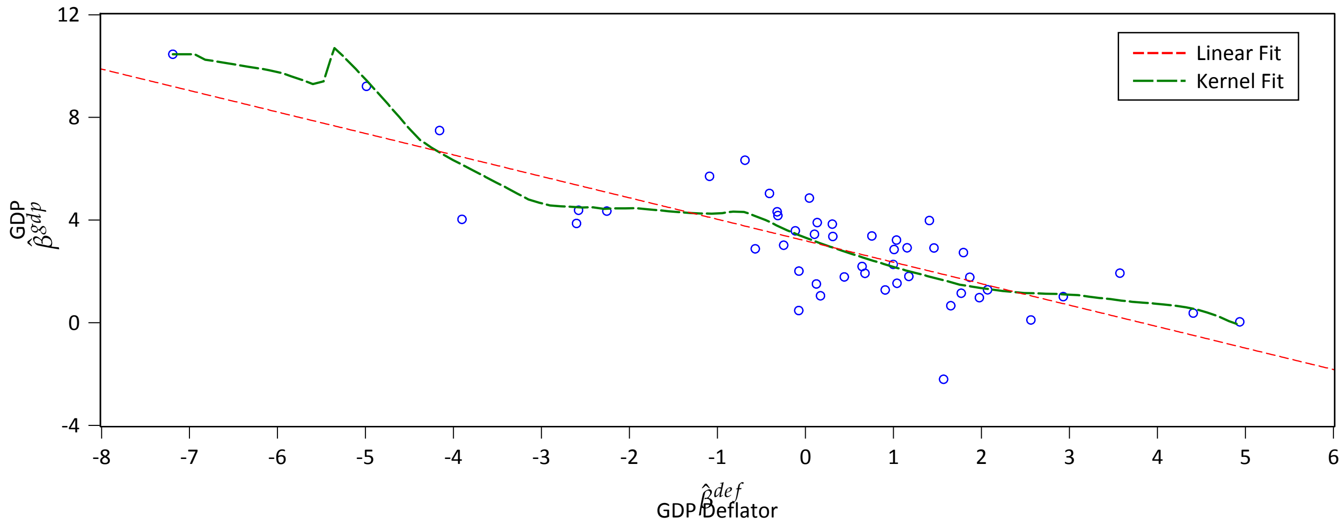


Figure 4: Scatter plot of the $\hat{\beta}^{gdp}$ and $\hat{\beta}^{def}$ coefficients together with a linear regression and a non-parametric (Kernel) regression fit. The Nadaraya-Watson Kernel regression estimator was used together with the simple plug-in (rule of thumb) bandwidth of Silverman (1986) (see, for example, Pagan and Ullah, 1999, Chapter 3 for the computational details).

Appendix: Additional BMA and Lasso estimation results

Table A.1: Posterior Inclusion Probabilities for $\hat{\beta}^{def}$ from BMA regressions

Variable name	Description	PIP
crisis	Financial crisis experience (0,1 dummy variable)	0.9974
cba_political	Central bank political independence	0.9967
prudential1	Integration of prudential supervision	0.9071
s02cgp0	Number of Branches per 100,000 Adults, Commercial Banks(1)	0.6100
s07bsk0	Return on Equity (%)	0.5881
s01bis0	Outstanding Domestic Private Debt Securities/GDP (%)	0.5684
s14ifs0	Gross Portfolio Equity Liabilities/GDP (%)	0.4715
s03bsk0	Non-Interest Income / Total income (%)	0.4406
cba_economic	Central bank economic independence	0.4148
eca	Europe and Central Asia (ECA) region dummy	0.3301
s13ifs0	Gross Portfolio Debt Assets/GDP (%)	0.3147
s15ifs0	Gross Portfolio Debt Liabilities/GDP (%)	0.3112
s12ifs0	Gross Portfolio Equity Assets/GDP (%)	0.3074
s01ifs0	Private Credit/GDP (%)	0.3046
s03bis0	Outstanding International Private Debt Securities/GDP	0.2811
s03ifs0	Credit to Government and SOEs/GDP (%)	0.2799
s05bsk0	Cost to Income Ratio (%)	0.2767
s09ifs0	Private Credit to Deposits (%)	0.2573
s02bis0	Outstanding Domestic Public Debt Securities/GDP (%)	0.2524
s01axc0	Insurance Premiums (Life)/GDP (%)	0.2494
gdp_ppp	GDP per Capita PPP adjusted	0.2473
s01ess0	Percent of Firms With Line of Credit, All Firms (%)	0.2397
s05bis0	Consolidated Foreign Claims of BIS-Reporting Banks/GDP(%)	0.2035
s02ess0	Percent of Firms With Line of Credit, Small Firms (%)	0.1813
s01fsi0	Regulatory Capital to Risk-Weighted Assets (%)	0.1261
s01wdi0	Stock Market Turnover Ratio (%)	0.1221
s04bis0	Outstanding International Public Debt Securities/GDP (%)	0.1158
s04fsi0	Provisions to NPLs (%)	0.1042
s05wdi0	Number of Listed Companies(1)	0.1027
s02fsi0	Bank Capital to Assets (%)	0.1016
dist_crisis	Cumulative number of crises experienced by a country	0.1011
s02axc0	Insurance Premiums (Non-Life)/GDP (%)	0.0987
s03fsi0	NPLs to Total Gross Loans (%)	0.0980
s02nbf0	Mutual Fund Assets/GDP (%)	0.0974
s06bsk0	Return on Assets (%)	0.0963
s08bsk0	3 Bank Asset Concentration (%)	0.0889
s01wfe0	Percent Market Capitalization of Top 10 Largest Companies (%)	0.0887
s01_s03	Private Credit/Number of Listed Companies (%)	0.0812
s10bsk0	Liquid Assets / Deposits and Short Term Funding (%)	0.0757
s01nbf0	Pension Fund Assets/GDP (%)	0.0751
governance1	Kaufmann *et al.* (2010) overall governance indicator	0.0646
tradepgdp	Openness (imports plus exports over GDP)	0.0606

Notes: This table shows the Posterior inclusion probabilities (PIPs) of the 42 possible economic, financial and institutional development indicators for $\hat{\beta}^{def}$ computed from a Bayesian Model Averaging procedure, where a Zellner g−prior was used for the specification of the hyperparameter g in the variance prior of $\varphi^{def}|\sigma_\epsilon$. The MC^3 algorithm of Madigan and York (1995) was used to generate draws from the model space. A chain with 75 million MCMC draws was run, where the first 25 million were discarded as a burn-in sample. The dashed line in the table above marks the cut off value at PIP = 25%.
(1)denotes values that have been log transformed.

Table A.2: Lasso penalised regression estimates of ϕ^{def}

Variable name	Description	Lasso estimate of ϕ^{def}
crisis	Financial crisis experience (0,1 dummy variable)	2.1993
cba_political	Central bank political independence	−3.2696
prudential1	Integration of prudential supervision	−1.0071
s01bis0	Outstanding Domestic Private Debt Securities / GDP (%)	−0.0495
s03bsk0	Non-Interest Income / Total income (%)	$\Rightarrow 0$
cba_economic	Central bank economic independence	−3.6348
s02cgp0	Number of Branches per 100,000 Adults, Commercial Banks$^{(1)}$	1.9805
s07bsk0	Return on Equity (%)	$\Rightarrow 0$
s14ifs0	Gross Portfolio Equity Liabilities / GDP (%)	$\Rightarrow 0$
eca	Europe and Central Asia (ECA) region dummy	$\Rightarrow 0$
s13ifs0	Gross Portfolio Debt Assets / GDP (%)	$\Rightarrow 0$
s15ifs0	Gross Portfolio Debt Liabilities / GDP (%)	$\Rightarrow 0$
s12ifs0	Gross Portfolio Equity Assets / GDP (%)	$\Rightarrow 0$
s01ifs0	Private Credit / GDP (%)	$\Rightarrow 0$
s03bis0	Outstanding International Private Debt Securities / GDP (%)	$\Rightarrow 0$
s03ifs0	Credit to Government and SOEs / GDP (%)	$\Rightarrow 0$
s05bsk0	Cost to Income Ratio (%)	0.0884
s09ifs0	Private Credit to Deposits (%)	$\Rightarrow 0$
s02bis0	Outstanding Domestic Public Debt Securities / GDP (%)	$\Rightarrow 0$
s01axc0	Insurance Premiums (Life) / GDP (%)	$\Rightarrow 0$
gdp_ppp	GDP per Capita PPP adjusted	$\Rightarrow 0$

Notes: This table shows the Lasso penalised regression estimates of ϕ^{def}. These were computed with a mean squared error (MSE) cross-validated complexity parameter λ. Coefficients that are shrunk towards zero by the Lasso estimator are denoted by $\Rightarrow 0$.
$^{(1)}$denotes values that have been log transformed.

Table A.3: Posterior Inclusion Probabilities for $\hat{\alpha}$ from BMA regressions

Variable name	Description	PIP
s05bis0	Consolidated Foreign Claims of BIS-Reporting Banks/GDP(%)	0.9601
cba_political	Central bank political independence	0.8951
eca	Europe and Central Asia (ECA) region dummy	0.8805
s01wdi0	Stock Market Turnover Ratio (%)	0.8066
s02cgp0	Number of Branches per 100,000 Adults, Commercial Banks(1)	0.7012
s13ifs0	Gross Portfolio Debt Assets/GDP (%)	0.6953
s09ifs0	Private Credit to Deposits (%)	0.6404
s12ifs0	Gross Portfolio Equity Assets/GDP (%)	0.6088
s06bsk0	Return on Assets (%)	0.4485
s05wdi0	Number of Listed Companies(1)	0.3193
s02nbf0	Mutual Fund Assets/GDP (%)	0.2702
s02fsi0	Bank Capital to Assets (%)	0.2129
governance1	Kaufmann *et al.* (2010) overall governance indicator	0.1715
s10bsk0	Liquid Assets / Deposits and Short Term Funding (%)	0.1389
crisis	Financial crisis experience (0,1 dummy variable)	0.1177
s01wfe0	Percent Market Capitalization of Top 10 Largest Companies (%)	0.1095
s01ifs0	Private Credit/GDP (%)	0.1061
s15ifs0	Gross Portfolio Debt Liabilities/GDP (%)	0.0926
s01nbf0	Pension Fund Assets/GDP (%)	0.0874
s04fsi0	Provisions to NPLs (%)	0.0868
s03bis0	Outstanding International Private Debt Securities/GDP	0.0840
s02axc0	Insurance Premiums (Non-Life)/GDP (%)	0.0755
s01_s03	Private Credit/Number of Listed Companies (%)	0.0747
s04bis0	Outstanding International Public Debt Securities/GDP (%)	0.0699
s14ifs0	Gross Portfolio Equity Liabilities/GDP (%)	0.0672
dist_crisis	Cumulative number of crises experienced by a country	0.0650
s01ess0	Percent of Firms With Line of Credit, All Firms (%)	0.0646
s03ifs0	Credit to Government and SOEs/GDP (%)	0.0628
s01bis0	Outstanding Domestic Private Debt Securities/GDP (%)	0.0617
s02ess0	Percent of Firms With Line of Credit, Small Firms (%)	0.0605
cba_economic	Central bank economic independence	0.0600
s03bsk0	Non-Interest Income / Total income (%)	0.0575
s01fsi0	Regulatory Capital to Risk-Weighted Assets (%)	0.0556
s03fsi0	NPLs to Total Gross Loans (%)	0.0519
s05bsk0	Cost to Income Ratio (%)	0.0515
s07bsk0	Return on Equity (%)	0.0490
s08bsk0	3 Bank Asset Concentration (%)	0.0467
s01axc0	Insurance Premiums (Life)/GDP (%)	0.0447
gdp_ppp	GDP per Capita PPP adjusted	0.0444
s02bis0	Outstanding Domestic Public Debt Securities/GDP (%)	0.0431
prudential1	Integration of prudential supervision	0.0402
tradepgdp	Openness (imports plus exports over GDP)	0.0401

Notes: This table shows the Posterior inclusion probabilities (PIPs) of the 42 possible economic, financial and institutional development indicators for $\hat{\alpha}$ computed from a Bayesian Model Averaging procedure, where a Zellner g−prior was used for the specification of the hyperparameter g in the variance prior of $\varphi^{def}|\sigma_{\epsilon}$. The MC^3 algorithm of Madigan and York (1995) was used to generate draws from the model space. A chain with 75 million MCMC draws was run, where the first 25 million were discarded as a burn-in sample. The dashed line in the table above marks the cut off value at PIP = 25%.
(1)denotes values that have been log transformed.

Table A.4: Lasso penalised regression estimates of ϕ^{α}

Variable name	Description	Lasso estimate of ϕ^{α}
`s05bis0`	Consolidated Foreign Claims of BIS-Reporting Banks/GDP(%)	-0.0121
`cba_political`	Central bank political independence	0.2456
`eca`	Europe and Central Asia (ECA) region dummy	-0.2521
`s01wdi0`	Stock Market Turnover Ratio (%)	$\Rightarrow 0$
`s02cgp0`	Number of Branches per 100,000 Adults, Commercial Banks$^{(1)}$	0.8110
`s13ifs0`	Gross Portfolio Debt Assets/GDP (%)	$\Rightarrow 0$
`s09ifs0`	Private Credit to Deposits (%)	$\Rightarrow 0$
`s12ifs0`	Gross Portfolio Equity Assets/GDP (%)	0.0083
`s06bsk0`	Return on Assets (%)	$\Rightarrow 0$
`s05wdi0`	Number of Listed Companies$^{(1)}$	$\Rightarrow 0$
`s02nbf0`	Mutual Fund Assets/GDP (%)	$\Rightarrow 0$

Notes: This table shows the Lasso penalised regression estimates of ϕ^{α}. These were computed with a mean squared error (MSE) cross-validated complexity parameter λ. Coefficients that are shrunk towards zero by the Lasso estimator are denoted by $\Rightarrow 0$.
$^{(1)}$denotes values that have been log transformed.