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Abstract: Current data provide macroeconomic information for a large number of countries and for a long period of time (macro panels). This causes that in these panels slope heterogeneity and cross-section dependence (CSD) are a rule rather than the exception, leading to fixed effects slope estimators to be biased and inconsistent. This paper analyzes gross capital flows to emerging economies employing the Augmented Mean Group (AMG) model to account for slope heterogeneity and CSD. The results suggest that the AMG performs better than the fixed effects model. In addition, this work also suggests that not only the heterogeneity across countries is important to analyze capital inflows to emerging economies, but also the different responses of the different types of capital inflows to movements in macroeconomic variables.
Keywords: Capital Flows, Push and Pull Factors, Slope Heterogeneity, Common Factors, Cross-Section Dependence
JEL Classification: C33, F3, F21, G15

Resumen: Los datos actuales proporcionan información macroeconómica para un número grande de países por un periodo largo de tiempo (paneles macro). Esto ocasiona que en dichos paneles la heterogeneidad en las pendientes y la correlación transversal (CSD) sean la regla y no la excepción, dando lugar a que los estimadores del modelo de efectos fijos sean sesgados e inconsistentes. Este trabajo analiza flujos brutos de capital hacia las economías emergentes empleando el modelo Augmented Mean Group (AMG) que toma en cuenta la heterogeneidad de las pendientes y la CSD. Los resultados sugieren que el AMG se comporta mejor que el modelo de efectos fijos. Además, este trabajo también sugiere que no sólo la heterogeneidad entre países es importante para analizar las entradas de capital a las economías emergentes, sino también las diferentes respuestas de los distintos tipos de entradas de capital a movimientos en las variables macroeconómicas.
Palabras Clave: Flujos de Capital, Factores de Atracción y Empuje, Heterogeneidad en las Pendientes, Factores Comunes, Correlación Transversal

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1. Introduction

It is well documented in the literature that inflows of foreign capital encourage economic growth and may even improve welfare in the recipient country. However, such inflows may also give rise to severe macroeconomic imbalances, such as credit bubbles, that threaten financial and macroeconomic stability. Moreover, when facing adverse economic conditions a sudden retrenchment of foreign capital have significant deteriorating effects as occurred to emerging economies at the end of the 1990s.

Since then, emerging economies have implemented strong macroeconomic and fiscal policies that not only helped them to outperform advanced economies and to overcome the negative effects of the recent financial crisis, but also turned emerging economies into an attractive place for foreign investors in the search for yield in the context of an extremely lax monetary policy and close to zero interest rates in advanced economies. This surge of foreign capital has encouraged research directed to study capital flows behavior to emerging economies.

A significant fraction of this research makes use of panel data techniques (in particular the fixed effects model has been widely used). However, most of the econometric theory on panel data is designed to analyze survey data usually comprised of a big number of cross sections (large N) observed by very short periods of time (small T). On the other hand, recent macroeconomic data where a big number of individuals (large N) are observed for longer periods of time (large T) have become available. For example, Ahmed and Zlate (2013) use data from the Balance of Payments Statistics published by the IMF that covers quarterly net flows for a sample of 12 emerging economies from 2002:Q1 to 2012:Q2. Also, Byrne and Fiess (2011) use a sample of 78 countries and gathers quarterly inflow data from Euromoney Bondware from 1993Q1 to 2009Q1.

This type of panel data, sometimes called ”data fields”; ”panel time-series”; or ”macro panels” (see Eberhardt (2012)), have significant differences in comparison to typical micro panel data (large N and small T). For instance, in contrast to micro panel data where parameter homogeneity and cross section independence are usually assumed, when T is larger than or of the same order of N it is very likely that parameter heterogeneity and cross-section dependence exist (either among variables and/or residuals) as noted by Pesaran and Smith (1995) and Haque et al. (1999).[1]

The mentioned authors proved that the estimation of the traditional fixed effects model in the presence of parameter heterogeneity leads to inconsistent estimators.[2] In addition, the presence of cross-section dependence leads to imprecise estimates and even identification problems (see Eberhardt and Teal (2011), Eberhardt and Bond (2009), Sarafidis and Wansbeek (2012) and Phillips and Sul (2007)).

Nonetheless, the literature on capital flows still applies the fixed effects model when assessing the determinants of such flows, ignoring the possibility of slope heterogeneity and, with exception of Fratzscher (2012) and Alberola et al. (2012), also ignoring the presence of cross-section dependence. Recent literature provides two panel data models that accommodate both, slope heterogeneity and cross section dependence: Pesaran (2006) "Common Correlated Effects Mean Group (CCEMG)" model and Eberhardt and Bond (2009) "Augmented Mean Group (AMG)" model. These models differentiate from each other in how they treat the common correlated effects. The CCEMG treats them as nuisance parameters whereas in the AMG such factors represent a common dynamic process which is accounted for by subtracting it from the dependent variable.

This work contributes to the literature by estimating such panel data models that accommodate slope heterogeneity and cross-section dependence in a panel of gross portfolio and gross aggregate capital inflows for 18 of the most representative emerging economies.[3] In addition, this work contrasts these new models against a fixed effects model accounting for cross-section dependence (FE-DK hereafter) in order to assess the differences between both methods.

The results of this work are the following: The determinants of gross inflows identified as significant by the AMG model are mostly quite different from those with a significant effect in the FE-DK model. When contrasting the AMG against the FE-DK we observe that in the case

[1]Pesaran and Baltagi (2007) stated that if T is significantly bigger than N, for example $5 \leq N \leq 10$ and $T >= 80$ it is more adequate to use Zellner SURE methodology, but with $20 \leq T < 80$ and $N > 10$ the SURE methodology becomes impractical.

[2]In the fixed effects model it is assumed that all heterogeneity is captured by the fixed effects parameter and that there is slope homogeneity across individuals

[3]Slope heterogeneity and cross-section dependence are confirmed by statistical tests proposed by Baltagi (2008) and Swamy (1970) in the first case and Pesaran (2004) in the second case.

of gross portfolio inflows the set of determinant factors is bigger in the first than in the second model. Nonetheless, when a determinant is common across models some significant differences in either magnitude or sign are found. In the case of gross aggregate inflows, both the AMG and the FE-DK provide some puzzling results. In the AMG model a higher global risk leads to a rise in gross aggregate inflows, whilst the FE-DK model finds that U.S. liquidity conditions and the second stage of quantitative easing program (QE2) have a negative impact on such inflows.

These results may be due to aggregation of different functional categories of foreign capital that respond differently to macroeconomic variables, i.e., if each functional category of gross inflows (direct investment, portfolio investment and other investment) responds differently to push and pull factors, this may be the cause of such counterintuitive results. Haque et al. (1999) argue that this differentiated respond across-countries, either in magnitude or direction, is due to time varying country conditions such as that one country is at different phase of the economic cycle than other. Both, the AMG and the FE-DK models, confirmed that gross direct investment and gross other investment inflows have mostly different determinants.

In general, the results suggest that the AMG model is more successful in identifying significant factors of gross portfolio inflows and has a better fit (according to the RMSE criteria) than the FE-DK model. However, this does not mean that the FE-DK model is not a good model but that when dealing with macro panels where there exist strong slope heterogeneity and CSD models that take these features into account are the most adequate as stated by Pesaran and Smith (1995), Haque et al. (1999), Eberhardt and Bond (2009), Eberhardt and Teal (2011) and Chudik and Pesaran (2013).

The CCEMG is excluded from the discussion since it provides no clear insight of the determinants of capital inflows to emerging economies given that no significant factors were found in the estimation procedure.

Finally, if differences across types of inflows are not taken into account, it may be the case that implementing a policy which is optimal to manage portfolio inflows, for example, could have undesired effects in direct investment, cross-border lending or both. Thus, it is important for policy designers to balance the effects of the available policies across inflows and select the most proper one.

The paper is organized as follows: The next section provides a brief narrative of the recent events in capital flows toward emerging economies and its determinants as suggested by the recent literature. The third section includes a description of the data used. The fourth section argues why slope heterogeneity and cross-section dependence are important in large N and large T panels, and statistical tests to detect them are performed. In addition, in this section simple slope heterogeneous panel data models are estimated. The fifth section briefly explains the Common Correlated Effects Mean Group and the Augmented Mean Group models designed to account for slope heterogeneity and cross-section dependence. The sixth section provides the results of this analysis. The seventh section briefly discusses the implications for policy of these results. The eighth section concludes.

2. Recent Developments in Capital Flows to Emerging Economies

Inflows of capital are usually thought as drivers of economic growth and investment that help to finance current account imbalances. However, these flows are also a source of financial vulnerabilities and macroeconomic imbalances, as occurred during the Mexican crisis in 1994 and the Asian crisis in 1997. After these crises, emerging economies implemented several reforms that paved the path to an improvement in their macroeconomic fundamentals. Such progress derived into very optimistic growth prospects which supported a resurgence of capital flows toward emerging economies up to the beginning of the recent global financial crisis when these flows plummeted.[4]

The strengthening of macroeconomic fundamentals not only made emerging economies more resilient to the effects of the global financial crisis, but also contributed to their relatively faster economic healing in the months after the crisis. Such resilience when combined with a very lax monetary policy and an unprecedented injection of liquidity in advance economies spurred a new wave of capital flows towards emerging economies which has stimulated a resurgence of the capital flows literature.[5]

[4]For a very detailed analysis of capital flows in emerging economies during and after the financial crisis see IMF (2011), IMF (2012) and Ahmed and Zlate (2013).

[5]This new wave of capital flows has been characterized by a rise in the participation of portfolio investment and other investment, usually bank loans.

However, recent literature must consider the implications for capital flows of the improvement in economic and financial conditions of emerging economies in the last decade. Rothenberg and Warnock (2011) and Forbes and Warnock (2012) noted that in the last years emerging economies have increased their holdings of foreign assets significantly, so that net capital flows are no longer driven solely by the behavior of foreign capital towards emerging economies (gross foreign inflows or simply gross inflows), but also by the acquisition of foreign assets by domestic agents (gross domestic outflows or simply gross outflows) which may be determined by different factors.

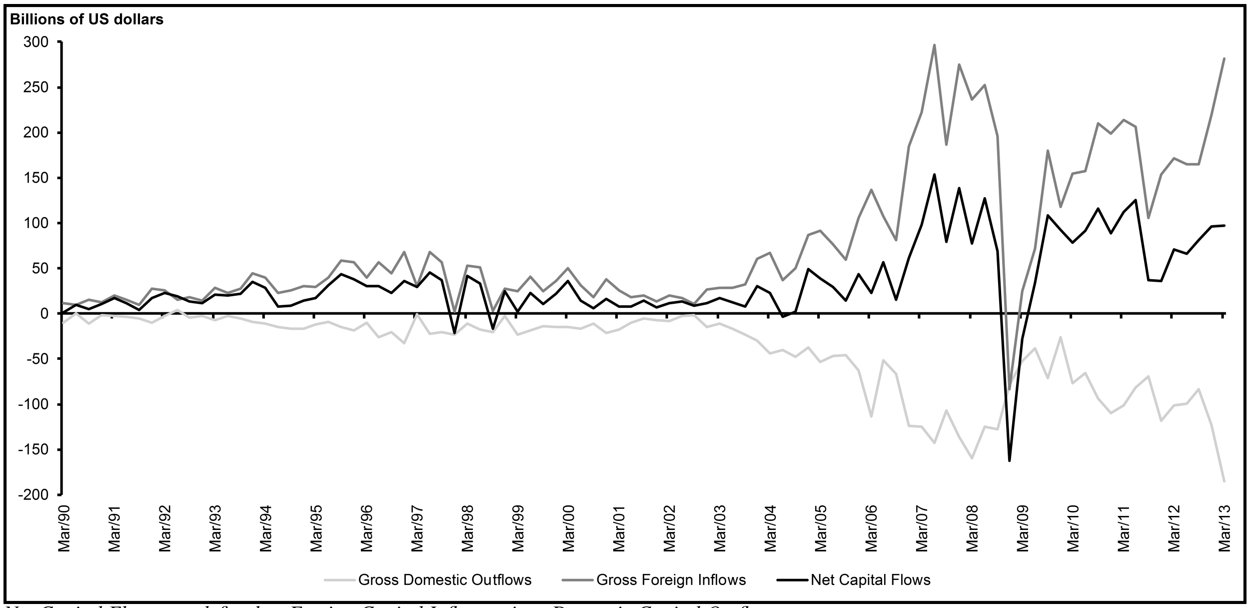
Moreover, Forbes and Warnock (2012) and Broner et al. (2013) found that not only gross flows have increased in size or volume, but also in volatility widening the gap between gross and net flows, the last ones being relatively more stable. This was not an issue in the 1990s and 2000s since holdings of foreign assets in emerging economies were quite small so that data on net flows reflected a big share of the behavior on capital inflows (see for instance: Calvo et al. (1993), Fernandez-Arias (1996), Taylor and Sarno (1997), Montiel and Reinhart (1999) and Baek (2006)). Recent literature mainly uses gross capital inflows data, albeit studies still draw upon net flows data such as Ahmed and Zlate (2013) and Kapetanios et al. (2011).[6]

Figure 1 shows the evolution of gross foreign inflows and gross domestic outflows as well as net capital flows in emerging economies. Given the small volume of gross domestic outflows, up to 2003 net flows were very close to gross inflows confirming that net flows in fact did reflect the behavior of gross capital inflows to emerging economies. From 2004 and up to Lehman's bankruptcy both gross inflows and outflows grew at a very fast pace and the gap between net flows and gross inflows became wider. Note that during the last global financial crisis foreign capitals retrenched whereas domestic capitals returned to emerging economies.

In the second half of 2009 gross inflows and outflows gradually returned to the levels observed prior to the financial crisis and the evolution of net flows began to exhibit a somewhat different behavior from that of gross inflows. In particular, in 2012 while gross inflows kept on growing, the rise in gross outflows drove net flows down.

[6]Additionally, the importance of gross flows has been recently highlighted by Obstfeld (2012) who claims that the international gross balance of liabilities and assets has been one of the main channels throughout financial collapse has been globally spread.

Figure 1: Quarterly Foreign Capital Inflows, Domestic Capital Outflows and Net Capital Flows in Emerging Economies



Net Capital Flows are defined as Foreign Capital Inflows minus Domestic Capital Outflows

Sample: Argentina, Brazil, Bulgaria, Chile, Colombia, Czech Rep., Hungary, India, Indonesia, Israel, Korea, Mexico, Peru, Poland, Romania, Russia, Thailand, Turkey and Ukraine.

Source: IMF International Balance of Payment Statistics.

2.1. Capital Flows Determinants

Recent studies have found that either domestic characteristics (pull factors) as well as foreign shocks (push factors) do have an impact on the behavior of capital flows. Among the typical pull factors found to be important for capital flows are domestic GDP growth rate and some measure of country risk (usually either S&P ranking or EMBIs) come out as frequent (see Ahmed and Zlate (2013), Kabadayi et al. (2012) and Fratzscher (2012) among others). Regarding the push factors, usually the U.S. interest rates and the U.S. GDP growth rate are the most common followed by global risk, usually represented by the VIX (see Forbes and Warnock (2012), Byrne and Fiess (2011), etc.). In turn, the evidence on the effects of the U.S. unconventional monetary policy has been contradictory. In one hand, Ahmed and Zlate (2013) found that U.S. unconventional monetary policy has not had a positive significant effect on capital flows, whereas Fratzscher et al. (2012) states that such unconventional measures have been significant for net inflows.

Furthermore, Fratzscher (2012) uncovered that besides strong macroeconomic fundamentals, other individual country characteristics such as institutional quality and policy implementation played an important role in attracting capital flows to emerging economies after the financial crisis. What is more, the author found that pull factors are the most important determinants of capital inflows, but the effects of these shocks are markedly heterogeneous across countries.

The objectives of this study are: First, to determine the existence of slope heterogeneity in a panel data model for gross portfolio and gross aggregate capital inflows to emerging economies. To achieve this goal two poolability tests are performed, the Roy-Zellner test suggested by Baltagi (2008) and the Swamy (1970) test of parameter stability. Second, in the case that slope heterogeneity is confirmed, static heterogeneous panel data models will be estimated and contrasted against a typical fixed effects model. Third, as mentioned by Pesaran (2004), Sarafidis and Wansbeek (2012), Phillips and Sul (2007) and Eberhardt and Bond (2009) cross-section dependence is a major issue when dealing with cross-country data. Then, existence of cross-section dependence is evaluated by implementing Pesaran (2004) test to the residuals obtained from the estimated models in the previous step. If cross-section dependence is present then it is quite likely that the estimators obtained before are biased and probably reflect spurious relations as noted by Phillips and Sul (2007) and Chudik and Pesaran (2013). Finally, more complicated models that accommodate both slope heterogeneity and cross-section dependence will be estimated.

3. Data

Capital flows data were obtained from the Balance of Payments Statistics published by the IMF for a set of 18 of the most important emerging economies[7]. The data is classified in three fundamental categories: Direct investment, representing long term investment with significant

[7]These countries are: Argentina, Brazil, Bulgaria, Chile, Colombia, Czech Republic, Hungary, India, Indonesia, Israel, Korea, Mexico, Peru, Poland, Romania, Russia, Thailand, Turkey and Ukraine. Singapore and Hong Kong were omitted from the beginning since they are considered as Asian financial centers which means that the behavior of capital inflows to these economies my be affected for very different reasons. China is not included since capital flows data for this country begin in 2010. Thailand and Philippines were also excluded due to lack of data.

influence in an enterprise. Portfolio investment, formed mainly by equity and debt securities. Other investment, principally composed by interbank loans and transfers.

These functional categories are divided into ”net incurrence of liabilities” and ”net acquisition of assets”. The IMF defines net incurrence of liabilities as the difference between the acquisition and the sale of domestic assets by foreign investors. Similarly, net acquisition of assets is defined as the difference between total acquisition and total sale of foreign assets by domestic investors. In the literature these two categories are also known as gross inflows and gross outflows respectively. In addition to analyze gross portfolio, an aggregate measure called gross aggregate inflows defined as the sum of gross direct, portfolio and other investment inflows will be studied.

According to the literature, two groups of explanatory variables are defined: pull and push factors. Pull factors provide information about the economic conditions in each country such as growth and macroeconomic stability. Push factors are usually beyond emerging economies control and are represented by foreign variables such as global risk, global liquidity, etc.

In this study, the selected variables included in the group of pull factors are: domestic real GDP and nominal exchange rate of growth, the Standard & Poors (S&P) ratings as proxy for country risk, domestic money market interest rates, and the international commodities price index excluding oil.[8]

In turn, U.S. macroeconomic variables are used as proxies for global economic (pull) factors that may have an effect on capital inflows. The selected variables are: U.S. real GDP growth rate, U.S. money market interest rates, U.S. monetary base ($M0$) as percentage of GDP as proxy of global liquidity, and the VIX index as a measure of global risk.

The model also includes a set of dummy variables to control for Lehman's bankruptcy episode, and the first two quantitative easing programs:[9]. The first dummy denoted ”crisis” is equal to 1 from $Q3:2008$ to $Q2:2009$. The dummy representing the first quantitative easing ”QE1” is equal 1 from $Q4:2008$ to $Q1:2010$. Lastly, QE2 denoting the second quantitative easing is equal to 1 from the $Q4:2010$ to $Q2:2011$. All gathered data is at quarterly frequency from $Q1:2000$

[8]EMBIs were also considered as a measure of country risk. However, the lack of data for some countries, like India, made the use of EMBIs inefficient

[9]The dates for the duration of the QE1 and QE2 programs were obtained from Neely (2013)

to $Q4$: 2012. The data was obtained from the International Financial Statistics and Balance of Payment statistics databases published by the IMF, individual central banks, Bloomberg and Haver Analytics.

4. Macro vs Micro Panel Data Methods

As mentioned above, one of the most common econometric models used in the capital flows literature is the panel fixed effects model. This model is the main workhorse in microeconometrics where the data used is usually comprised of a big number of cross sections (large N) observed through short time periods (small T). It primarily relies in the following assumptions: Unobserved individual time-constant effects exist, no slope variation across individuals (slope homogeneity), and independent errors with mean zero and constant variance.[10] If all these assumptions hold, then the FE estimator will be consistent.

On the other hand, increasing availability of economic data, in particular macroeconomic data, has changed the size of panel datasets from the typical large N small T panel (hereafter micro panels) to a large N large T panels (hereafter macro panels). Macro panels face different challenges than standard panel data models. For instance, Pesaran and Smith (1995) and Haque et al. (1999) show that in cross-country panel data the assumption of slope homogeneity will not hold due to economic and institutional differences. If indeed slopes parameters are not homogeneous, it might lead to inconsistency of the fixed effects model.

In addition, the assumption of independent errors will almost never hold in macro panels. Phillips and Sul (2007) state that if cross-section dependence (correlation) exist across individuals, then estimated parameters may be significantly biased and in a worst case scenario identification problems may be present.

Thus, detecting slope heterogeneity and cross-section dependence is a crucial step when working with macro panels. Identifying slope heterogeneity can be done by implementing the so called poolability tests proposed by Baltagi (2008) and Swamy (1970). In turn, testing for cross-section dependence in large N and large T panels can be done with Pesaran (2004) cd test.

[10] Although this assumption is easily relax by adjusting the standard errors to control for heteroskedasticity, autocorrelation and cross-sectional or spatial dependence as noted by Driscoll and Kraay (1998)

4.1. *Slope Heterogeneity and Cross-Section Dependence*

Let's assume that gross capital inflows can be modeled in the following way:

$$y_{i,t} = \alpha_i + X_{i,t}\beta_i + \epsilon_{i,t} \qquad i = 1, \ldots, N \quad t = 1, \ldots, T \tag{1}$$

where $y_{i,t}$ is the vector of gross capital inflows as percent of GDP, $X_{i,t}$ be the matrix of regressors composed by pull and push factors and $\epsilon_{i,t}$ is the vector of residuals.

If slope homogeneity is assumed then equation 1 can be pooled and estimated by fixed effects models. However, if the slope parameters are not homogeneous, the fixed effects model will be inconsistent. Testing for slope homogeneity can be done by implementing the Roy-Zellner, or the Swamy (1970) parameter consistency test that assumes that slope parameters are randomly distributed. Baltagi (2008) recommends the use of the Roy-Zellner poolability test since it accounts for non-spherical disturbances. In this sense, this test is a generalization of the Chow test. In particular, if the model to estimate is $y_{i,t} = \alpha_i + \beta_i x_{i,t} + \epsilon_{i,t}$ the Roy-Zellner test assumes that $\epsilon_{i,t} = \eta_i + u_{i,t}$ where $\eta_i \sim N(0, \sigma^2_\eta)$ and $u_{i,t} \sim N(0, \sigma^2_u)$. In contrast, the Chow test assumes that $\epsilon_{i,t} \sim N(0, \sigma^2)$. The null hypothesis in the Roy-Zellner test is $H_0 : \beta_i = \beta$.

Table 1 shows the results of these tests for each of the three functional categories of gross capital inflows, as well as for the aggregate. It is clear that for all specifications the hypothesis of slope homogeneity is strongly rejected. Thus, models that account for heterogeneous slopes are required to explain the behavior of gross inflows.

Table 1: Poolability Tests

	FDI Flows	*Portfolio Flows*	*Other Flows*	*Total Flows*
Roy-Zellner	871.19***	569.97***	817.47***	1074.91***
	(0.00)	(0.00)	(0.00)	(0.00)
Swammy (1970)	1772.65***	689.24***	968.7***	1141.86***
	(0.00)	(0.00)	(0.00)	(0.00)

P-values in parenthesis. + significant at 10% ** significant at 5% *** significant at 1%.

Given that slope heterogeneity leads to significant bias of the fixed effects estimator, Pesaran and Smith (1995) proposed the Mean Group estimator (MG). This estimator accounts for slope heterogeneity by not imposing the same slope to all N, but by averaging each slope across N, i.e. The MG ($\hat{\beta}^{MG}$) is obtained by first using OLS to get individual estimates of the slopes parameters, i.e. let $\hat{\beta}_i^{OLS} = (X_i'X_i)^{-1}X_i'y_i$ be the vector of estimated parameters for country i obtained by OLS. Then, the MG will be given by: $\hat{\beta}^{MG} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_i^{OLS}$. Pesaran and Smith (1995) demonstrate that the MG is an unbiased and consistent estimator of the population average.

Then, $\hat{\beta}^{MG}$ is the unweighted average of country specific estimates and so it is sensible to outliers. To minimize the effect of outliers, Eberhardt (2012) suggests the robust regression method of Hamilton (1992) which gives less emphasis to outliers.[11]

In addition, the Swamy (1970) random coefficients model (RCM) can be implemented. The RCM model provides a feasible GLS estimator equal to the weighted average of individual OLS parameters, i.e. the RCM estimator is given by $\beta^{RCM} = \sum_{i=1}^{N} W_i\hat{\beta}_i^{OLS}$, where the weighting matrix, W_i, is a function of the errors variance covariance matrix.

Table 2 contrasts the estimated parameters from the MG, RCM and a standard fixed effects model for gross portfolio and gross aggregate inflows variables. For each model some differences exist regarding the variables that appear significant. It is also clear that there are some differences in the signs of some variables as well as some differences in the magnitudes of the estimated parameters between models.

Even more important, Table 2 shows the results of Pesaran (2004) cross-section dependence test. All models exhibit cross-section dependence problems in the residuals. Therefore, models that can accommodate both, slope heterogeneity and cross-section dependence are required so as to provide a more adequate analysis of gross capital inflows to emerging economies.

Both, the MG and the RCM models described so far also account for country specific fixed effects by the inclusion of the intercept (see Pesaran and Smith (1995), Haque et al. (1999) and Swamy (1970) for details).

[11]The robust regression method consist on running individual regressions and gather the residuals. Then, weights are calculated based on absolute residuals, i.e. let u_i be the i^{th} residual, then for some constant s the i^{th} scaled residual is $e_i\frac{u_i}{s}$ where s is a function of the mean absolute deviation from the medial residual

5. Heterogeneous Common Factors Panel Data Models

Recent literature has recently proposed two different models to account for slope heterogeneity and cross-section dependence: the "Common Correlated Effects Mean Group Model (CCEMG)" designed by Pesaran (2006), and the Augmented Mean Group model (AMG) proposed by Eberhardt and Bond (2009) and Eberhardt and Teal (2011). Assuming for simplicity a single regressor, then for all $i = 1, \ldots, N$ and all $t = 1 \ldots, T$ let

$$y_{i,t} = \beta_i' x_{i,t} + u_{i,t} \tag{2}$$

$$u_{i,t} = \alpha_{1i} + \lambda_i f_t + \varepsilon_{i,t} \tag{3}$$

$$x_{i,t} = \alpha_{2i} + \lambda_i f_t + \gamma_i g_t + \nu_{i,t} \tag{4}$$

where f_t, g_t are unobservable time variant common factors with country specific factor loadings λ_i, γ_i; α_{1i} and α_{2i} are country specific fixed effects; and $\varepsilon_{i,t}$ and $\nu_{i,t}$ iid errors with mean zero and finite variances.

The terms f_t and g_t induce cross-section dependence in both the errors and the regressors. Moreover, f_t allows for possible cross-section dependence between the errors and the regressors. The main difference between the CCEMG and the AMG is how they estimate these factors.

The CCEMG model treats the common factors as nuisance parameters. This model solves the issue of cross-section dependence by including as additional regressors the cross-sectional averages of the regressors ($\bar{x}$) as well as the dependent variable ($\bar{y}$). Pesaran (2006) proved that these averages can account for the unobserved common factors f_t. The issue regarding the differentiated impact of common factors is solved by estimating individual equations and then computing the average of the factor loadings. Given that this is in fact the MG procedure, slope heterogeneity is also assumed by construction.

However, the CCEMG has a big drawback, as noted by Eberhardt (2012), in that the estimated slope parameters of the regressors and the averages have not an easy interpretation. Thus, these authors propose the AMG estimator, which as in the CCEMG, it accounts for slope heterogeneity and CSD. The main difference between these two estimators is that in contrast to the CCEMG, the

AMG does not regard the unobserved common factors as nuisance, but it assumes that such factors represent a common dynamic process (CDP) which can be estimated. Eberhardt and Bond (2009) refer to the CDP as *"...represents the levels-equivalent mean evolvement of unobserved common factors across all countries..."*

The AMG is obtained as follows: First, obtain an estimate of the CDP. This is done by estimating a pooled difference OLS model with time dummy variables. The estimated parameters of these time dummies will represent the CDP. Second, the CDP is then added to the model by either subtracting it from the dependent variable, i.e. $\tilde{y}_{i,t} = y_{i,t} - CDP$, or by including it in each of the N regressions. In this analysis, the CDP is subtracted from the dependent variable. Third, estimate N individual regressions and compute the averages or the individual estimated slopes as in Pesaran and Smith (1995).

6. Results

This section presents the determinants of gross portfolio and gross aggregated capital inflows to emerging economies as implied by the AMG model. Unfortunately, the CCEMG model provides no insight on the determinants of gross inflows to emerging economies, since no significant variables were found and so it is omitted from results. As in the case of the MG estimator, the AMG is adjusted for outliers using Hamilton (1992) robust regression method.

The AMG estimated parameters are contrasted against those obtained from estimating a regular fixed effects model accounting for cross-section dependence in the residuals, using the Driscoll and Kraay (1998) estimator (FE-DK).

6.1. Gross Portfolio Inflows

Table 3 provides the determinants of gross portfolio inflows suggested by the AMG and the FE-DK models described above. The AMG model suggests that push factors are the main determinants of gross portfolio inflows, being country risk the sole pull factor that has a significant impact. The estimated parameters suggest that a rise in gross portfolio inflows can be explained by a lower country risk (an increase in the S&P ranking), a faster growth of the U.S. economy, and a rise in available liquidity. Also, the results suggest that the second quantitative easing program did have a significant positive impact on gross portfolio flows. On the other hand, a rise in global risk perception (higher VIX index) leads to a retrenchment of portfolio flows from emerging economies. A positive estimated parameter of U.S. interest rates variable may appear counterintuitive. However, it is quite possible that a rise in U.S. money market interest rates could lead to a hike of emerging economies interest rates as well so as to keep these economies pulling in foreign capital.

In turn, the FE-DK model suggest that gross portfolio inflows decrease with a depreciation of the nominal exchange rate, higher country and global risks, and the recent financial crisis. All such estimated parameters in the fixed effects model also exhibit the expected signs.

Contrasting these two models it is observed that the AMG model is more successful in identifying a higher number of significant determinants than the FE-DK. Also, there exist two common pull factors identified by the AMG and the FE-DK models: country risk and global risk aversion. The estimated parameters of such variables do not differ significantly between these two models. However, one must take into account that given the presence of slope heterogeneity the estimated parameters of the FE-DK model are biased. Lastly, the root means squared error (RMSE) indicates that the AMG has a better fit (RMSE =2.48) than the FE-DK model (RMSE = 3.16).

6.2. Gross Aggregate Inflows

Table 4 shows the determinants of the gross aggregate inflows as implied by the AMG and the fixed effects models. According to the AMG model, pull and push factors are the main determinants of gross aggregate inflows. The results suggest that these inflows increase with a depreciation of the exchange rate, a lower country risk and a rise in available foreign liquidity. Surprisingly, the results points to higher global risk aversion as a factor increasing such inflows.

The fixed effects model also points to both pull and push factors as main determinants of gross aggregate inflows: Domestic GDP and commodity prices attract aggregate inflows, whilst higher foreign money market interest rates also have a positive effect. However, as in the case of the AMG model, the FE-DK model also finds a couple of unexpected results. For instance in this model rising available liquidity or introducing an extraordinary injection, QE2 program, lead to a retrenchment of gross aggregate inflows.

These results may be due to aggregation of different functional categories of foreign capital that respond differently to macroeconomic variables, i.e., if each functional category of gross inflows (direct investment, portfolio investment or other investment) responds differently to push and pull factors, this may be the cause of such counterintuitive signs.

In order to confirm this, both the AMG and the fixed effects models are estimated for gross direct and gross other investment inflows in Table 5 and Table 6 respectively. The results confirm that factors affecting gross direct investment are different than those determining gross portfolio or gross other investment inflows within and across models. Nevertheless, when a specific determinant happens to be significant within or across models some important differences in either magnitude or sign take place. For example, Table 6 shows that in the AMG model U.S. GDP growth rate has a negative significant effect on gross direct inflows (coefficient of -0.4118), whereas it has a significant positive effect in gross portfolio inflows (coefficient of 1.1127); liquidity conditions in the U.S. ($M0/GDP$) increase gross direct and gross portfolio inflows (coefficients of 0.1419 and 0.0729 respectively) in contrast with a negative significant effect on gross other inflows (coefficient of -0.1069).

The comparison of FE-DK and AMG models shows that U.S. liquidity conditions have a negative significant effect (-0.1498) on gross direct investment in the FE-DK model but a significant positive effect (0.1419) in the AMG model. Also real GDP growth has a significantly bigger impact in gross other inflows in the AMG model (0.3702) than in the FE-DK (0.1437). The opposite is also true for US liquidity conditions which have a smaller negative impact in the AMG model (-0.1069) than in the FE-DK model (-0.1655). Finally, for gross aggregate inflows the same liquidity measure has a negative estimated parameter (-0.3169) in the FE-DK model, but a positive sign (0.4014) in the AMG model.

Note that even if some pull or push factor are significant in both the AMG and the FE-DK models, in some cases there are important differences in the magnitude of the effect. For instance, in the FE-DK model domestic real GDP growth rate has a smaller estimated parameter in gross other inflows (coefficient of 0.1437) than it has in the AMG model (coefficient of 0.3702).

As a way to compare between the FE-DK and the AMG models the root mean squared error (RMSE) is provided for all cases. Looking at this statistic is easy to see that the AMG model has a better fit than the FE-DK in all cases. Also, both models achieve the minimum RMSE value when analyzing gross portfolio inflows.[12]

The results in Table 6 also show that the extraordinary injection of liquidity, QE1 and QE2, had different effects on portfolio investment and other investment gross inflows. These results highlight the negative impact that QE1 had on other investment inflows, which may appear puzzling. However, the implementation of this program did not lead to a raise in bank lending but on the contrary banks tightened lending requirements and began to accumulate cash. Such behavior also implied that their cross-border lending operations were halted resulting in a fall of other investment flows to emerging economies which explains the negative sign shown in Table 6.

7. Conclusion

It is quite common in the literature of capital flows to emerging economies to use panel data models. In particular, the fixed effects model. This model has proved to be an excellent tool to analyze data composed by a large number of individuals which are observed by a very short period of time. However, recent macroeconomic data provides information for a large number of countries and for large periods of time. These type of panels are known in the literature as ”macro panels”.

Current literature that disentangles macro panels properties state that these type of panels suffer from slope heterogeneity and cross-section dependence in the residuals and sometimes even in the regressors, challenging the assumptions of the fixed effects model of slope homogeneity and independent errors. If not taken into account, slope heterogeneity and cross-section dependence could lead to biased and inconsistent estimators as well as to identification problems. Recent literature proposes the use of heterogeneous common factor models to account for both slope heterogeneity and cross-section dependence: Pesaran (2006) common correlated effects mean group model (CCEMG) and Eberhardt and Bond (2009) augmented mean group model (AMG).

This work estimates the CCEMG and AMG models in a panel of 18 of the most representative emerging economies with 52 quarter of macroeconomic data. Unfortunately, the CCEMG model

[12]The differences may still be bigger between these models given that the reported RMSE in the AMG model is calculated over non-weighted residuals, i.e without weighting down outliers.

provides no insight on the determinants of gross inflows to emerging economies since no significant variables were found and so it is omitted from results. Hence, only the results of the AMG are reported and also contrasted against a regular fixed effects model but accounting for cross-section dependence by implementing Driscoll and Kraay (1998) estimator (FE-DK).

The results show that both the AMG and the FE-DK do have strengths and weaknesses. However, the AMG appears to be more stable. According to the AMG, gross portfolio and gross aggregate inflows are mostly determined by push factors. In one hand, gross portfolio inflows depend on only one domestic factor (country risk) and five external factors. In the other hand, gross aggregate inflows are determined by four external factors only. Among the pull factors, the second quantitative easing program and U.S. real GDP growth rate have the higher significant impact in both gross portfolio and gross aggregate inflows. This work also shows how each type of capital inflow (direct, portfolio and other inflows) has their own set of determinants, and in the few cases where the same variable affects different inflows, the estimated parameter can be different in either magnitude or sign from one inflow to another. It also shows how taking into account cross-section dependence and slope heterogeneity helps to improve the fit of the model, as measured by the root mean squared error (RMSE).

These results do not imply that the fixed effects model is not a good model but rather that when working with cross-country panels with a time dimension larger than or equal to the number of individuals slope heterogeneity and cross-section dependence become important. Then, models that take these into account are the most adequate as noted by Pesaran and Smith (1995), Haque et al. (1999), Eberhardt and Bond (2009), Eberhardt and Teal (2011) and Chudik and Pesaran (2013).

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Table 2: Heterogeneous vs Homogeneous Panel Data Models.

Gross Portfolio and Gross Aggregate Inflows to Emerging Economies

	Gross Portfolio Inflows			Gross Aggregate Inflows		
	Fixed Effects[a]	*Mean Group*[b]	*Random Coef.*	*Fixed Effects*	*Mean Group*	*Random Coef.*
PULL FACTORS						
Real GDP growth rate	0.0206	-0.0447	0.0461	0.1562**	0.2785	0.1903
	(0.5405)	(0.6112)	(0.6085)	(0.0269)	(0.1238)	(0.4044)
FX growth rate	-0.0386**	-0.0583***	-0.0609***	-0.0154	-0.1021***	-0.0528
	(0.0178)	(0.0002)	(0.0000)	(0.7239)	(0.0004)	(0.1898)
S&P Ranking	0.4426***	0.2984		0.4218	0.5857	
	(0.0073)	(0.3419)		(0.2531)	(0.2192)	
Int. Commodity Price Index	0.0363	1.6497	2.3948***	7.2054**	4.0408+	8.6740***
	(0.9633)	(0.3091)	(0.0202)	(0.0298)	(0.0546)	(0.0000)
Interest rates	-0.0065	0.0302	0.0311	-0.0144	0.0661	0.1398
	(0.7279)	(0.6729)	(0.3908)	(0.7280)	(0.4505)	(0.5228)
PUSH FACTORS						
U.S. Real GDP growth rate	0.5616**	0.5541***	0.5043***	-0.0095	0.8275**	0.1982
	(0.0332)	(0.0096)	(0.0077)	(0.9913)	(0.0239)	(0.7050)
U.S. interest rates	-0.0581	-0.0295	-0.0821	0.4029	0.3699+	0.3969**
	(0.5172)	(0.7850)	(0.5163)	(0.1393)	(0.0754)	(0.0362)
U.S. $M0$/GDP	0.0068	0.0855	-0.0196	-0.3022***	-0.2859**	-0.4220***
	(0.6309)	(0.1589)	(0.7514)	(0.0001)	(0.0139)	(0.0030)
VIX	-0.0282**	-0.0381+	-0.0320**	-0.0001	0.0146	-0.0058
	(0.0451)	(0.0645)	(0.0189)	(0.9959)	(0.6530)	(0.8808)
DUMMY VARIABLES						
Crisis	-1.1094**	-0.8174	-0.5751	-0.9317	-1.3723+	-1.0834
	(0.0496)	(0.1275)	(0.2060)	(0.4216)	(0.0719)	(0.2326)
QE1	0.2375	-0.1132	0.0837	0.1945	-0.3860	-0.0710
	(0.5693)	(0.8511)	(0.8545)	(0.8440)	(0.7041)	(0.9456)
QE2	0.5701	-0.0976	-0.2401	-1.8374	0.4297	-1.6262
	(0.2793)	(0.8611)	(0.5570)	(0.3942)	(0.5925)	(0.2954)
Cross-Section Dependence						
CDS Test[c]	65.98***	7.44***	72.49***	64.19***	4.43***	65.83***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	887	887	889	887	887	889
Countries	18	18	18	18	18	18

a Fixed effects with robust standard errors.

b Mean of slope coefficients adjusted by outliers following Hamilton(1992) robust regression method.

c Pesaran (2004) cross-section dependence test. Null hypothesis is cross-section independence.

Intercept and country fixed effects not reported but included.

P-values in parentheses. + significant at 10% ** significant at 5% * * * significant at 1%.

Table 3: Heterogeneous Common Factors and Fixed Effects Panel Data Models.

Gross Portfolio Inflows

	Fixed Effects DK[a]	Augmented Mean Group[b]
PULL FACTORS		
FX grwoth rate	-0.0437**	
	(0.0140)	
S&P Ranking	0.4496***	0.4723***
	(0.0001)	(0.0007)
PUSH FACTORS		
U.S. Real GDP growth rate		1.1127***
		(0.0000)
U.S. interest rates		0.6146***
		(0.0000)
U.S. $M0$/GDP		0.0729**
		(0.0115)
VIX	-0.0373**	-0.0332+
	(0.0192)	(0.081)
DUMMY VARIABLES		
Crisis	-1.7624***	
	(0.0005)	
QE2		2.6979***
		(0.0000)
RMSE[c]	3.1573	2.4825
Observations	912	923
Countries	18	18

[a] DK refers to Driscoll and Kraay (1998) estimator that corrects for serial correlation, heteroskedasticity and cross-section dependence in the error term.

[b] AMG model corrected by outliers using Hamilton (1992) robust regression method.

[c] RMSE not affected by robust regression.

Intercept and country fixed effects not reported but included.

P-values in parentheses. + significant at 10% ** significant at 5% *** significant at 1%.

Table 4: Heterogeneous Common Factors and Fixed Effects Panel Data Models.

Gross Aggregate Inflows

	Fixed Effects DK[a]	Augmented Mean Group[b]
PULL FACTORS		
Real GDP growth rate	0.1813***	
	(0.0024)	
Int. Commodity Price Index	9.3467***	
	(0.0000)	
PUSH FACTORS		
U.S. Real GDP growth rate		2.7735***
		(0.0000)
U.S. interest rates	0.3707***	0.2980**
	(0.0013)	(0.0216)
U.S. $M0$/GDP	-0.3169***	0.4014***
	(0.0000)	(0.0048)
VIX		0.1056***
		(0.0085)
DUMMY VARIABLES		
QE2	-2.2846***	
	(0.0035)	
RMSE[c]	16.2536	5.6590
Observations	929	932
Countries	18	18

[a] DK refers to Driscoll and Kraay (1998) that corrects for serial correlation, heteroskedasticity and cross-section dependence in the error term.

[b] AMG model corrected by outliers using Hamilton (1992) robust regression method.

[c] RMSE not affected by robust regression.

Intercept and country fixed effects not reported but included.

P-values in parentheses. + significant at 10% ** significant at 5% *** significant at 1%.

Table 5: Fixed Effects Models Corrected by Cross-Section Dependence

	Direct Inflows	Portfolio Inflows	Other Inflows
PULL FACTORS			
Real GDP growth rate			0.1437***
			(0.0001)
FX growth rate		-0.0437**	
		(0.0140)	
S&P Ranking		0.4496***	
		(0.0001)	
Int. Commodity Price Index	3.77***		
	(0.0018)		
PUSH FACTORS			
U.S. interest rates	0.2144**		
	(0.0286)		
U.S. $M0$/GDP	-0.1498***		-0.1655***
	(0.0000)		(0.0000)
VIX		-0.0373**	
		(0.0192)	
DUMMY VARIABLES			
Crisis		-1.7624***	
		(0.0005)	
QE2	-2.6857***		
	(0.0003)		
RMSE	10.0174	3.1573	7.8744
Observations	932	912	929
Countries	18	18	18

Fixed effect models using Driscoll & Kraay (1998) that corrects for serial correlation, heteroskedasticity and cross-section dependence in the error term.

Intercept and country fixed effects not reported but included.

P-values in parentheses. + significant at 10% $**$ significant at 5% $***$ significant at 1%.

Table 6: Augmented Mean Group Model Corrected by Outliers

	Direct Inflows	Portfolio Inflows	Other Inflows
PULL FACTORS			
Real GDP growth rate			0.3702***
			(0.0001)
FX growth rate	-0.0524***		
	(0.0004)		
S&P Ranking		0.4723***	0.7864***
		(0.0007)	(0.0018)
PUSH FACTORS			
U.S. real GDP growth rate	-0.4118***	1.1127***	
	(0.0001)	(0.0000)	
U.S. interest rate		0.6146***	
		(0.0000)	
U.S. $M0$/GDP	0.1419***	0.0729**	-0.1069+
	(0.0013)	(0.0115)	(0.0644)
VIX		-0.0332+	-0.1159***
		(0.0810)	(0.0000)
DUMMY VARIABLES			
QE1			-2.9026***
			(0.0000)
QE2		2.6979***	
		(0.0000)	
RMSE	5.9559	2.4825	3.1611
Observations	915	923	927
Countries	18	18	18

AMG uses Hamilton (1992) robust regression method to reduce the effects of outliers.

Intercept in the AMG model accounts also for individual fixed effects as proved by Pesaran & Smith (1995). Estimated parameters not reported.

RMSE not affected by robust regression.

P-values in parentheses. + significant at 10% ** significant at 5% *** significant at 1%.