Eurasian Journal of Economics and Finance, 8(4), 2020, 231-245
DOI: 10.15604/ejef.2020.08.04.004

EURASIAN JOURNAL OF ECONOMICS AND FINANCE

www.eurasianpublications.com

IMPLICATIONS OF CAPITAL FLOWS FOR DOMESTIC CREDIT GROWTH: EVIDENCE FROM PANEL DATA ANALYSIS

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Received: September 18, 2020 Accepted: December 10, 2020

Abstract

Following the 2007-2009 global crisis, high credit growth became an issue of concern with an emphasis on its relationship with capital flows. It is argued that large and volatile international capital flows lead to credit expansion, which in turn, may cause economic and financial instabilities when it reaches excessive levels, particularly in developing countries. This paper aims to investigate the association between credit growth and capital inflows in the context of developing countries by using panel data analysis. The methodology employed in the study offers a number advantages by allowing for heterogeneity and cross-sectional dependence in the panel, while also considering the endogeneity issue. The overall results of the study provides evidence for the impact of capital inflows, more particularly other capital inflows, on credit growth in the sample. This finding suggests a more direct relationship between capital inflows and credit creation as other inflows mostly comprise international banking and trade credits. It is not surprising given the fact that banking sector has a critical role in the financial systems of developing countries. The significance of international dimension for credit creation through other capital inflows and the intermediary role of the banking system should have monetary policy implications, in the macroprudential or more conventional fashion.

Keywords: Credit Growth, Capital Flows, Developing Economies, Common Correlated Effects Estimator

JEL Classifications: F3, F65, G15, C23

1. Introduction

In the aftermath of the 2007-09 global crisis, credit growth gained a renewed interest by academic and policy making circles, including the international organizations like the IMF and the World Bank. While rapid credit expansion is considered as a critical issue, global factors behind it have come to the fore, and capital flows have been pointed out among others.

Credit expansion prior to the crisis, as well as afterwards, was accompanied by remarkable capital flows across the world. As Gauvin *et al.* (2017) outline, during the two years before the crisis cumulated gross capital inflows into advanced and developing economies were respectively 39% and 16% of GDP, whereas cumulated real credit growth rates were 18% and 40%. Following the normalization of the US monetary policy in 2013, international inflows to these countries fell to 15% and 9% of GDP, respectively. The corresponding cumulated real credit growth was 7% and 14%. These figures indicated that, though to different extents in advanced and developing countries, credit tended to move together with capital inflows.

Although credit expansion and capital flows have been a worldwide phenomenon, the case of developing economies has been particularly highlighted. Before the global crisis, in the 2000s, and even in the 1990s, these economies experienced serious problems due to high credit growth rates, and volatile and damaging capital flows with the intensifying financial globalization.

The world economy has witnessed enormous changes in the past few decades. Increasing international financial integration and liberalization of financial markets have constituted a crucial dimension of this transformation with substantial impacts on developing economies. Developing economies liberalized their financial systems followed by the steps taken toward liberalization of capital accounts from the late 1980s. Financial innovation and structural changes along with international integration have led to the expansion and development of domestic financial systems with implications for credit creation.

With the intensifying integration of economies, capital flows have expanded, and their nature and dynamics have portrayed considerable changes. Developing economies became the target of large volumes of flows in various forms starting in the 1980s, with a hike in the 1990s, and then in the 2000s. Capital flows have provided these economies with large amount of resources and helped expansion of financial systems, however, leading to serious problems along with. Despite the expected benefits, a large number of empirical studies have offered inconclusive evidence regarding the macroeconomic effects of international financial integration and capital flows.[1] Furthermore, large and volatile capital flows have appeared to intensify macroeconomic and financial vulnerabilities particularly in developing countries, which have less developed financial systems. Capital flows have created new forms of instabilities in the recipient countries through various channels. The credit growth is considered as one of these potential channels, among others, such as currency mismatches, inflation, exchange rate appreciation, asset price booms, and so on.

Therefore, although credit creation is often perceived as favorable for economic development and growth, rapid domestic credit expansion stemming from capital inflows is considered to create destabilizing effects on the economies. It is thought so especially when it reaches excessive levels leading to boom-bust cycles, which in turn, may end up in financial crisis. As a result, a number of studies in the literature attempt to determine the critical levels of credit expansion, which may cause macroeconomic instabilities, whereas one other line of research focuses on the determinants of credit expansion with a specific emphasis on capital flows.

This paper aims to investigate the association between credit expansion and international capital movements in the context of developing countries. However, it does not particularly focus on the credit boom-and-bust cycles stemming from capital flows. The paper uses panel data analysis for domestic credit growth with capital flow measure(s) and a number of control variables over the period of 1990-2019. In comparison with the previous work, the methodological approach employed in the paper, namely the common correlated effects (CCE) estimator, offers some advantages. This methodology allows for cross-sectional dependence and heterogeneity across the panel, while also considering the endogeneity issue. The overall findings of the paper indicate an association between credit growth and capital inflows.

[1] There is an enormous literature on the implications of international financial integration and capital flows from different perspectives. See e.g. Eichengreen *et al.* (1998), Kose *et al.* (2009), Rodrik and Subramanian (2009), Stockhammer (2010), Kose *et al.* (2011), Aizenman *et al.* (2009), Akyuz (2014), Rey (2015).

Furthermore, despite the differences in the country-specific outcomes, the results suggest that the composition of capital inflows matters; the impact of other capital inflows appears to be more evident. Underlining the importance of the composition of capital inflows should have monetary policy implications, which cannot be discussed in detail within the content of the study.

The rest of the paper is organized as follows. The next section briefly reviews the literature on the association between credit growth and international capital inflows, whereas Section 3 describes the data set and model specification. Section 4 is devoted to the empirical analysis with the discussion of methodological issues and the findings of the study. Finally, Section 5 draws some conclusions.

2. Credit expansion and implications of international capital flows

Despite the perception of credit growth as a part of financial development, and hence, beneficial to investment and economic growth, the debate around credit expansion has increasingly focused on its potentially adverse implications. Credit growth is considered to be critical when it records high levels. In an expansionary economic phase, financial institutions are optimistic and very likely to lend high-risk borrowers, leading to an accumulation of bad loans. High credit expansion can further threaten macroeconomic stability as growth in credits to private sector may overstimulate aggregate demand, and cause the economy to overheat, with implications for inflation, current account deficits, interest rates, asset prices, and real exchange rate.

In a rather recent line of research, credit expansion is associated with credit boom-bust cycles and macroeconomic effects of credit booms are widely debated (Jorda *et al.* 2011; Mendoza and Terrones, 2012; Schularick and Taylor, 2012). It is argued that rapid credit growth can be a leading indicator of economic and financial problems, possibly resulting in financial crises, especially when it reaches ‘excessive’ levels. As a result, a group of studies focus on dynamics of credit growth and try to determine critical levels of credit expansion which may trigger credit booms, and then busts (Gourinchas *et al.* 2001; Tornell and Westermann, 2002; IMF, 2004; Hilbers *et al.* 2005; Sa, 2006; Coudert and Pouvelle, 2010). The relevant credit series is decomposed into its long- and short-run components by a filtering method, mostly by the Hodrick-Prescott (HP) (1981) technique. Deviations from long-term trends are calculated, and an actual credit indicator significantly exceeding its long-term trend indicated by the HP filter is considered as signaling a credit boom, which may end with a credit crunch.

In the studies concentrating on determinants of credit growth beyond identifying the critical levels that lead to credit booms, the association between credit expansion and international capital flows is underlined and capital flows are often thought to be one of its main drivers (Hernandez and Landerretche, 1999; Sa, 2006; Furceri *et al.*, 2011; Lane and Milesi-Ferretti, 2011; Calderon and Kubota, 2012; Magud *et al.,* 2012; Mendoza and Terrones, 2012; Lane and McQuade, 2014; Rey, 2015; Gauvin *et al*. 2017; Igan and Tan, 2017). Among others, for instance, Lane and Milesi-Ferretti (2011) emphasize the rapid credit growth and high current account deficits in some economies during the pre-crisis period and raise the question regarding the interaction between domestic credit growth and capital flows. Furthermore, the presence of such a relation would suggest domestic credit growth being a key channel to understand the implications of international capital flows for domestic macroeconomic problems (Lane and McQuade, 2014). In her influential paper where she postulates global financial cycles, Rey (2015) emphasizes the commonalities in asset prices, capital flows, leverage and credit creation.

Some of these studies distinguish between categories of capital inflows by assuming that composition of capital flows matters for credit creation process. For instance, Igan and Tan (2017) use disaggregated data on capital flows, namely direct, portfolio, and other flows, and further examine the credit growth by sectors, i.e. growth of credits to nonfinancial corporations and households. They find that other flows are linked to rapid growth in both sectors. Lane and McQuade (2014) differentiate between debt inflows and equity inflows and maintain that domestic credit growth is related to the former. Similarly, Furceri *et al.* (2011) examine the role of different forms of capital inflows and underline the debt-driven inflows.

Depending on the pull and push factors, capital flows can influence domestic credit growth through various channels. With regard to supply side implications for credit growth, international flows can affect the funding conditions faced by domestic banks and non-bank economic agents.[2] Owing to the increased international financial integration, domestic banks and large non-financial corporations can seek funding from international money and bond markets or from foreign affiliates. Foreign direct investors and portfolio investors also provide resources in various forms. However, most of domestic nonfinancial corporations and households can engage with international financial system indirectly through the intermediation of the domestic banking system. Therefore, they are affected by international capital flows to the extent that these flows influence the provision of credit by domestic banks.[3]

In a globally expansionary phase, domestic banks tend to issue more credit as capital inflows provide liquidity and there are more resources at their disposal. When international banks apply more tolerant conditions on domestic banks in supplying funding, domestic banks transmit these conditions to their borrowers. Additionally, the entry of foreign capital may intensify competition and pose a threat, pushing the banks to loosen lending standards and issue more credit in response to increased competition (Dell'Ariccia and Marquez, 2006; Dell'Ariccia *et al*. 2012).

Capital flows may influence domestic credit growth through the demand side implications as well (Hernandez and Landerretche, 1999). For instance, appreciation of stock and house prices may increase household wealth, which in turn stimulates consumption and demand for credit (Sa and Wieladek, 2010; Sa *et al*. 2014). Similarly, capital inflows may boost asset prices, which enhance firm value, improve balance sheets, and decrease the cost of external financing, encouraging the corporate sector's demand for credit (Jansen, 2003; Kim and Yang, 2011; Olaberria, 2011).

3. Data and model specification

This study employs a panel data methodology comprising thirteen emerging economies, which have commonalities with regard to their economic and financial structures, and to the nature of their integration to the world economy. The choice of the sample is further determined by data availability. On the other hand, for instance, China is intentionally excluded due to its peculiar domestic and international dynamics, and its changing position in the world economy.

The data used in the empirical analysis cover the period of 1990-2019, and are mostly obtained from the World Bank World Development Indicators (WDI) database, while the capital flows series are taken from the IMF's Balance of Payments Statistics.

Table 1 gives the average annual figures for credit growth (*crgr*), capital inflows (*total*, and then disaggregated as *fdi*, *portfolio* and *other* inflows) as percentage of GDP, and economic growth (*gdpgr*) for the sample countries over the period of analysis. Average credit growth shows a significant variation, whereas the GDP growth rates and capital inflow variables appear to be comparatively closer across the sample.

Our baseline specification to investigate the link between credit growth and international capital flows can be written as follows:

$$crgr_{\mathrm{it}} = \beta inflow_{\mathrm{it}} + \delta X_{\mathrm{it}} + \varepsilon_{\mathrm{it}}$$

where *crgr* is the growth rate of the domestic credit to private sector-to-GDP ratio and *inflow* represents total capital inflows as well as subcategories (foreign direct investment, portfolio, and other flows) as percentage of GDP. *X* denotes the set of control variables.

[2] In a similar vein, the procyclical effects of capital flows on domestic credit can be quite critical as a sudden stop in inflows may lead to damaging effects on the liquidity in the economies where credit mechanism is strongly linked to external financing.

[3] It should also be underlined that banks do not only involve in the credit creation process directly through the funding they provide from international markets. They also take part in the process indirectly as they intermediate all kind of international financial operations.

Table 1. Credit growth and capital inflow averages

Country	*crgr*	*total*	*fdi*	*portfolio*	*other*	*gdpgr*
Argentina	3.16	3.45	2.23	1.21	0.00	2.82
Brazil	6.50	3.92	2.76	1.29	-0.13	2.40
Chile	7.92	9.61	6.15	2.08	1.39	4.58
Colombia	6.58	5.42	3.27	1.40	0.76	3.47
Indonesia	5.60	2.14	1.24	1.07	-0.17	4.86
South Korea	9.39	3.02	0.88	1.66	0.47	5.01
Malaysia	8.27	5.85	4.04	0.67	1.15	5.68
Mexico	6.28	4.59	2.51	1.86	0.22	2.47
Peru	11.77	5.38	3.76	1.29	0.33	4.56
Philippines	8.71	4.23	1.68	1.35	1.20	4.62
South Africa	4.63	5.36	1.28	3.13	0.95	2.31
Thailand	6.53	3.56	2.67	0.95	-0.06	4.15
Turkey	10.37	4.26	1.24	1.15	1.86	4.44

Source: World Bank WDI and IMF Balance of Payments Statistics; authors' calculations

In the above specification, the credit variable is employed as the percentage change rather than the level of domestic private credit-GDP ratio. Igan and Tan (2017) distinguish between credits to households and to nonfinancial corporations by using the data compiled by Bank for International Settlements. Although this distinction can provide valuable insights regarding the impacts of capital inflows on different sectors, we could not undertake our analysis with these credit variables due to insufficient data across the sample.

International capital inflows series used in the paper are obtained from the IMF's Balance of Payments Statistics. These statistics provide the data on cross-border flows that are recorded in net terms and shown separately for assets and liabilities. The term '(net) capital inflows' in the study does not imply the difference between capital inflows and outflows, but 'net transactions in liabilities'. To investigate the association with the credit growth, net capital inflows is used in two different forms. First, related models of the analysis are run with total capital inflows. Then, in order to detect whether the composition of international flows matter, the analysis is also carried out with the direct, portfolio, and other investment inflows.

In addition to these, the study uses the real GDP growth (*gdpgr*) to consider the interaction of credit growth with overall economic activity, and inflation (*inf*), real interest rate (deposit interest rate) (*r*) and change of nominal exchange rate (*er*) to consider the impact of price adjustments on credit expansion, all measured annually. We use deposit interest rate in place of lending rate, and change of nominal exchange rate in place of real exchange rate index due to the difficulties to obtain the relevant data for all countries in the sample.

4. Empirical analysis
4.1. Preliminary analysis

A critical issue in panel data analysis relates to the possibility of cross-sectional dependence in the data, which suggests the existence of common factors across the individual units in the panel. The cross-section dependency, for instance, implies that a shock affecting one country may spillover onto the others, and in a highly integrated world economy, this possibility rises. Furthermore, cross-sectional dependence has implications for the unit root and cointegration tests as well as for the choice of estimation techniques, and hence, should be investigated prior to the empirical estimation.

One of the procedures to examine cross-section dependency is the cross-sectional dependence Lagrange multiplier (CD_{LM}) test developed by Breusch and Pagan (1980). The Breusch-Pagan LM test exploits the sum of squared coefficients of correlation among cross-sectional residuals obtained through OLS. The test statistic CD_{LM} can be calculated as

$$CD_{LM} = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^2$$

where $\hat{\rho}_{ij}$ is the sample estimate of the pair-wise correlation of the residuals (Pesaran, 2004). Under the null hypothesis of 'no cross-sectional dependence' ($Cov\ (u_{it}, u_{js)} = 0$), with fixed *N* and $T \to \infty$, the CD_{LM} statistic is distributed as χ^2 with *N(N-1)/2* degrees of freedom.

In addition, Pesaran (2004) proposes an alternative test as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right)$$

and shows that under the null hypothesis of no cross-sectional dependence $CD \xrightarrow{d} N(0,1)$ for $N \to \infty$ and sufficiently large *T* (Hoyos and Sarafidis, 2006).

The findings from the Breusch-Pagan and Pesaran tests for the variables are reported in Table 2 with 'constant' and 'constant and trend' options. According to the results of the Pesaran CD test, the null hypothesis of no cross-sectional dependence cannot be rejected for the real interest variable in the model with constant, and for the real interest rate and inflation variables in the model with constant and trend. However, the null hypothesis can be rejected for the majority of the variables in both options for the tests at 1% significance, providing evidence for the presence of cross-sectional dependence across the countries of interest.

Table 2. Cross-section dependence tests for variables

Variables	Constant				Constant and Trend			
	CD_{LM}		CD		CD_{LM}		CD	
	Statistic	***p-value***	**Statistic**	***p-value***	**Statistic**	***p-value***	**Statistic**	***p-value***
crgr	151.045	0.000	-2.906	0.002	146.879	0.000	-2.623	0.004
total	106.839	0.017	-3.245	0.001	123.531	0.001	-3.223	0.001
Fdi	137.771	0.000	-3.118	0.001	132.744	0.000	-3.007	0.001
portfolio	110.083	0.010	-2.230	0.013	110.083	0.010	-2.230	0.013
other	104.759	0.023	-2.817	0.002	112.122	0.007	-2.832	0.002
gdpgr	232.881	0.000	-3.052	0.001	260.918	0.000	-3.123	0.001
r	195.219	0.000	-0.439	0.330	194.745	0.000	-0.346	0.365
inf	286.204	0.000	2.313	0.010	243.270	0.000	1.036	0.150
er	400.731	0.000	7.442	0.000	431.183	0.000	8.496	0.000

Note: Lag length is taken as 3.

Having identified cross-sectional dependence in the variables, to investigate time-series properties of the variables a second generation panel unit root test, namely the CIPS test (Pesaran, 2007), is employed. The CIPS test utilizes the standard ADF regression with the cross-section averages of the lagged levels and first-differences of the individual series. The test procedure includes estimation of the separate cross-sectionally Augmented Dickey-Fuller (CADF) regressions, and hence, allows for different autoregressive parameters for each country in the panel. The CADF regression is given by

$$\Delta x_{it} = z_{it}\gamma_i + \rho_i x_{i,t-1} + \sum_{j=1}^{k_i}\varphi_{ij}\Delta x_{it-j} + \alpha_i\bar{x}_{t-1} + \sum_{j=0}^{k_i}\eta_{ij}\Delta\bar{x}_{t-j} + v_{it}$$

where $\bar{x}_t$ is the cross-section mean of x_{it}, i.e. $\bar{x}_t = N^{-1}\sum_{i=1}^{N}x_{it}$. The null hypothesis is expressed as each series contains a unit root, $H_0 = \rho_i = 0$ for all *i*, while the alternative hypothesis holds as at least one of the individual series in the panel is (trend) stationary, $H_1 =$

$\rho_i < 0$ for at least one *i*. To test the null hypothesis, the CIPS statistic is computed as the average of the individual CADF statistics

$$CIPS\ (N,T) = N^{-1}\sum_{i=1}^{N} t_i(N,T)$$

where $t_i(N,T)$ is the cross-sectionally augmented Dickey Fuller statistic for the *i* th cross-section unit given by the *t*-ratio of the coefficient of $y_{i,t-1}$ in the CADF regression (Pesaran, 2007).

Table 3 presents the CADF (CIPS) unit root test results with 'constant' and 'constant and trend' options. The CADF test results suggest that all variables are stationary according to both options at 1%, except for *total* and *other* variables. Total capital inflows and other investment inflows appear to be difference-stationary in the option with constant and trend at 1% significance level.

Table 3. Unit root tests: CADF

	Constant		**Constant and Trend**	
	CIPS Statistics	**Critical Value**	**CIPS Statistics**	**Critical Value**
crgr	-3.700***		-4.027***	
total	-2.629***		-2.756*	
fdi	-2.942***		-3.026***	
portfolio	-2.671***		-3.155***	
other	-2.726***	%1 -2.45	-2.730*	%1 -2.96
gdpgr	-3.096***	%5 -2.25	-3.595***	%5 -2.76
r	-3.440***	%10 -2.14	-3.470***	%10 -2.66
inf	-2.954***		-3.576***	
er	-3.500***		-3.328***	
Δtotal	-		-4.264***	
Δother	-		-4.835***	

Note: Lag length is taken as 3. Critical values for the CIPS test are obtained from Pesaran (2007). *, **, *** indicate significance levels at the 10%, 5% and 1%, respectively.

In a panel data analysis, it is also critical to investigate whether estimated coefficients are homogeneous or not across the panel. As Breitung (2005) underlines, the assumption of slope homogeneity will result in misleading estimates if the panel is heterogeneous. Based on a standardized version of Swamy's (1970) test, Pesaran and Yamagata (2008) developed a test to identify slope homogeneity for panel data with large *N* and *T*. The test assumes that $\varepsilon_{i,t}\ and\ \varepsilon_{j,s}$ are independently distributed for $i \neq j\ and\ t \neq s$, and allows for a heterogeneous variance (Bersvendsen and Ditzen, 2020). Pesaran and Yamagata (2008) delta statistic can be written as:

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right)$$

when $(N,\ T) \rightarrow \infty$, and the error terms are normally distributed, the $\tilde{\Delta}$ test has an asymptotic standard normal distribution under the null hypothesis of 'homeogeneity'. The small sample properties of the $\tilde{\Delta}$ test can be improved when there are normally distributed errors by using the following mean and variance bias adjusted version:

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - E\ (\tilde{Z}_{it})}{\sqrt{var(\tilde{Z}_{it})}}\right)$$

where $E(\tilde{Z}_{it})$ = k, $\sqrt{var(\tilde{Z}_{it})} = 2k(T-k-1)/(T+1)$. In Pesaran and Yamagata (2008), the null hypothesis of interest is $H_0: \beta_i = \beta \text{ for all } i,$ against the alternatives $H_1: \beta_i \neq \beta_j \; for \text{ a non} - \text{zero fraction of pairwise slopes for } i \neq j$.

Table 4 presents the results for cross-section dependence and homogeneity tests for the regressions in our analysis. The Breusch-Pagan LM and Pesaran CD test statistics given in the first part of the table suggest cross-sectional dependence in cointegration equations at 5% significance level for all model specifications. According to the delta tests, the null hypothesis of homogeneity is rejected for the models at 5%, indicating that all estimated slope coefficients are heterogenous.

Table 4. Cross-Section Dependence and Homogeneity Tests

	Cross-Section Dependence Tests				**Homogeneity Tests**			
	***LM* (BP, 1980)**		***CD* (Pesaran, 2004)**		$\tilde{\Delta}$		$\tilde{\Delta}_{adj}$	
	Statistic	***p-value***	**Statistic**	***p-value***	**Statistic**	***p-value***	**Statistic**	***p-value***
Model 1a	144.092	0.000	7.073	0.000	4.665	0.000	4.918	0.000
Model 1b	113.840	0.005	4.295	0.000	2.078	0.019	2.232	0.013
Model 1c	113.395	0.006	4.274	0.000	3.574	0.000	3.915	0.000
Model 1d	114.401	0.005	4.315	0.001	3.710	0.000	4.148	0.000
Model 1e	108.055	0.014	3.645	0.000	6.599	0.000	7.536	0.000
Model 2a	128.195	0.000	5.203	0.000	2.969	0.001	3.253	0.001
Model 2b	106.569	0.018	3.394	0.001	2.211	0.014	2.472	0.007
Model 2c	109.002	0.012	3.301	0.001	2.783	0.003	3.178	0.001
Model 2d	109.654	0.011	3.329	0.001	3.636	0.000	4.246	0.000
Model 2e	105.74	0.020	2.981	0.003	5.005	0.000	5.982	0.000

Note: The basic model specifications: *Model 1a*: $crgr_{it} = \beta_0 + \beta_1 total_{it}$ and *Model 2a* $crgr_{it} = \beta_0 + \beta_1 fdi_{it} + \beta_2 portfolio_{it} + \beta_3 other_{it} + \varepsilon_{it}$ are extended by the inclusion of GDP growth rate (*gdpgr*), real interest rate (*r*), inflation (*inf*) and change in exchange rate (*er*) variables consecutively to generate the *b, c, d,* and *e* versions of each model.

In the next stage of the analysis, to determine whether there is a long-run relationship between the variables the Westerlund (2008) Durbin-Hausman cointegration test is employed. The test procedure considers cross-sectional dependence in the panel and provides two statistics, namely the Durbin-Hausman group (DH_g) and Durbin-Hausman panel (DH_p) statistics. The group statistic is used to identify whether there is a cointegrating relationship among the variables when the panel is found heterogeneous.

The test has the null hypothesis of no cointegration in the panel data and has an asymptotic normal distribution. Two proposed test statistics (DH_g and DH_p) are based on the Durbin-Hausman principle, whereby the two estimators of a unit root in the residuals of an estimated regression are compared (Tong and Yu, 2018). The test statistics that are suggested by Westerlund (2008) are computed as follows:

$$DH_g = \sum_{i=1}^{n} \hat{S}_i(\check{\phi}_i - \hat{\phi}_i)^2 \sum_{t=2}^{T} \hat{e}_{it-1}^2$$

$$DH_p = \hat{S}_n(\check{\phi} - \hat{\phi})^2 \sum_{i=1}^{n}\sum_{t=2}^{T} \hat{e}_{it-1}^2$$

For the panel test, the null and alternative hypotheses are formulated as $H_0: \phi_i = 1 \text{ for all } i = 1, \ldots, n \text{ versus } H_1^p: \phi_i = \phi \text{ and } \phi < 1 \text{ for al} l\ i$. Hence, in this case, we are in effect presuming a common value for the autoregressive parameter both under the null and alternative hypotheses. Thus, if this assumption holds, a rejection of the null should be taken as evidence in favor of cointegration for all n units.

The group and panel statistics of the Durbin-Hausman panel cointegration test developed by Westerlund (2008) are given in Table 5. The statistics suggest that the null hypothesis of no cointegration is rejected at 1% significance level for all model specifications, implying a long-run relationship between the variables. Having identified the presence of long-run relationship, the coefficients of the cointegration relationship is estimated below by using the CCE methodology, which considers cross-sectional dependence and heterogeneity in the data.

Table 5. Durbin Hausman cointegration test

	DurbinH_group		***DurbinH_panel***	
	Statistics	***p-value***	**Statistics**	***p-value***
Model 1a	122.185	0.000	42.446	0.000
Model 1b	37.168	0.000	51.221	0.000
Model 1c	23.204	0.000	33.380	0.000
Model 1d	68.596	0.000	29.432	0.000
Model 1e	25.603	0.000	26.648	0.000
Model 2a	197.869	0.000	62.734	0.000
Model 2b	25.489	0.000	38.975	0.000
Model 2c	16.810	0.000	30.913	0.000
Model 2d	42.684	0.000	25.638	0.000
Model 2e	48.189	0.000	27.172	0.000

4.2. Estimation and discussion of results

In a panel analysis, estimations can be inconsistent and misleading due to common factors included in error terms. Hence, it is crucial to consider cross-sectional dependence that arises from multiple factors that cannot be observed or controlled for. There is a number of estimation techniques advanced to control for cross-sectional dependence across the panel. This study employs the common correlated effects (CCE) estimator proposed by Pesaran (2006) to account for the cross-sectional dependence as well as heterogeneity in the data. The CCE estimator asymptotically eliminates strong as well as weak forms of cross-sectional dependence in large panels (Pesaran, 2006). Further, it can be used regardless whether *T* is greater than *N* or not. Baltagi *et al.* (2018) show that Pesaran's (2006) procedure is still valid to consider cross-sectional dependence stemming from error factors even in the presence of endogeneity and structural changes in slopes and error factor loadings.

There are two versions of the CCE estimator for the mean value of individual coefficients, β_i. The CCE mean group (CCEMG) estimator is used in the presence of heterogeneity in the data and allows coefficients of interest to vary across countries. The CCEMG estimator, $\hat{b}_{MG}$ is defined as a simple average of the individual CCE estimators, $\hat{b}_i$ of β_i , and shown as:

$$\hat{b}_{MG} = N^{-1} \sum_{i=1}^{N} \hat{b}_i.$$

If the individual slope coefficients, β_i, are the same, efficiency can be achieved from pooling observations over cross-section units. That is how the second CCE estimator, the common correlated effects pooled (CCEP) estimator, performs. The CCEP estimator, $\hat{b}_P$ is defined by

$$\hat{b}_P = \left(\sum_{i=1}^{N} \theta_i X_i' \bar{M}_\omega X_i \right)^{-1} \sum_{i=1}^{N} \theta_i X_i' \bar{M}_\omega y_{i.}$$

y_{it} is the observation on the *i* th cross-section unit at time *t* for *i* =1, 2, …, *N*, *t* = 1, 2, …, *T* and supposed to be generated according to the linear heterogeneous panel data model:

$$y_{it} = \alpha_i' d_t + \beta_i' x_{it} + e_{it},$$

where d_t is a n × 1 vector of observed common effects (including deterministic variables such as intercepts or seasonal dummies), x_{it} is a k × 1 vector of observed individual-specific regressors on the *i* th cross-section unit at time *t*, and the errors have the multifactor structure:

$$e_{it} = \gamma_i' f_t + \varepsilon_{it},$$

in which f_t is the m × 1 vector of unobserved common effects and ε_{it} are the individual-specific (idiosyncratic) errors assumed to be independently distributed of (d_t, x_{it}) (Pesaran, 2006).

Depending on the results suggested by the homogeneity tests in Table 4, the common correlated effects mean group (CCEMG) estimator is employed and results are reported in Table 6 and Table 7 for two sets of model specifications with total capital inflows (*Model 1*) and with disaggregated fdi, portfolio and other capital inflows series (*Model 2*).

Table 6. CCE mean group estimates for Model 1

	Model 1a	*Model 1b*	*Model 1c*	*Model 1d*	*Model 1e*
total	0.823*** (3.28)	0.433* (1.56)	0.255 (0.91)	0.465* (1.62)	0.173 (0.82)
gdpgr	-	1.217*** (2.64)	1.239*** (2.76)	0.927*** (2.63)	0.912*** (2.42)
r	-	-	0.297* (1.53)	0.215 (0.70)	0.337 (0.86)
inf	-	-	-	-0.444* (-1.49)	0.121 (0.37)
er	-	-	-	-	-0.452*** (-3.34)

Note: *t*-statistics are given in parentheses and critical values for the *t*-ratios are 2.32, 1.64 and 1.28 for 1%, 5% and 10% respectively. ***, **, * indicate significance levels at the 1%, 5% and 10%.

The basic models (*Model 1a* and *Model 2a*) with two alternative representations of capital inflows are extended by the inclusion of economic growth, interest rate, inflation and exchange rate variables to construct *b, c, d,* and *e* specifications.

Overall, the estimation results show an association between credit growth and capital inflows across the panel. On the other hand, differentiating between alternative forms of capital inflows, i.e. between foreign direct investments, portfolio inflows and other inflows, offers further insight for the channel of this relationship by providing significant results in the models. The model specifications in Table 7 indicates insignificant impact of international portfolio inflows, whereas foreign direct investments have a negative impact on domestic credit growth. The results imply a rather direct relationship between credit expansion and other capital inflows, which mostly comprise international bank loans and trade credits. These findings are consistent with the work carried out by, for instance, Furceri *et al*. (2011), Lane and McQuade (2014), and Igan and Tan (2017).

Furthermore, in both group of results a positive link between credit expansion and GDP growth is strongly confirmed, as the test statistics for *gdpgr* variable are significant at 1% for each model specification in Table 6 and Table 7.

In addition, with regard to the model specifications comprising other control variables, *Model 1c* and *Model 2c* show statistically significant (at 10%) positive impact of interest rate on credit growth, whereas *Model 1d* and *Model 2d* suggest statistically significant (at 10% and 5% respectively) negative impact of inflation on credit growth across the panel. *Model 1e* and *Model 2e* indicate statistically significant negative impact of exchange rate variable across the panel, whereas the real interest rate and inflation variables appear insignificant in these models.

Table 7. CCE mean group estimates for Model 2

	Model 2a	*Model 2b*	*Model 2c*	*Model 2d*	*Model 2e*
fdi	-0.483* (-1.50)	-0.597** (-2.19)	-1.149** (-1.77)	-0.583* (-1.46)	-0.758* (-1.43)
portfolio	0.510 (1.00)	0.013 (0.03)	-0.192 (-0.42)	-0.175 (-0.38)	-0.031 (-0.14)
other	1.801*** (4.56)	1.154*** (3.50)	1.210*** (3.00)	1.151*** (3.00)	0.452* (1.43)
gdpgr	-	1.490*** (3.95)	1.508*** (3.57)	1.192*** (3.51)	0.844*** (2.42)
r	-	-	0.304* (1.35)	0.015 (0.05)	0.133 (0.58)
inf	-	-	-	-0.295** (-1.85)	0.188 (0.97)
er	-	-	-	-	-0.383*** (-3.47)

Note: *t*-statistics are given in parentheses and critical values for the *t*-ratios are 2.32, 1.64 and 1.28 for 1%, 5% and 10% respectively. ***, **, * indicate significance levels at the 1%, 5% and 10%.

Having presented the panel data results for alternative model specifications above, Table 8 and Table 9 report the country-specific results provided by the CCEMG estimator for *Model 1e* and *Model 2e* respectively.[4]

Table 8. CCE Mean Group Countries Estimates for *Model 1e*

Country	*total*	*gdpgr*	*r*	*inf*	*er*
Argentina	0.347*** (8.46)	0.131*** (3.85)	-0.162** (-2.13)	0.074*** (2.47)	-0.174*** (-24.86)
Brazil	-0.542 (-1.04)	3.113*** (4.28)	0.002 (0.01)	-0.091*** (-4.33)	0.133*** (5.32)
Chile	0.063 (0.38)	-0.504** (-1.90)	0.856*** (5.10)	0.546*** (2.53)	-0.706*** (-13.32)
Colombia	0.100 (1.01)	0.741*** (2.99)	0.216*** (6.00)	0.081*** (3.68)	-0.294*** (-8.65)
Indonesia	-0.694*** (-3.49)	3.563*** (11.38)	-0.488*** (-5.48)	-0.399*** (-4.07)	-0.062** (-2.00)
S. Korea	0.041 (0.07)	0.603 (0.73)	-0.296 (-0.33)	-1.493* (-1.42)	-0.357 (-1.14)
Malaysia	-0.568*** (-3.01)	1.694*** (2.88)	4.846*** (6.06)	3.204*** (5.66)	-1.152*** (-8.06)
Mexico	-0.379 (-1.20)	0.435*** (2.70)	-0.190* (-1.51)	-0.259*** (-4.11)	-0.228*** (-8.44)
Peru	-0.178 (-1.14)	0.590*** (2.38)	0.139 (0.81)	0.239*** (4.19)	-0.274*** (-4.64)
Philippines	0.549* (1.46)	0.766* (1.54)	0.234 (0.64)	-0.233 (-0.80)	-0.116 (-1.21)
S. Africa	1.732** (1.73)	1.871 (1.23)	-0.337 (-0.39)	1.284** (1.83)	-1.447*** (-6.49)
Thailand	1.588** (2.20)	-1.326 (-1.25)	-0.668 (-0.70)	-1.517** (-2.08)	-1.091*** (-3.10)
Turkey	0.187 (0.99)	0.171 (0.56)	0.229 (0.74)	0.136 (2.03)**	-0.114*** (-4.39)

Note: *t*-statistics are given in parentheses and critical values for the *t*-ratios are 2.32, 1.64 and 1.28 for 1%, 5% and 10% respectively. ***, **, * indicate significance levels at the 1%, 5% and 10%.

[4] Country-specific estimations are obtained for all model specifications as defined in Table 4. Due to the space limitations, we do not report those results here.

Country-specific estimations offer varying results, which are difficult to generalize over the sample. For instance, GDP growth rate appears to have less significant impact on individual countries despite the strong association indicated by the panel results. Given the relatively lower significance level in *Model 2e* in Table 7, results for other capital inflows seem to be consistent with the panel estimation; on the other hand, most of the countries still have a significant relationship between other capital inflows and credit growth. Strong impact of exchange rate variable in panel estimations of *Model 1e* and *Model 2e* is also revealed by the country-specific results given in Table 8 and Table 9. Interestingly, despite being insignificant in panel estimations, inflation variable presents a strong impact on credit growth in individual countries, but with opposing signs.

The variation observed in the mean group estimates as well as in comparison with the panel results imply the need for detailed country analyses to detect the dynamics behind the association between capital inflows and credit expansion.

Table 9. CCE Mean group countries estimates for *Model 2e*

Country	*fdi*	*portfolio*	*other*	*gdpgr*	*r*	*inf*	*er*
Argentina	-0.075 (-0.77)	0.311*** (4.32)	0.727*** (6.06)	0.114*** (2.65)	-0.172*** (-2.49)	0.061*** (2.54)	-0.165*** (-27.50)
Brazil	-1.122* (-1.39)	-0.670 (-0.36)	0.932 (1.14)	2.873*** (2.97)	-0.043 (-0.21)	-0.093*** (-3.88)	0.123*** (3.51)
Chile	-0.366** (-1.88)	0.068 (0.40)	0.350* (1.46)	-0.366** (-1.69)	0.760*** (6.91)	0.616*** (3.95)	-0.615*** (-10.08)
Colombia	0.050 (0.23)	0.133 (1.02)	-0.121 (-0.57)	0.545** (2.22)	0.163*** (3.13)	0.015 (0.50)	-0.327*** (-10.22)
Indonesia	0.950** (1.98)	-1.648*** (-3.64)	-1.926*** (-5.63)	4.025*** (11.50)	-0.502*** (-4.48)	-0.248*** (-2.51)	-0.136*** (-9.71)
South Korea	-6.151** (-1.88)	-0.463 (-0.45)	0.811 (0.76)	0.619 (0.74)	0.620 (0.64)	-0.455 (-0.53)	-0.438* (-1.29)
Malaysia	-0.302 (-0.24)	-0.297 (-0.80)	-0.011 (-0.04)	1.408* (1.48)	2.171 (0.82)	1.310 (0.71)	-0.830*** (-6.06)
Mexico	-0.874* (-1.39)	-0.832*** (-2.51)	0.847** (2.07)	0.662*** (3.68)	-0.093 (-0.51)	-0.338*** (-4.17)	-0.154*** (-4.40)
Peru	0.032 (0.14)	-0.028 (-0.15)	-0.217** (-1.94)	0.189 (1.05)	0.039 (0.34)	0.211*** (2.45)	-0.255*** (-2.71)
Philippines	0.220 (0.36)	0.722** (1.85)	0.492* (1.48)	0.498 (0.97)	-0.187 (-0.89)	-0.726*** (-3.18)	0.088 (0.95)
South Africa	1.535 (0.46)	1.548 (1.26)	3.226*** (2.40)	0.423 (0.23)	0.474 (0.62)	1.784** (2.26)	-1.072*** (-6.06)
Thailand	-2.506** (-2.22)	0.844 (0.96)	1.007** (2.27)	-0.075 (-0.09)	-1.491** (-2.11)	0.188 (0.16)	-1.054*** (-2.70)
Turkey	-1.252** (-1.81)	-0.085 (-0.11)	-0.238 (-0.90)	0.050 (0.17)	-0.007 (-0.03)	0.115** (1.77)	-0.139*** (-4.63)

Note: *t*-statistics are given in parentheses and critical values for the *t*-ratios are 2.32, 1.64 and 1.28 for 1%, 5% and 10% respectively. ***, **, * indicate significance levels at the 1%, 5% and 10%.

5. Conclusion

Eruption of the 2007-2009 global crisis renewed the interest in high credit growth with an emphasis on its association with capital flows. It is argued that large and volatile capital flows lead to credit expansion, which in turn may cause economic and financial instabilities when it reaches excessive levels. More particularly, developing countries have been at the center of the debates.

With regard to the credit expansion, a group of studies have attempted to determine the critical levels of credit growth which may lead to boom-bust cycles, and hence, macroeconomic instabilities. One other group have focused on the determinants of credit expansion, and in these studies, capital flows are considered one of the drivers of credit expansion.

This paper aims to investigate the association between credit growth and capital inflows in the context of developing countries by using panel data analysis. The methodology employed in the study allows for heterogeneity and cross-section dependency in the panel, and considers the endogeneity implications. The overall results of the study provide evidence for the impact of capital inflows, more particularly other capital inflows, on credit growth in the sample. This finding suggests rather a more direct relationship between capital inflows and credit creation as other inflows mostly comprise international banking and trade credits. This is not surprising given the fact that banking sector still has a critical role in the financial systems of developing countries.

Volume and volatility of capital inflows limit the space for monetary policy in relation to credit growth. For instance, the tightening monetary policy stance through an increase in interest rates to restrain credit expansion may trigger even more capital inflows. The rapid credit growth has revived the debate and implementation of macroprudential policy tools, which focus on dynamics of domestic credit expansion. The significance of international dimension for credit creation through other capital inflows and the intermediary role of banking system should have monetary policy implications, in the macroprudential or a more conventional fashion.

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