



# **Is the Anti Money Laundering Compliance Convenient?**

**International Capital Flows  
and Stigma Effect in Latin  
America: The Case of Paraguay**

**Donato Masciandaro**

**Inter-American  
Development Bank**

Capital Markets and  
Financial Institutions  
Division

Institutions for  
Development Sector

**DISCUSSION PAPER**

No. IDB-DP-311

**September 2013**

# **Is the Anti Money Laundering Compliance Convenient?**

**International Capital Flows  
and Stigma Effect in Latin  
America: The Case of Paraguay**

Donato Masciandaro



Inter-American Development Bank

2013

<http://www.iadb.org>

The opinions expressed in this publication are those of the authors and do not necessarily reflect the views of the Inter-American Development Bank, its Board of Directors, or the countries they represent.

The unauthorized commercial use of Bank documents is prohibited and may be punishable under the Bank's policies and/or applicable laws.

Copyright © 2013 Inter-American Development Bank. All rights reserved; may be freely reproduced for any non-commercial purpose.

Roberto de Michele, robertodem@iadb.org

## Abstract\*

This study analyzes the international financial flows of Latin America in order to verify existence and direction of the “Stigma Effect.” Is the AML/CFT financial regulation that addresses the money laundering and terrorism finance phenomena relevant in shaping the pattern of international banking movements? We test if the FAFT listing–delisting events are effective sticks and carrots for the targeted countries in influencing cross-border banking flows. The tests are based on a theoretical framework, where the stigma effect holds if doing business with a listed country produces nonlinear monetary and/or reputational costs. We focus on the 34 Latin American countries in the period 1996-2007 using annual panel data. We find evidence that the list in–list out mechanism can influence the banking inflows, provided that some conditions hold. The relevance of the stigma effect seems to depend on the one side on the efficiency of the international capital markets and on the other side on specific features of the listed/delisted country: regulatory lightness, banking profitability, growth per capita. The empirical specification is applied in evaluating the case of Paraguay using a time series analysis with quarterly data. The study finds that the Paraguayan listing episode was likely to produce perceptible effects on both capital inflows and outflows.

**JEL Codes:** E42, F34, F21, F36, O4, G21, K00

**Keywords:** International capital flows, anti money laundering regulation, FAFT blacklisting, Latin America, Paraguay

---

\* The author, of Paolo Baffi Centre and Department of Economics, Bocconi University and SUERF, gratefully appreciates the helpful comments of Oscar Boidanich (FIU, Paraguay), Jorge Corvalan (Central Bank of Paraguay), Roberto De Michele (IDB), Francisco De Michelis (IDB), Mariano Federici (IMF), Pedro Garay (IDB), Juan Felix Marteau (IMF Consultant), Santiago Pena (Central Bank of Paraguay), Carlino Velazquez (Central Bank of Paraguay), and Nelson Valiente (Banking Supervision, Central Bank of Paraguay). The Central Bank of Paraguay provided extensive data, and Olga Balakina and Ferruccio Martucci provided excellent research assistance.

## 1. Introduction

This paper analyses the international financial flows towards Latin American countries in order to verify existence and direction of the so called Stigma Effect , i.e. if the financial regulation which address the money laundering and terrorism finance phenomena is relevant in shaping the pattern of capital movements. The results are applied in evaluating the case of Paraguay.

Country compliance with the international standards of the Anti-Money Laundering and Combating the Financing of Terrorism – thereafter **AML/CFT** – policy is playing an increasing role in the national policymaking all around the world.

Established by the Financial Action Task Force (**FAFT**) in 1999, the international standard consists today of 49 Recommendations, dealing respectively with anti-money laundering (forty ) and combating terrorist financing (nine). From 2000 FAFT issues periodically lists - thereafter **Blacklists-** of Non – Cooperative Countries and Territories (**NCCTs**), which identify the jurisdictions that FAFT believes are non-compliant with the international best practices.

In order to prevent and combat the illegal financial flows the international organisations haven't hard legal commitment to impose; therefore they invented the blacklisting as a soft law practice. The aim of the list procedures is to put the blacklisted country (**BLC**) under intense international financial pressures, using the “name and shame” approach in order to produce the so called *stigma effect* (Masciandaro 2005a and 2008): an inverse relationship between blacklisting and international capital flows. Two sources of pressures on a BLC country are expected to work.

On the one side most countries evaluate financial transactions coming from or transferring to a BLC to be a suspicious activity, which triggers more stringent and more costly scrutiny. Banks operating in multiple jurisdictions are increasingly preoccupied by the **monetary costs**, including the compliance costs. The AML/CFT cost of compliance seems to continue to rise, at an average rate of 45 per cent (KPGM 2011).

On the other side the financial transactions with a BLC can produce **reputational costs**. Suspicion financial transactions are increasingly under the attention of supranational organizations, national policymakers and their regulators, and international media as well. For a banking institution participation in opaque financial transactions can produce increasing reputational risks. Just to quote the more recent and meaningful episodes, it is worth mentioning that in 2012-13 different international banks – Royal Bank of Scotland, Standard Chartered, Unicredit Group, Barclays, Hong Kong Shanghai Banking Corporation (HSBC), JPMorgan Chase, Citigroup among others – were investigated and/or alleged and/or fined and/or solicited to improve compliance for illicit financial transactions (Powell 2013). Transactions with BLC countries can produce similar negative reputational effects.

Because of the potential damages of the stigma effect, the international financial institutions may have a strong incentive to avoid business with BLC countries.

In the same vein the stigma effect can be considered an application of the general “name and shame” approach – i.e. institutional organizations disclose non compliance to the public supplementing the disclosure with form of official opprobrium (Brummer 2012) - which is increasingly applied in the international context to address policy coordination problems among national policymakers and regulators (Greene et Boehm 2012).

But existence and direction of the stigma effect are far to be obvious. As it has been pointed out in previous studies – Masciandaro 2005a and 2008 and Masciandaro et al. 2007 – the AML/CFT non-compliance attitude of a country can be attractive under specific conditions, such as the potential existence of a worldwide demand for non-transparent financial transactions. A BLC country can be attractive for banking and non-banking institutions seeking to promote lighted regulated products and services to their wealthy and/or sophisticated clients. The international banking industry can have an incentive to take advantages from the existence of BLC countries.

Therefore the stigma effect can become a carrot, rather than to be a stick. The *stigma paradox* can emerge, as a peculiar case of regulatory arbitrage that creates the so called “race to the bottom” strategy in eluding the more prudent regulation (Barth et al. 2006). This strategy can sensibly influence the international capital flows (Houston 2011).

Finally we have to consider a third possibility: the behaviour of the international banking institutions in the cross border business is simply driven by motivations other than the stigma effect (Kurdle 2009). In this case the *stigma neutrality* holds.

In general the relevance of the stigma effect becomes even more important in a period when, policymakers, regulators and scholars are seeking to understand which institutional and regulatory as well as historical features can attract or discourage the international capital movements (Papaioannu 2009, Reinhardt et al. 2010, , Houston et al. 2011, Qureshi et al. 2011, Milesi Feretti and Tille 2011, Chitu et al. 2013). The financial effects of regulation can be particularly relevant when the AML/CFT rules are under discussion; the more recent international cases concern the Vatican State and Cyprus as well.

This paper aims to address theoretically and empirically trend, magnitude and robustness of the stigma effect, by focusing on the financial effects of the FAFT blacklisting on the relationships between the international financial institutions and the BLC banking systems. So far the empirical evidence is rare and mixed (Kurdle 2009) - with cases of stigma effect, stigma paradox and stigma neutrality - and therefore inconclusive.

To understand what kind of influence that the FAFT blacklisting has over the BLC countries, the research is focused on how international capital flows respond to the stigma signals provided by the FAFT. The stigma effect is based on the assumption that the blacklisting procedures change the attractiveness of a country. The AML/CFT non – compliance attitude of a country can reduce – listing option – or increase– delisting option – the overall financial transactions (volume effect) and/ or its efficiency (cost effect). We transform these intuitions in a

motivating theory, highlighting that to find out the stigma effect we need asymmetry between costs and benefits in doing banking business with a risky country.

Following the suggestions of our theoretical framework we aim to find evidence if and how the FAFT blacklisting deters the volume of the financial transactions, using an econometric panel data analysis. Why can the blacklisting have deterring effects? The crucial claim is that the stigma becomes a signal to distinguish between compliant and non-compliant countries and that non-compliance is costly, due the existence of higher monetary costs and/or higher reputational costs. Consequently the international financial institutions allocate their activities accordingly. The inverse is true when delisting procedures are implemented.

In this study we focus our attention on the 34 Latin American countries in the period 1996-2007. The period of investigation was chosen because of several reasons. First of all, in 2007 the FATF Black list was “empty”: all countries, which previously were in the list, became compliant with the FATF conditions. Secondly, this period does not include on the one side the peak of the Latin American debt and currency crisis – i.e. the Mexican crisis of 1994 - and on the other side the Global Financial Crisis of 2008. It is interesting to note that the listing-delisting experience characterizes a relevant part of the Latin American countries, particularly during the period 2000-2002, where a share between 20% and 25% of the over sample was present in the FAFT black lists (see Figure 7 below).

Results of the research to consequences of the listing and delisting by the FATF are applied on a specific country: Paraguay. The shortcomings of the AML/CFT setting in Paraguay were officially signalled in 2009 (IMF 2009). In February 2010 Paraguay was included in the list as a jurisdiction with AML/CFT deficiencies, for which they have developed an action plan with the FATF. High political commitment in Paraguay and subsequent policy measures made the FATF decide to remove this country from its list. On February 2012 FAFT announced that Paraguay was no longer subject to its monitoring process.

Anticipating our main results, we find that, given the international capital mobility, the robustness of the stigma effect – empirically the blacklisting factor - can depend on two main conditions, which determine the country attractiveness: the regulatory architecture – the regulatory lightness factor - and the economic framework – the banking profitability factor and the wealth factor. We studied two different scenarios: perfect and imperfect capital mobility (without and with capital hysteresis).

In the perfect mobility scenario, we find that: 1) the blacklisting factor and the regulatory lightness factor can be detected, and they are significant using the random effects model; 2) the relevance of the blacklisting factor depends on the international banking inflow movements; 3) the wealth effect is significant; 4) the banking profitability factor is stronger when the country banking sector is more deep and traditional.

In the imperfect mobility scenario, the blacklisting factor, the regulatory lightness factor, the banking profitability factor and the wealth factor can be still detected, and their relevance depends on the international banking outflows movements.

Finally we applied our framework in testing the case of Paraguay and using the available quarterly data: the blacklisting factor can be lightly detected in both the banking inflows and outflows.

Summing up, we can say that the FAFT decisions seem to produce financial effects on the listed/delisted country, and the relevance of these effects is linked to the country regulatory and banking features. Light touch regulation, traditional and deep banking system and overall dimension of the country increase the robustness of the stigma effect. Furthermore also the efficiency of the international banking flows - degree of capital mobility – is relevant: more capital mobility increases the role of the banking inflows respect to the banking outflows in determining the stigma effect.

Using our results and acknowledging its evident limits for predictive reasons, we can claim that the efforts of Paraguay in increasing its compliance with the international standards are likely to produce positive effects on its reputation in the international financial markets. We discovered that the stigma effect can be relevant: the banking flows are likely to be discouraged when a country is listed and vice versa the international banking activity is attracted when a country is delisted. The nature of the capitals which are influenced by the listing/delisting events is likely to depends on how efficient the markets are: the inflows seem to be more sensible when the efficiency increases. In the same contest maintaining ad strengthening the financial nature of the FIU can produce incremental but not crucial benefits.

The possibility that the stigma effect can be relevant for Paraguay increases if we take into account three structural features of the country. On the one side its financial regulatory setting seems to be so far relatively market friendly, at least comparing it with the other Latin American countries: therefore the regulatory lightness factor is likely to hold and the relevance of the stigma effect increases. On the other side its banking system is still relatively underdeveloped: more financial deepening would increase the banking profitability factor with its catalytic consequences on the relevance of the AML/CFT compliance policy of Paraguay. The same it is likely be true if the growth per capita will increase; it causes a stronger wealth effect with its associated consequences on the importance of the stigma effect.

The study is organized as follows: after that Section 2 describes the existing literature on the stigma effect, Section 3 outlines a theoretical framework in order to give robust and consistent micro foundations to our macroeconomic empirical analysis. Section 4 analyses empirically the Latin American countries and case of Paraguay. Section 5 concludes, discussing policy implications an future possible directions for the research.



## 2. The Stigma Effect: Related Literature

The black listing procedures have been introduced in 2000 and from that time relatively few economic studies on the stigma effect appear to be made.

The first theoretical and empirical discussion of the stigma effect as a controversial issue has been made in Masciandaro (2005a). The study started highlighting the fact that in the aftermath of September 11th, 2001, growing attention had been paid to the role of the lax financial regulation in facilitating the money laundering and terrorist financing phenomena (criminal finance). Two interacting principles are commonly featured in the debate on the relationship between money laundering and regulation: a) illegal financial flows are facilitated by lax financial regulation; b) countries adopting lax financial regulation do not co-operate in the international effort aimed at combating criminal finance (International Monetary Fund 1998, Holder 2003).

These two principles characterize the mandate of the Financial Action Task Force (FATF) for the prevention of money laundering and terrorism finance. On the one hand, to address the problems associated with criminal finance risks it is fundamental to develop legal standards for regulation. The FAFT standards (Recommendations) became the benchmark for measuring the degree of laxity of AML/CFT financial regulation in every country setting.

On the other hand, to monitor the compliance of countries with international standards and to face the problem of lack of international harmonization and coordination, the FAFT uses a list of specific criteria—consistent with the standards—to determine the BLC jurisdictions, commonly described as blacklists (Alexander 2001, Masciandaro 2005a, Verdugo Yepes 2011). The blacklist instrument represents the cornerstone of the international effort to reduce risks that some countries or territories became havens for criminal financial activities, postulating the stigma effect, i.e. the threat for listed countries to face a drop in the international capital flows and then an erosion of the BLC country competitive advantages (Hampton and Christensen 2002).

Here the possibility of a stigma paradox comes. Focusing on the supply of regulation, the study notes that various jurisdictions, notwithstanding the blacklist threat, delay or fail to change their rules, confirming their non-cooperative attitude (*reluctant friend effect*). Furthermore, notwithstanding the fact that most jurisdictions in the black list have enacted regulatory measures in an effort to be removed from it, it is remained to be proved that a regulatory reform is sufficient to guarantee that a country has really changed its non-cooperative attitude, causing a decreasing appeal for the black capital flows (*false friend effect*). The existence of the two consequences can nullify the stigma effect, producing the stigma neutrality or the stigma paradox.

The theoretical analysis under discussion has developed the assumption that lax financial regulation may be a strategic dependent variable for national policymakers seeking to maximize the net benefits produced by any public policy choice. Therefore, given the structural features and endowments of their own countries, some policymakers may find it profitable to adopt financial regulations which accommodate the needs of opaque

financial flows – whose existence is considered by assumption - and therefore may choose *de facto* to be a BLC jurisdiction.

The potential incentives to be a BLC country have been empirically tested using cross sectional tests, finding that the probability of being a BLC jurisdiction can be linked to specific country features (Masciandaro 2005a, Verdugo Yepes 2011, Schwarz 2011). The rationale of strategy of being a BLC country has been further explored for a theoretical point of view (Unger and Rawlings 2008, Gnutzmann et al. 2010). Recently also the interactions between the FATF and the national governments have been analyzed using a principal – agent framework (Ferwerda 2012).

The economics of the stigma effect was deeply analyzed in Picard and Pieretti 2011, focusing on the incentives of the banks located in a BLC country for complying with the AML/CFT regulation. The blacklisting practice is interpreted as an international pressure policy on the BLC bank, and the stigma effect holds when the pressure policy gets strong enough. More precisely the stigma effect becomes effective when the reputational costs linked with the blacklisting procedures - which can harm the bank costumers - are higher than the AML/CFT regulation compliance costs. In the model international policymakers act efficiently and then they implement the optimal blacklisting pressure. In the real world non efficient policymakers are likely to exist; therefore the blacklisting pressure can be insufficient and the BLC country will continue to attract financial flows, creating the stigma paradox.

The possibility of the stigma paradox has been empirically demonstrated in Rose and Spiegel (2006). Using bilateral and multilateral data from over 200 countries into a gravity framework, the study analyzes the determinants of the international capital flows, finding that for a country status of tax haven and/or money launderer assigned by the international organizations can produce beneficial effects. The analysis confirmed that the desire to circumvent national laws and regulations can be a driver in shifting financial assets abroad.

The search for the impact of the blacklisting was also implemented in Kurdle 2008. Using ARIMA techniques on the sample of the blacklisted countries the study analyses the financial effects of entering and leaving from the list. The results are inconclusive: all three effects – stigma effect, stigma paradox and stigma neutrality – can be found, depending time to time on the observed jurisdiction.

### 3. International Capital Flows and Stigma Effect: The Motivating Theory

In order to highlight the key elements of determining the possible relationship between capital flows and FAFT black listing we shall use a skeleton model, in order to present and isolate the economic intuitions in a compact and consistent manner.

We build on the framework introduced in Masciandaro (2005a) and (2008) , modifying and expanding it to explain the banking incentives of determining its level of business with a BLC country. We ask the following

question: Under which conditions the potential monetary and reputational costs linked with the blacklisting risks provide incentives for an international bank to change its business decisions?

Let us assume a world with  $n$  countries with perfect competitive banking markets, where  $n-1$  countries define and implement an international AML/CFT regulation to produce public goods – as financial stability and integrity – while the free riding country  $F$  designs a non compliant regulation.

The country  $F$  faces a risk to be included in a black list established by the other  $n-1$  countries. In other words there is a probability different from zero that the international community – i.e. all the countries but country  $F$  – changes the global regulatory environment, introducing a black list and applying the name and shame approach.

In order to develop the more general analysis of the issue and considering that we are investigating an international financial environment where also expectations matter, we define a country as BLC when its probability to be listed is different from zero. In other words the financial markets evaluate the risk of a country to be AML/CFT non-compliant. This hypothesis is consistent with the present situation of the world where the widespread AML/CFT compliance is relatively low (Verdugo Yepes 2011).

The blacklisting procedures imply banning and obstacles for the bank in doing business with the BLC countries, creating an indirect enforcement device on banking firms (Fitzgerald 2004). When a country  $n$  is listed, the Financial Intelligence Units (FIUs) of the  $n-1$  countries issue guidelines to address the risks the banks can face in operating with the jurisdiction characterized by AML/CFT deficiencies. Usually the FIU guidance lists the obligations of the banks to comply with reinforced due diligence rules (see for example FinCEN 2011).

It is important to highlight that the listing – or delisting – event can hit both inflows and outflows of the BLC country, essentially for three reasons. First of all high – or low – supervisory costs bore by the  $n-1$  countries are applied to all the banks, whatever its residence is. Secondly an international bank can do its banking business with the BLC country managing both inflows and outflows. Thirdly the money laundering financial flows are characterized *per se* by mechanisms involving both outflows and inflows of capital.

Therefore when a country is blacklisted its capital flows suffer higher regulatory costs as well as the reputation of bank owners and managers is at risk. The probability for a BLC country to be effectively included in the black list is equal to  $p$ , where  $0 < p < 1$ .

In this world an international bank is active, and its overall volume of business is equal to  $W=1$ . The international banker can decide to allocate a share  $Y$  of its business to the country  $F$ , where  $0 < Y < 1$ . Given the perfect competition in the banking world market, the international bank is price-taker – i.e. the returns on the banking activities are given and the banker can choose just its optimal quantity choices.

In determining the level of its BLC business - which obviously represents a capital flow for the country  $F$  - the banker takes into account both expected benefits and losses.

The expected benefits  $B$  to the banker depend on the volume of the business activity in the two relevant markets, the country  $F$  ( $B_f$ ) and the other countries ( $B_w$ ) respectively. Given the business activity, in each market the banking benefits depend also on the expected net rate of return. The net rate of return is different between

the two markets: let us suppose that the parameter  $b$  - with  $b > 0$  - represents the return differential - the *profitability factor* - between investing in country  $F$  and otherwise.

The possibility of a positive excess return of investment in a BLC country can be justified by the worldwide existence of capital owners which like non transparent regulations, which has been already empirically tested (Rose and Spiegel 2006) and by the fact that the financial firms can be consciously and/or unconsciously involved in money laundering operations, configuring the money laundering as a financial sector crime<sup>1</sup>. The existence of a demand for opaque financial services explains also the fact that some countries and territories – as in our model the country  $F$  – can find it optimal to strategically design and implement lax AML/CFT regulations (Masciandaro 2005a and 2008, Unger and Rawlings 2008, Gnutzmann et al. 2010, Picard and Pieretti 2011).

Similarly to Rose and Spiegel (2006) and Picard and Pieretti (2011) we suppose that the bank wishes to please heterogeneous clients. More precisely – as in Picard and Pieretti (2011) - we assume that there are two classes of customers: ordinary costumers and special costumers. The special clients seek more privacy and opaqueness than the ordinary ones. Special clients demand for banking services can be considered more sophisticated and therefore more profitable for the international bank, i.e. the corresponding net expected return is higher.

The special clients can generate both inflows and outflows from country  $F$ , given that opaque lover clients are likely to exist elsewhere (Brada et al. 2011). Similarly to Rose and Spiegel (2006) we take into account that the expected return in moving assets with a BLC country has to be greater than all the corresponding costs but the AML/CFT regulatory ones. Alternatively we could suppose that each client can delegate to the bank a portfolio diversification between transparent and opaque transactions, where the relative shares depend on her own preferences – in Brada et al. (2011) special clients can diversify using domestic bank, foreign banks and also setting up firms overseas.

Therefore, assuming for simplicity that the normal worldwide return – i.e. in any country different from  $F$  - is zero and taking into account that investing in country  $F$  means to face the listing risk, the banking benefits are as follows:

$$B_F = (1 + b)(1 - p)Y \quad (1)$$

$$B_W = (1 - Y) \quad (2)$$

In parallel the expected costs  $C$  to the banker depend on the volume of the business activity in country  $F$ , taking into account the AML/CFT regulatory costs. In all but the country  $F$  the AML/CFT compliance costs are proportional to the business activity through a parameter  $c \geq 0$ . The AML/CFT regulation produces costs for the banks, given that the intermediaries have to monitor transactions and report suspicious activity to government

---

<sup>1</sup> On the measurement of money laundering through banking intermediaries see Ardizzi et al. 2013.

agencies. It is likely that the banks act rationally and strategically when they face the AML/CFT compliance costs (Takàtz 2011).

In the country F the regulatory costs depend on the black listing event. If the BLC country is not effectively listed, the compliance costs parameter is by definition smaller than  $c$  (again for simplicity it is equals to zero). Therefore the parameter  $c$  represents the *regulatory lightness factor*: greater AML/CFT costs increase the incentive in doing business with the BLC country. If the listing occurs the bank will suffer from non linear costs, given the existence of both greater supervisory costs and of reputational costs (Picard and Pieretti 2011). The sensitivity of the bank to paying the costs of doing business with a BLC country depends on a parameter  $d$  - *reputational factor* - with  $d > 0$ .

Therefore the banking costs are as follows:

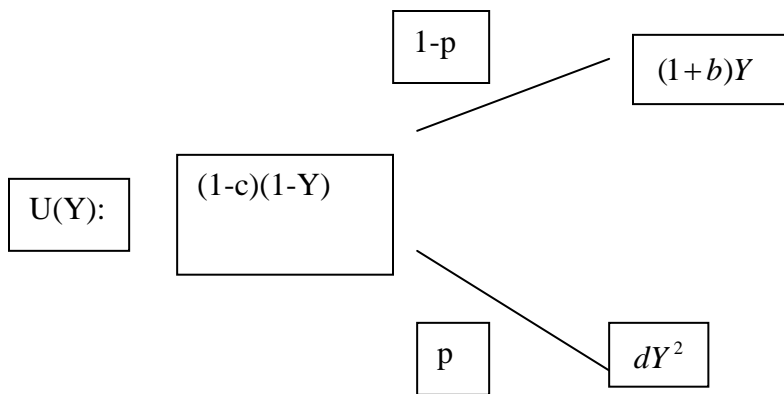
$$C_W = c(1-Y) \tag{3}$$

$$C_F = pdY^2 \tag{4}$$

The banker, modelled as a risk-neutral agent, can now define the optimal level of activity in the BLC country. The banker utility  $U$  can be specified as (Figure 1) :

$$U(Y) = (1-c)(1-Y) + (1-p)(1+b)Y - pdY^2 \tag{5}$$

Figure 1 Defining the Optimal Level of International Bank Flows with a BLC Country



And the optimal level  $Y^*$  of foreign activities in country F is equal to:

$$\frac{\partial U}{\partial Y} = -(1-c) + (1-p)(1+b) - 2pdY = 0 \quad (6)$$

$$Y^* = \frac{(1-p)(1+b) - (1-c)}{2pd} \quad (7)$$

The capital flows between the international bank and the BLC country depend essentially on four factors, which we can discuss as follows:

$$\frac{\partial Y^*}{\partial b} = \frac{(1-p)}{2dp} > 0 \quad (8)$$

$$\frac{\partial Y^*}{\partial c} = \frac{(1-p)}{2dp} > 0 \quad (9)$$

First of all, expressions (8) and (9) show that two factors produce unambiguous catalytic effects on the capital flows: excess return and compliance costs. Both *higher profitability* – greater profitability factor  $b$  - in investing in the BLC country and *higher regulatory gains* – greater regulatory lightness factor  $c$  - mean higher levels of capital flows.

Furthermore:

$$\frac{\partial Y^*}{\partial d} = \frac{p - b(1-p) - c}{2d^2p} < 0 \quad \text{iff } (b+c) > p(1+b) \quad (10)$$

Secondly, from expressions (10) it is evident that two mentioned above capital flow catalysts determine also the effects of the bank listing costs. The greater is the catalyst the higher is the negative association of the capital flows with higher listing costs suffered of the international bank. Therefore greater reputational factor  $d$  is more likely to occur.

Finally let us zoom on our key variable: the probability that the non compliant country will be listed, i.e. *the blacklisting factor*. It is evident that higher probability can produce low levels of capital flows – the stigma effect – under well-defined conditions. More precisely the growth of the banking flows is inversely associated with changes in the probability of black listing:

$$\frac{\partial Y}{\partial p} = \frac{(1-c) - (1+b)}{2p^2d} < 0 \quad (12)$$

$$\frac{\partial^2 Y}{\partial^2 p} = \frac{c-b}{dp^3} > 0 \quad (13)$$

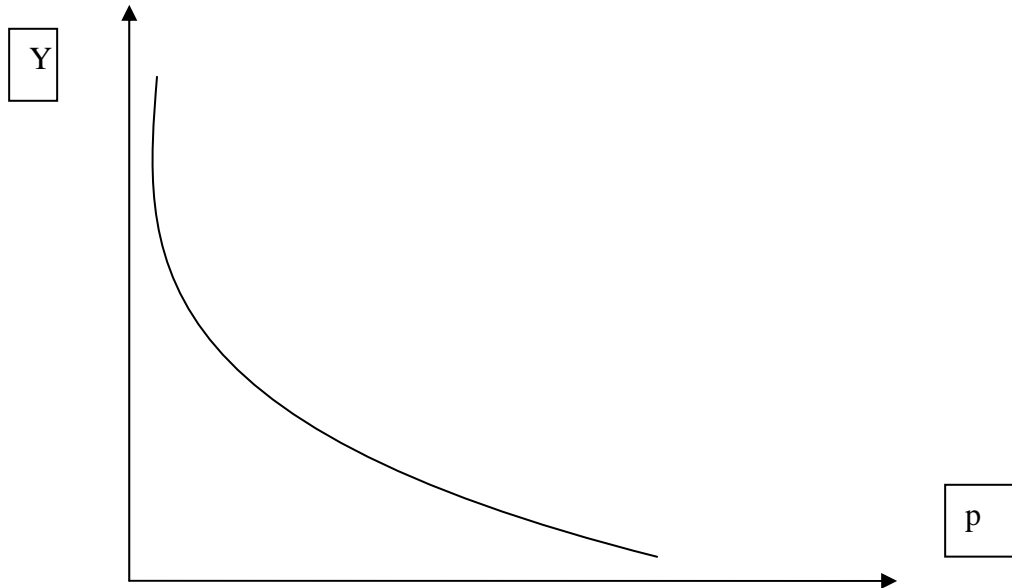


Figure 2 International Bank Flows and Black Listing Risk

The economics is clear. First of all, provided the non linearity of the black listing costs - expression (4) - the listing event reduces unambiguously the capital flows of the BLC country. The stigma effect holds. Secondly the relative dimension of two catalysts – the regulatory arbitrage factor and the profitability factor – are relevant in determining the shape of the stigma effect: the capital flow sensitivity will be greater the higher the regulatory factor will be. Otherwise the stigma paradox effect can emerge.

In fact the stigma effect is evident only if doing banking business in a BLC country produces asymmetric effects in the benefits and costs, i.e. if the benefits are linear while the costs are non linear. If we suppose that the bank enjoys also non linear benefits in expanding its business toward the BLC country:

$$B_F = (1+b)(1-p)Y^2 \tag{14}$$

In this case the optimal level  $Y^{**}$  of foreign activities in country F is equal to:

$$Y^{**} = \frac{(1-c)}{2[(1-p)(1+b) - pd]} \tag{15}$$

Now the relationship between the capital inflows and the probability to be black listed is ambiguous:

$$\frac{\partial Y^{**}}{\partial p} = \frac{(1-c)[d + (1+b)]}{[(2d^2 + 4(1+b)d + 2(1+b)^2)p^2 - (4(1+b)d + 4(1+b)^2)p + 2(1+b)^2]} \quad (16)$$

The black listing threat cannot be sufficient to face the appetite of the international bank to expanding its business in BLC countries. Therefore the answer to the initial question – under which conditions the stigma effect holds – can be found in the asymmetry between non linear costs and linear benefits for an international bank in doing business with a BLC country, while at the same time the compliance costs of the international AML/CFT regulation are linear. In other words the features of the stigma effect are conditioned on the relevance of at least three factors: the compliance costs of the best practices in the international AML/CFT regulation; the profitability and costs in doing business with a BLC country.

This answer confirmed in a framework focused on the banking strategy some specific results obtained analysing the government strategy in designing AML/CFT policies, i.e that the stigma effect holds when the black listing opportunity costs are larger than the compliance costs ( Masciandaro 2005a and 2008, Picard and Pieretti 2011). Otherwise the effect on the banking asset distribution is ambiguous from both the theoretical (Rose and Speigel 2006) and empirical (Kudrle 2009) perspectives.

#### 4. Stigma Effect: The Empirical Analysis

##### 4.1 Baseline Specification

In section 3 we concluded that the international banking flows of a BLC country are negatively associated with its blacklisting factor – the stigma effect - provided that doing banking business with a BLC country produces non linear costs, while the corresponding benefits as well as the AML/CFT international standard compliance costs are linear. The regulatory and economic appealing of the BLC country are crucial multipliers of the stigma effect.

Given that intangibles are largely present in the shape of costs and benefits – i.e. reputational assets – which are difficult to identify, one possible way to investigate their existence and robustness is to analyse in the real world relationships between the international capital inflows and the country records in being in and out from the FAFT lists. The listing and delisting stories can be proxies of the banking risks in developing activities with non compliant countries.

Our theoretical results can be used to build up an empirical analysis. Doing a logarithmic transformation of the expression (12):

$$\log y = \log[c + b - (1+b)p] - \log p - \log d - \log 2 \quad (17)$$



It is even more clear - expressions (18),(19) and (20) below – that greater profitability(parameter  $b$ ) and/or greater regulatory lightness factor (parameter  $c$ ) are more likely to produce on the one side positive effects on the banking flows with the BLC country and on the other side the stigma effect. In fact:

$$\frac{\partial \log y}{\partial p} = -\frac{c+b}{p(c+b)-(1+b)p^2}; \frac{\partial \log y}{\partial p} < 0 \quad (18)$$

$$\frac{\partial \log y}{\partial c} = \frac{1}{(c+b)-(1+b)p}; \frac{\partial \log y}{\partial c} > 0 \quad (19)$$

$$\frac{\partial \log y}{\partial b} = \frac{(1-p)}{(c+b)-(1+b)p}; \frac{\partial \log y}{\partial b} > 0 \quad (20)$$

It is also confirmed that banking flows suffer when costs for a cross border bank of doing business with a blacklisted country increase:

$$\frac{\partial \log y}{\partial d} = -\frac{1}{d}; \frac{\partial \log y}{\partial d} < 0 \quad (21)$$

Here we assume that in the international financial markets these costs are homogeneous among intermediaries and constant in the observation period, given that in the theoretical model they depend on choices of the policymakers and regulators of all the countries but the BLC one, which we suppose to be part of the *ceteris paribus* condition.

Besides while in principle both real and financial flows can be affected by the stigma effect, it seems to be natural to focus on the capital flows, given that the foreign direct investments – FDI – are usually slower to reach to changes in the economic and regulatory environment (Kurdle 2008). Among financial variables, so far the literature is silent about which financial flow is likely to respond in the most significant way to the blacklisting event, showing the stigma effect (Kurdle 2008).

Therefore to examine the relation between bank capital flows and blacklisting we estimate the following panel data regression:

$$\begin{aligned} \text{BankFlow}_{c,t} = & \alpha_0 + \alpha_1 \text{BlackListing}_{c,t} + \alpha_2 \text{GPDPP} + \beta_i \text{Creg}_{c,t} + \gamma_j \text{Cprof}_{c,t} + \\ & + \lambda_h X_{c,t} + \varphi_c + \mu_t + \varepsilon_{c,t} \end{aligned} \quad (22)$$

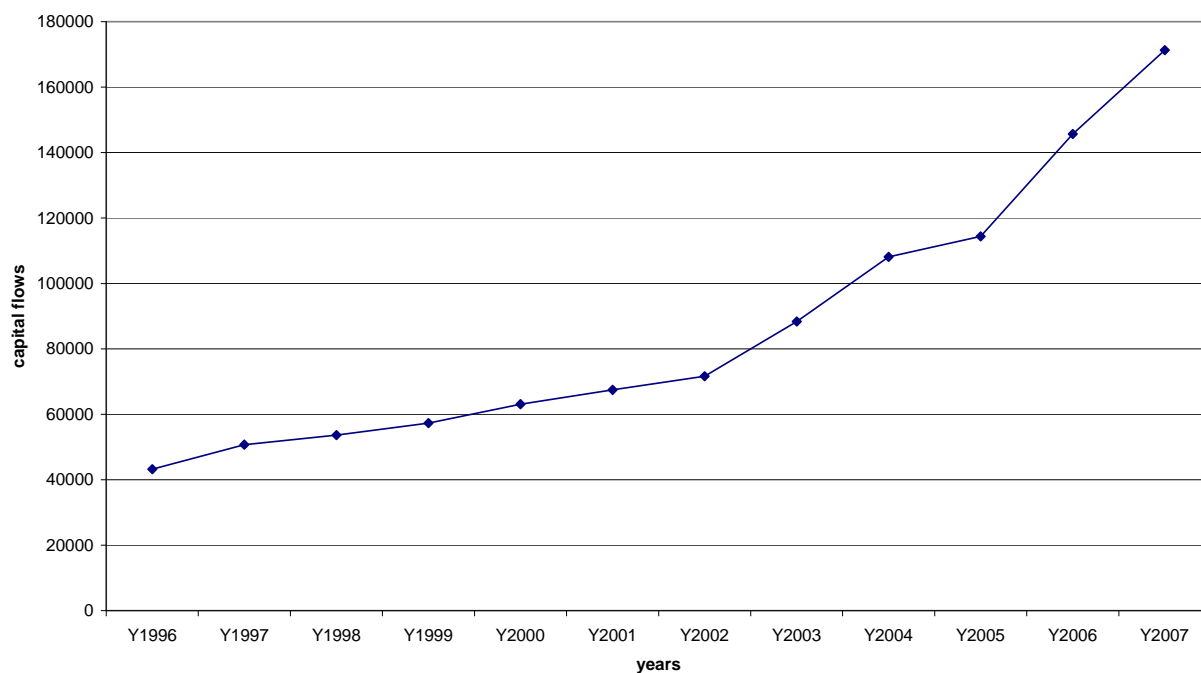
In the baseline specification (22)  $c$  and  $t$  indicate the country and time (year) respectively, the independent variable is our variable of interest - the blacklisting factor – while the two vectors  $Creg$  and  $Cprof$  include the

control variables which represent respectively the banking regulatory lightness factor and the bank profitability factor; the standard control for the size effect – log of the GDP per capita - is added (variable *GNPPC*, positive expected sign). The vector X includes other macro and institutional control variables; finally we include also the country effects and the time effect.

#### 4.2 Variables, Data Sources and Descriptives

We implement our empirical study on the 34 Latin American countries in the period 1996-2007 ( list of countries: Table 1). The period of investigation was chosen because of several reasons. First of all, in 2007 the FATF Black list was “empty”: all countries, which previously were in the list, became compliant with the FATF conditions. Secondly, this period doesn’t include on the one side the peak of the Latin American debt and currency crisis – i.e. the Mexican crisis of 1994 - and on the other side the Global Financial Crisis of 2008. During the investigated period the overall international banking activity of the Latin America<sup>2</sup> consistently increased, both in its absolute (Figure 3) and GDP weighted (Figure 4) values<sup>3</sup>.

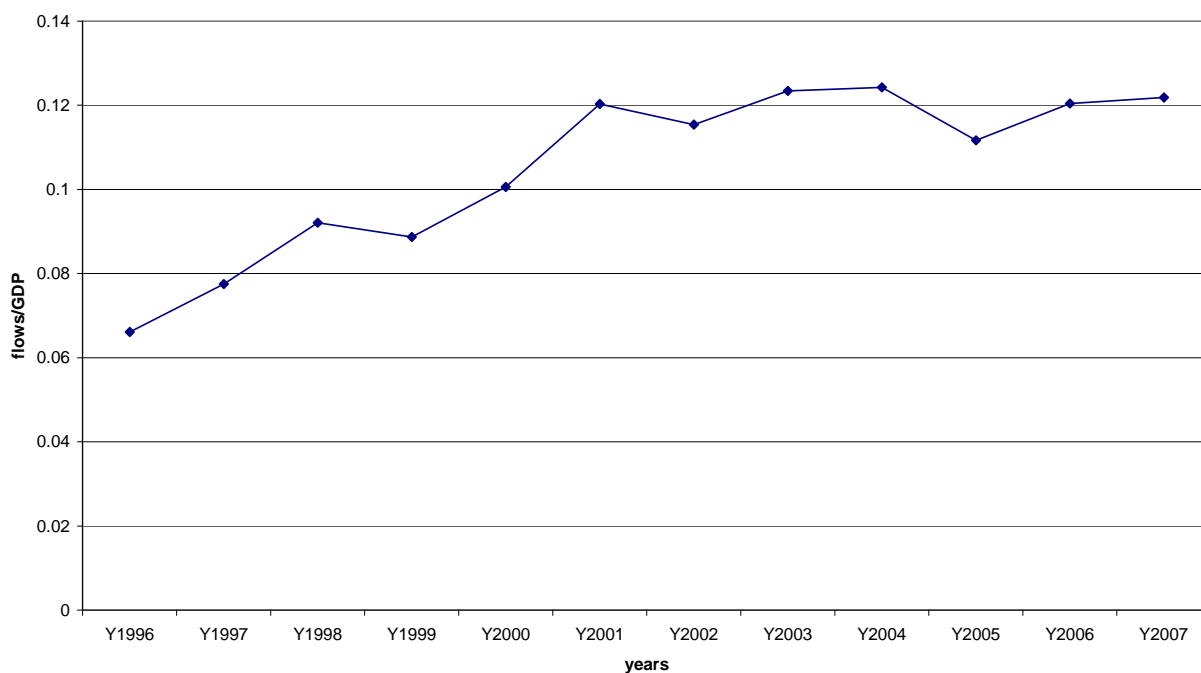
**Figure 3 Total Banking Flows in Latin America (1996-2007) (average value per year)**



<sup>2</sup> The variable is described in Section 4.1.1.

<sup>3</sup> In computing the average values in both figures we excluded Paraguay, in order to facilitate the descriptive comparisons in Section 5.

Figure 4 Weighted Total Banking Flows in Latin America (1996-2007) (average per year on GDP)



In the descriptives the features of the Paraguay – in the following figures: red bar - are highlighted through a comparison with the other 33 Latin American countries in an extended period (1996-2011); the comparison is facilitated build up the figures of a 35<sup>th</sup> simulated Latin American country – in the following figures: green bar - using the average values of all the countries but the Paraguay.

#### 4.2.1 International Bank Flows

We use international bank flow measures to identify our dependent variable. We use measures from the BIS data: external assets (all sectors), external liabilities (all sectors). We construct annual external assets and external liabilities variables using for year (t) the amounts of the January of the year (t+1).

Our main dependent variable *ETFLOWS* represents the external total flows, which we obtained summing up assets and liabilities. The choice of the total flows is the more consistent with the theoretical analysis – section 3 - where we explained the reasons why the blacklisting – or delisting – event can hit both the inflows and the outflows of the BLC country. Besides the same measure – although weighted using the GDP – has been recently used in the literature (Lane and Milesi Ferretti 2003, Ramon-Ballester and Wezel 2007). However we will also analyse separately inflows and outflows to better explain the results emerging from the total flows.

The International Banking Statistics published by the Bank of International Settlements (BIS) provides data regarding the international flow of bank liabilities and assets of the 34 Latin American countries for the period from 1996 till 2007. The BIS Locational Banking Statistics publish quarterly information on all balance sheet positions - and some off-balance sheet positions in the area of trustee business - which represents financial claims or liabilities vis-à-vis non-residents, as well as financial claims or liabilities vis-à-vis residents in foreign currency. Banks report data to the monetary authority in their respective reporting country or center, and nationally aggregated data are then transmitted to the BIS. The Data are regularly published in Table 2A (assets and liabilities) and Table 3A (loans and deposits) of the BIS Quarterly Review under the title, “External positions of banks in all currencies vis-à-vis all sectors” and “External loans and deposits of banks in all currencies vis-à-vis all sectors” respectively.

The development of the cross border banking activity in Latin America increased during the period, observing both the asset side (Figure 5) and the liability side (Figure 6).

**Figure 5 External Banking Assets of Latin America 1996-2007 (average value per year)**

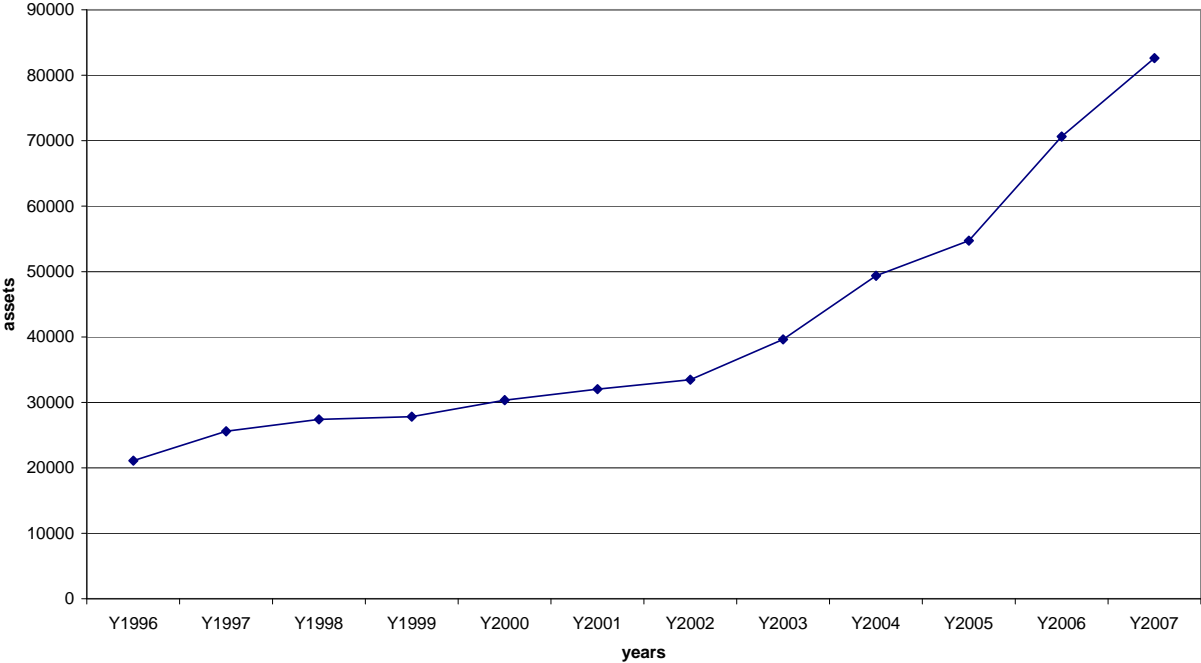
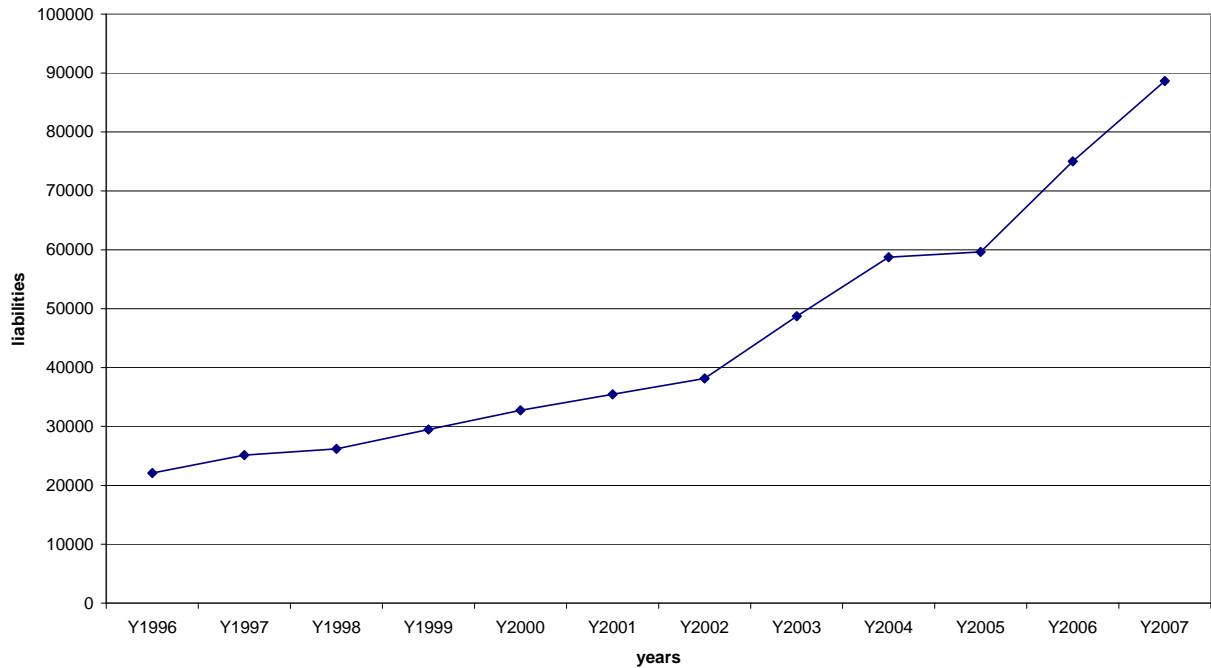
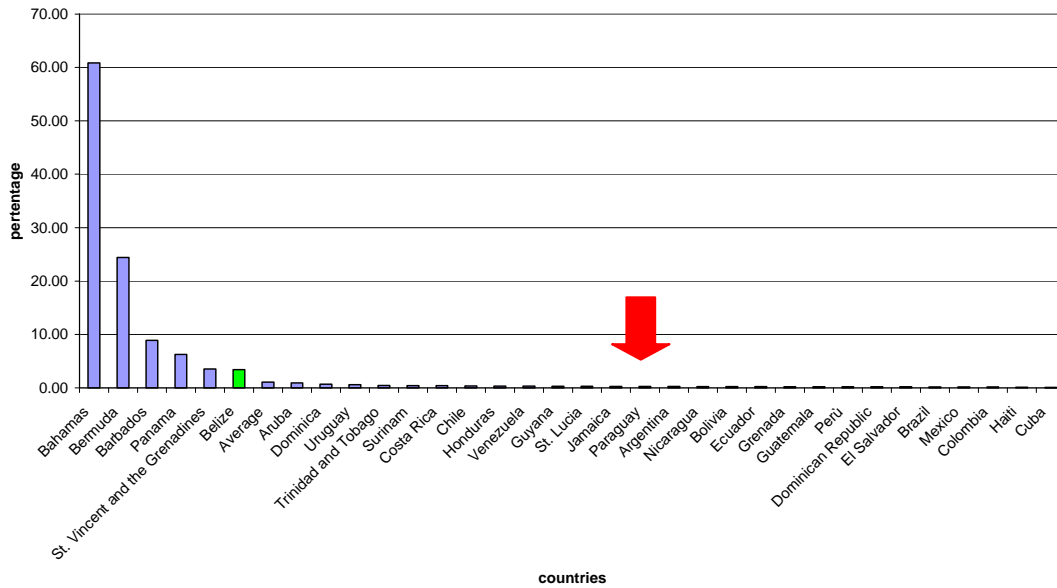


Figure 6 External Banking Liabilities of Latin America 1997-2007 (average value per year)



Paraguay shows a low level of the ratio between total external flows and GDP (Figure 6A) (20<sup>th</sup> country on 34), well below the Latin American average value. However the average level is strongly influenced by the presence of the so called offshore countries, as it is evident looking at the first four countries in the abovementioned figure: Cayman Islands, Bahamas, Bermuda and Barbados. It is interesting to note that on January 2013 and after long time the government of Paraguay returned to the international bonds market issuing USD 500 million – 2% of its GDP - in with a 10-year international bonds; 97% of the bonds were bought by US investors and the demand of USD 5.573 millions far surpassed the supply. In the period 2011-2012 only four Paraguayan entities has issued bonds in the international markets, with increasing amount (Figure 6c, horizontal axis), increasing maturity (Figure 6c, vertical axis), decreasing yields (Figure 6c, dimension of the bubbles ) (BBVA 2013).

Figure 6A Total External Flows on GDP (Latin American Countries, average (1997-2007))



The stable underdevelopment of the international banking activity of Paraguay is confirmed looking at the time evolution of the flows during the period 1996-2011, comparing the Paraguayan figure with the Latin American average (Figure 6B).

Figure 6B Paraguay External Flows (1996-2011)

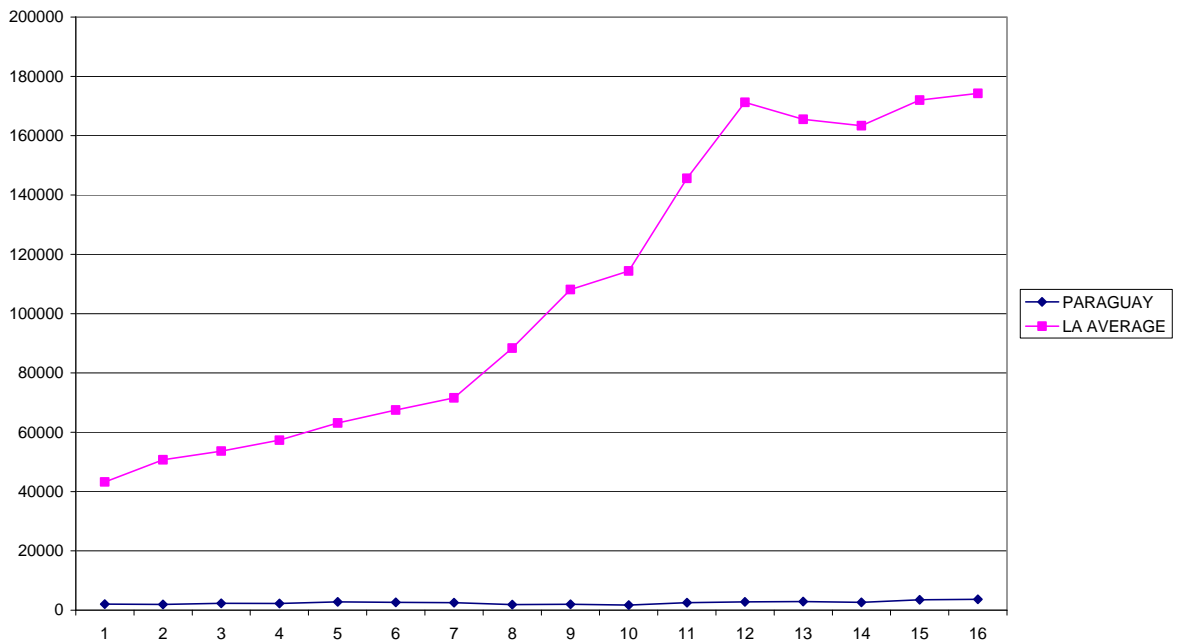
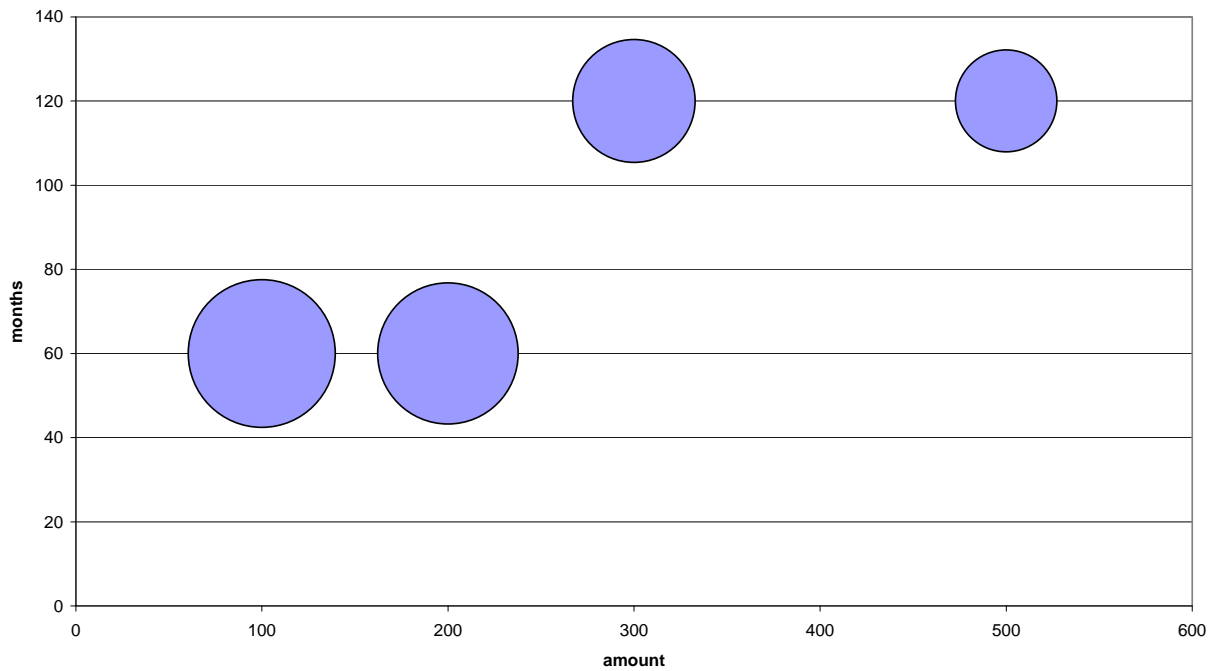


Figure 6c Paraguay International Bonds 2011-2012

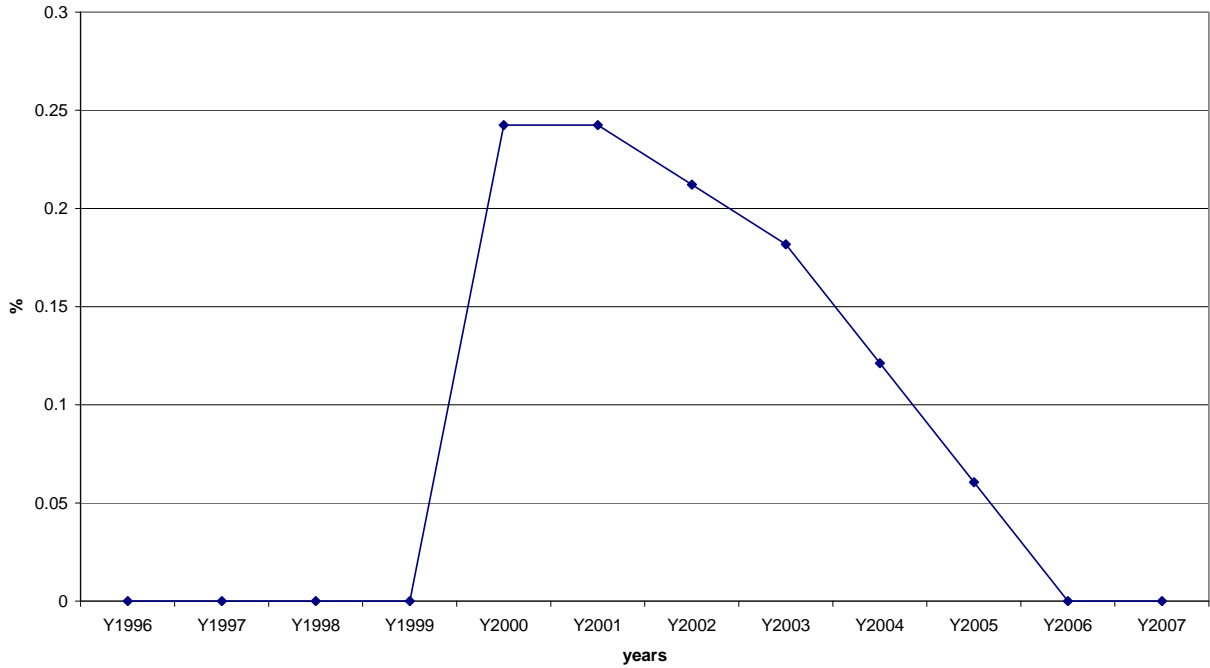


#### 4.2.2 Blacklisting Factor

The variable of interest in this research is the Blacklisting Factor, which captures the role of the risk of a country to be listed by FAFT in influencing the international banking business. The expected sign of the Blacklisting Factor is negative. Looking for the best approximation we use the records of the blacklisting- delisting events. We build up year by year dummy variable *FATFLIST*, which is equal to 1 if the country is listed in the Financial Action Task Force list of "Non-Cooperative Countries or Territories" and 0 if the country complies with the FATF best practices. The FATF variable was constructed using the Financial Action Task Force Reports.

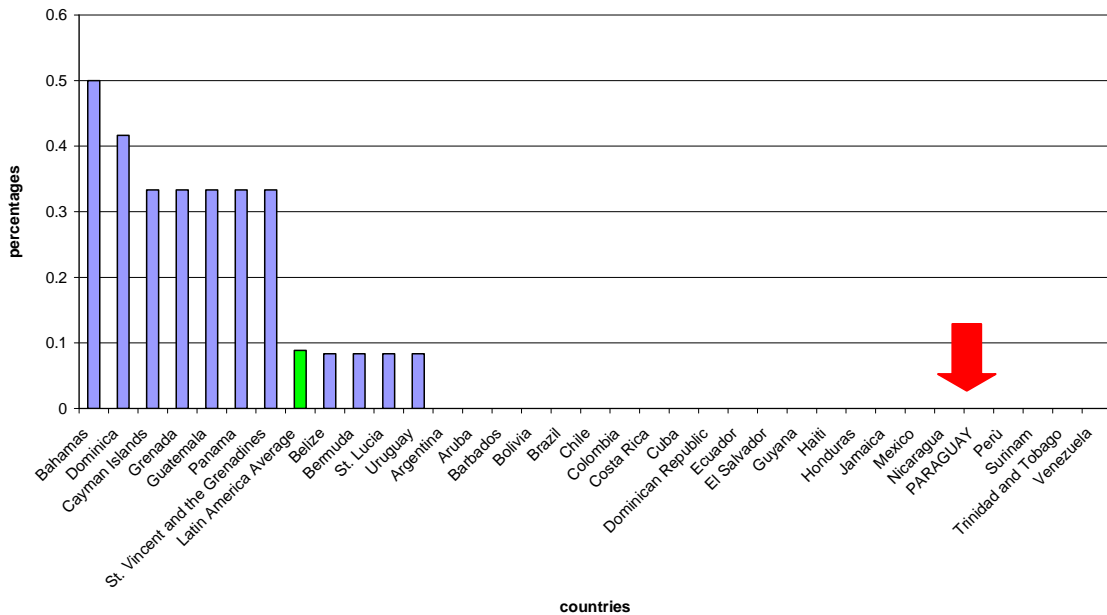
It is interesting to note that the listing-delisting experience characterizes a relevant part of the Latin American countries. The listing risk seems to be particularly high during the period 2000-2002, where a share between 20% and 25% of the sample was listed by the FAFT (Figure 7).

**Figure 7 Blacklisting Cases in Latin America 1996-2007 (% of the overall sample)**



For each country we can build up a simple descriptive Index of the Listing Risk, using the ratio between the number of years of the listing experience – if any – and the total number (twelve) of years. Paraguay shows the lowest level of listing risk; later on its index increased, given its listing experience between June 2011 and February 2012.

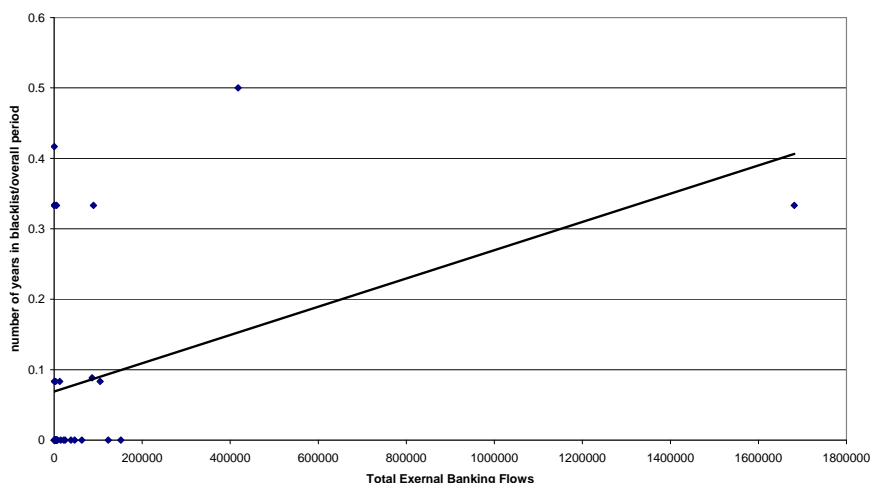
**Figure 7A Blacklisting Risk (Latin American countries, average 1996-2007)**





Are the blacklisting experiences associated with the international banking flows? A simple cross sectional descriptive analysis can be performed using the Listing Risk. Putting together the index and the data on the capital flows (Figure 8) it seems that the listed countries didn't suffer any drop in their international banking activity; vice versa, the stigma paradox seems to hold. But the cross country description can be really misleading: we need to introduce the time dimension and to perform an econometric analysis (see section 4.3 below).

Figure 8 Blacklisting and External Total Banking Flows (average per country)



#### 4.2.3 Regulatory Lightness Factor

In the theoretical analysis – Section 3 – we noted that the existence and the robustness of the stigma effect are likely to depend on other regulatory and economic factors. First of all we highlighted the possible role of the regulatory lightness factor, which captures the attitude of the financial intermediaries to looking for the more efficient regulation, i.e. the regulation with lighter compliance costs. However it is worth remembering that after the Great Recession experience (Dalla Pellegrina and Masciandaro 2012, Masciandaro et al. 2012), the light touch approach in regulation and supervision seems to address a trade off between efficiency – i.e. minimization of the compliance costs - and effectiveness – i.e. minimization of instability risks.

In principle the light touch regulation approach can be relevant in considering both the general features of the overall banking regulation and the specific characteristics of the AML/CBT. Therefore we use two different kind of indicators of regulatory arbitrage.

First of all we identify country by country and year by year the level of banking regulation efficiency using an index of financial repression. The intuition is quite simple: more financial repression means less efficient

regulation, which reduces the regulatory attractiveness of a country and consequently its international banking flows. The expected sign is negative.

To build up the Financial Repression Index (*FINREPR*) we use a set of variables from the World Bank data set (World Bank 2008). To construct the Index we use three dummy variables based on the answers contained in the "Banking Regulation Survey" to the question on the extent to which banks may engage in (a) underwriting, brokering and dealing in securities, and all aspects of the mutual fund industry, (b) insurance underwriting and selling, and (c) real estate investment, development, and management. For each question, the variable takes the value of 1 if the answer is "restricted" or "prohibited" and 0 if the answer is "permitted" or "unrestricted". The index is the indicator function: it takes value 1 if sum of the dummy variables from the survey is higher than 0 and 0 otherwise. During the period the financial repression in Latin America seems to be on average relatively high and constant (Figure 9).

**Figure 9 Financial Repression in Latin America (average per year)**

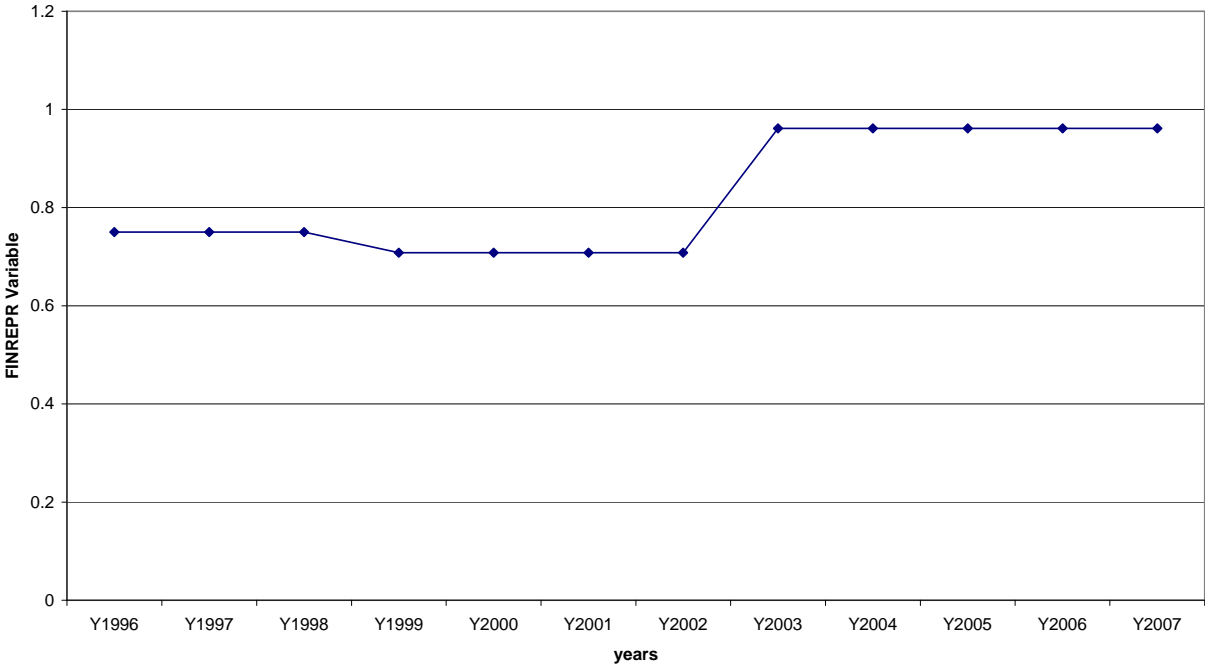
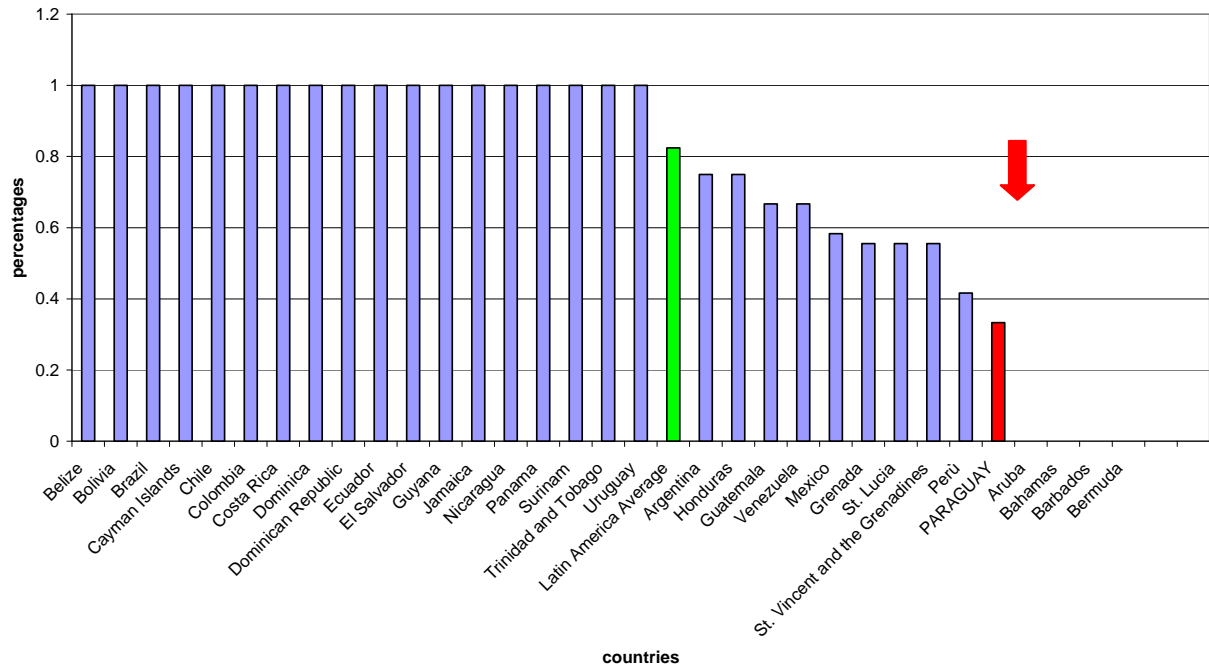


Figure 9A Financial Repression Index (Latin American Countries, average 1996-2007)



In Paraguay the level of financial repression seems to be below the average (28<sup>th</sup> country on 32) (Figure 9A), where is worth noting that the most liberalized regulations seem to characterized the so called offshore country.

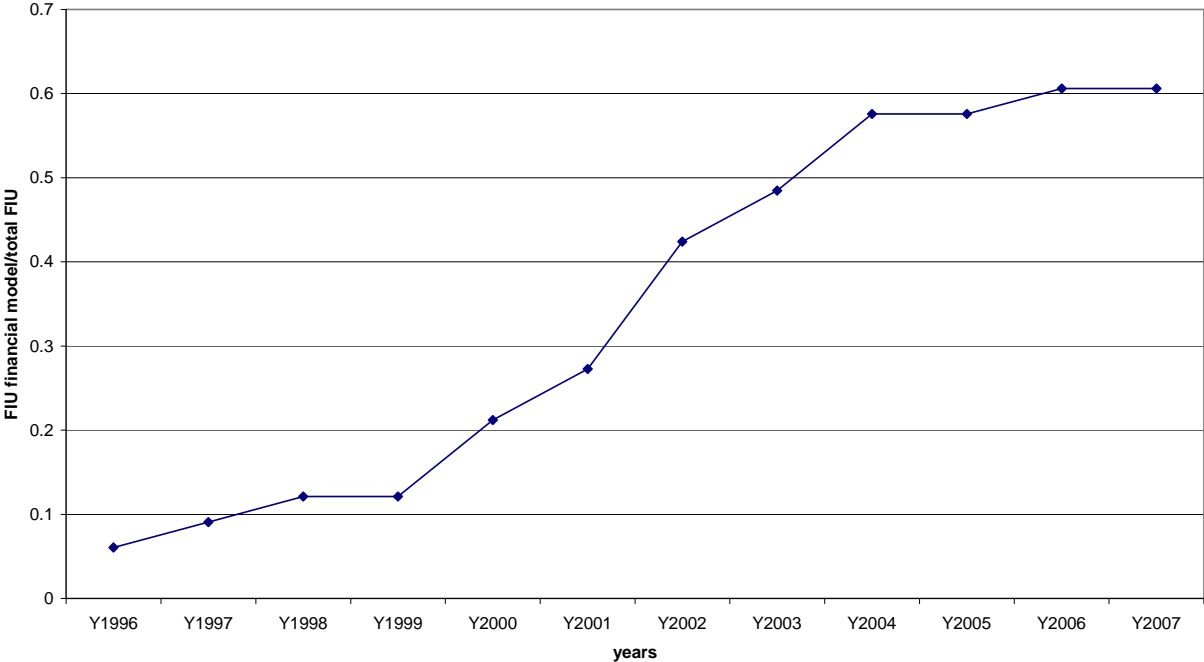
Secondly we define the level of AML/CFT regulation efficiency using one specific feature of the AML/CFT regulatory architecture, which obviously has to be completely independent from the listing risk. We pick up as AML/CFT indicator the model of the Financial Intelligence Unit (FIU), for two crucial and consistent reasons. On the one side, there are different model of FIU, and the FAFT leave any country free to choose the preferred model: its Recommendation 29 – devoted to the Financial Intelligence Units – doesn't prejudice a country's choice for a particular model (FATF 2012).

On the other side, it has been argued (Masciandaro 2005b) that the FIU model can matter in increasing the efficiency of the AML/CFT rule implementation, being the best model the so called "Financial FIU model", i.e. when the FIU is subordinated to the Minister of Finance, or to the Central Bank. or to the Financial Supervisory Authority. The rationale is represented by the fact that being the Financial FIU an insider authority it has advantages in collecting and managing data and information minimizing at the same time the costs for the banks. The banks would prefer the Financial FIU model. Under this assumption the expected sign is positive.

We build up year by year the FINFIU dummy variable, which is equal to 1 if the FIU model that the country adopted is the financial one and 0 otherwise. The FINFIU variable was constructed using the information available for each country on its FIU model (Table 2), using in particular the FIU websites. During the period the FIU

Financial Model became the more common one (Figure 10); on average its share goes from less than 10% to more than 60%. Paraguay adopted a hybrid FIU model.

Figure 10 The FIU Financial Model in Latin America (average per year)

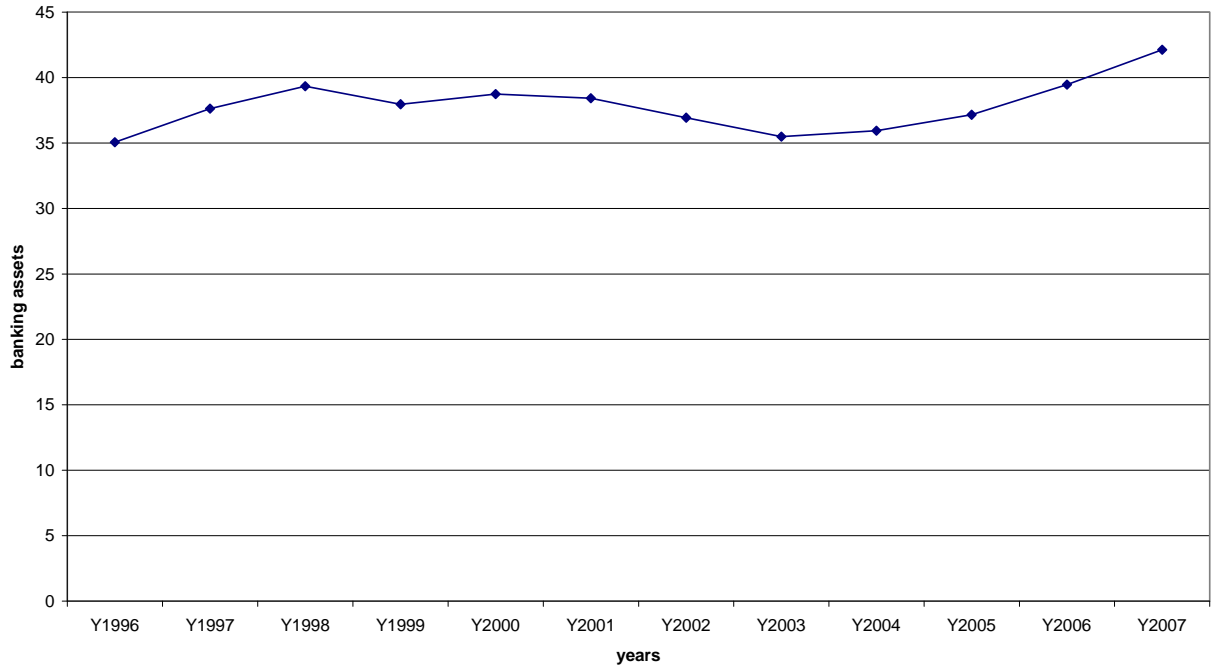


4.2.4 Banking Profitability Factor

In the theoretical analysis – Section 3 - we highlighted the importance of banking profitability in driving the international banking flows. We control for the banking appealing of the different countries using principally two different measures of financial deepening (size and revenues), where the financial deepening represents a standard determinant in the analysis of the behavior of the international banking flows (Ramon-Ballester and Wezel 2007).

First of all in order to describe the depth of the banking industry of the country using a size variable we adopt the measure from the GFDD (Deposit money bank assets to GDP, or DMA). The selected aggregate is equal to the amount of total assets held by deposit money banks as a share of GDP. Assets include claims on domestic real nonfinancial sector which includes central, state and local governments, nonfinancial public enterprises and private sector. Deposit money banks comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits. In the empirical analysis the corresponding variable *BANKDEEP* represents an index of the Traditional Banking Deepening; the expected sign is positive. During the period the traditional banking deepening seems to be on average relatively low and stable (Figure 11).

Figure 11 Traditional Banking Deepening in Latin America (average per year; share on GDP)



The size of the banking system in Paraguay seems to be relatively underdeveloped (23<sup>rd</sup> country on 31) (Figure 11A); however extending the time horizon up to 2010 the financial deepening shows a positive trend, after the crisis which hits Paraguay (Franks et al. 2005, IMF 2011) (Figure 11B).

Figure 11A Financial Deepening (Latin American Countries (average, 1996-2007))

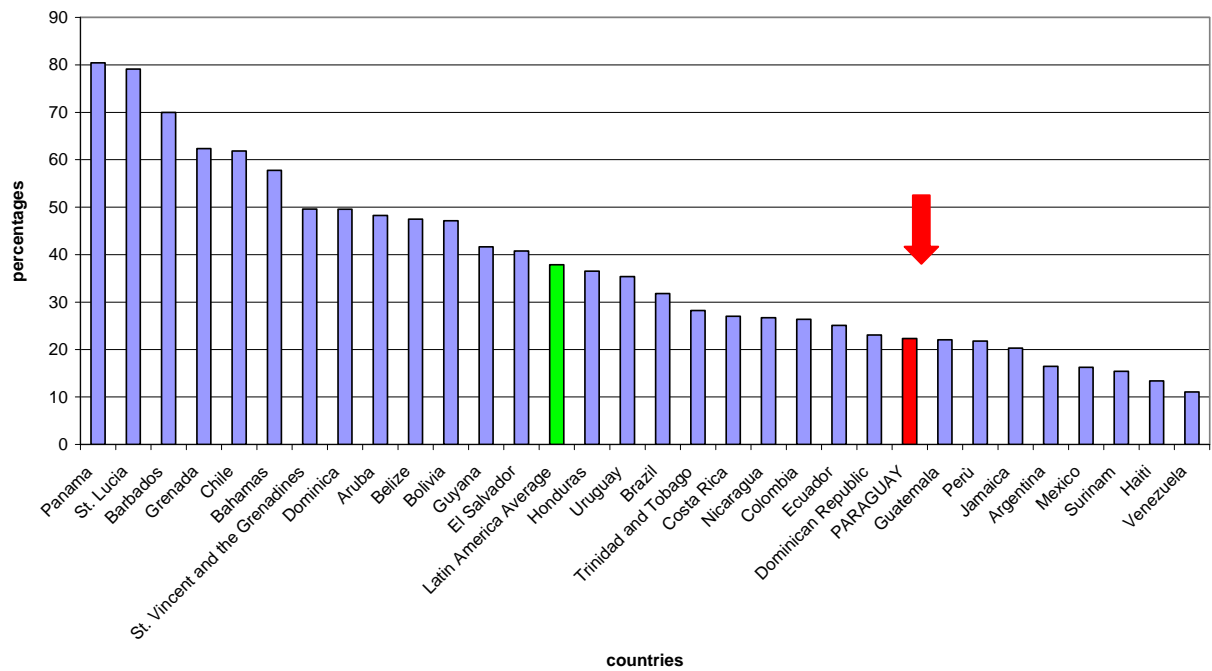
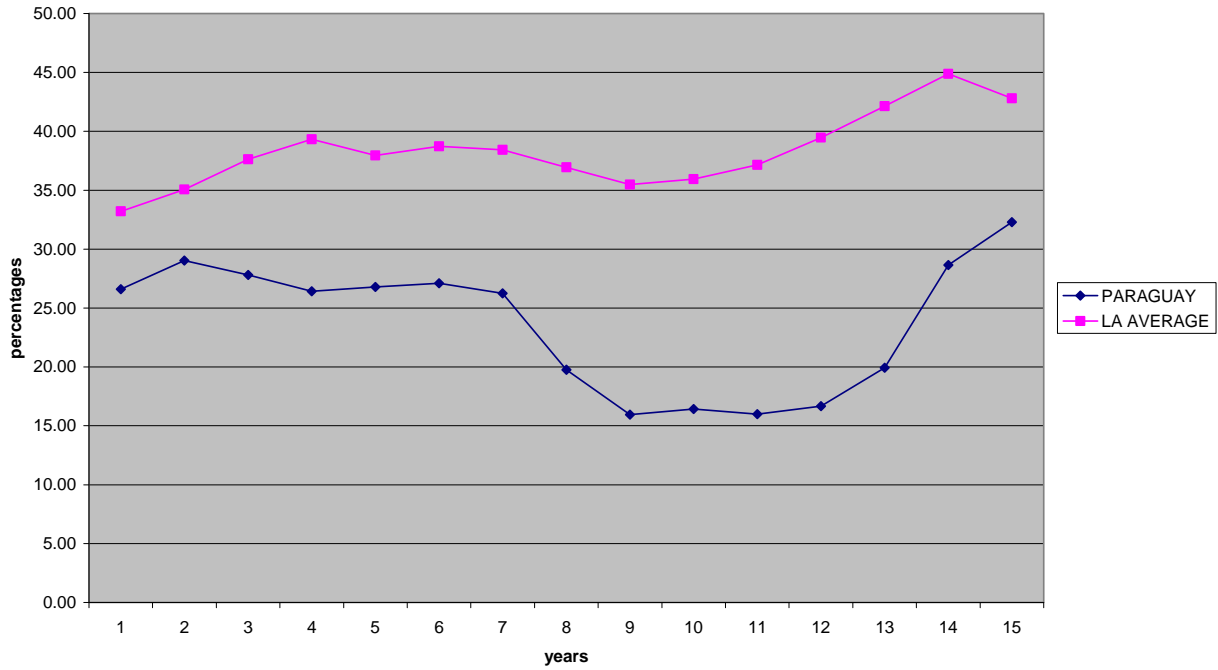


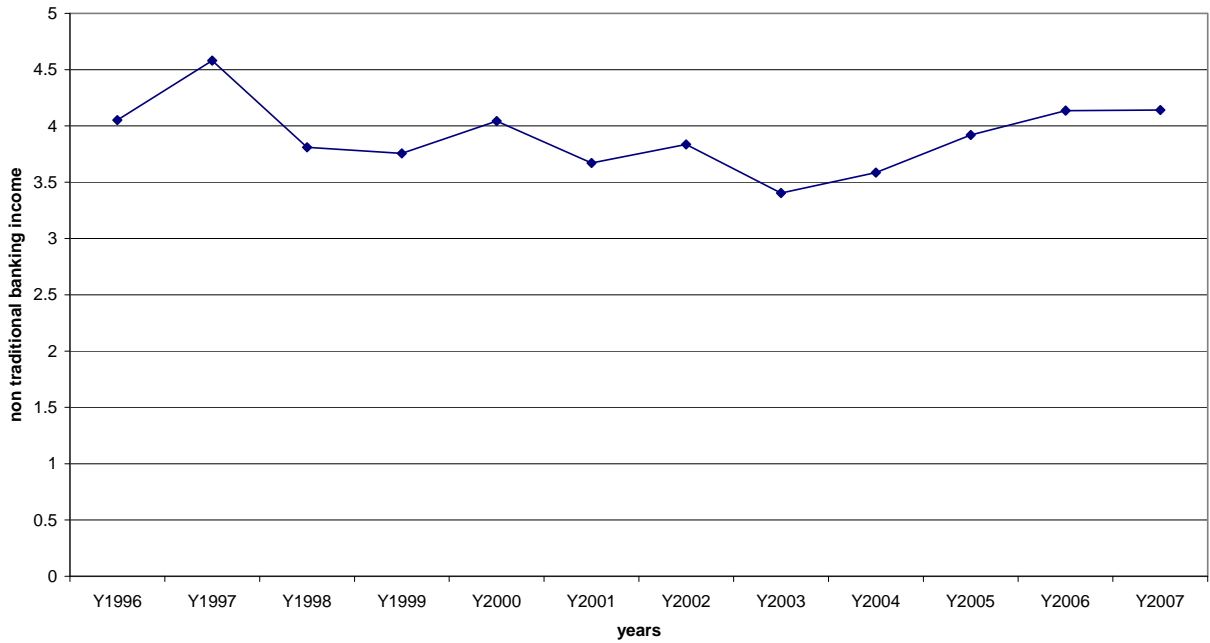
Figure 11B Financial Deepening in Paraguay (1996-2010)



Secondly we use Net Interest Margin (NIM) from the “Global Financial Development Database” as the measure of financial deepening when we adopt a revenue variable. The net interest margin can be considered also an indicator of the degree of innovation in the banking business. The selected variable is calculated as bank’s income that has been generated by non-interest related activities as a percentage of total income (net-interest income plus non-interest income). Non-interest related income includes net gains on trading and derivatives, net gains on other securities, net fees and commissions and other operating income.

In the same vein the variable can be considered an index of the traditional banking: less non interest incomes means more traditional banking. In the empirical analysis the corresponding variable *INNOBANK* has undetermined sign: ex ante it is not clear if a more sophisticated banking industry increases or decreases the country appeal. The sign of the *INNOBANK* variable is therefore undermine. During the period the traditional banking deepening seems to be on average really high and stable, given that the index is low and stable (Figure 12).

**Figure 12 Innovative Banking Deepening in Latin America 1996-2007 (average per year; share on total banking income)**



Among the Latin American countries Paraguay seems to have a relatively more diversified banking revenues setting (2<sup>ND</sup> country on 31) (Figure 12A), with a share of non traditional banking revenues with is systematically greater than the Latin American countries (excluding the drop in 2003-2004 after the abovementioned crisis; Franks et al. 2005, IMF 2011).

**Figure 12A Non traditional banking revenues (Latin American countries, 1996-2007)**

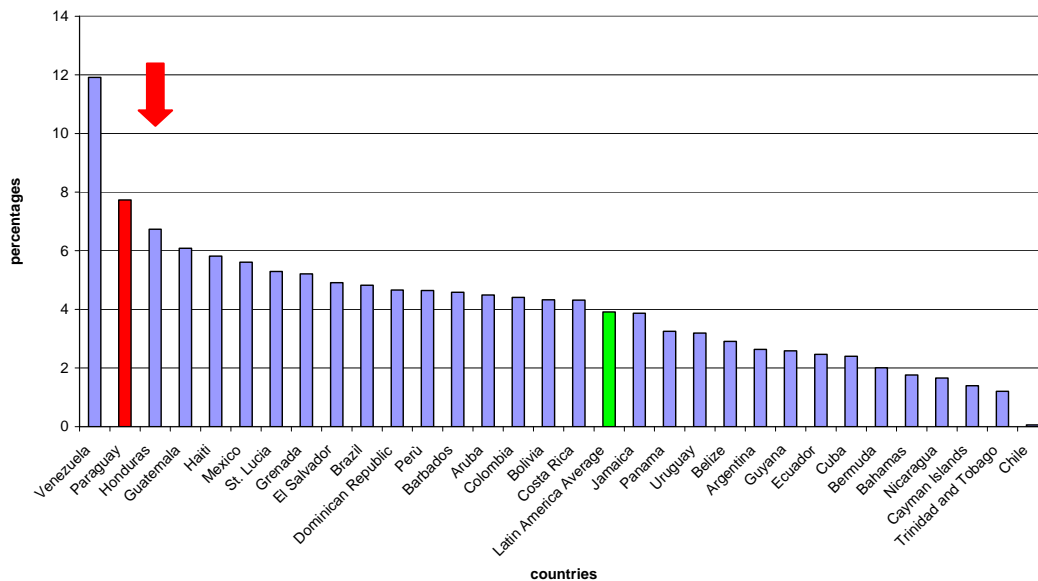
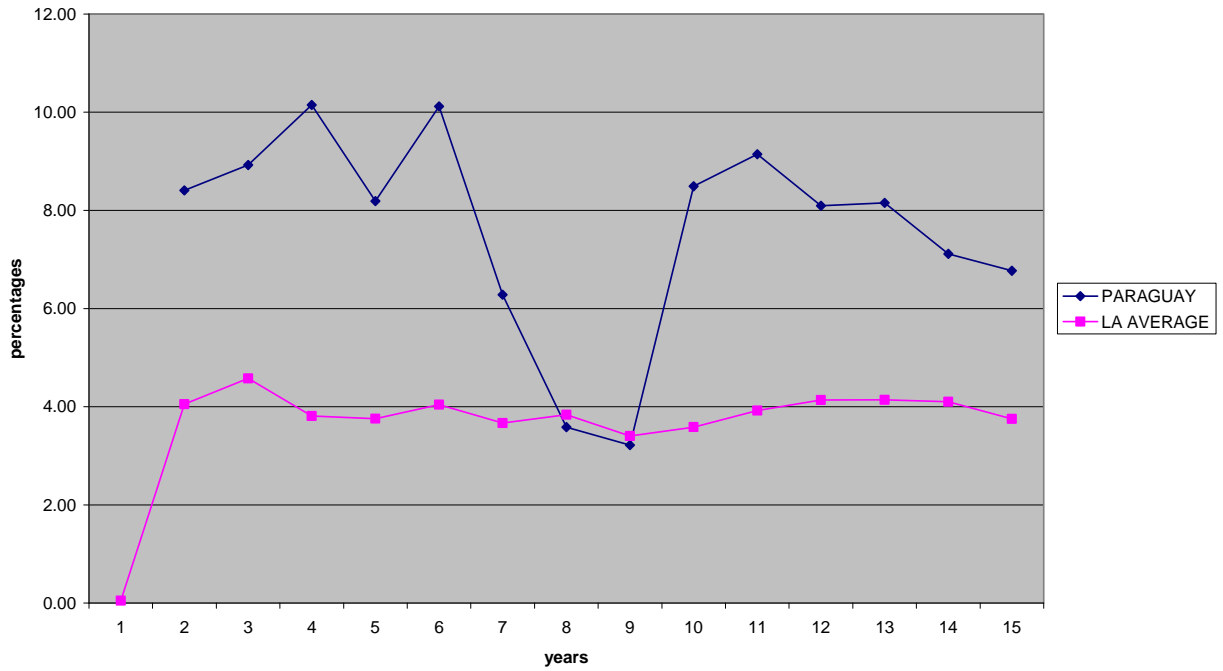


Figure 12B Non traditional banking revenues in Paraguay (1996-2010)



We control also for the banking stability, using the standard bank Z score variable, which is included in the macroeconomic controls (see below), with a positive expected sign. Paraguay shows a relatively low average level of banking stability (31<sup>st</sup> country on 34) (Figure 12C). In the 1990s one of the main structural problems of Paraguay was a weak banking system (Franks et al. 2005), but the time profile shows that the z values tend to improve (Figure 12D); at the end of the period most banks appeared resilient to shocks (IMF 2011).



Figure 12C Banking Stability (1996-2007)

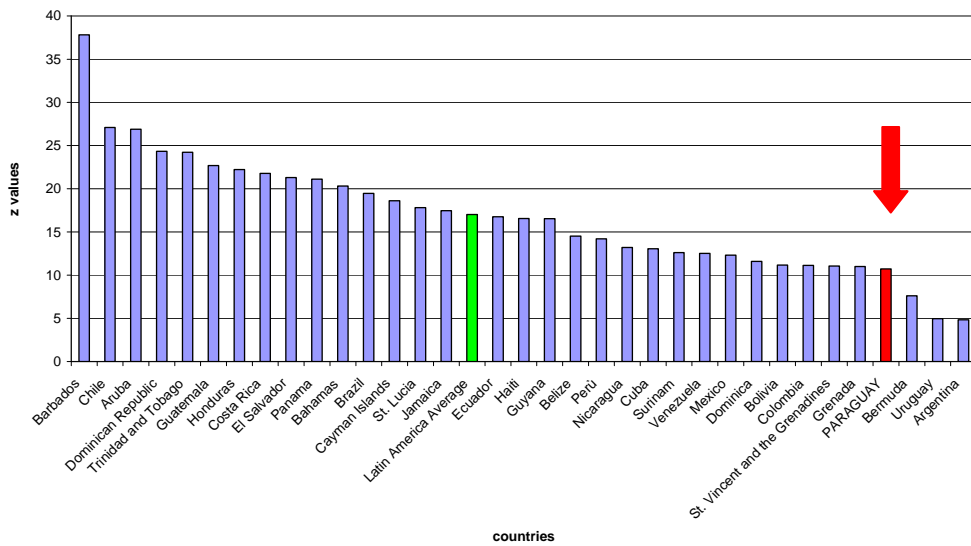
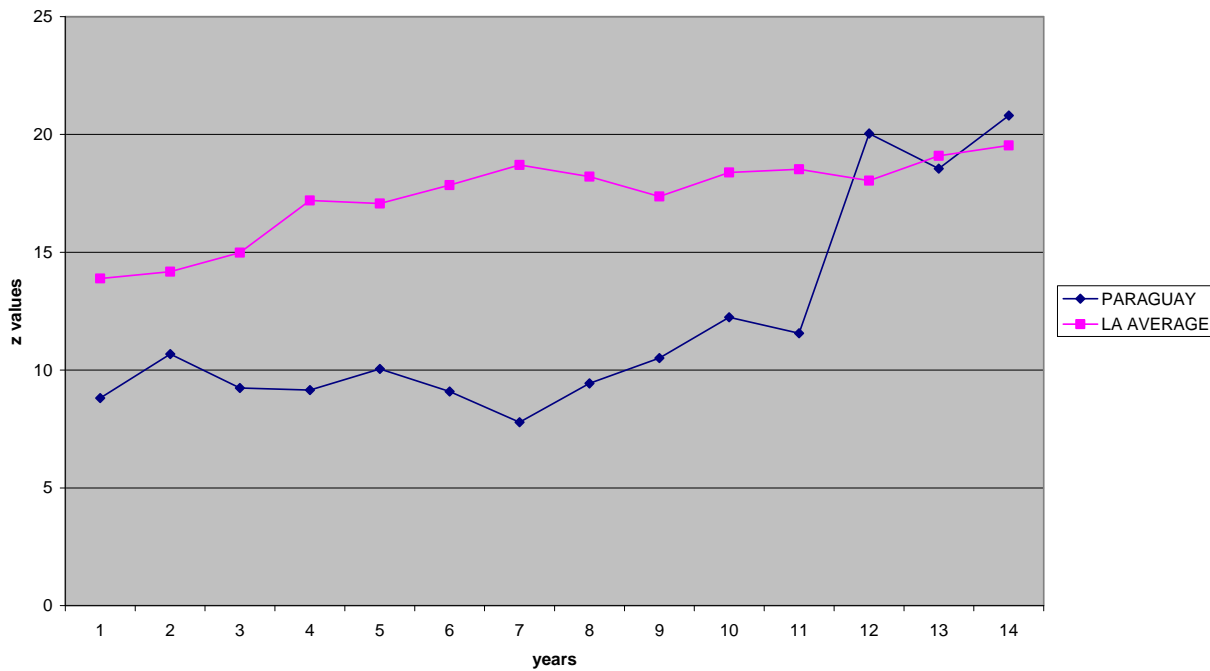


Figure 12D Banking Stability in Paraguay (1996-2010)



#### 4.2.5 Macroeconomic Controls

As macro control variables we use the standard drivers common in the literature to account for the behaviour of banking international flows.

Macroeconomic factors can impact on the international banking flows. First of all we use the GDP per capita (*GDPPC* variable) to represent the wealth of the nation equalized by size of population. In general wealth is likely to be directly associated with international banking flows; larger countries export and import more financial capital (among others Papaioannou 2009, Reinhart et al. 2011); the expected sign is positive. Paraguay shows a national product per capita relative low (28<sup>TH</sup> country on 33) (Figure 12E), with a positive time evolution, after a long period of slow growth (Franks et al. 2005), which seems to design a catching up respect to the Latin American average values (Figure 12F).

Figure 12E GDP per capita (Latin American countries, log, 1996-2007)

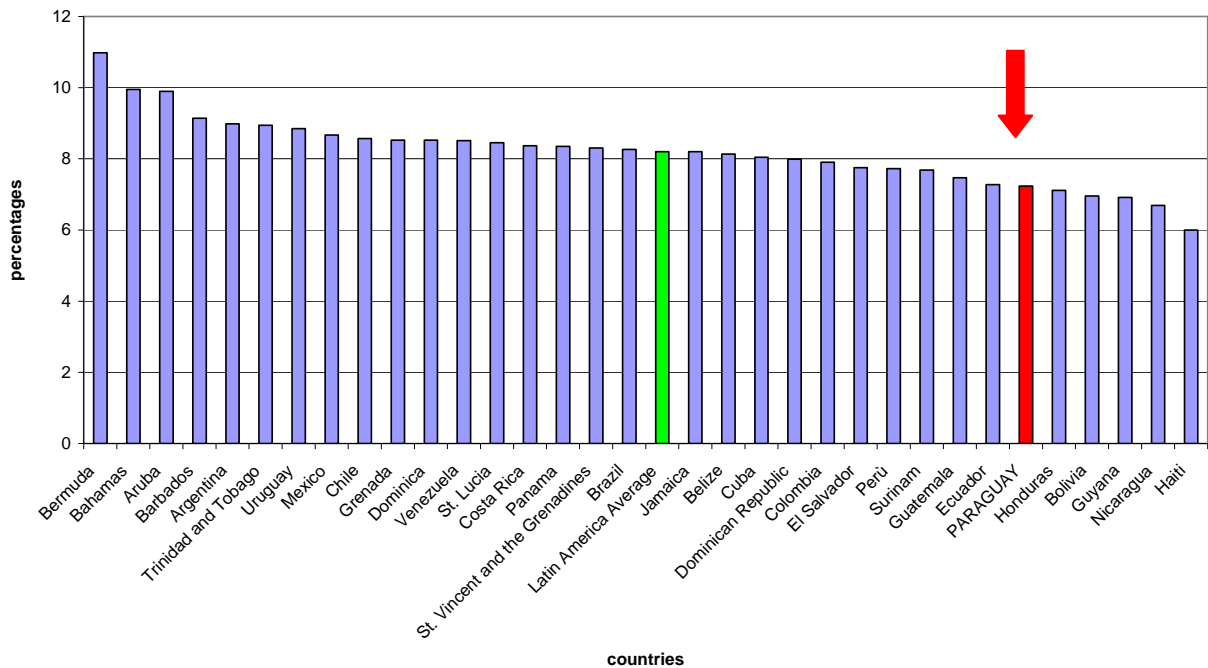
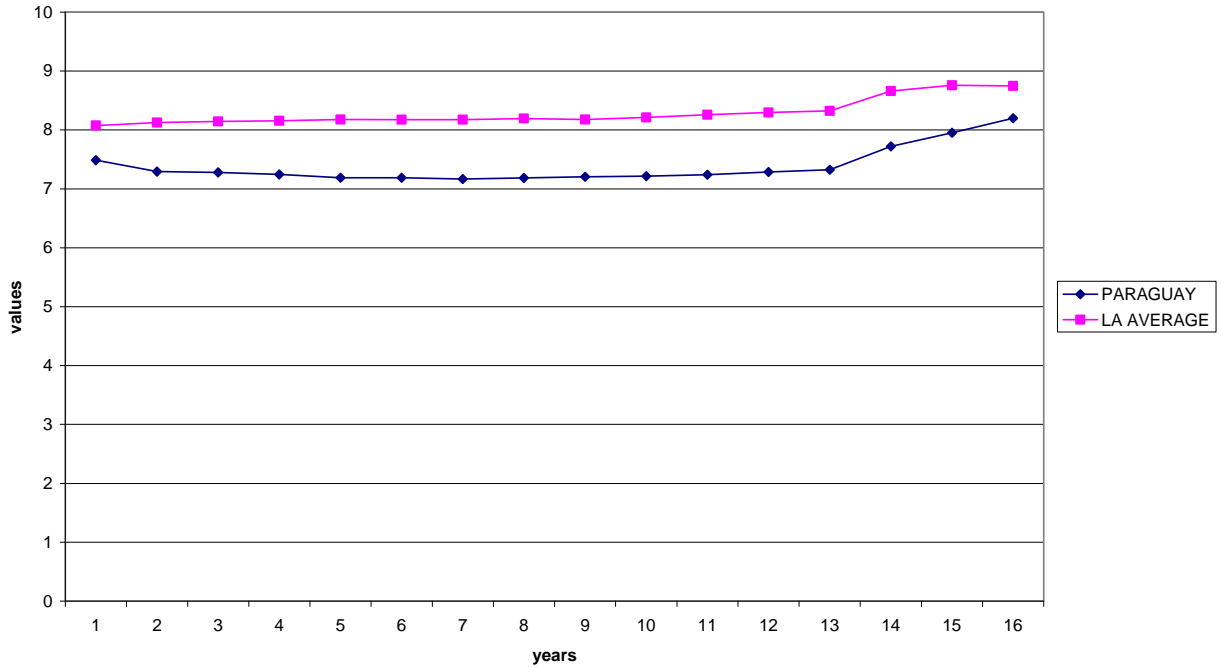


Figure 12 F GPD per capita in Paraguay (log, 1996-2011)



Secondly we control for inflation, where inflation is likely to produce both less inflows and more outflows, as well as uncertainty and volatility (among others Braga 2004). Therefore on the total flows the expected sign is undermined. We used two variables (*inflation* and *deflator* variables) with the same results. On average the inflation in Paraguay seems to be both slightly above the average (11th country on 29) (Figure 12G), relatively volatile (Figure 12H); and still rising at the end of the period (IMF 2011).

Figure 12G Inflation (Latin American countries, 1996-2007)

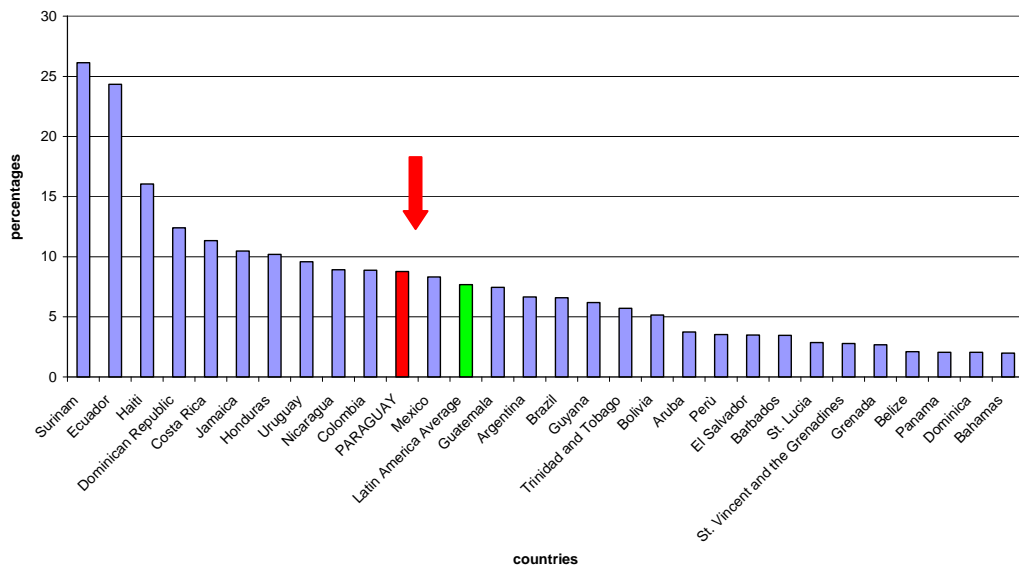
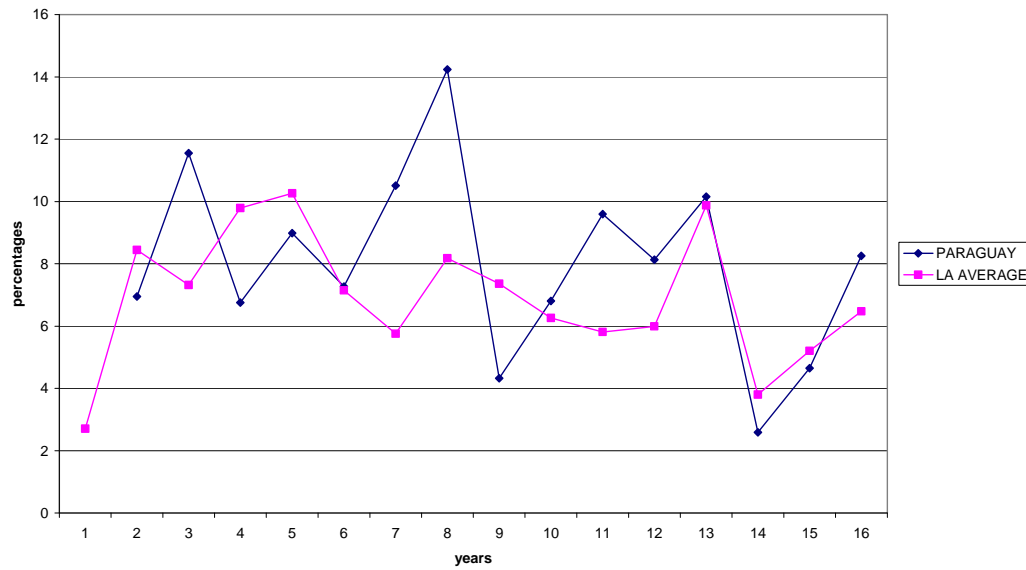


Figure 12H Inflation in Paraguay (1996-2011)



Thirdly we take into account the fact that international banking flows can be caused by risk-return considerations (among others Ramon-Ballester and Wezel 2007), which we captured using the real rate of return (*rir* variable) and the effective real exchange rate (*reer* variable). Given the international rate of return, we assume that the movements of both the real interest rate and the exchange rate can measure the country expected return spread. We assume that higher spreads - i.e. higher real interest rates and/ lower effective exchange rates - are likely to increase the inflows and at the same time to depress the outflows. The expected sign of both variables is undermined.

On average the real interest rate in Paraguay seems to be relatively high (4<sup>th</sup> country on 31) (Figure 12I) and volatile (Figure 12L).

Figure 12I Real Interest Rate (Latin American Countries, 1996-2007)

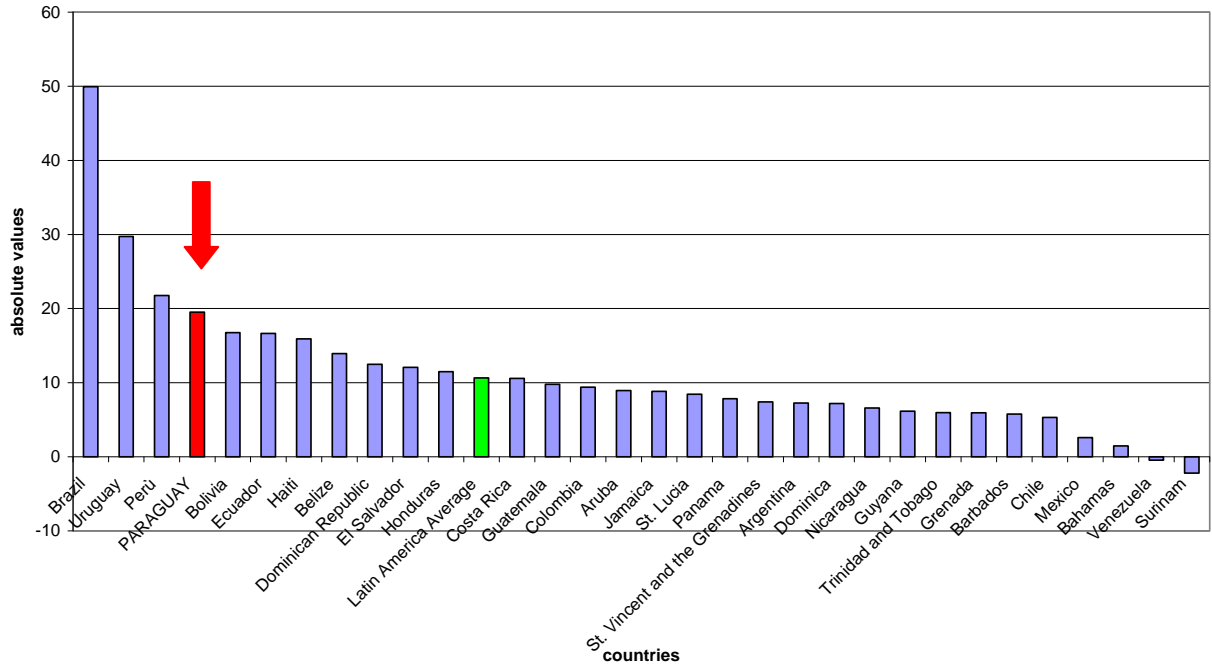
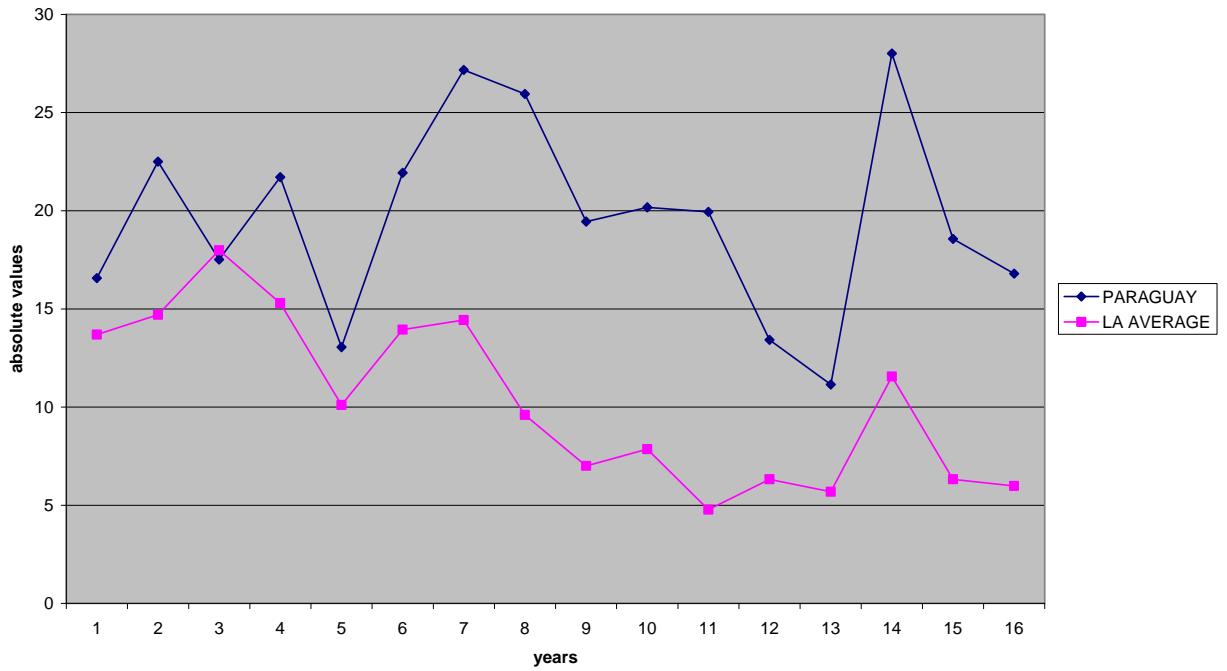


Figure 12L Real Interest Rate in Paraguay (1996-2011)



The real effective exchange rate in Paraguay seems to be relatively high (2<sup>nd</sup> country on 34) (Figure 12M), i.e. the guarany has been a weak currency during the period (Figure 12N).

Figure 12M Real Effective Exchange Rate (Latin American Countries, 1996-2007)

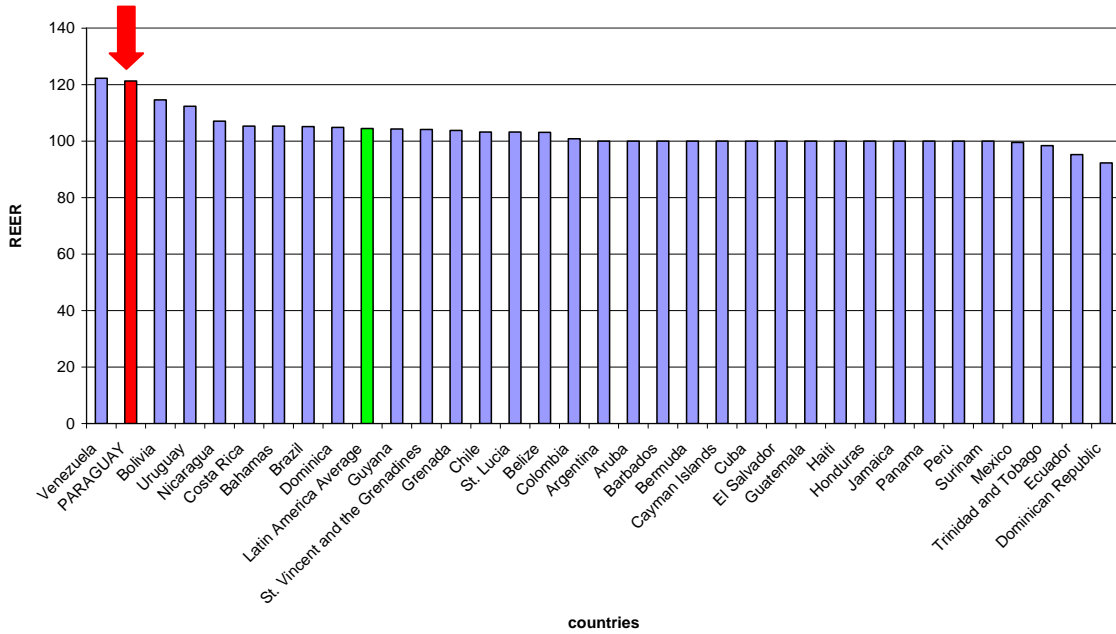
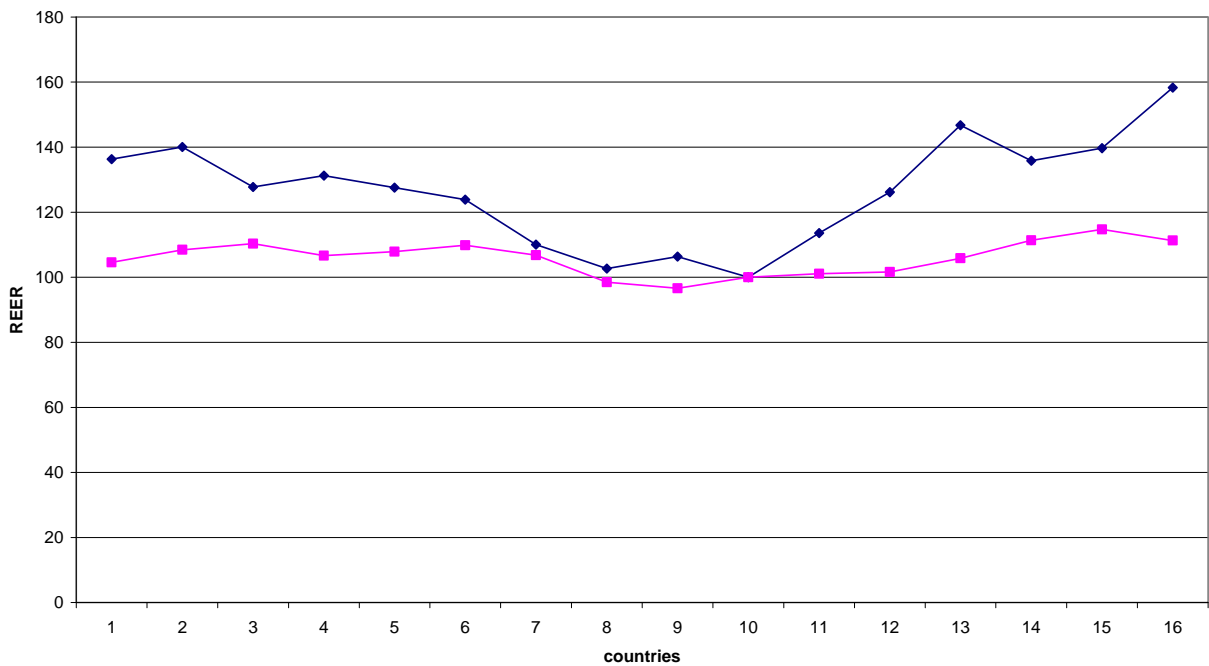


Figure 12N Real Effective Exchange Rate in Paraguay (1997-2011)



#### 4.2.6 Institutional Controls

In addition to macroeconomic drivers, political and institutional factors can be important determinants for international banking flows. We test the possible role of both the political quality and the institutional quality.

The political variables has been analyzed as potentially affecting the capacity of a country to increase its international banking flows, where the level of stability and its expected direct relation with the capital flows has been the most tested variable. As a source of data for political control variables – *Polity2* and *Durable* variables – we use database from the Polity IV Project, University of Maryland.

Polity2 represents an indicator of political quality. The variable is a modified version of the POLITY variable added in order to facilitate the use of the POLITY regime measure in time-series analyses. It modifies the combined annual POLITY score by applying a simple treatment to convert instances of “standardized authority scores” (i.e., -66, -77, and -88) to conventional polity scores (i.e., within the range, -10 to +10). The Polity score is computed by subtracting the Autocracy score from the Democracy score. Autocracy score and Democracy score are calculated from rated levels of both autocracy and democracy respectively, for each country and year using coded information on the general qualities of political institutions and processes, including executive recruitment, constraints on executive action, and political competition. The variable *Durable* indicates the number of years since the most recent regime change. It is used as a measure of the stability of political regimes.

The political quality in Paraguay seems to be slightly above the average (14<sup>th</sup> country on 24) (Figure 12O) and tententially increasing during the period (Figure 12P), after a long period of weak and high instable political setting (Franks et al. 2005).

Figure 12O Political Quality (Latin American countries, 1996-2007)

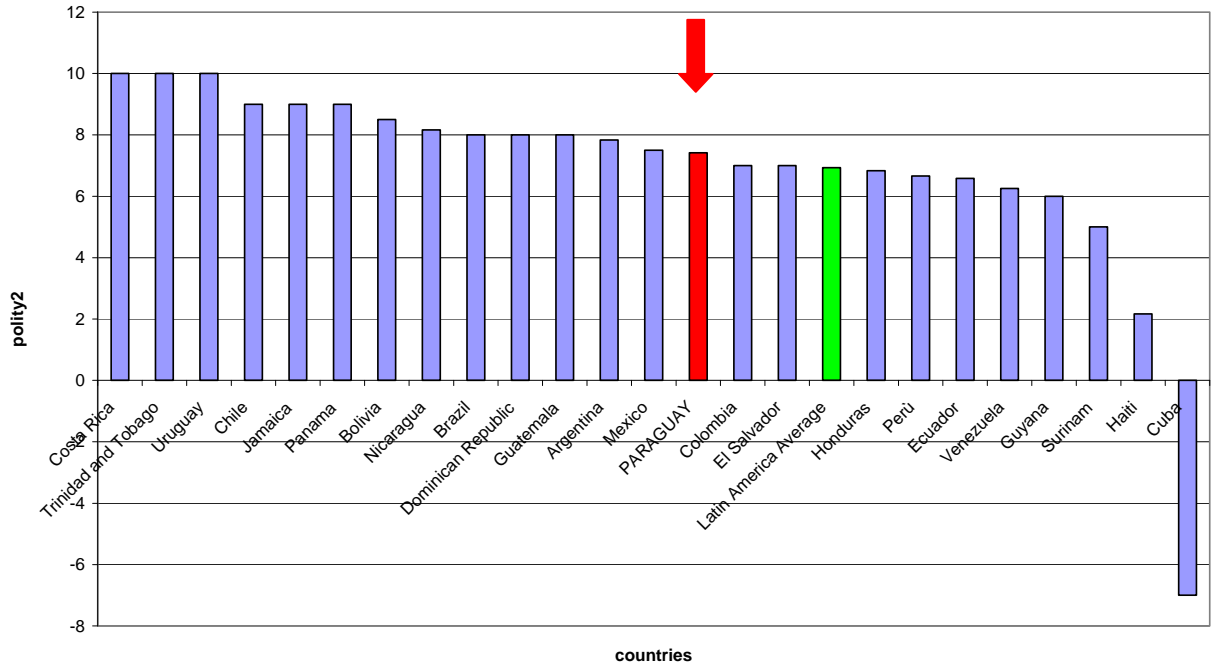
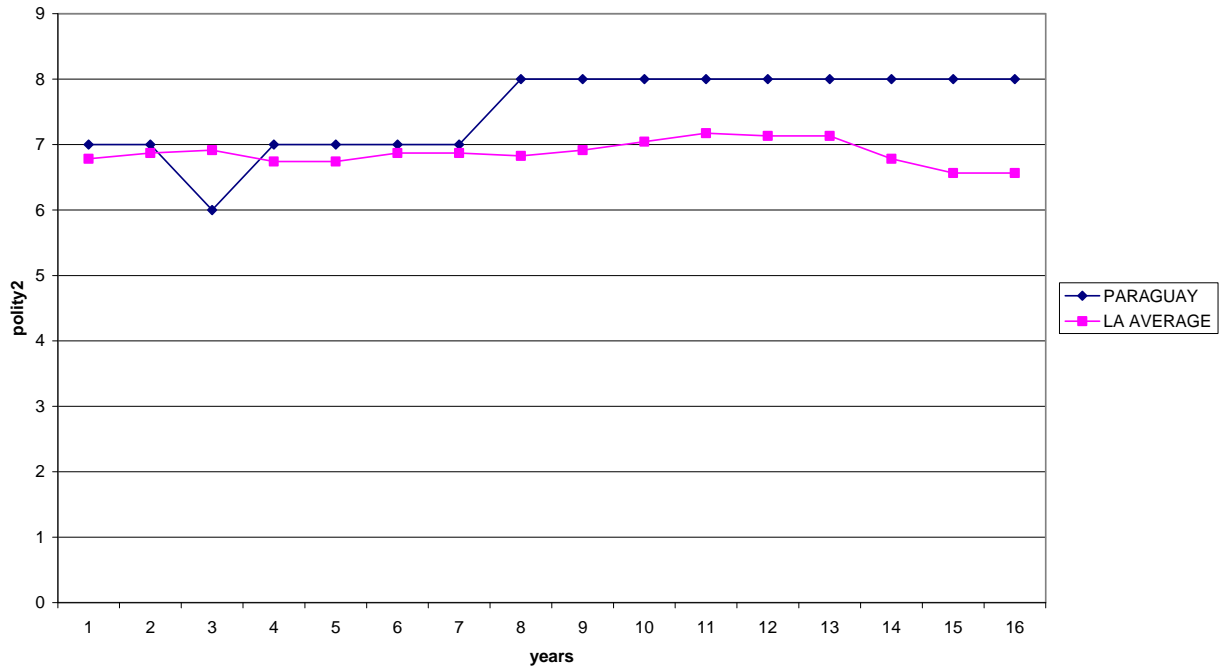


Figure 12P Political Stability in Paraguay (1996-2011)



Also the political stability in Paraguay seems to be below the average (18<sup>th</sup> country on 24) (Figure 12Q) and increasing in the end of period (Figure 12R), after that the 1990s were characterized by high political instability (Franks et al. 2005).



Figure 12Q Political Stability (Latin American countries, 1996-2007)

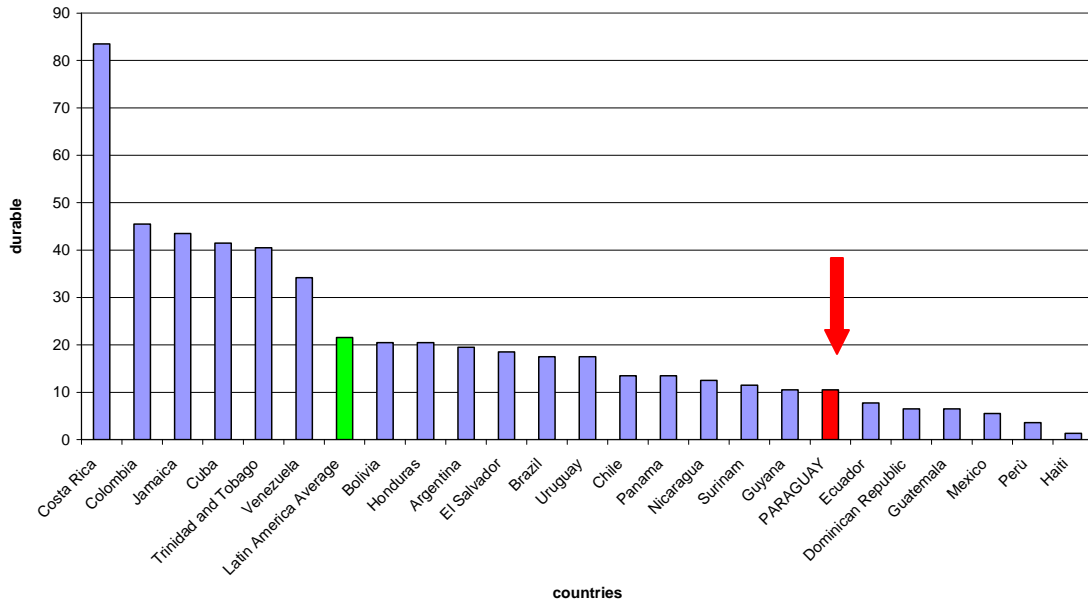
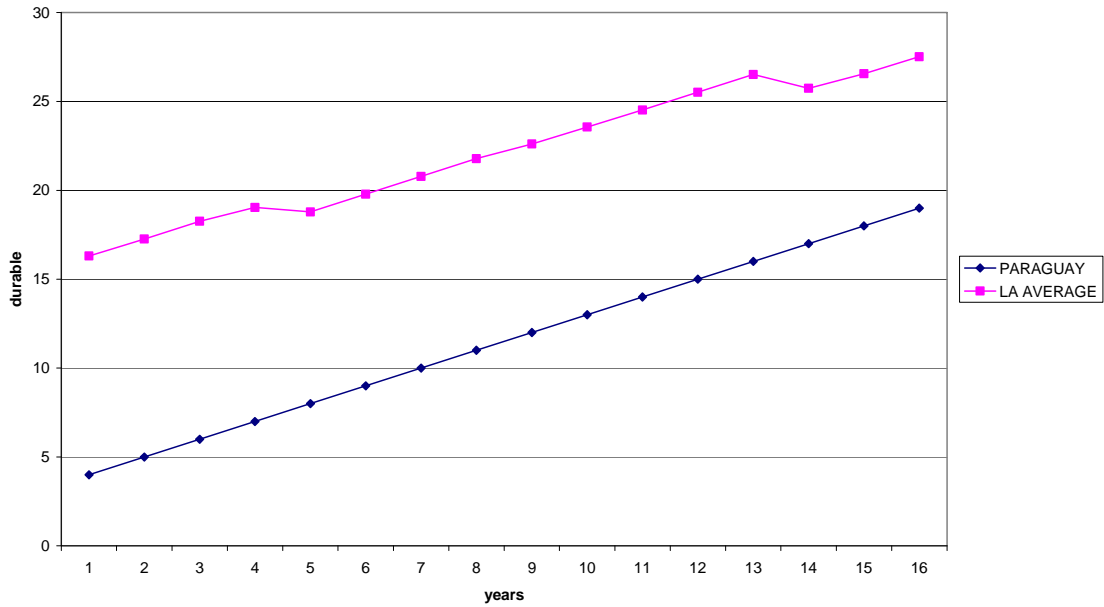


Figure 12R Political Stability in Paraguay (1996-2011)



In explaining the international banking movements the quality of the public institutions can play an important role. It has been supposed that increasing quality in public governance produces increasing efficiency and therefore more capital flows; the expected sign is positive. The World Bank Worldwide Governance Indicators

data base (Kaufmann et al. 2008) is used as a source of variables to control for public governance quality in the country.

We use variables which reflect the subjective estimation of one or another characteristic of the governance in the country. As the measure of the level of “freedom” in all spheres in the country we use the Voice and Accountability index (*Voice* variable). This variable reflects perception of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media. The index Political Stability and Absence of Violence (*Noviolence* variable) reflects perception of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including politically-motivated violence and terrorism. This can be considered a measure of the stability of the government itself. The Government Effectiveness index (*Goveff* variable) is a measure of perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. To measure perception of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development we use the Regulatory Quality index (*RegQua* variable). The Rule of Law index (*Rulelaw* variable) reflects perception of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. To control for the level of corruption in the country we use Control for Corruption measure (*Nocorru* variable).

Among the six public governance indicators, the more relevant in our empirical analysis – see below – will be the government stability index (no violence variable). In Paraguay the government stability is well below the average (29<sup>th</sup> country on 34) (Figure 12T), reflecting the serious governance problems of the 1990s (Franks et al. 2005), although in the last years the indicator is slightly better (Figure 12U).

Figure 12T Government Stability (Latin American countries, 1996-2007)

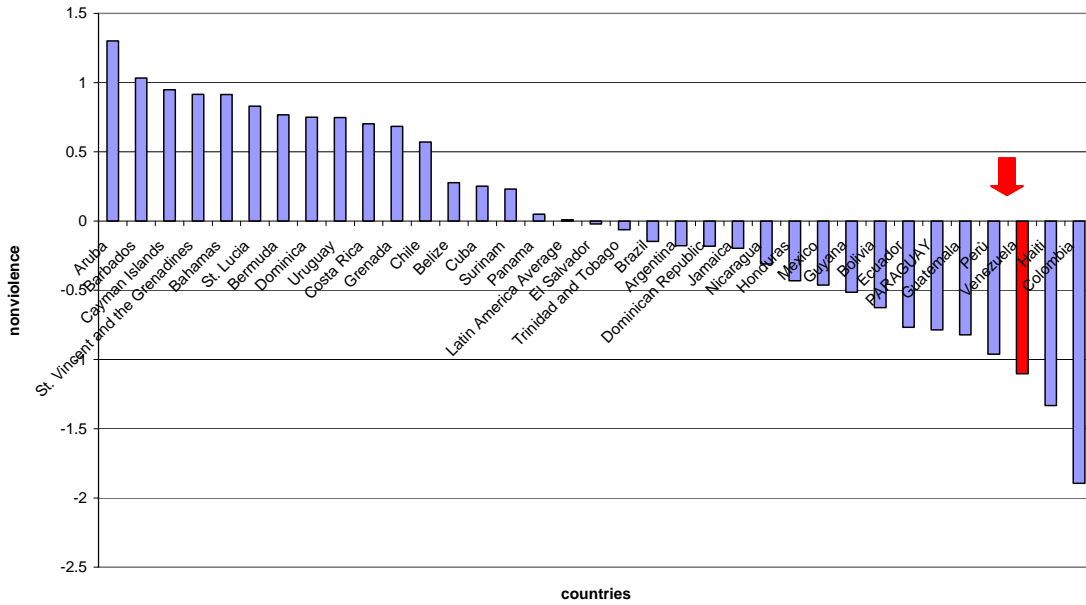
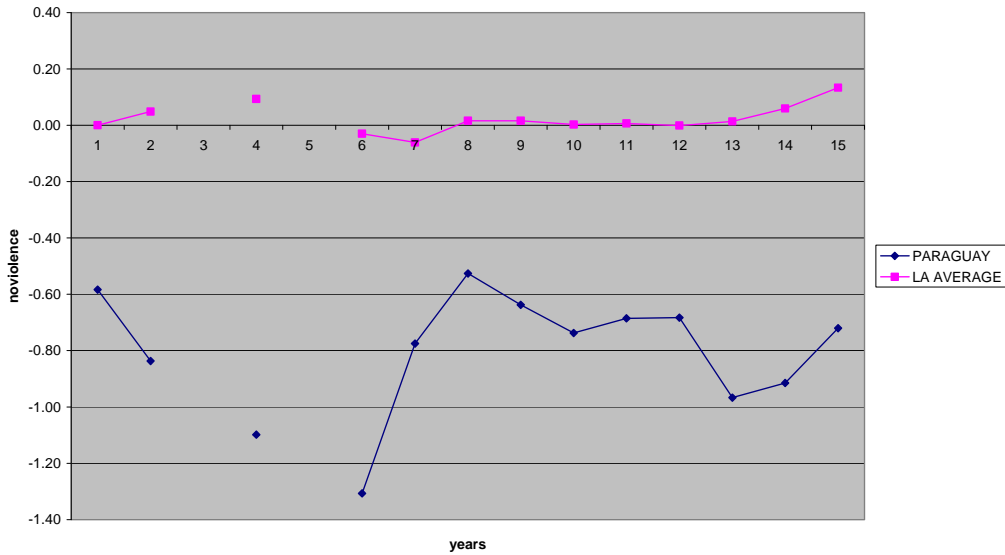


Figure 12U Government stability in Paraguay (1996-2011)



The complete descriptive statistics for all the variables described above are given in Table 3, while details on sources are given in Table 4.

### 4.3 Empirical Strategy

In this sub Section we present our empirical results concerning the relationship between the blacklisting factor and the international banking flows, using our baseline specification and where initially the left hand side variable is defined as the total external flows:

$$ETFlow_{c,t} = \alpha_0 + \alpha_1 BlackList_{c,t} + \alpha_2 GPDpc + \beta_1 FinRpr + \beta_2 FinFiu + \gamma_1 DeepBank + \gamma_2 InnoBank_{c,t} + \lambda_h X_{c,t} + \varphi_c + \mu_t + \varepsilon_{c,t} \quad (23)$$

Where in the specification (23)  $c$  and  $t$  respectively indicate the country (full sample: 34 countries as independent entities) and time (full period: 12 years). It should be remembered that we based our analysis on two crucial assumptions.

We consider the listing-delisting events as exogenous changes, which are independent from the dynamics of the capital flows. An international organization – the FAFT – evaluate the AML/CFT architectures country by country against its standards, releasing lists of the jurisdictions which fail to be complied. Later the FACT can reverse its choices, implement a delisting of the targeted country. The delisting decision is conditional on its own evaluation of the design and the implementation of the AML/CFT reforms.

During a period in which a country is listed, the FAFT recommends that all the national supervisors strengthen the monitoring of all the banking transactions with the targeted countries, increasing the compliance costs for the banks. Consequently we assume that the FAFT listing/delisting decisions produce effects in the banking and financial decision makers, which react to the monetary and reputational losses and gains related to the listing-delisting events.

In other words initially we perform the analysis excluding the hypothesis that both the international capital flows and the FAFT decisions are affected by the same variables. As it will be evident below, we assume that the FAFT decisions are driven by well defined deficiencies in the AML/CFT regulations, while the bank strategies can be influenced by the overall financial regulatory setting and eventually by features of the AML/CFT regulation different from the characteristics observed by the FAFT. In the same vein we exclude reverse causation between capital flows and FAFT decisions.

Furthermore we assume that the relevance of the listing-delisting events depend on the existence of two more factors - the regulatory lightness factor and the banking profitability factor – which influence the sensibility of the bankers respect to the blacklisting procedures.

Consequently the parameters  $\alpha$ ,  $\beta$  and  $\gamma$  are the main coefficients of interest, representing our *unconstrained* baseline specification. Including the vector of controls  $X$  we have our *constrained specification*. We test the existence and robustness of the stigma effect using three frameworks: *pooled OLS*, *static panel* (fixed and random effects), *dynamic panel*.

The three frameworks correspond to different economic setting. We start assuming that in the listing/delisting time sequence the country features doesn't matter; however we wonder if the simple pooling can produces insightful information. Then we naturally and necessarily account for the time invariant country heterogeneity, estimating a static panel with both fixed and random effects. At this stage we assume that the capital markets are perfectly efficient; then we do not take in account any lags and/or frictions. Finally we consider the possibility that in the capital flow movements lags can be relevant in testing the importance of the blacklisting factor. Therefore we implement dynamic panel data tests. In all the regressions we use an unbalance dataset and adopt for the errors the robust specification to control for heteroskedasticity.

#### 4.4 Results

##### 4.4.1 Pooled OLS

We start taking a look at the naïve pooled OLS estimations; we use directly our constrained baseline specification (Table 5).

Among our variables of interest we note that the blacklisting factor, the regulatory lightness factor and the wealth factor show significant coefficients. However we know that the estimations are likely to be heavily biased, being the pooled cross section approach inadequate to address in an effective way the stigma effect issue. In investigating the possible financial effects of the listing-delisting sequence is essential to disentangle the role of time (within variation) respect from the possible influence of the time invariant country effect (between variation) in analyzing reactions of the banking flows to – negative or positive – shocks represented by the FAFT decisions.

##### 4.4.2 Static Panel

Turning to panel regression techniques is therefore the necessary step in order to use in an efficient way all the information contained in the time series of the country capital flows. We assume that in the Latin American region, other things being equal, the reaction of the international banking flows is the same when a listing or delisting event happens.

We start the regressions including the country fixed effects, claiming that the capital movements can be affected by different and unobserved country specific factors. We assume that each Latin American country has its own peculiar and unknown characteristics that may influence the banking flows. We try to remove the effects of country time invariant features in order to assess the influence of the blacklisting events.

We start testing the unrestricted baseline specification (Table 6) and five preliminary results seem to be evident:

a) the blacklisting factor holds: the total banking flows react negatively and significantly when a country is listed or delisted; b) the same is true for the regulatory lightness: more financial repression reduces the international banking business; c) the traditional banking deepening matters: the size of the country banking

system is directly associated with the international capital movements; d) the wealth factor is a driver; e) finally, the FIU financial model seems to be appreciated by the banks, but the coefficient is not significant.

Now more severe tests have to be implemented, controlling for both macro and institutional features. Observing the two set of control variables, it is evident that the institutional control variables present a richer dataset than the macro control variables: 2580 observations instead of 1338. At the same time looking at the correlation matrixes of the two sets of control variables (Tables 7 and 8) we acknowledge a greater risk of collinearity in the institutional set. Therefore the two set of variables present symmetric pros and cons: the institutional variables offer more information, with higher risk of collinearity, and vice versa.

Starting with the fixed effects restricted specification (Table 9), we find that: a) the stigma effect is confirmed, b) as well as the regulatory lightness factor and c) the banking profitability factor - in this case through the traditional banking variable, which signals that capital flows seem to prefer the more traditional banking systems. Among the control variables, only the real exchange rate is significant: higher depreciation increases the total international capital flows.

We turn to the random effects specification (Table 10), given that the features of the database – the number of years is smaller than the number of countries – necessarily suggest to perform both techniques, knowing that in general the choice between fixed and random effects implies a trade off between higher bias risk (random effects) and higher variance risk (fixed effects) (Clark and Linzer 2012). Effectively It has been noted that in our tests with the fixed effects model the percentage of variance with is due to differences across countries – between variance – (Rho values) is high, with the corresponding risk of obscuring the value of the within information in explaining the role of the blacklisting factor.

Therefore here we assume that the role of the country effect in determining the international banking flows is randomly distributed, admitting its variance – which is absent in the pooled model - but limiting it respect to the fixed effects model.

Among our variable of interests, the stigma effect, the regulatory lightness factor and the wealth factor are significant. Among the control variables, the relevant macroeconomic indicators are the real interest rate and the banking stability. Both variables produce positive effects on the total international capital flows. Regarding the institutional variables and applying the usual *caveat* on the risk of collinearity, we have three indicators – no violence, government effectiveness and no corruption – which influence positively the capital flows, while the influence of the rule of law variable is a puzzling negative one.

We decide to consider the results obtained using both approaches – fixed effects and random effects – given that performing the Hausman Test – with conventional standard errors – (Table 11) we can't reject the hypothesis that the random effects model can produce more efficient results. Furthermore and unsurprisingly the Breush and Pagan Test (Table 12) also confirms that in investigating our database the random effects model can be more efficient than the pooled model. However also with the random effects model the percentage of variance with is due to differences across countries – between variance – (Rho values) remains high.

As final step we test our restricted specifications distinguishing between banking inflows and banking outflows, checking if any difference emerges.

Using the fixed effects specification, the inflows (Table 13) are significantly associated with the blacklisting factor, the traditional banking factor - again directly associated with the capital flows – and the exchange rate depreciation. The cross border inflows seem to be sensible to the stigma effect. Further the international banking activity seem to prefer the countries with traditional banking systems and weak currencies. Using the random effects specification (Table 14) the relevant drivers among our variables of interest are the blacklisting factor, the regulatory lightness factor and the wealth factor. Among the control variables, three institutional variables – no violence, government effectiveness and no corruption – are significant with the expected (positive) sign, while two other institutional variables – rule of law and political quality – are significant with the negative sign. The real interest rate and the bank stability are both significant.

Analyzing the outflows with the fixed effects specification (Table 15), the stigma effect still exists, but it is not significant, while the regulatory lightness factor and the traditional banking factor remain relevant. The same is true for the political quality and the real exchange rate depreciation. Using the random effects (Table 16) the stigma effect is again significant, as well as the regulatory lightness factor and the wealth effect. Among the control variables, the relevant macro variables are the real interest rate and the banking stability while three public governance indicators – no violence, rules of law and no corruption – have positive effects in stimulating the banking activity abroad. The rule of law variable exhibits again a significant and negative coefficient.

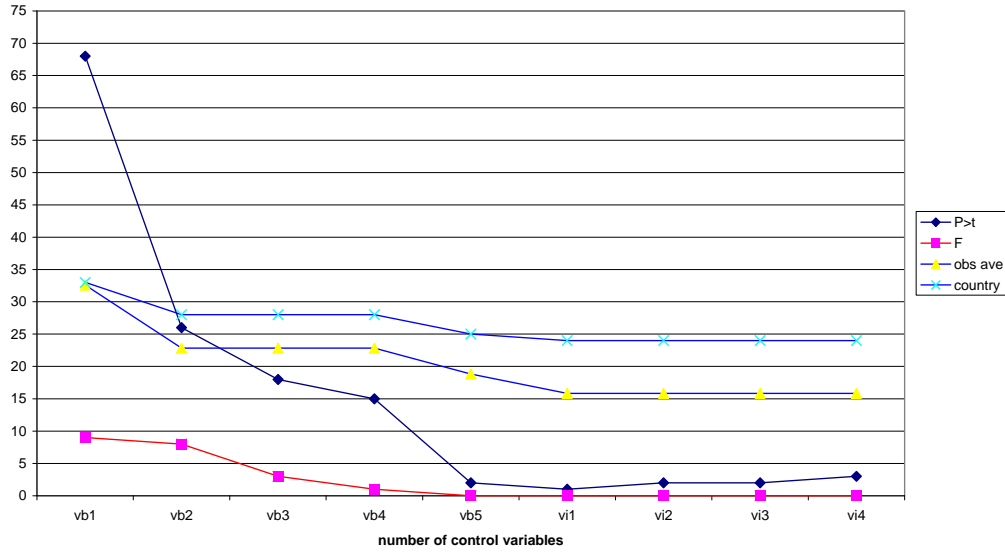
At the end of the static panel tests and before the post estimation controls, which are our preliminary conclusions on both the stigma effect and the overall results?

We can summarize the empirical results on the stigma effect, focusing on our main dependent variable – the total banking flows – and starting with the fixed effects specifications. We illustrate (Figure 13) the evolution of the stigma effect significance – P values – starting from the baseline specification – first five variables – then adding the institutional control variables – eight variables – and then the macro control variables – four variables. The sequence of the control variables follows the number of available observations (descending order). In the same figure we also describe the corresponding evolution of the regression significance - test F values – as well as of the number of countries and the average number of observations – total number of observations divided the number (twelve) of years.

Being mindful of the fact that the stigma effect ever exhibits the right expected sign – negative relationship between blacklisting event and total banking flows – it is evident that its significance depend on both the regulatory factor and the profitability factor: it drops below 5% when the baseline specification is complete. The baseline specification is also a significant regression with a representative sample (25 countries, 226 observations). After increasing the number of control variables the stigma effect coefficient significance fluctuates between 2% and 9 % and the regression significance remains constant, while by construction the

number of countries decreases, as well as the available observations; at the end we have 20 countries and 119 observations.

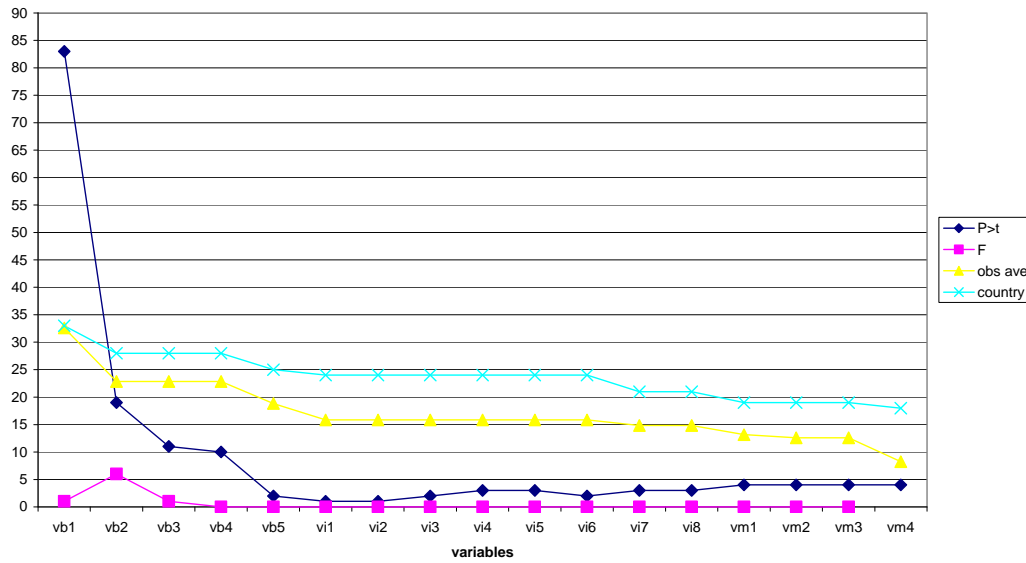
Figure 13 Stigma Effect P, Regression F, Observations and Countries (FE)



Using the specifications with random effects (Figure 14) the stigma effect again exhibits the right expected sign and this fact confirms that its significance depends on both the regulatory factor and the profitability factor: it drops below 5% when the baseline specification is complete. Still the baseline specification is a significant regression and the increase of the number of control variables maintains the significant of the sigma effect constant and high (fluctuations between 2% and 4 %). The evidences on the number of observations and countries re obviously identical to the aforementioned cases with fixed effects.



Figure 14 Stigma Effect P,Regression F, Observations and Countries (RE)



If we wish to summarize all the empirical results (Table A below: fixed effects= white columns, random effects = grey columns) we can observe that: a) the more relevant variables are the blacklisting factor and the financial lightness factor; b) the relevance of the blacklisting factor is stronger in the international banking inflow movements. Further: c) the banking profitability factor is stronger when the country banking sector is more traditional (*caveat*: low coefficient significance); d) weaker currencies increase the international banking flows (*caveat*: too small dataset, problems with the variance matrix) ; e) the quality of the institutions matter (*caveat*: collinearity risk, cases of sign ambiguity); f) the international banking activity is positively correlated with high real rate and banking stability. Finally g) the banking flows are positively associated with the financial nature of the FIUs, but the coefficient is not significant.

TABLE A	TEFFE	TEFRE	ELFFE	ELFRE	EAFRE	EAFRE
GDPPC (+)		*		*		**
FAFTLIST (-)	**	**	**	**		*
FINREPR (-)	***	***		***	***	***
INNOBANK (-)	*		*		**	
NOVIOLENCE (+)		***		***		***
GOVEFF (+)		**		***		***
RULELAW (-)		***		***		***
NOCORRUPTION (+)		**		**		***
POLITY2				* (-)	* (+)	

RIR (+)		***		***		***
REER (+)	***		***		***	
BANKZ (+)		**		**		*

\*\*\* = P<0.01; \*\* = P<0.05; \* = P<0.10

Finally we have to perform the robustness tests. With static panel data there are always reasons to suspect that country errors are correlated over time. Therefore we have to control our restricted specifications assuming that the disturbing term is the first order auto-regressive and computing the autocorrelation with the Durbin – Watson statistics.

Starting from the total banking international flows, the fixed effects model (Table 17) produces a non significant regression. For the sake of completeness the specific results are that coefficients of the blacklisting factor and of the regulatory lightness are still negative, but now are not significant. The profitability factor – through the traditional banking factor - is significant. The same is true for the real exchange rate factor and for the stability factor, which however shows a negative sign. Conversely the random effects model (Table 18) produces significant regressions, as well as significant coefficients for the blacklisting factor, the regulatory lightness factor, the bank profitability factor – through the banking deepening factor - and the wealth factor. Also the real exchange rate is significant.

For the inflows, the fixed effects model (Table 19) produces again non significant regression; the coefficients of the blacklisting factor and of the regulatory lightness factor are negative but not significant. The profitability factor – through the traditional banking factor - is significant; the stability factor is significant with a negative sign. With the random effects model (Table 20) significant regression has been obtained. The coefficients for the blacklisting factor and the wealth factor are significant; the political quality is significant, with a negative sign.

Ending with the banking outflows, the fixed effects model (Table 21) shows non significant regression; the coefficients of the blacklisting factor is negative but not significant. The regulatory lightness factor and the profitability factor – through the traditional banking factor - are significant; the stability factor is significant with a negative sign. The real exchange rate is positively significant. The random effects model (Table 22) offers significant regression. The coefficient for the blacklisting factor is negative but not significant: the regulatory lightness and the wealth factor are significant; the real exchange rate and the political stability are significant, respectively with positive and negative signs.

In conclusion, taking into account also the possibility of auto-correlation in the residuals, we can note that (Table B below: fixed effects= white columns, random effects = grey columns): a) the blacklisting factor and the regulatory lightness factor can be detected, and they are significant using the random effects model; b) the relevance of the blacklisting factor depends on the international banking inflow movements; c) the wealth effect is significant; d) the banking profitability factor is stronger when the country banking sector is more deep and traditional. Furthermore: e) weaker currencies increase the international banking outflows (*caveat*: too small

dataset) ; f) the political quality decreases the banking inflows, (*caveat*: collinearity risk, sign ambiguity); g) the political stability decreases the banking outflows (*caveat*: collinearity risk); finally h) the banking flows are positively associated with the financial nature of the FIUs, but the coefficient is never significant.

TABLE B	TEFFE	TEFRE	ELFFE	ELFRE	EAFFE	EAFRE
<b>GDPPC (+)</b>		***		***	**	***
<b>FAFTLIST (-)</b>		*		*		
<b>FINREPR (-)</b>		***			**	***
<b>INNOBANK (-)</b>	**		**		**	
<b>DEEPBANK (+)</b>		*				
NOVIOLENCE (+)						
GOVEFF (+)						
RULELAW (-)						
NOCORRUPTION (+)						
POLITICAL QUALITY				* (-)		
POLITICAL STABILITY						** (-)
RIR (+)						
REER (+)	**	**			*	**
BANKZ	** (-)		** (-)		* (-)	

\*\*\* = P<0.01; \*\* = P<0.05; \* = P<0.10

#### 4.4.3 Dynamic Panel

We can test one more perspective: other things being equal, the international capital flows can depend on lagged values. In other words we can suppose the existence of *international capital hysteresis*. We can say that the static and dynamic panel tests analyse the stigma effect issue respectively without and with financial hysteresis.

If we assume that the modifications of the bank strategies in allocating their international activity described in the theoretical Section 3 are costly, we can think that the banking flows will react with delay to the listing-delisting events caused by the FAFT decisions. The dynamic of the adjustments can depend on two factors. On the one hand, the role of the difference between the existing level of banking flows and the optimal one, which motivates the inclusion in the baseline specification of lags of the dependent variable. On the other hand the existence of information and transaction costs, which can justify the inclusion the lags of the drivers.

We have the panel with the following features: a) small number of time observations and large number of country units; b) independent variables which can be strictly exogenous, i.e. uncorrelated with errors; c) possibility of specific country effects; d) possibility of heteroskedasticity and auto-correlation within country, but not across them; e) only available instrumental variables are internal, being based on lags of the instrumented covariates.

Therefore it is natural to implement the Arellano Bond estimation technique (Roodman 2006). We use the restricted specification with all variables but the real exchange rate; in this manner we minimize the loss of observations (94 observations for 18 countries, instead of 60 observations for 12 countries) and avoid problems with the variance matrix. We focus our attention on the main covariates of the baseline specification, which already showed its relevance in the static panel tests: the blacklisting factor, the regulatory lightness factor, the banking profitability factor; the wealth factor. As usual we adopt for the errors the robust specification.

We apply the Arellano Bond one step estimator (Table 23), using the first three lags of the international banking flows as regressors to avoid serial correlation problems. The one lagged value of the dependent variable positively and significantly influences the dynamics of the international banking flows. All our variables of interest – blacklisting, regulatory lightness, banking profitability and wealth factors – are significant with the expected signs. Among the control variables, two covariates show significant and negative effect: government effectiveness and inflation. The Arellano Bond test for serial correlation has been implemented (Table 24): as expected there is evidence against the null hypothesis in the one lagged errors, while the same hypothesis is rejected in the two and three lagged errors, suggesting that there is no evidence of model misspecification.

Can we assume that all regressors are strictly exogenous? We wonder if there is any present covariate which could react if a past shock in the international banking flows occurred. We test this possibility assuming existence of predetermined variables (while we exclude the existence of endogenous covariates, i.e. variables which react also if a present shock occurs). In our regressions, we can assume that the macroeconomic variables – banking deepening and traditional banking factors, growth, inflation, real interest rate and banking stability - could be considered as predetermined regressors (Table 25). Performing this *macro predetermined specification*, variables

of interest – blacklisting, regulatory lightness, banking profitability and wealth factors – are still significant with the expected signs. Now among the control variables only inflation matter: more inflation depresses the international capital flows. The Arellano Bond test for serial correlation (Table 26) rejects the model misspecification hypothesis.

Finally we can test if our dynamic specification fits separately the inflows and outflows of capital. On the one side and starting from the inflows it is evident (Tables 27 and 28) that the regressions are unreliable; the results are confirmed using the macro predetermined specification (Tables 29 and 30).

On the other side the outflows data (Tables 31 and 32) show that the covariates of interest – blacklisting, regulatory lightness, banking profitability and wealth factors – are significant with the expected signs. Among the control variables only banking stability matters: more instability increases the capital outflows. The macro predetermined specification (Tables 33 and 34) confirms all the results but the banking stability effect.

In conclusion of this step, were we considered the possibility of international capital hysteresis, our main results can be summarized as follows (Table C below): the blacklisting factor, the regulatory lightness factor, the banking profitability factor and the wealth factor can be still detected, and their relevance depends on the international banking outflow movements. Besides inflation and banking instability significantly influence the international banking activity: more inflation reduces the overall flows, while more banking instability increases the capital outflows. Among the institutional variables, the government effectiveness positively affects the total flows.

TABLE C	TE	TEMR	EA	EAMR
<b>GDPPC (+)</b>	**	**	***	***
<b>FAFTLIST (-)</b>	**	**	**	**
<b>FINREPR (-)</b>	***	**	**	**
<b>INNOBANK (-)</b>	***		***	***
<b>GOVEFF (+)</b>	*			
<b>INFLATION (-)</b>	**	*		
<b>BANKZ (-)</b>			*	

\*\*\* = P<0.01; \*\* = P<0.05; \* = P<0.10

Finally we can wonder which are the consequences of our tests if we assume that the hysteresis is particularly strong, i.e. the international banking movements are characterized by relevant persistency. The quickness of capital mobility in reacting to listing events is smaller if we think that every past change influences

the present path for a very long time. To address this even more extreme hypothesis we use the Arellano Bover estimation, without and with the macro restricted specification.

In the dynamics of the total banking flows (Tables 35 and 36) we find that blacklisting factor is negative but non significant, while regulatory lightness and banking profitability factors are significant. Using the macro restricted specification (Tables 36 and 37) blacklisting factor is again significant, but the hypothesis of miss-specification is not rejected. Focusing on outflows the unrestricted (Tables 39 and 40) and the macro restricted (Tables 41 and 42) specifications produce tests which show that blacklisting factor, regulatory lightness factor and the wealth factor are ever significant, while banking profitability factor is significant, but with two different variables. We can say that the less capital markets are efficient, the more banking outflows are the drivers of our covariates (Table D below). Among the control variables, more quality of regulation and less political quality increase outflows.

TABLE D	EA	EAMR
<b>GDPPC (+)</b>	**	**
<b>FAFTLIST (-)</b>	**	**
<b>FINREPR (-)</b>	**	**
<b>INNOBANK (-)</b>	**	
DEEPBANK		*
REGULATORY QUALITY	*	
POLITY (-)		*

\*\*\* = P<0.01; \*\* = P<0.05; \* = P<0.10

4.5 Time Series: the case of Paraguay

On February 2010 the FAFT identified Paraguay among the jurisdictions which have strategic AML/CFT deficiencies<sup>4</sup>. We interpret this decision as a listing event. In the subsequent reviews of compliance – June 2010, October 2010, February 2011, June 2011, the FAFT acknowledged that the Paraguay has taken steps towards improving its AML/CFT regime, but maintain the country into the list<sup>5</sup>. On February 2012 the FAFT welcomed Paraguay’s significant progress in improving its AML/CFT regime and noted that Paraguay has largely met its

<sup>4</sup> [www.fatf-gafi.org/countries/n-r/paraguay/](http://www.fatf-gafi.org/countries/n-r/paraguay/)  
<sup>5</sup> Ibidem

commitment; therefore Paraguay was therefore no longer subject to FATF's monitoring process<sup>6</sup>. This is what we call a delisting event.

If the stigma effect holds, these events could have been expected to influence the Paraguay capital flows with the rest of the world: the listing event might have been expected to raise the risk on financial transaction with the Paraguay, depressing them. The delisting event is likely to cause the opposite reaction. Such effects could have been motivated by the decisions of the international banking and financial firms, which has been theoretically described in Section 3 and tested with longitudinal data in the previous paragraphs of Section 4.

Given the available data, we can analyse the listing episode only, wondering if it causes effects on the international capital flows of Paraguay. Whether or not these consequences materialized is also an important policy question, given that Paraguay has to continue to address the full range of AML/CFT issues<sup>7</sup>, and the narrative told us that the delisting episode was appreciated by the international financial markets.

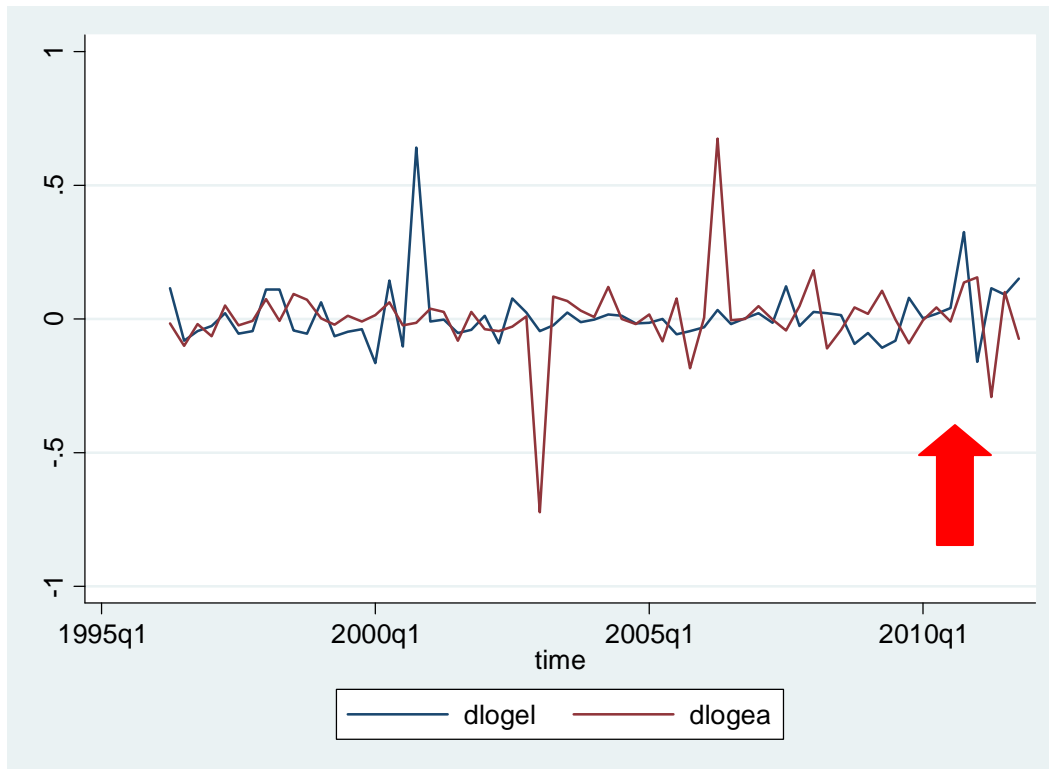
We can try to test our specification using the data on Paraguay. We consider the international capital flows of Paraguay in the period 1996-2011, using quarterly data. Starting with the Box Jenkins approach, we evaluate the features of both capital inflows and outflows as time series. Using the logarithmic transformation of both variables and taking the first moments we can approximate the rates of growth of the two capital flows. The time evolution (Figure 13) shows that: a) the capital flows are likely to be non stationary series; b) in the blacklisting period (2010-211) positive and negative turbulences characterized both capital flows, increasing the interest for further inspections.

---

<sup>6</sup> Ibidem

<sup>7</sup> Ibidem

Figure 13: Capital Inflows and Outflows in Paraguay (1996-2011, rates of growth)



The subsequent correlograms of the inflow (Figure 14) and outflow (Figure 15) series confirm that we can reject the assumption that these flows are stationary ones. In both cases the use of the Box Pierce Test Q shows that some autocorrelation coefficients are likely to be different from zero.



Figure 14: Correlogram of Capital Inflows in Paraguay

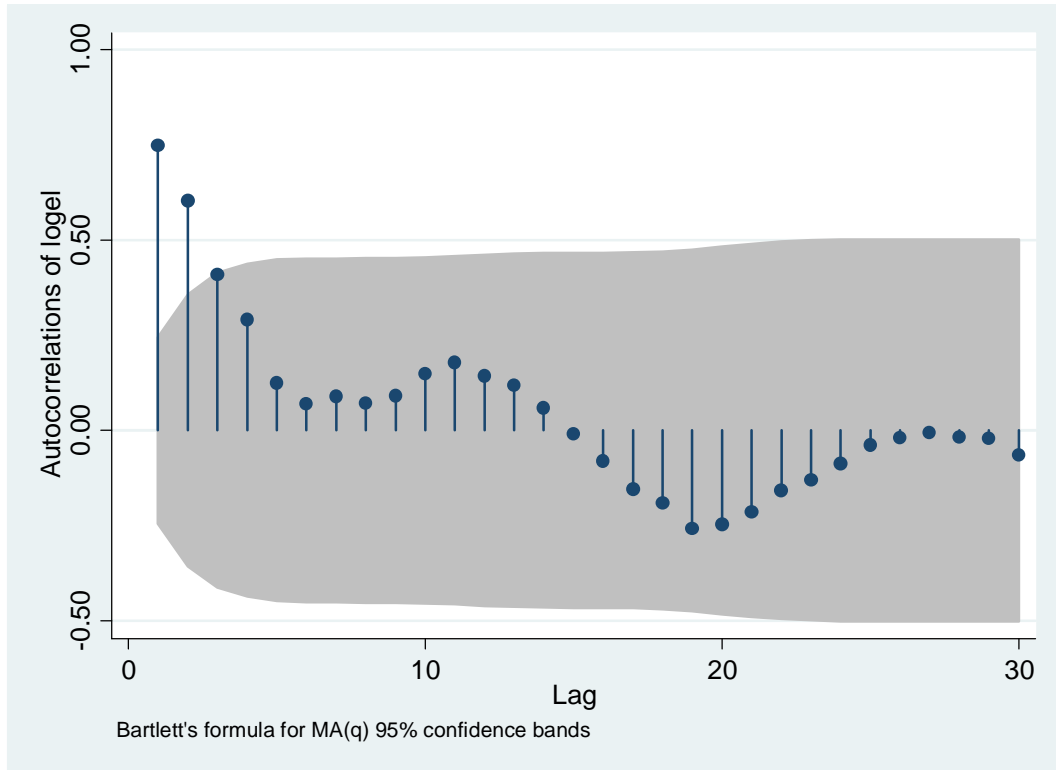
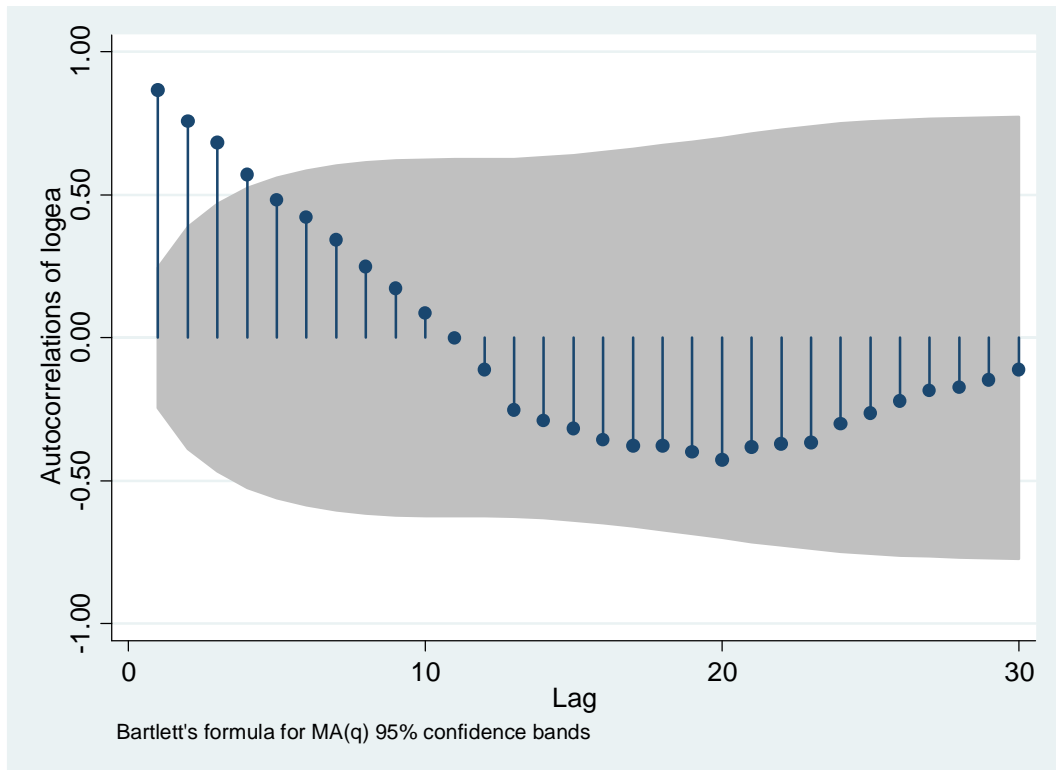


Figure 15: Correlogram of Capital Outflows in Paraguay

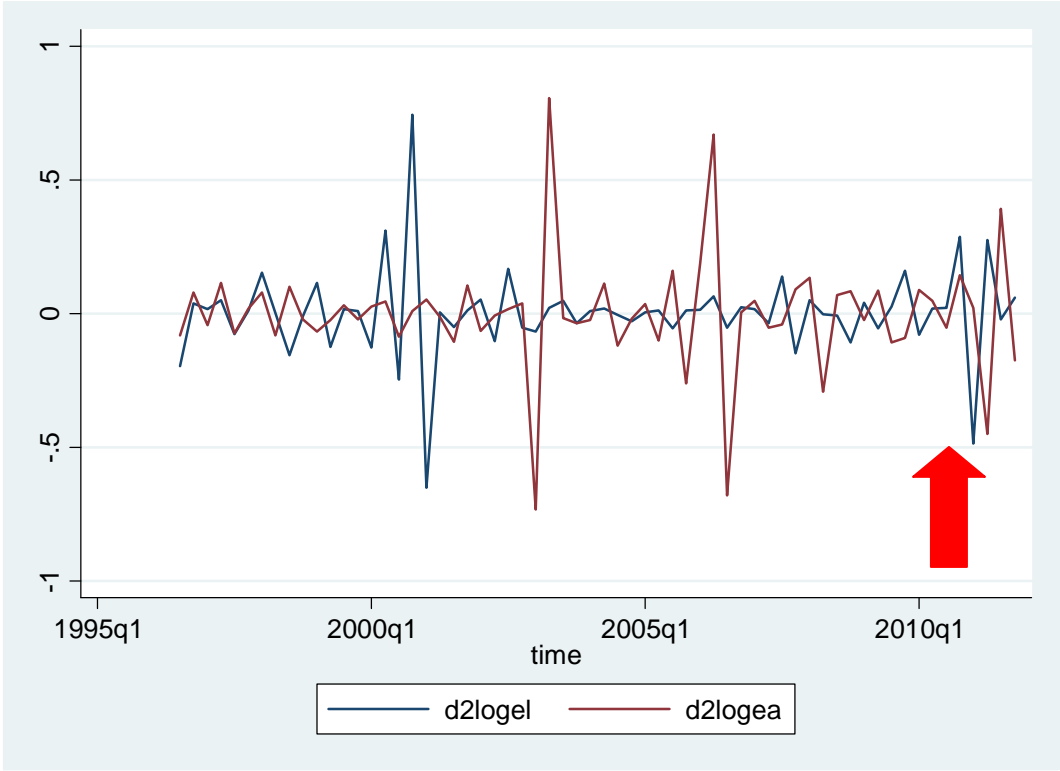


In order to test the robustness of the signal of non stationarity we use the Augmented Dickey-Fuller (ADF) test for unit root, starting with five lags (conventionally four quarters plus one) and the trend component and looking for the specifications that reflect the best fit. With the ADF test the null hypothesis is the presence of a unit root; if the test statistic does not exceed the 5% critical value in absolute terms, the non stationarity assumption cannot be rejected.

After subsequent iterations, for the inflows (Table 43) the test statistic with one lag (2.208) is smaller than the 5% critical value (3.488); therefore we cannot reject the hypothesis of autocorrelation. The same is true for the outflows (Table 44): the test statistic with one lag (1.949) is smaller than the 5% critical value (3.488). The results are confirmed if we eliminated the trend component in testing inflows (Table 45) and outflows (Table 46).

If the rates of growth of the capital flows are non stationary, we wonder if the stationary can be found investigating the acceleration/deceleration (velocity) of these series (second differences). The time evolution of the velocity trends in the capital flows (Figure 16) shows that: a) the capital inflows are more likely to be a stationary series; b) in the blacklisting period (2010-211) still turbulences are present in both flows.

Figure 16: Capital Inflows and Outflows in Paraguay (1996-2011, accelerations of the rates of growth)



The subsequent correlograms of the inflow acceleration (Figure 17) and outflow acceleration (Figure 18) confirm that now we cannot reject the assumption that these flows are stationary ones, particularly if we look at the inflow trend. In both cases the use of the Box Pierce Test Q shows that almost all the autocorrelation coefficients are likely to be equal to zero.

Figure 17: Correlogram of Capital Inflow Acceleration in Paraguay

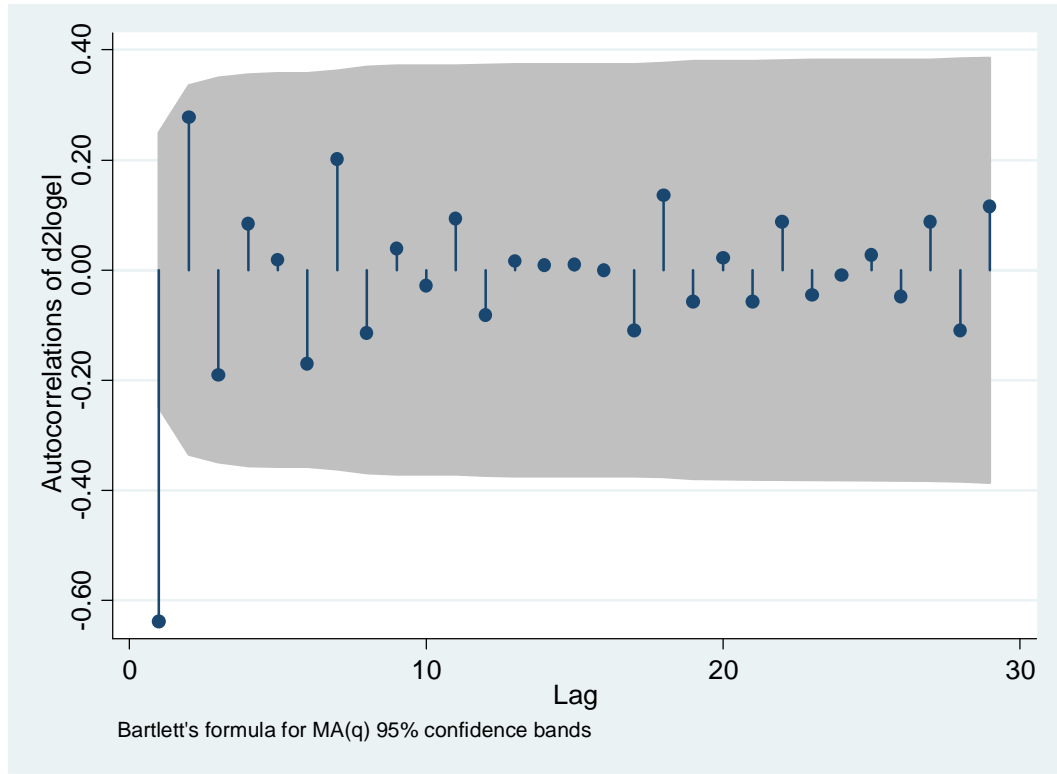
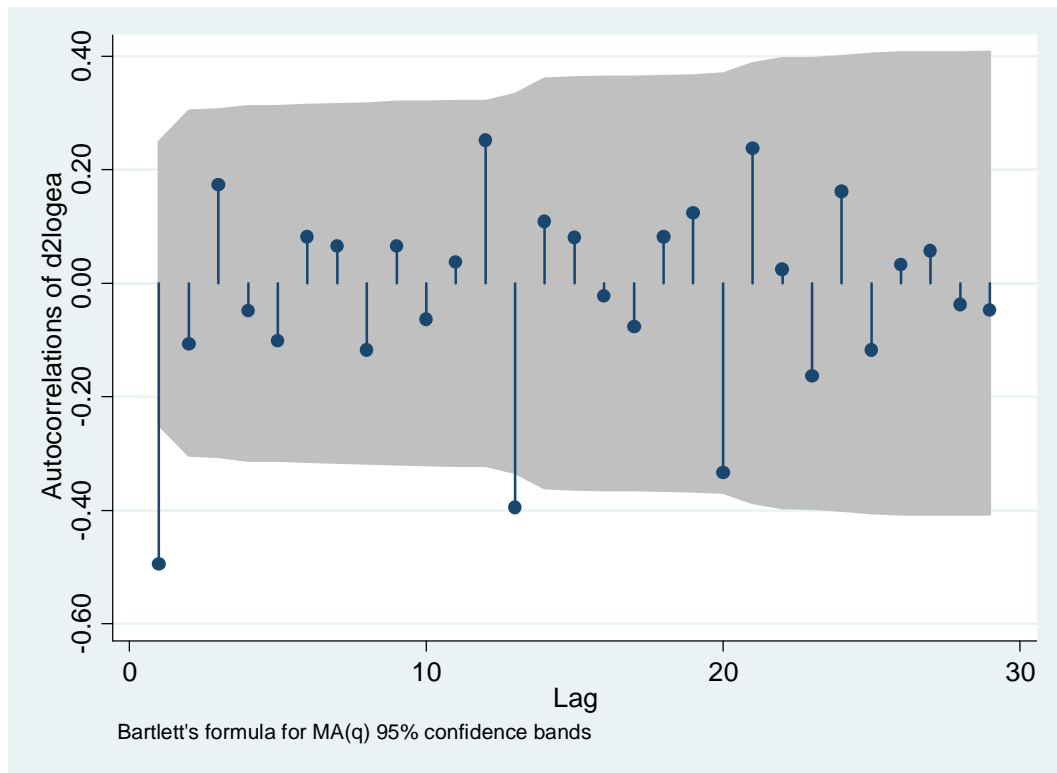


Figure 18: Correlogram of Capital Outflow Acceleration in Paraguay



Therefore in order to test the robustness of the signal of stationarity we use the Augmented Dickey-Fuller (ADF) test, starting again with five lags and the trend component.

For the inflows (Table 47) the test statistic with two lags (6.967) is greater than the 5% critical value(3.491); therefore we can reject the hypothesis of autocorrelation, assuming stationarity. Also for the outflows (Table 48) we obtain stationarity : the test statistic with one lag (10.709) is greater than the 5% critical value (3.490).

The stationary of the velocities of the capital flows means that the regular assumptions of the OLS model hold; we can run the regressions. For the inflows, the specification (24) for the inflow velocity  $d2\log el_t$  is as follows (Table 49) (Wald Test=92.83) :

(24)

$$d2\log el_t = 0.001 - 0.797d2\log el_{t-1}^{***} - 0.233 d2\log el_{t-2}^{***} + \varepsilon_t$$

While for the outflow velocity  $d2\log ea_t$  (Table 50) we have the specification (25) (Wald Test= 70.41)

(25)

$$d2\log ea_t = -0.003 - 0.718d2\log ea_{t-1}^{***} - 0.718d2\log ea_{t-2}^{***} + \varepsilon_t$$

\*\*\* = P<0.01; \*\* = P<0.05; \* = P<0.10

The correlograms of the residuals (Figure 19 and Figure 20) show that for the inflows all the autocorrelation coefficients are likely to be equal to zero, while for the outflows all but one are likely to be zero.

Figure 19: Correlogram of the Residuals in the Capital Inflow Acceleration Estimate

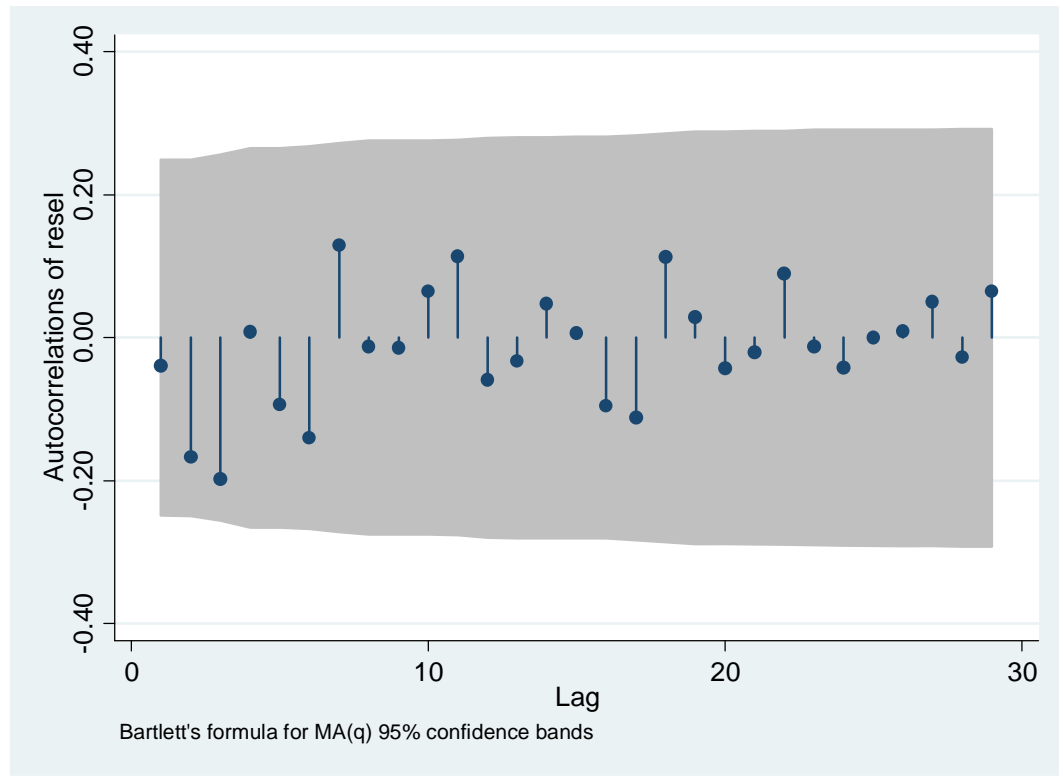
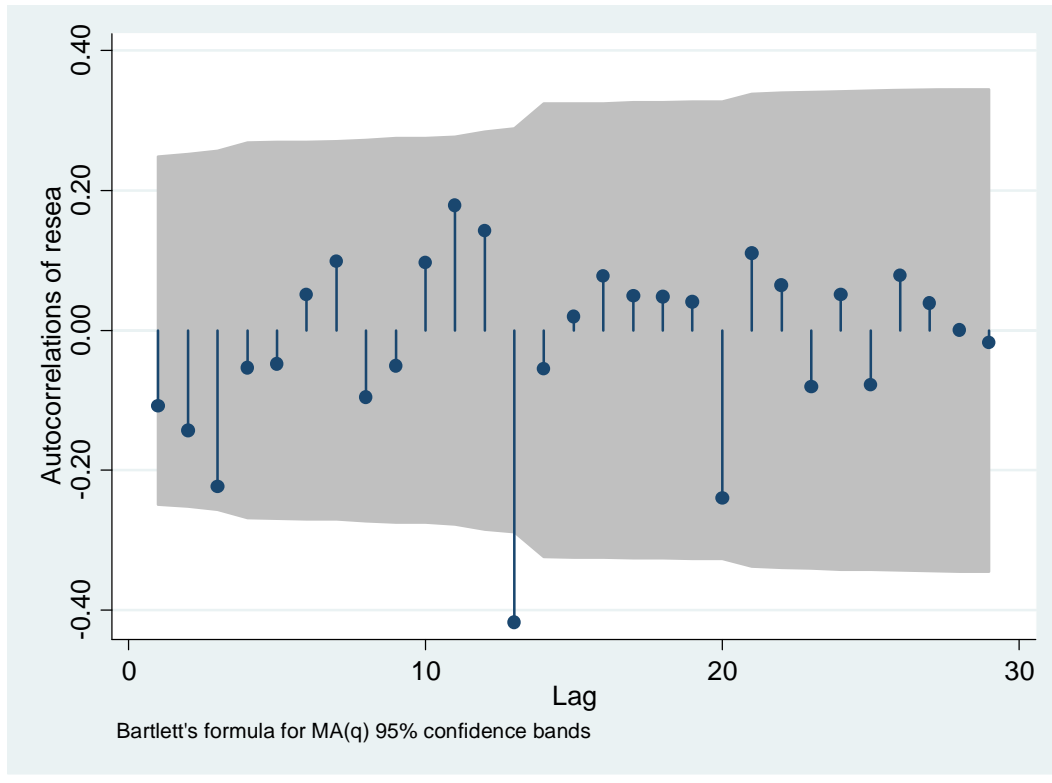


Figure 20: Correlogram of the Residuals in the Capital Outflow Acceleration Estimate



Therefore the international capital flows of Paraguay can be described focusing on their dynamics – velocity – and using an autoregressive process with two lags. Now we can wonder how much of an impact on flows the listing event actually had. As we already noted (Figure 16) the quarterly data after the first 2010 quarter exhibit sensible volatility. We cannot reject *a priori* that the event had any effect on financial flows; a further inspection is needed. Our empirical strategy follows two steps: firstly we wonder if other variables different from the listing event can influence the pattern of the capital flows, increasing the robustness of our specification; secondly we investigate the role – if any - of the listing episode.

A more complete characterization of the international financial flows behaviour would take into account the possible role of the relevant macro variables. On this respect we test the variables used in our restricted baseline specification, obviously with the data availability constraint. On this respect in our quarterly data base some variables are missing and produces collinearity biases: the regulatory lightness factor and all the institutional controls. Therefore we eliminate these variables from our tests.

To test the role of the macro variables we have to avoid to use non stationary series. We differenced the quarterly data to generate stationary series. Using the first differences of the log transformations, the ADF tests (Tables 51-57) show that we can reject the hypothesis of autocorrelation - i.e. stationarity - for the following

variables: banking profitability factor (traditional banking deepening and innovative banking deepening), banking stability, GDP per capita, inflation, real rate of return, effective real exchange rate.

Now we can perform the regressions incorporating time to time each macro variable. Testing the inflows the inclusion of the macro variable produces non significant results (Tables 58 -64). The same is true when the tests are performed using the outflows (Table 65-71).

Therefore we follow to use the specifications (24) and 25) in wondering if the listing episode of Paraguay produces effects on the international capital flows. We explore two different assumptions, using as usual the first differences to obtain stationary series:

a) Announcement Effect : we assume that the capital flow adjustments to changes in listing occurs as reaction to the announcement news. The variable *listingnews* assumes value 1 when the listing is announced – first quarter of 2010 – and zero otherwise.

b) Period Effect : In this case we assume that the capital flow adjustments to changes in listing occurs as reaction to the announcement news and hold up to the delisting announcement. The variable *listingperiod* assumes value 1 during the period of listing and 0 otherwise.

Starting with the announcement effect, we can note that the inclusion of the listing variable is negatively correlated both with the inflows (Table 72) and with the outflows (Table 73), although the coefficients are not significant and the robustness essentially doesn't change. The stigma effect is only lightly detectable.

Regarding the period effect, the inclusion of the listing variable is positively correlated both with the inflows (Table 74) and with the outflows (Table 75), the coefficients are not significant and the robustness essentially the same. The stigma effect is not detectable.

Finally we can perform a robustness check modifying the dependent variable, i.e. instead of using log transformations of the capital flows we build up the first differences of the original variables, which represent their growth. First of all the time evolution of the growth of the capital flows (Figure 21) confirms that: a) the capital inflows are more likely to be a stationary series; b) in the blacklisting period (2010-211) the turbulences are still evident. The correlograms of the inflow growth (Figure 22) and outflow growth (Figure 23) confirm that we cannot reject the assumption that the flows are stationary ones, particularly if we look at the inflow trend. In both cases the use of the Box Pierce Test Q shows that almost all the autocorrelation coefficients are likely to be equal to zero.

Figure 21: Capital Inflows and Outflows in Paraguay (1996-2011, growth)

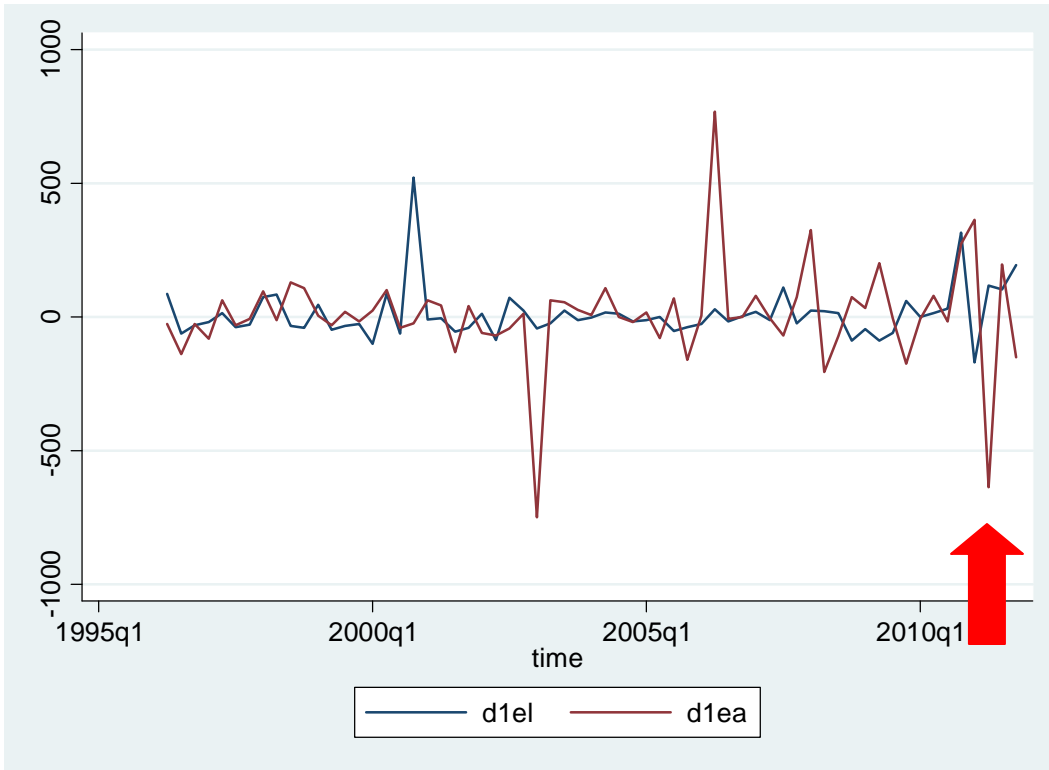


Figure 22: Correlogram of Capital Inflow Growth in Paraguay

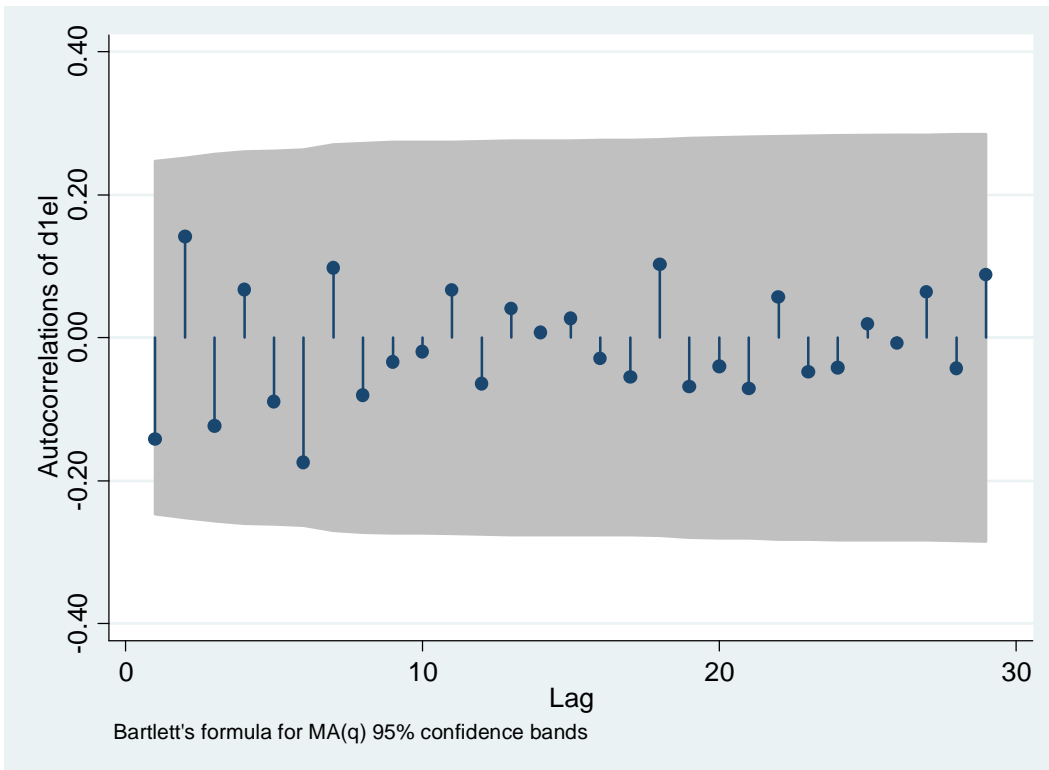
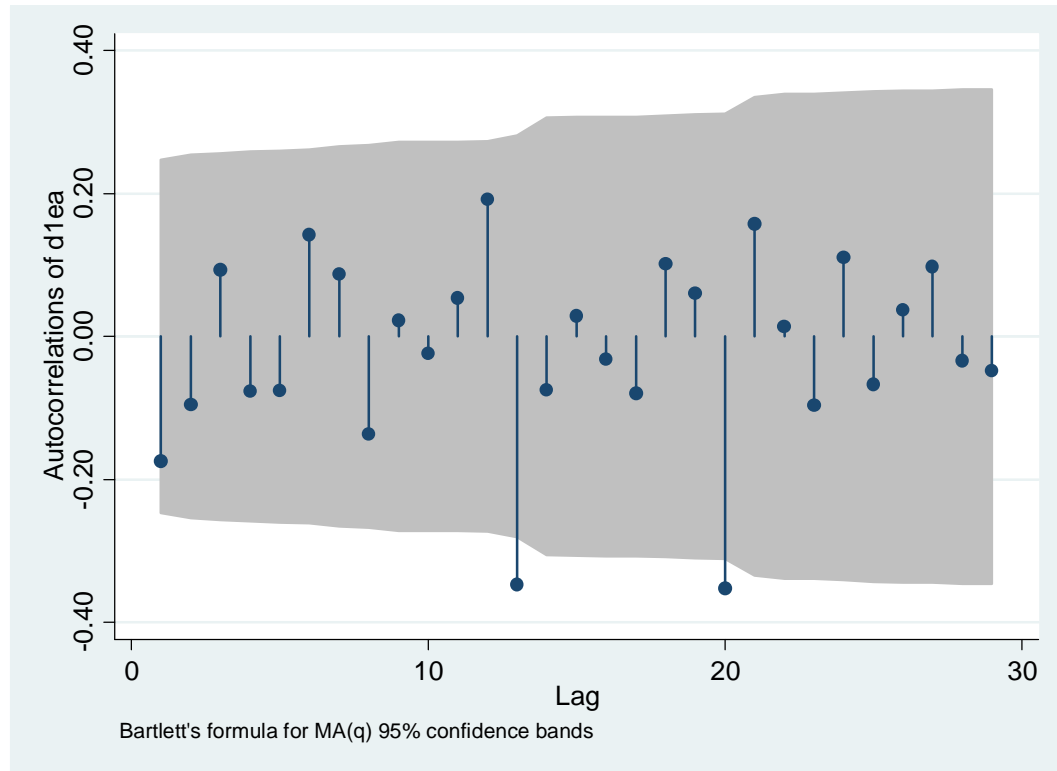




Figure 23: Correlogram of Capital Outflow Growth in Paraguay



We control for the robustness of the stationarity assumption using the ADF test, starting as usual with five lags and the trend component. For the inflows (Table 76) the test statistic with five lags (3.775) is greater than the 5% critical value(3.493); therefore we can reject the hypothesis of autocorrelation, assuming stationarity. Also for the outflows (Table 77) we obtain stationarity : the test statistic with one lag (3.831) is greater than the 5% critical value (3.490).

The stationary of the growth of the capital flows means that the regular assumptions of the OLS model hold; we can run the regressions. For the inflows, the specification (26) using for the inflow growth the first difference  $\delta d1el_t$  is as follows (Table 78) (Wald Test=71.39) :

(26)

$$\delta d1el_t = 1.790 - 0.867d1el_{t-1}^{***} - 0.478 d1el_{t-2}^{***} - 0.280d1el_{t-3}^{***} - \varepsilon_t$$

While for the first difference of the outflow growth  $\delta d1ea_t$  (Table 79) we have the specification (27) (Wald

Test= 46.26

(27)

$$\delta d1ea_t = -1.240 - 0.780d1ea_{t-1}^{***} - 0.509d1ea_{t-2}^{***} + \varepsilon_t$$

\*\*\* = P<0.01; \*\* = P<0.05; \* = P<0.10

The correlograms of the residuals (Figure 24 and Figure 25) show that for the inflows all the autocorrelation coefficients are likely to be equal to zero, while for the outflows all but one are likely to be zero.

Figure 24: Correlogram of the Residuals in the Capital Inflow Growth Estimate

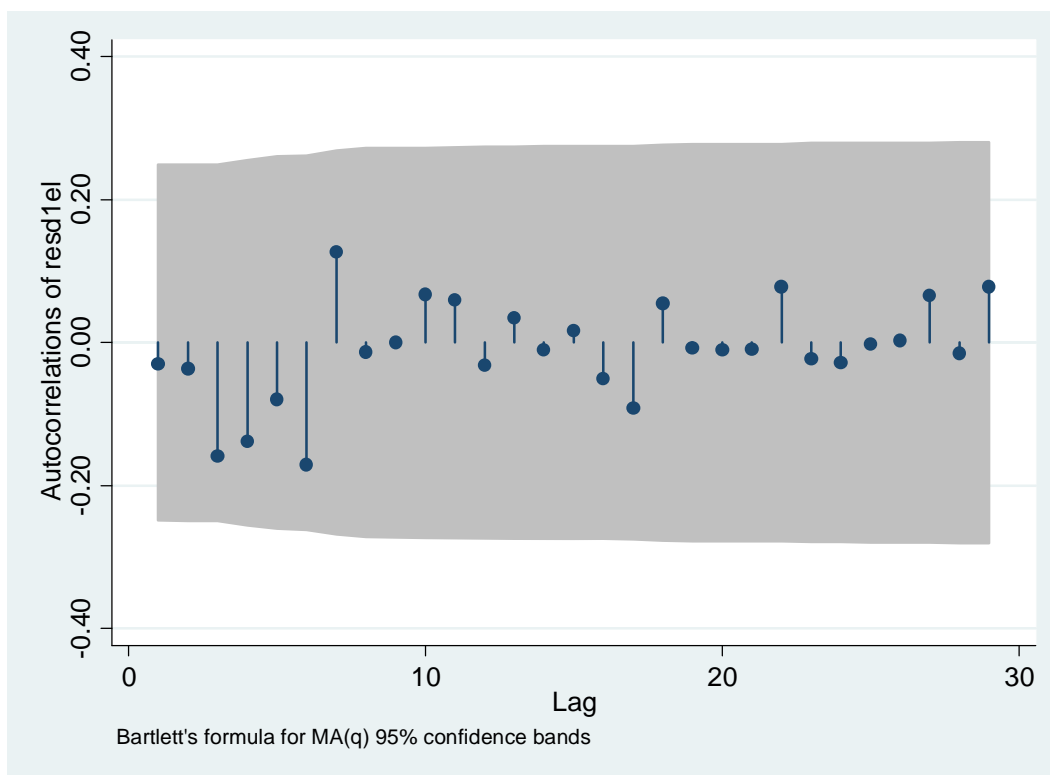
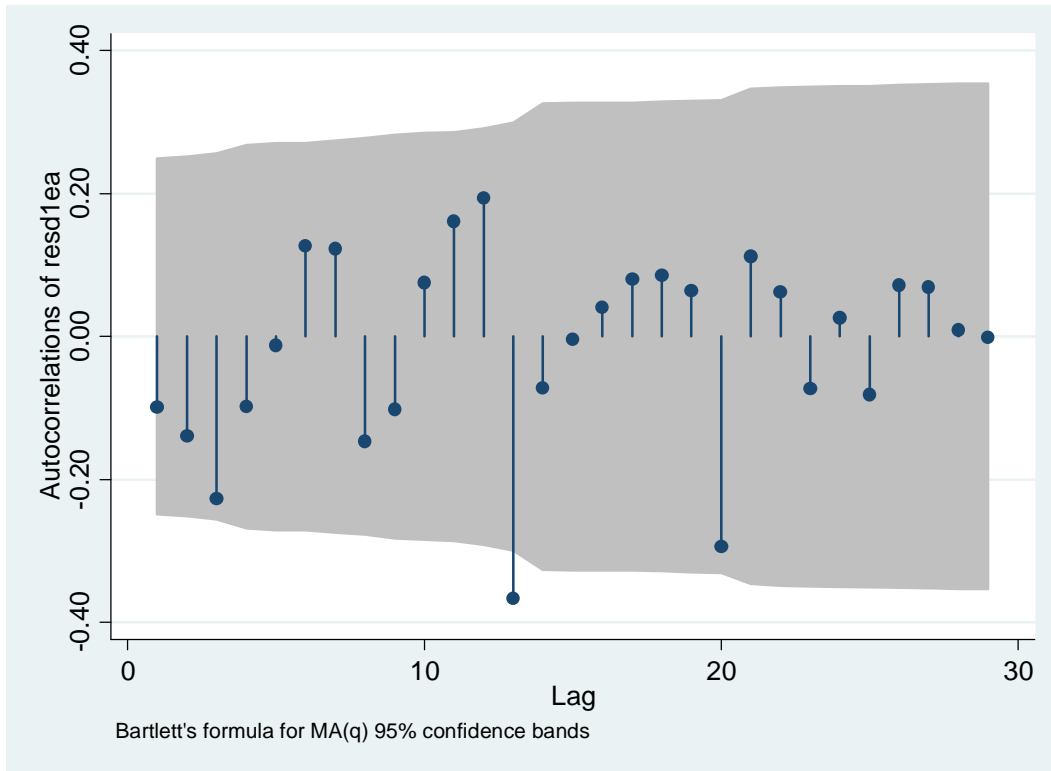


Figure 25: Correlogram of the Residuals in the Capital Outflow Growth Estimate



We can claim that one more description of the international capital flows of Paraguay can be obtained using their growth through an autoregressive process with respectively three (inflows) and two (outflows) lags. Now we can check if the listing event had an impact, exploring again the two different assumptions (announcement effect and period effect).

Starting with the announcement effect (Tables 80 and 81), we show that the inclusion of the listing variable is negatively correlated with the outflows; the coefficients are not significant and the robustness increases. The stigma effect is detectable in the outflows.

Regarding the period effect (Table 82 and 83) we reach the same conclusion: the inclusion of the listing variable is again negatively correlated with the outflows; the coefficients are not significant and the robustness increases.

In conclusion, evidence has been found that the inclusion of Paraguay in the FATF list have had detectable but light effects on the international capital flows of the country. The lack of robustness is unsurprising, for both empirical and theoretical reasons.

On the empirical ground, we acknowledge the limited experience of listing and in general the small size of the data. Further the delisting episode is too recent for collecting the necessary data base. Consequently the power of the econometric analysis in detecting the stigma effect is very low.

On the theoretical ground, the weakness of the stigma effect can depend on the relative perceptions in the international capital markets regarding the costs and benefits in doing business with a listed country. In the theoretical part of the study – Section 2 – we stressed that the stigma effect holds only the expected costs are non linear respect to the shape of the expected benefits.

At the same time, putting all together the empirical results – cross section and time series - and acknowledging their natural limits for predictive reasons, we can claim that the efforts of Paraguay in increasing its compliance with international standards are likely to produce positive effects on its reputation in international financial markets.

We discovered that in general the stigma effect can be relevant: banking flows are likely to be discouraged when a country is listed and vice versa international banking activity is attracted when a country is delisted. The nature of capitals which are more influenced by listing/delisting events is likely to depends on how the markets are efficient: inflows seem to be more sensible when efficiency increases. In the same contest reforms which increase the financial nature of the FIU can produce incremental benefits.

The possibility that the stigma effect can be relevant for Paraguay increases if we take into account three structural country features. On the one hand its financial regulatory setting seems to be increasingly market friendly oriented. Therefore the regulatory lightness factor is likely to hold and the stigma effect relevance increases. On the other hand the Paraguayan banking system is still relatively underdeveloped: more financial deepening would increase the banking profitability factor with its catalytic consequences on the relevance of AML/CFT compliance policy of Paraguay. The same it is likely be true if the growth per capita will increase; it causes a stronger wealth effect with its associated consequences on importance of stigma effect.

## 5. Conclusions

In this study we analyse the relationship between international capital movements and FAFT listing/ delisting events in Latin America during the years from 1996 to 2007. Our aim is to study existence and robustness of the so called stigma effect and apply our empirical results in evaluating the case of Paraguay.

We test if international banking activity responds to the “name and shame” approach, which has been introduced in combating money laundering and terrorism finance. Consequently we wonder if it is possible to detect financial gains for a country in implementing AML/CFT policies consistent with the international standards.

To understand the effects that the FAFT decisions have over listed countries we focus on how banks react to higher potential costs which can emerge or disappear when a country is listed or delisted. In the theoretical analysis the stigma effect emerges if we assume asymmetry between costs and benefits for an international bank in doing business with a country which risks to be listed.

Following the suggestions of our motivating theory and empirically testing it we find that the robustness of the stigma effect - blacklisting factor - can depend on two main conditions, which determine country attractiveness: regulatory architecture – regulatory lightness factor - and economic framework – banking profitability factor and wealth factor. We analyse two different scenarios: perfect and imperfect capital mobility.

In the perfect capital mobility scenario, we find that: 1) blacklisting factor and regulatory lightness factor can be detected and they are significant; 2) the relevance of blacklisting factor depends on international banking inflow movements; 3) wealth effect is significant; 4) banking profitability factor is stronger the more the country shows a deep and traditional banking sector.

In the imperfect capital mobility scenario, blacklisting factor, regulatory lightness factor, banking profitability factor and wealth factor can be still detected and their relevance depends on international banking outflow movements.

Summing up, we can say that the FAFT decisions seem to produce financial effects on the listed/delisted countries and the relevance of these effects is linked to country regulatory and banking features: light touch regulation, traditional and deep banking system and overall dimension of the country increase the robustness of stigma effect. Furthermore also the efficiency of international banking flows - i.e. degree of capital mobility – is relevant: more capital mobility increases the role of banking inflows respect to banking outflows in determining the stigma effect.

These findings can have implications for better understanding the interactions between international capital markets and national policies when the “name and shame” approach in regulation is adopted. If the reasons why breaching or adopting the FAFT standards is not without financial consequences become more clear, the overall policy design to contrast the AML/CFT phenomena is likely to be more effective.

In order to apply our results to evaluate the possible effects of listing/delisting events in the case of Paraguay, we zoom on its peculiar characteristics in terms of international banking flows, blacklisting factor, regulatory lightness factor, banking profitability factor and wealth factor.

First of all the research question is *per se* particularly important for Paraguay. We note that the international banking activity with Paraguay is so far relatively underdeveloped; therefore the country can have strong incentives to know which aspects of the regulatory setting can increase or decrease the attractiveness of Paraguay in international capital markets.

Furthermore addressing costs and benefits of listing/delisting events is not a theoretical issue: Paraguay was included by the FAFT as a jurisdiction with AML/CFT deficiencies and then, after a set of policy actions devoted to reform the AML/CFT architecture, the international organization decide to remove the country from its list.

Our conclusion is strictly linked to available empirical baseline, which automatically defines its limits. With sufficient available data the empirical study could take into account the specific banking flows between source and recipient countries, applying a gravity model (Papaioannou 2009). In the same vein if more robust quarterly data should be available the analysis could try to evaluate directly the effects of the recent listing/delisting events in Paraguay. As time goes by, more observations will become available to evaluate the delisting episode. One more step in future research could be to analyze real cross border flows. Finally it could be interesting to study the relationships between banking costs and/or banking prices - as left hand side variables - and blacklisting factor - as covariate – provided the availability of detailed country banking data.

## 6. References

- Alexander, K. (2001), The International Anti-Money Laundering Regime: The Role of the Financial Action Task Force, *Journal of Money Laundering Control*, vol.4, n.3, 231-248.
- Ardizzi G., Petraglia C., Piacenza M., Schneider F. and Turati G. (2013), Money Laundering as a Financial Sector Crime, CESifo Working Paper Series, n.4127.
- Barth J.R., Caprio J. and R. Levine (2006), *Rethinking Bank Regulation: Till Angels Govern*, Cambridge, Cambridge University Press.
- Brada J.C, Drabek Z. and M.F. Perez (2011), Illicit Money Flows as Motives for FDI, *Journal of Comparative Economics*, (forthcomings).
- Brummel C. (2012), *Soft Law and the Global Financial System: Rule Making in the 21<sup>st</sup> Century*, Cambridge University Press, New York.
- Chitu I., Eichengreen B. and Mehl A.J. (2013), History, Gravity and International Finance, NBER Working Paper Series, National Bureau of Economic Research, n. 18697.
- Clark T.S and D.A Linzer (2012), Should I Use Fixed or Random Effects?, Working Paper Series, Department of Political Science, Emory University, March.
- Dalla Pellegrina L. and D. Masciandaro (2009), The Risk Based Approach in the New European Anti-Money Laundering Legislation: a Law and Economics View, *Review of Law and Economics*, Vol.5(2), 290-317.
- Dalla Pellegrina L. and D. Masciandaro (2012), Good Bye Light Touch? Macroeconomic Resilience, Banking Regulation and Institutions, Working Paper Series, Paolo Baffi Centre, Bocconi University, Milan, n.
- FATF (2012), *International Standard on Combating Money Laundering and the Financing of Terrorism and Proliferation. The FATF Recommendations*, Financial Action Task Force, FATF/OECD, Paris.
- Ferwerda J. (2012), The International Fight Against Money Laundering, in *The Multidisciplinary Economics of Money Laundering*, Chapter 7, Dissertation Series, Tjalling C. Koopmans Institute, School of Economics, Utrecht University, Ridderprint, Ridderkerk, 97-118.
- FinCEN (2011), Guidance to Financial Institutions Based on the FAFT Publication on Anti-Money Laundering and Counter-Terrorist Financing Risks, Financial Crimes Enforcement Network, Department of the Treasury, Washington D.C., July, 13.
- FitzGerald V. (2004), Global Financial Information, Compliance, Incentives and Terrorist Funding, *European Journal of Political Economy*, 20, 387-400.
- Fraga A. (2004.), Latin America since the 1990s: Rising from the Sickbed?, *Journal of Economic Perspectives*, 18(2), 89-106.
- Franks J., Mercer-Blackman V., Sab R. and R. Benelli (2005), *Paraguay. Corruption, Reform and the Financial System*, International Monetary Fund, Washington D.C..

- Greene E.F. and J.L. Boehm (2012), The Limits of “Name- and- Shame” in the International Financial Regulation, *Cornell Law Review*, 97(5), 1083-1140.
- Gnutzmann H., K.J. Mc Carthy , B. Unger (2010), Dancing with the Devil: Country Size and the Incentive to Tolerate Money Laundering, *International Review of Law and Economics*, 30, 244-252.
- Holder, W.E (2003), The International Monetary Fund’s Involvement in Combating Money Laundering and the Financing of Terrorism, *Journal of Money Laundering Control*, vol.6, n.4, 383-387.
- Hampton M.P and J. Christensen (2002), Offshore Pariahs? Small Island Economies, Tax Havens, and the Reconfiguration of Global Finance, *World Development*, 30(6), 1657-1673.
- Houston J.F., Lin C. and Y. Ma (2011), Regulatory Arbitrage and International Bank Flows, *Journal of Finance*, forthcoming.
- IMF (1998), *Money Laundering. The Importance of International Countermeasures*, address by Michel Camdessus, Plenary Meeting of the FATF, International Monetary Fund, Washington D.C., pp. 1-4.
- IMF (2009), Paraguay: Detailed Assessment Report on Anti-Money Laundering and Combating the Financing of Terrorism, *IMF Country Report Series*, International Monetary Fund, Washington D.C., n. 235.
- IMF (2011), Paraguay: Financial System Stability Assessment-Update, *IMF Country Report Series*, International Monetary Fund, Washington D.C., n. 235.
- Kaufmann D., Kraay A. and M. Mastrucci, (2008), Governance Matters VII: Aggregate and Individual Governance Indicators, 1996-2007, *Policy Research Working Paper Series*, World Bank, Washington, DC, n. 4654.
- KPMG, (2011), *Global Anti – Money Laundering Survey*, at kpmg.com.
- Kudrle, R., (2009), Did Blacklisting Hurt the Tax Havens?, *Journal of Money Laundering Control*, Vol. 12 (1), 33-49.
- Lane P. and G.M. Milesi Ferretti (2003), International Financial Integration, *IMF Staff Papers*, International Monetary Fund, 50, 82-113.
- Masciandaro D., (2005a), False and Reluctant Friends? National Money Laundering Regulation, International Compliance and Non-Cooperative Countries, *European Journal of Law and Economics*, 2005, n.20, 17-30.
- Masciandaro D., (2005b), Financial Supervision Unification and Financial Intelligence Units: A Trade Off? *Journal of Money Laundering Control*, Vol. 8(3), 354-370.
- Masciandaro, D., (2008), Offshore Financial Centres: the Political Economy of Regulation, *European Journal of Law and Economics*, Vol. 26, 307-340.
- Masciandaro D, Takats E. and Unger B., (2007), *Black Finance. The Economics of Money Laundering*, Edward Elgar, Cheltenham.
- Masciandaro D., Pansini R.V. and M. Quintyn (2012), The Economic Crisis: Did Supervisory Architecture and Governance Matter, *Journal of Financial Stability*, forthcoming.
- Milesi Ferretti G.M and Tille C., (2011), The Great Retrenchment: International Capital Flow During the Global Financial Crisis, *Working Paper Series*, Hong Kong Institute for Monetary Research, n.38.



- Papaioannou E. (2009), What Drives International Financial Flows? Politics, Institutions and Other Determinants, *Journal of Development Economics*, 88, 269-281.
- Picard P.M and P. Pieretti (2011), Bank Secrecy, Illicit Money and Offshore Financial Centres, *Journal of Public Economics*, 95 (7-8), 942-955.
- Powell J.H. (2013), Anti-Money Laundering and the Banking Secrecy Act, Board of Governors of the Federal Reserve System, Committee on Banking, Housing and Urban Affairs, U.S. Senate, Washington D.C., March 7. mimeo.
- Qureshi M.S., Ostry J.D., Ghosh A.R. and M. Chamon (2011), Managing Capital Inflows: The Role of Capital Controls and Prudential Policies, *Working Paper Series*, NBER, n.17363.
- Ramon – Ballester F. and T. Wezel (2007), International Financial Linkages of Latin American Banks. The Effects of Political Risks and Deposit Dollarization, *ECB Working Paper Series*, European Central Bank, n.744.
- Reinhardt D., Ricci L.A. and T. Tressel (2010), International Capital Flows and Development: Financial Openness Matter, *IMF Working Paper Series*, International Monetary Fund, n.235.
- Roodman (2006), Ho to Do Xtabond2: An Introduction to Difference and System GMM in Stata, Working Paper Series, Center for Global Development, n.13.
- Rose A.K. and M. Spiegel (2006), Offshore Financial Centers: Parasites or Symbionts?, *Economic Journal*, 117(523), 1310-1335.
- Schwarz P. (2011), Money Launderers and Tax Havens: Two Sides of the Same Coin?, *International Review of Law and Economics*, 31, 37 – 47.
- Takàtz E. (2011), A Theory of “Crying Wolf”: The Economics of Money Laundering Enforcement, *Journal of Law, Economics and Organization*, 27(1), 32-78.
- Unger B. and Rawlings G. (2008), Competing for Criminal Money, *Global Business and Economics Review*, 10(3), 331-352.
- Verdugo Yepes C. (2011), Compliance with the AML/CFT International Standard: Lessons from a Cross-Country Analysis, *IMF Working Paper Seris*, International Monetary Fund, n.177.
- World Bank (2008), Bank Regulation and Supervision Survey, World Bank Group, Washington D.C:

## 7. Tables

Table 1: List of Countries

### **Countries**

Argentina  
Aruba  
Bahamas  
Barbados  
Belize  
Bermuda  
Bolivia  
Brazil  
Cayman Islands  
Chile  
Colombia  
Costa Rica  
Cuba  
Dominica  
Dominican Republic  
Ecuador  
El Salvador  
Grenada  
Guatemala  
Guyana  
Haiti  
Honduras  
Jamaica  
Mexico  
Nicaragua  
Panama  
Paraguay  
Perù  
St. Lucia  
St. Vincent and the Grenadines  
Surinam  
Trinidad and Tobago  
Uruguay  
Venezuela  
Latin America Average

Table 2: Financial Intelligence Unit Models

Country	FIU	Model	Financial Nature
Argentine	Unidad de Información Financiera (UIF)	Judicial	No
Aruba	Meldpunt Ongebruikelijke Transacties - Ministerie van Financiën (MOT)	Administrative	Yes
Bahamas	Financial Intelligence Unit (FIU)	Administrative	Yes
Barbados	Financial Intelligence Unit (FIU)	Administrative	Yes
Belize	Financial Intelligence Unit (FIU)	Hybrid	No
Bermuda	Financial Intelligence Agency (FIA)	Administrative	No
	Financial Investigations Unit of the Bermuda Police Force.	Law Enforcement	No
Bolivia	Unidad de Investigaciones Financieras (UIF)	Administrative	Yes
Brazil	Conselho de Controle de Atividades Financeira (COAF)	Administrative	Yes
Cayman Islands	Financial Reporting Authority (CAYFIN or FRA)	Administrative	Yes
	Financial Reporting Unit (FRU)	Hybrid	No
	Financial Investigation Unit (FIU)	Law Enforcement	No
Chile	Unidad de Análisis Financiero (UAF)	Administrative	Yes
Colombia	Unidad de Información y Análisis Financiero (UIAF)	Administrative	No
Costa Rica	Unidad de Análisis Financiero (UAF)	Administrative	No
Cuba	No FIUs		
Dominica	Financial Intelligence Unit (FIU)	Administrative	Yes
Dominican Republic	Unidad de Análisis Financiero (UAF)	Administrative	No information
Ecuador	Financial Intelligence Unit (FIU)	Administrative	Yes
El Salvador	Unidad de Investigación Financiera (UIF)	Hybrid	No

Grenada	Financial Intelligence Unit (FIU)	Administrative	No
Guatemala	Intendencia de Verificación Especial (IVE)	Administrative	Yes
Guyana	Financial Intelligence Unit (FIU)	Administrative	Yes
Haiti	Unité Central de Renseignement Financier (Ucref)	Law Enforcement	No
Honduras	Unidad de Informacion Financiera (UIF)	Administrative	Yes
Jamaica	Financial Investigation Division (FID)	Hybrid	Yes
Mexico	Unidad de Inteligencia Financiera (UIF)	Administrative	Yes
Nicaragua	Comisión de Análisis Financiero (CAF)	Administrative	Yes
Panama	Unidad de Analisis Financiero (UAF)	Administrative	Yes
Paraguay	Secretaria de Prevención de Lavado de Dinero o Bienes (SEPRELAD)	Hybrid	Yes
Perù	Unidad de Inteligencia Financiera del Peru (UIF)	Administrative	Yes
St. Lucia	Financial Intelligence Agency (FIA)	Administrative	No
St. Vincent and the Grenadines	Financial Intelligence Unit (FIU)	Hybrid	Yes
Surinam	“Meldpunt Ongebruikelijke Transacties” (MOT)	Administrative	No
Trinidad and Tobago	Financial Intelligence Unit (FIU)	Administrative	Yes
Uruguay	Unidad de Información y Análisis Financiero (UIAF)	Administrative	Yes
Venezuela	Unidad Nacional de Inteligencia Financiera (UNIF)	Administrative	Yes

Table 3: Descriptive Statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
etflows	overall	83770.79	337621.5	49	3787978	N = 408
	between		292843.4	1.249.167	1681531	n = 34
	within		174782	-1014068	2190218	T = 12
fatflist	overall	0.085784	0.280389	0	1	N = 408
	between		0.151432	0	0.5	n = 34
	within		0.23729	-0.4142157	1.002.451	T = 12
finrepr	overall	0.826241	0.379576	0	1	N = 282
	between		0.254124	0	1	n = 29
	within		0.295612	0.0762411	1.409.574	T-bar = 9.72414
finfiu	overall	0.365196	0.482076	0	1	N = 408
	between		0.346953	0	1	n = 34
	within		0.339521	-0.5514706	1.198.529	T = 12
bankdeep	overall	3.735.362	2.043.455	7.266.263	1.084.113	N = 369
	between		1.947.839	1.107.055	8.044.131	n = 31
	within		6.879.507	1.703.382	6.666.386	T-bar = 11.9032
innobank	overall	4.042.736	3.024.126	-7.518.235	2.346.585	N = 336
	between		2.282.298	0.0541637	1.191.411	n = 31
	within		1.914.119	-5.940.549	1.559.447	T-bar = 10.8387
gdppc	overall	8.170.431	0.971599	5.940.642	1.112.069	N = 391
	between		0.99326	599.971	1.097.633	n = 33
	within		0.100888	7.812.635	8.528.919	T = 11.8485
inflation	overall	7.713.459	1.019.683	-1.268.887	9.877.309	N = 345
	between		6.057.932	1.994.203	2.613.992	n = 29
	within		8.254.871	-1.434.618	8.034.663	T-bar = 11.8966
Deflator	overall	8.075.104	1.024.636	-2.347.888	1.032.144	N = 391
	between		6.243.862	1.036.423	2.961.965	n = 33
	within		8.183.303	-2.144.037	8.166.985	T = 11.8485
Rir	overall	1.106.015	1.365.583	-373.445	9.391.508	N = 358
	between		9.743.203	-2.210.433	4.994.503	n = 31
	within		9.535.554	-2.709.584	7.524.323	T = 11.5484
Reer	overall	1.050.246	1.248.606	67.74	1.562.825	N = 254
	between		6.295.739	9.226.499	1.222.914	n = 34
	within		1.017.001	7.712.237	1.433.027	T = 7.47059
Voice	overall	0.314985	0.697898	-1.89	1.57	N = 335
	between		0.687933	-1.736	1.241	n = 34
	within		0.160762	-0.2700149	0.775985	T-bar = 9.85294

noviolence	overall	-0.01436	0.7842	-2.38	1.42	N = 335
	between		0.776181	-1.896	1.3	n = 34
	within		0.212624	-0.7053582	0.568642	T-bar = 9.85294
goveff	overall	0.020661	0.726485	-1.68	1.96	N = 333
	between		0.722314	-1.42	1.525	n = 34
	within		0.17781	-0.5693394	0.650661	T-bar = 9.79412
regqua	overall	0.135255	0.732127	-1.62	1.64	N = 333
	between		0.705692	-1.441	1.47	n = 34
	within		0.221268	-0.5367448	1.104.255	T-bar = 9.79412
rulelaw	overall	-0.13101	0.824288	-1.91	1.49	N = 335
	between		0.825222	-1.636	1.277	n = 34
	within		0.14809	-0.5390149	0.415985	T-bar = 9.85294
Nocorruption	overall	0.017598	0.812936	-1.82	1.55	N = 333
	between		0.810292	-1.411	1.413	n = 34
	within		0.182218	-0.5157357	1.001.598	T-bar = 9.79412
polity2	overall	6.954.861	3.547.789	-7	10	N = 288
	between		3.438.379	-7	10	n = 24
	within		1.103.395	1.288.194	1.178.819	T = 12
Durable	overall	2.107.639	1.868.446	0	89	N = 288
	between		1.869.887	1.333.333	83.5	n = 24
	within		3.586.415	1.332.639	3.332.639	T = 12

Table 4: Sources

<b>DEPENDENT VARIABLES</b>		<b>DEFINITION AND INFORMATION</b>	<b>SOURCE</b>
Total External Flows (all_sector) ( <b>ETFLOWS</b> )		Asset positions (see below) + Liability positions (see below)	
External Assets (all_sector)		Asset positions vis-à-vis banks and non-banks located in a country other than the country of residence of the reporting banking office.	Bank for International Settlements (BIS) Locational banking statistics
External Liabilities (all_sector)		Liability positions vis-à-vis banks and non-banks located in a country other than the country of residence of the reporting banking office.	Bank for International Settlements (BIS) Locational banking statistics
External Assets (non bank_sector)		Asset positions vis-à-vis non-banks located in a country other than the country of residence of the reporting banking office.	Bank for International Settlements (BIS) Locational banking statistics
External Liabilities (non bank_sector)		Liability positions vis-à-vis non-banks located in a country other than the country of residence of the reporting banking office.	Bank for International Settlements (BIS) Locational banking statistics
External Deposits (all_sector)		Special types of deposit, classified in the category "loans and deposits". They are foreign trade-related credits/debts and deposits received and made on a trust basis. Based on banks and non banks data.	Bank for International Settlements (BIS) Locational banking statistics
External Loans (all_sector)		Special types of loans, classified in the category "loans and deposits". They are foreign trade-related credits/debts and international loans received and granted on a trust basis. Based on banks and non banks data.	Bank for International Settlements (BIS) Locational banking statistics
External Deposits (non bank_sector)		Special types of deposit, classified in the category "loans and deposits". They are foreign trade-related credits/debts and deposits received and made on a trust basis. Based on non banks data.	Bank for International Settlements (BIS) Locational banking statistics
External Loans (non bank_sector)		Special types of loans, classified in the category "loans and deposits". They are foreign trade-related credits/debts and international loans received and granted on a trust basis. Based on non banks data.	Bank for International Settlements (BIS) Locational banking statistics
<b>INDEPENDENT VARIABLES</b>	<b>TOPIC</b>	<b>DEFINITION AND INFORMATION</b>	<b>SOURCE</b>
Log GDP per Capita ( <b>GDPPC</b> )	Macroeconomics	The natural logarithm of the GDP per capita. GDP per capita is gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are based on constant 2000 U.S. dollars.	World Bank national accounts data, and OECD National Accounts data files.

FATF BlackList ( <b>FAFTLIST</b> )	FATF Policy	FATF BlackList is a Dummy variable that takes the value of 1 if the Country was blacklisted or monitored during the study period, 0 otherwise.	FATF Annual and Overall Reviews of Non-Cooperative Countries or Territories; FATF web site.
Overall Activities Restrictions Index ( <b>FINREPR</b> )	Bank Regulation	Overall Activities Restrictions Index is a Dummy variable that takes the value of 1 if the banks of the countries are subject to some restrictions in their operations, 0 if they are totally free in their investment choices. The index is built starting from an indicator that can take the values of 0, 1, 2 or 3. This indicator is the sum of 3 dummy variables based on the answers contained in the "Banking Regulation Survey" of Barth et al. to the question on the extent to which banks may engage in (a) underwriting, brokering and dealing in securities, and all aspects of the mutual fund industry, (b) insurance underwriting and selling, and (c) real estate investment, development, and management. For each question, the variables takes the value of 1 if the answer is "restricted" or "prohibited" and 0 if the answer is "permitted" or "unrestricted". The Overall Activities Restrictions Index is equal to 0 if the indicator is equal to 0, 1 otherwise. It's a dummy variable that takes the value of 1 if a Financial Intelligence Unit exist and it has a financial nature (i.e. is under an authority or an entity involved in financial markets), 0 otherwise.	Barth J.R., Caprio G. Jr., Levine R. "Banking Regulation Survey" 2000, for data from 1996 to 1999; Barth J.R., Caprio G. Jr., Levine R. "Banking Regulation Survey" 2003, for data from 2000 to 2003; Barth J.R., Caprio G. Jr., Levine R. "Banking Regulation Survey" 2007, for data from 2004 to 2008.
FIU Financial model ( <b>FINFIU</b> )	AML/CFT Regulation		Information taken from the FIUs' web site
Bank Private Credit to GDP (%) ( <b>BANKDEEP</b> )	Financial Institutions Depth (size)	The financial resources provided to the private sector by domestic money banks as a share of GDP. Domestic money banks comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits.	International Financial Statistics (IFS) - International Monetary Fund (IMF)
Net Interest Marginal (%) ( <b>INNOBANK</b> )	Financial Institutions Depth (revenue)	Bank's income that has been generated by non-interest related activities as a percentage of total income (net-interest income plus non-interest income). Non-interest related income includes net gains on trading and derivatives, net gains on other securities, net fees and commissions and other operating income.	Bankscope
<b>MACRO CONTROL VARIABLES</b>	<b>TOPIC</b>	<b>DEFINITION AND INFORMATION</b>	<b>SOURCE</b>



GDP (current USD)	Macroeconomics	GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in current U.S. dollars. Dollar figures for GDP are converted from domestic currencies using single year official exchange rates. For a few countries where the official exchange rate does not reflect the rate effectively applied to actual foreign exchange transactions, an alternative conversion factor is used.	World Bank national accounts data, and OECD National Accounts data files.
Growth of GDP (annual %)	Macroeconomics	Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2000 U.S. dollars. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources.	World Bank national accounts data, and OECD National Accounts data files.
Real Interest rate (%) (RIR)	Macroeconomics	Real interest rate is the lending interest rate adjusted for inflation as measured by the GDP deflator.	World Bank
Real Effective Exchange Rate (REER)	Macroeconomics	The effective exchange rate is a weighted average of a basket of foreign currencies, and it can be viewed as an overall measure of the country's external competitiveness. The real effective exchange rate is the nominal effective exchange rate divided by a price deflator (they use the CPI). Index 2005 =100.	IFS, IMF data.
Inflation, consumer prices (annual %) (INFLATION)	Macroeconomics	Inflation as measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services.	World Bank
Inflation, GDP deflator (annual %)+A15	Macroeconomics	Inflation as measured by the annual growth rate of the GDP implicit deflator shows the rate of price change in the economy as a whole. The GDP implicit deflator is the ratio of GDP in current local currency to GDP in constant local currency.	World Bank
Bank Z Score	Banking Stability	It captures the probability of default of a country's banking system, calculated as a	Bankscope

INSTITUTIONAL CONTROL VARIABLES	TOPIC	DEFINITION AND INFORMATION	SOURCE
Voice and Accountability (VOICE)	Public Governance	<p>weighted average of the z-scores of a country's individual banks (the weights are based on the individual banks' total assets). Z-score compares a bank's buffers (capitalization and returns) with the volatility of those returns.</p> <p>It reflects perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media. It reflects perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including politically-motivated violence and terrorism.</p>	The Worldwide Governance Indicators, Kaufmann et al. 2008, World Bank.
Political Stability and Absence of Violence (NOVIOLENCE)	Public Governance	<p>It reflects perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.</p>	The Worldwide Governance Indicators, Kaufmann et al. 2008, World Bank.
Government Effectiveness (GOVEEFF)	Public Governance	<p>It reflects perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.</p>	The Worldwide Governance Indicators, Kaufmann et al. 2008, World Bank.
Regulatory Quality (REGQUA)	Public Governance	<p>It reflects perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.</p>	The Worldwide Governance Indicators, Kaufmann et al. 2008, World Bank.
Rule of Law (RULELAW)	Public Governance	<p>It reflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.</p>	The Worldwide Governance Indicators, Kaufmann et al. 2008, World Bank.
Control of Corruption (NOCORRUPTION)	Public Governance	<p>This variable is indicator of political quality. It is a modified version of the POLITY variable added in order to facilitate the use of the POLITY regime measure in time-series analyses. It modifies the combined annual POLITY score by applying a simple treatment to convert instances of "standardized authority scores" (i.e., -66, -77, and -88) to conventional polity scores (i.e., within the range, -10 to +10). The Polity score is computed by</p>	The Worldwide Governance Indicators, Kaufmann et al. 2008, World Bank.
Polity 2 (POLITY2)	Political Control		Polity IV Project, University of Maryland

subtracting the Autocracy score from the Democracy score.

Durable (**DURABLE**)

Political Control

This variable indicates the number of years since the most recent regime change. It is an indicator of political stability

Polity IV Project, University of Maryland

Table 5

Linear regression

Number of obs = 99  
 F( 17, 80) = .  
 Prob > F = .  
 R-squared = 0.7772  
 Root MSE = 28815

etflows	Robust					[95% Conf. Interval]	
	Coef.	Std. Err.	t	P> t			
fatflist	-110328.1	34000.53	-3.24	0.002	-177991.3	-42664.9	
finrepr	-68286.72	14163.36	-4.82	0.000	-96472.7	-40100.73	
finfiu	13820.29	12530.6	1.10	0.273	-11116.39	38756.98	
gdppc	28325.42	11460.28	2.47	0.016	5518.742	51132.1	
bankdeep	171.3229	549.1725	0.31	0.756	-921.5652	1264.211	
innobank	1505.897	2752.262	0.55	0.586	-3971.279	6983.073	
voice	-27744.66	23277.55	-1.19	0.237	-74068.46	18579.14	
noviolence	30222.18	8064.288	3.75	0.000	14173.74	46270.63	
goveff	61935.1	19757.23	3.13	0.002	22616.95	101253.2	
regqua	15484.73	16945.65	0.91	0.364	-18238.19	49207.65	
rulelaw	-106388.5	20091.32	-5.30	0.000	-146371.5	-66405.52	
nocorruption	36895.31	10741.94	3.43	0.001	15518.18	58272.44	
polity2	-15286.75	6801.747	-2.25	0.027	-28822.66	-1750.844	
durable	46.72284	262.3109	0.18	0.859	-475.2926	568.7383	
inflation	102.2682	289.5379	0.35	0.725	-473.9306	678.467	
rir	1324.03	222.8881	5.94	0.000	880.4687	1767.591	
reer	681.7116	458.3228	1.49	0.141	-230.3798	1593.803	
bankz	1461.801	608.0962	2.40	0.019	251.6516	2671.951	
_cons	-133961	100578.5	-1.33	0.187	-334118.7	66196.6	

**Table 6**

```

Fixed-effects (within) regression      Number of obs   =    226
Group variable: country                Number of groups =    25

R-sq:  within = 0.2647                  Obs per group:  min =     2
      between = 0.0537                                avg   =    9.0
      overall  = 0.1525                                max   =   12

corr(u_i, Xb) = -0.3924                  F(6,24)         =    4.23
                                          Prob > F         =    0.0048

```

(Std. Err. adjusted for 25 clusters in country)

etflows	Robust					
	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
fatflist	-10082.56	4317.999	-2.34	0.028	-18994.47	-1170.647
finrepr	-10792.23	3400.594	-3.17	0.004	-17810.71	-3773.745
finfiu	1440.425	3800.203	0.38	0.708	-6402.808	9283.659
gdppc	45621.65	23066.44	1.98	0.060	-1985.143	93228.44
bankdeep	382.5425	186.5491	2.05	0.051	-2.475857	767.5609
innobank	-975.5142	630.0794	-1.55	0.135	-2275.934	324.9058
_cons	-334888.1	180267.4	-1.86	0.076	-706941.8	37165.61
sigma_u	49368.836					
sigma_e	10045.18					
rho	.960245	(fraction of variance due to u_i)				

Table 7

	voice	noviol-e	goveff	regqua	rulelaw	nocorr-n	polity2	durable
voice	1.0000							
noviolence	0.5312	1.0000						
goveff	0.7070	0.6066	1.0000					
regqua	0.7624	0.3940	0.8011	1.0000				
rulelaw	0.7846	0.7151	0.8901	0.7896	1.0000			
nocorruption	0.5168	0.6797	0.8351	0.5787	0.8590	1.0000		
polity2	0.7989	0.1136	0.3571	0.6421	0.4410	0.0991	1.0000	
durable	0.1665	0.2203	0.2758	0.1187	0.2849	0.3180	0.0193	1.0000

Table 8

	inflat-n	rir	reer	bankz
inflation	1.0000			
rir	0.1393	1.0000		
reer	-0.3097	0.2345	1.0000	
bankz	-0.0545	-0.1985	-0.2360	1.0000

Table 9

```

Fixed-effects (within) regression      Number of obs   =    99
Group variable: country                Number of groups =    18

R-sq:  within = 0.5454                  Obs per group:  min =    1
      between = 0.0129                    avg =    5.5
      overall = 0.0587                    max =   10

corr(u_i, Xb) = -0.7006                 F(11,17)        =    .
                                           Prob > F         =    .

```

(Std. Err. adjusted for 18 clusters in country)

etflows	Robust					
	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
fatflist	-20378.77	8096.294	-2.52	0.022	-37460.46	-3297.083
finrepr	-14385.64	3616.403	-3.98	0.001	-22015.58	-6755.692
finfiu	1314.92	4241.057	0.31	0.760	-7632.928	10262.77
gdppc	1280.278	32726.67	0.04	0.969	-67766.95	70327.51
bankdeep	412.7032	284.9894	1.45	0.166	-188.5719	1013.978
innobank	-2826.906	1432.832	-1.97	0.065	-5849.917	196.1052
voice	-8470.482	9547.018	-0.89	0.387	-28612.93	11671.97
noviolence	252.6655	5093.218	0.05	0.961	-10493.09	10998.42
goveff	-1717.567	7997.762	-0.21	0.833	-18591.37	15156.24
regqua	1226.033	9397.392	0.13	0.898	-18600.73	21052.8
rulelaw	-1065.954	18819.99	-0.06	0.955	-40772.66	38640.76
nocorruption	11072.72	9328.231	1.19	0.252	-8608.131	30753.56
polity2	-558.3559	2836.458	-0.20	0.846	-6542.76	5426.048
durable	1747.316	1041.126	1.68	0.112	-449.2686	3943.9
inflation	8.6351	110.6992	0.08	0.939	-224.9198	242.19
rir	-74.37356	108.0154	-0.69	0.500	-302.2662	153.5191
reer	438.3325	107.6519	4.07	0.001	211.2068	665.4583
bankz	-839.6844	729.6989	-1.15	0.266	-2379.215	699.8457
_cons	-30754.39	217315.8	-0.14	0.889	-489250.7	427741.9

—more—

Table 10

```

Random-effects GLS regression           Number of obs   =    99
Group variable: country                 Number of groups =    18

R-sq:  within = 0.0637                   Obs per group: min =    1
      between = 0.6933                               avg   =    5.5
      overall = 0.7772                               max   =   10

                                           Wald chi2(17)    =    .
corr(u_i, X) = 0 (assumed)               Prob > chi2     =    .

```

(Std. Err. adjusted for 18 clusters in country)

etflows	Robust					[95% Conf. Interval]	
	Coef.	Std. Err.	z	P> z			
fatflist	-110328.1	53905.05	-2.05	0.041	-215980.1	-4676.173	
finrepr	-68286.72	20654.93	-3.31	0.001	-108769.6	-27803.8	
finfiu	13820.29	16329.43	0.85	0.397	-18184.8	45825.38	
gdppc	28325.42	14867.1	1.91	0.057	-813.5647	57464.4	
bankdeep	171.3229	585.4298	0.29	0.770	-976.0985	1318.744	
innobank	1505.897	3438.717	0.44	0.661	-5233.865	8245.659	
voice	-27744.66	25303.56	-1.10	0.273	-77338.72	21849.4	
noviolence	30222.18	9741.989	3.10	0.002	11128.24	49316.13	
goveff	61935.1	19782.7	3.13	0.002	23161.72	100708.5	
regqua	15484.73	14798.63	1.05	0.295	-13520.05	44489.5	
rulelaw	-106388.5	34450.53	-3.09	0.002	-173910.3	-38866.74	
nocorruption	36895.31	15967.07	2.31	0.021	5600.428	68190.19	
polity2	-15286.75	9420.173	-1.62	0.105	-33749.95	3176.449	
durable	46.72284	386.5272	0.12	0.904	-710.8566	804.3023	
inflation	102.2682	424.967	0.24	0.810	-730.6519	935.1882	
rir	1324.03	325.5512	4.07	0.000	685.9614	1962.099	
reer	681.7116	490.2345	1.39	0.164	-279.1304	1642.554	
bankz	1461.801	711.6471	2.05	0.040	66.99885	2856.604	
_cons	-133961	135361.6	-0.99	0.322	-399264.9	131342.8	
sigma_u	0						
sigma_e	8858.8074						
rho	0	(fraction of variance due to u_i)					

—more—



Table 11

	----- Coefficients -----			
	(b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
fatflist	-11129.85	-11029.38	-100.475	1551.436
finrepr	-9391.687	-9656.684	264.997	1219.527
finfiu	-7322.081	-5223.385	-2098.696	1609.348
gdppc	32803.08	39513.11	-6710.039	9967.665
bankdeep	297.673	325.189	-27.51599	61.31518
innobank	-1967.5	-1901.662	-65.83877	271.8387
voice	-693.8866	-313.6453	-380.2413	2726.148
noviolence	-14510.69	-14197.62	-313.0747	1749.748
goveff	-18626.81	-17286.45	-1340.356	3297.82
regqua	23130.21	19830.02	3300.186	3558.258
rulelaw	7667.481	6431.836	1235.644	3432.653
nocorruption	14838.1	13932.55	905.5481	2229.351
polity2	1170.672	740.4949	430.1768	549.1664
durable	1695.203	1142.018	553.1849	405.2871
inflation	-5.163687	-18.18588	13.02219	39.96391
rir	-19.0093	-28.84143	9.832127	37.96216
bankz	-393.0822	-331.3233	-61.75885	123.1165

b = consistent under Ho and Ha; obtained from xtreg  
 B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

$$\begin{aligned} \text{chi2}(17) &= (b-B)'[(V_b-V_B)^{-1}](b-B) \\ &= 2.89 \\ \text{Prob}>\text{chi2} &= 0.9999 \end{aligned}$$

Table 12

Breusch and Pagan Lagrangian multiplier test for random effects

$$\text{etflows}[\text{country},t] = Xb + u[\text{country}] + e[\text{country},t]$$

Estimated results:

	Var	sd = sqrt(Var)
etflows	2.48e+09	49816.48
e	1.16e+08	10782.97
u	1.13e+10	106153

Test:  $\text{Var}(u) = 0$

$\text{chibar2}(01) = 354.97$   
 $\text{Prob} > \text{chibar2} = 0.0000$

Table 13

```

Fixed-effects (within) regression      Number of obs   =    99
Group variable: country               Number of groups =    18

R-sq:  within = 0.3837                Obs per group: min =    1
      between = 0.0384                    avg =    5.5
      overall = 0.1055                    max =   10

                                         F(11,17)       =    .
corr(u_i, Xb) = -0.7447                Prob > F        =    .

```

(Std. Err. adjusted for 18 clusters in country)

el	Robust		t	P> t	[95% Conf. Interval]	
	Coef.	Std. Err.				
fatflist	-16194.05	6396	-2.53	0.021	-29688.44	-2699.674
finrepr	-2691.923	3312.171	-0.81	0.428	-9679.993	4296.146
finfiu	3082.833	3143.862	0.98	0.341	-3550.137	9715.802
gdppc	-4606.751	19941.65	-0.23	0.820	-46679.95	37466.44
bankdeep	353.0646	244.2648	1.45	0.167	-162.2891	868.4183
innobank	-2068.445	1134.646	-1.82	0.086	-4462.339	325.4487
voice	-2879.697	5666.429	-0.51	0.618	-14834.82	9075.424
noviolence	924.2096	5581.259	0.17	0.870	-10851.22	12699.64
goveff	871.9239	4767.377	0.18	0.857	-9186.362	10930.21
regqua	899.5766	5628.979	0.16	0.875	-10976.53	12775.68
rulelaw	-2063.141	12127.16	-0.17	0.867	-27649.21	23522.92
nocorruption	5270.922	6218.514	0.85	0.408	-7848.995	18390.84
polity2	-3616.36	3317.256	-1.09	0.291	-10615.16	3382.438
durable	1215.247	864.0765	1.41	0.178	-607.7955	3038.289
inflation	-6.36088	84.88403	-0.07	0.941	-185.4505	172.7288
rir	-63.33792	80.54609	-0.79	0.442	-233.2753	106.5995
reer	256.6041	87.76125	2.92	0.009	71.44403	441.7641
bankz	-638.2685	607.4917	-1.05	0.308	-1919.964	643.4269
_cons	39503.16	139632.3	0.28	0.781	-255095.3	334101.6
sigma_u	38499.01					
sigma_e	7466.5876					
rho	.96374987 (fraction of variance due to u_i)					

Table 14

```

Random-effects GLS regression           Number of obs   =       99
Group variable: country                 Number of groups =       18

R-sq:  within = 0.0140                  Obs per group:  min =        1
      between = 0.7012                                avg   =       5.5
      overall  = 0.7528                                max   =       10

                                           Wald chi2(17)    =        .
corr(u_i, X) = 0 (assumed)              Prob > chi2      =        .

```

(Std. Err. adjusted for 18 clusters in country)

el	Robust				
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
fatflist	-75860.67	34629.07	-2.19	0.028	-143732.4 -7988.946
finrepr	-33561.92	12449.43	-2.70	0.007	-57962.35 -9161.493
finfiu	11266.42	11438.56	0.98	0.325	-11152.75 33685.58
gdppc	15223.5	9131.642	1.67	0.095	-2674.187 33121.19
bankdeep	36.63474	298.1125	0.12	0.902	-547.6551 620.9246
imobank	396.5995	2276.161	0.17	0.862	-4064.595 4857.794
voice	-12797.27	16848.03	-0.76	0.448	-45818.8 20224.26
noviolence	18741.09	6087.853	3.08	0.002	6809.116 30673.06
goveff	38038.93	12268.82	3.10	0.002	13992.49 62085.37
regqua	12887.59	9650.651	1.34	0.182	-6027.335 31802.52
rulelaw	-68702.43	22655.32	-3.03	0.002	-113106 -24298.82
nocorruption	21747.51	10287.41	2.11	0.035	1584.552 41910.47
polity2	-10588.75	6245.806	-1.70	0.090	-22830.31 1652.8
durable	106.9214	243.7376	0.44	0.661	-370.7955 584.6384
inflation	87.94062	274.8884	0.32	0.749	-450.8308 626.712
rir	899.7801	191.1731	4.71	0.000	525.0876 1274.473
reer	417.2775	324.4931	1.29	0.198	-218.7173 1053.272
bankz	941.1041	439.1333	2.14	0.032	80.41867 1801.789
_cons	-68518.18	78669.14	-0.87	0.384	-222706.9 85670.51
sigma_u	0				
sigma_e	7466.5876				
rho	0	(fraction of variance due to u_i)			

—more—

Table 15

```

Fixed-effects (within) regression      Number of obs   =    99
Group variable: country                Number of groups =    18

R-sq:  within = 0.6590                  Obs per group: min =    1
      between = 0.0028                    avg =    5.5
      overall = 0.0010                    max =    10

                                          F(11,17)       =    .
corr(u_i, Xb) = -0.6311                 Prob > F        =    .

```

(Std. Err. adjusted for 18 clusters in country)

ea	Robust				
	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
fatflist	-4184.716	3103.897	-1.35	0.195	-10733.37 2363.934
finrepr	-11693.71	2403.683	-4.86	0.000	-16765.04 -6622.385
finfiu	-1767.913	1734.513	-1.02	0.322	-5427.415 1891.589
gdppc	5887.029	16395.92	0.36	0.724	-28705.33 40479.39
bankdeep	59.63858	51.20602	1.16	0.260	-48.39668 167.6738
innobank	-758.4606	332.288	-2.28	0.036	-1459.527 -57.39419
voice	-5590.785	6033.706	-0.93	0.367	-18320.79 7139.222
noviolence	-671.5441	1612.386	-0.42	0.682	-4073.381 2730.293
goveff	-2589.491	3751.634	-0.69	0.499	-10504.75 5325.764
regqua	326.4568	4745.579	0.07	0.946	-9685.839 10338.75
rulelaw	997.1874	7361.618	0.14	0.894	-14534.47 16528.84
nocorruption	5801.794	3333.637	1.74	0.100	-1231.565 12835.15
polity2	3058.004	1472.768	2.08	0.053	-49.26439 6165.273
durable	532.0689	646.6106	0.82	0.422	-832.1602 1896.298
inflation	14.99598	38.6827	0.39	0.703	-66.61739 96.60935
rir	-11.03564	33.66748	-0.33	0.747	-82.06781 59.99654
reer	181.7284	43.42154	4.19	0.001	90.11701 273.3399
bankz	-201.4159	136.8165	-1.47	0.159	-490.0735 87.2416
_cons	-70257.55	105383.4	-0.67	0.514	-292597.1 152082
sigma_u	24397.522				
sigma_e	3433.0584				
rho	.98058418 (fraction of variance due to u_i)				

—more—

Table 16

```

Random-effects GLS regression           Number of obs   =    99
Group variable: country                 Number of groups =    18

R-sq:  within = 0.2027                   Obs per group:  min =    1
      between = 0.6762                       avg =    5.5
      overall  = 0.7944                       max =   10

                                           Wald chi2(17)   =    .
corr(u_i, X) = 0 (assumed)                Prob > chi2     =    .

```

(Std. Err. adjusted for 18 clusters in country)

ea	Robust				
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
fatflist	-34467.45	19611.91	-1.76	0.079	-72906.09 3971.189
finrepr	-34724.8	8280.751	-4.19	0.000	-50954.77 -18494.82
finfiu	2553.876	5228.332	0.49	0.625	-7693.467 12801.22
gdppc	13101.92	6074.736	2.16	0.031	1195.653 25008.18
bankdeep	134.6881	302.7561	0.44	0.656	-458.703 728.0792
innobank	1109.297	1213.786	0.91	0.361	-1269.68 3488.275
voice	-14947.39	9093.791	-1.64	0.100	-32770.89 2876.116
noviolence	11481.1	3870.216	2.97	0.003	3895.611 19066.58
goveff	23896.17	8057.954	2.97	0.003	8102.868 39689.47
regqua	2597.134	5687.746	0.46	0.648	-8550.642 13744.91
rulelaw	-37686.09	11978.09	-3.15	0.002	-61162.71 -14209.48
nocorruption	15147.8	5755.601	2.63	0.008	3867.028 26428.57
polity2	-4697.997	3386.754	-1.39	0.165	-11335.91 1939.919
durable	-60.19856	151.8006	-0.40	0.692	-357.7222 237.3251
inflation	14.32757	158.061	0.09	0.928	-295.4663 324.1214
rir	424.25	136.7779	3.10	0.002	156.1702 692.3298
reer	264.4341	171.5135	1.54	0.123	-71.72617 600.5943
bankz	520.6974	289.7256	1.80	0.072	-47.15437 1088.549
_cons	-65442.87	58229.98	-1.12	0.261	-179571.5 48685.8
sigma_u	0				
sigma_e	3433.0584				
rho	0	(fraction of variance due to u_i)			

—more—

Table 17

```

FE (within) regression with AR(1) disturbances  Number of obs   =    81
Group variable: country                        Number of groups  =    12

R-sq:  within = 0.3222                          Obs per group: min =    2
      between = 0.0020                          avg =    6.8
      overall = 0.0003                          max =    9

                                                    F(18,51) =    1.35
corr(u_i, Xb) = -0.2876                        Prob > F =    0.2002
    
```

etflows	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
fatflist	-23076.8	17778.51	-1.30	0.200	-58768.65 12615.05
finrepr	-18050.19	12897.83	-1.40	0.168	-43943.67 7843.285
finfiu	799.923	7568.435	0.11	0.916	-14394.34 15994.19
gdppc	12050.62	8168.689	1.48	0.146	-4348.709 28449.95
bankdeep	168.0135	312.9297	0.54	0.594	-460.2191 796.2461
innobank	-3713.614	1406.805	-2.64	0.011	-6537.894 -889.3343
voice	-10088.97	13743.78	-0.73	0.466	-37680.77 17502.82
noviolence	8378.925	7957.932	1.05	0.297	-7597.291 24355.14
goveff	10825.56	16745.52	0.65	0.521	-22792.48 44443.6
regqua	2989.965	13469.56	0.22	0.825	-24051.3 30031.23
rulelaw	-20994.99	16358.06	-1.28	0.205	-53835.17 11845.19
nocorruption	6868.022	10745.77	0.64	0.526	-14705 28441.05
polity2	-5232.57	5649.796	-0.93	0.359	-16575.01 6109.87
durable	831.8445	817.8261	1.02	0.314	-810.0099 2473.699
inflation	357.297	362.9601	0.98	0.330	-371.3758 1085.97
rir	-190.789	180.0151	-1.06	0.294	-552.1844 170.6064
bankz	-1264.586	518.9044	-2.44	0.018	-2306.33 -222.8414
reer	375.5807	196.5522	1.91	0.062	-19.01422 770.1757
_cons	-30732.87	12611.06	-2.44	0.018	-56050.62 -5415.123
rho_ar	.50079815				
sigma_u	54266.931				
sigma_e	10101.388				
rho_fov	.96651128	(fraction of variance because of u_i)			

```

F test that all u_i=0:      F(11,51) =    24.03      Prob > F = 0.0000
    
```

Table 18

```

RE GLS regression with AR(1) disturbances      Number of obs   =    99
Group variable: country                       Number of groups =    18

R-sq:  within = 0.3440                       Obs per group:  min =    1
        between = 0.5286                       avg =    5.5
        overall = 0.5012                       max =   10

corr(u_i, Xb) = 0 (assumed)                   Wald chi2(19)   =   50.21
                                                Prob > chi2     =   0.0001
    
```

```

-----+----- theta -----
min      5%      median      95%      max
0.3666  0.3666  0.6409   0.6409  0.6409
    
```

etflows	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
fatflist	-30592.28	18951.39	-1.61	0.106	-67736.31	6551.756
finrepr	-33769	12198.08	-2.77	0.006	-57676.78	-9861.208
finfiu	6697.947	6867.436	0.98	0.329	-6761.979	20157.87
gdppc	37333.03	9195.825	4.06	0.000	19309.54	55356.51
bankdeep	503.033	286.0783	1.76	0.079	-57.67006	1063.736
innobank	-1651.596	1272.416	-1.30	0.194	-4145.486	842.2943
voice	-3832.143	14595.95	-0.26	0.793	-32439.67	24775.39
noviolence	-1071.917	8096.44	-0.13	0.895	-16940.65	14796.81
goveff	16189.32	15370.67	1.05	0.292	-13936.64	46315.29
regqua	-2179.539	12307.35	-0.18	0.859	-26301.49	21942.42
rulelaw	-20339.99	15352.34	-1.32	0.185	-50430.02	9750.037
nocorruption	10225.08	9157.219	1.12	0.264	-7722.737	28172.9
polity2	-7303.781	5003.432	-1.46	0.144	-17110.33	2502.764
durable	-434.6354	291.3813	-1.49	0.136	-1005.732	136.4615
inflation	-5.923525	203.2149	-0.03	0.977	-404.2174	392.3703
rir	147.8251	178.4921	0.83	0.408	-202.0129	497.6631
bankz	-44.14801	504.2228	-0.09	0.930	-1032.406	944.1105
reer	395.2665	200.8513	1.97	0.049	1.605129	788.9278
_cons	-218991.6	78522.53	-2.79	0.005	-372892.9	-65090.29
rho_ar	.50079815	(estimated autocorrelation coefficient)				
sigma_u	21840.772					
sigma_e	15475.955					
rho_fov	.66574043	(fraction of variance due to u_i)				



Table 19

```

FE (within) regression with AR(1) disturbances  Number of obs   =    81
Group variable: country                        Number of groups  =    12

R-sq:  within = 0.2587                        Obs per group: min =     2
      between = 0.0743                        avg           =    6.8
      overall = 0.0438                        max           =     9

                                                F(18,51)         =    0.99
corr(u_i, Xb) = -0.5755                       Prob > F          =    0.4868
    
```

el	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
fatflist	-17297.5	13641.68	-1.27	0.211	-44684.31 10089.31
finrepr	-5447.16	9992.114	-0.55	0.588	-25507.17 14612.85
finfiu	-632.6697	5835.966	-0.11	0.914	-12348.86 11083.52
gdppc	4769.778	6380.167	0.75	0.458	-8038.942 17578.5
bankdeep	198.254	243.1341	0.82	0.419	-289.858 686.366
innobank	-2469.736	1084.386	-2.28	0.027	-4646.731 -292.7409
voice	-5870.655	10671.08	-0.55	0.585	-27293.75 15552.44
noviolence	4255.469	6123.921	0.69	0.490	-8038.814 16549.75
goveff	5671.627	12854.22	0.44	0.661	-20134.31 31477.56
regqua	2135.078	10420.47	0.20	0.838	-18784.88 23055.04
rulelaw	-11547.8	12712.36	-0.91	0.368	-37068.93 13973.32
nocorruption	5547.266	8268.553	0.67	0.505	-11052.55 22147.08
polity2	-2934.047	4403.362	-0.67	0.508	-11774.16 5906.07
durable	797.5493	645.0061	1.24	0.222	-497.3545 2092.453
inflation	209.8032	274.5117	0.76	0.448	-341.3021 760.9084
rir	-95.05068	138.3426	-0.69	0.495	-372.7851 182.6838
bankz	-879.1984	401.5408	-2.19	0.033	-1685.325 -73.07166
reer	239.3261	153.489	1.56	0.125	-68.81599 547.4682
_cons	-15296.81	9601.091	-1.59	0.117	-34571.81 3978.182
rho_ar	.52116538				
sigma_u	38445.542				
sigma_e	7810.8163				
rho_fov	.96035989	(fraction of variance because of u_i)			

F test that all u\_i=0: F(11,51) = 16.90 Prob > F = 0.0000

.  
.

Table 20

```

RE GLS regression with AR(1) disturbances      Number of obs   =    99
Group variable: country                       Number of groups =    18

R-sq:  within = 0.2010                        Obs per group:  min =     1
        between = 0.4978                       avg =     5.5
        overall = 0.5012                       max =    10

                                                Wald chi2(19)   =   35.09
corr(u_i, Xb) = 0 (assumed)                   Prob > chi2     =   0.0136
    
```

```

-----+----- theta -----+-----
min      5%      median      95%      max
0.3236  0.3236  0.5970      0.5970  0.5970
    
```

el	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
fatflist	-24951.14	13720.74	-1.82	0.069	-51843.3	1941.019
finrepr	-13534.94	8933.025	-1.52	0.130	-31043.35	3973.466
finfiu	6687.582	4966.486	1.35	0.178	-3046.553	16421.72
gdppc	20732.54	6440.468	3.22	0.001	8109.457	33355.63
bankdeep	268.1404	206.1561	1.30	0.193	-135.918	672.1989
innobank	-1239.395	928.497	-1.33	0.182	-3059.216	580.4253
voice	2857.786	10606.66	0.27	0.788	-17930.89	23646.46
noviolence	-830.643	5815.317	-0.14	0.886	-12228.45	10567.17
goveff	9431.11	11101.47	0.85	0.396	-12327.37	31189.59
regqua	2570.523	8910.713	0.29	0.773	-14894.15	20035.2
rulelaw	-16828.6	11156.45	-1.51	0.131	-38694.84	5037.639
nocorruption	6035.48	6637.269	0.91	0.363	-6973.328	19044.29
polity2	-6662.851	3576.161	-1.86	0.062	-13672	346.295
durable	-167.8648	201.8049	-0.83	0.406	-563.3951	227.6655
inflation	15.83592	147.7327	0.11	0.915	-273.7149	305.3868
rir	162.6531	128.4749	1.27	0.206	-89.15318	414.4593
bankz	-56.25862	360.8238	-0.16	0.876	-763.4603	650.943
reer	227.5045	147.4234	1.54	0.123	-61.44008	516.449
_cons	-112015	55601.11	-2.01	0.044	-220991.2	-3038.839
rho_ar	.52116538	(estimated autocorrelation coefficient)				
sigma_u	13493.399					
sigma_e	10575.387					
rho_fov	.61948023	(fraction of variance due to u_i)				

Table 23

```

Arellano-Bond dynamic panel-data estimation Number of obs      =      94
Group variable: country                    Number of groups     =      18
Time variable: years

Obs per group:   min =      1
                  avg =  5.222222
                  max =      6

Number of instruments =      63          Wald chi2(17)        =  4907.19
                                                Prob > chi2          =    0.0000
    
```

One-step results

(Std. Err. adjusted for clustering on country)

etflows	Robust					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
etflows						
L1.	1.356778	.1283502	10.57	0.000	1.105216	1.60834
L2.	-.1043271	.1842208	-0.57	0.571	-.4653933	.2567391
fatflist	-5270.083	2501.784	-2.11	0.035	-10173.49	-366.6767
finrepr	-9094.582	3697.313	-2.46	0.014	-16341.18	-1847.982
finfiu	-5035.024	2683.867	-1.88	0.061	-10295.31	225.2595
gdppc	47770.44	20326.19	2.35	0.019	7931.839	87609.04
bankdeep	376.8631	345.6965	1.09	0.276	-300.6896	1054.416
innobank	-3820.562	1346.549	-2.84	0.005	-6459.75	-1181.375
voice	-12423.9	11284.46	-1.10	0.271	-34541.04	9693.243
noviolence	1919.676	4004.557	0.48	0.632	-5929.111	9768.463
goveff	-10790.62	5662.543	-1.91	0.057	-21889	307.7627
regqua	-5264.159	11647.95	-0.45	0.651	-28093.72	17565.4
rulelaw	23057.87	14344.22	1.61	0.108	-5056.295	51172.03
nocorruption	6989.185	9489.781	0.74	0.461	-11610.44	25588.81
polity2	-1248.376	2736.901	-0.46	0.648	-6612.603	4115.852
durable	661.8104	785.2778	0.84	0.399	-877.3059	2200.927
inflation	-382.7315	173.3635	-2.21	0.027	-722.5177	-42.94533
rir	-207.0854	160.8458	-1.29	0.198	-522.3375	108.1666
bankz	-492.3839	383.9209	-1.28	0.200	-1244.855	260.0873
_cons	-348965.1	147708.9	-2.36	0.018	-638469.3	-59461.03

Instruments for differenced equation

GMM-type: L(2/.)etflows

Standard: D.fatflist D.finrepr D.finfiu D.gdppc D.bankdeep D.innobank D.voice D.noviolence D.goveff D.regqua D.rulelaw  
D.nocorruption D.polity2 D.durable D.inflation D.rir D.bankz

Instruments for level equation

Standard: \_cons

Table 24

Arellano-Bond test for zero autocorrelation in first-differenced errors

Order	z	Prob > z
1	-1.7663	0.0773
2	.71852	0.4724
3	.51271	0.6082

H0: no autocorrelation

Table 25

```

Arellano-Bond dynamic panel-data estimation Number of obs      =      94
Group variable: country                    Number of groups     =      18
Time variable: years

Obs per group:   min =      1
                  avg =  5.222222
                  max =      6

Number of instruments =    95          Wald chi2(17)        =  26945.67
                                                Prob > chi2          =    0.0000
    
```

One-step results

(Std. Err. adjusted for clustering on country)

etflows	Robust		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
etflows						
L1.	1.421195	.1567134	9.07	0.000	1.114043	1.728348
L2.	-.0603146	.1559776	-0.39	0.699	-.366025	.2453958
L3.	-.2831172	.1553275	-1.82	0.068	-.5875534	.0213191
gdppc	42845.33	18555.51	2.31	0.021	6477.195	79213.47
inflation	-310.4528	167.0189	-1.86	0.063	-637.8039	16.89818
rir	-90.77812	133.3293	-0.68	0.496	-352.0987	170.5425
bankz	-452.2126	362.042	-1.25	0.212	-1161.802	257.3768
bankdeep	237.2718	271.7238	0.87	0.383	-295.2972	769.8407
innobank	-2912.318	1243.168	-2.34	0.019	-5348.882	-475.7533
fatflist	-4380.648	2133.797	-2.05	0.040	-8562.814	-198.4826
finrepr	-6240.14	2598.16	-2.40	0.016	-11332.44	-1147.839
finfiu	-2165.61	2380.704	-0.91	0.363	-6831.703	2500.483
voice	-6967.044	8155.214	-0.85	0.393	-22950.97	9016.881
noviolence	998.044	3872.596	0.26	0.797	-6592.105	8588.194
goveff	-8444.4	5229.259	-1.61	0.106	-18693.56	1804.758
regqua	-4027.011	10642.44	-0.38	0.705	-24885.81	16831.79
rulelaw	13339.93	12279.69	1.09	0.277	-10727.82	37407.68
nocorruption	3097.929	6748.924	0.46	0.646	-10129.72	16325.58
polity2	1093.082	1944.211	0.56	0.574	-2717.502	4903.667
durable	416.458	541.1531	0.77	0.442	-644.1826	1477.098
_cons	-330721.9	134323.9	-2.46	0.014	-593991.9	-67451.88

Instruments for differenced equation

GMM-type: L(2/.) .etflows L(1/.) .gdppc L(1/.) .inflation L(1/.) .rir L(1/.) .bankz L(1/.) .bankdeep L(1/.) .innobank

Standard: D.fatflist D.finrepr D.finfiu D.voice D.noviolence D.goveff D.regqua D.rulelaw D.nocorruption D.polity2 D.durable

Instruments for level equation

Standard: \_cons

Table 26

Arellano-Bond test for zero autocorrelation in first-differenced errors

Order	z	Prob > z
1	-1.7178	0.0858
2	.69621	0.4863
3	.61769	0.5368

H0: no autocorrelation

Table 27

```

Arellano-Bond dynamic panel-data estimation Number of obs      =      94
Group variable: country                    Number of groups     =      18
Time variable: years

Obs per group:   min =      1
                  avg =  5.222222
                  max =      6

Number of instruments =      63      Wald chi2(17)        =  1816.01
Prob > chi2        =      0.0000

One-step results
(Std. Err. adjusted for clustering on country)

```

el	Robust		z	P> z	[95% Conf. Interval]	
	Coef.	Std. Err.				
el						
L1.	1.902843	.2024757	9.40	0.000	1.505997	2.299688
L2.	-.61292	.1180489	-5.19	0.000	-.8442916	-.3815483
L3.	-.4572425	.2389617	-1.91	0.056	-.9255988	.0111139
fatflist	483.0786	1031.32	0.47	0.639	-1538.272	2504.43
finrepr	-72.94612	1360.279	-0.05	0.957	-2739.044	2593.152
finfiu	-2005.557	1139.771	-1.76	0.078	-4239.468	228.3536
gdppc	9733.641	8506.291	1.14	0.253	-6938.384	26405.67
bankdeep	290.6774	142.7976	2.04	0.042	10.7993	570.5554
innobank	-1710.488	642.5474	-2.66	0.008	-2969.858	-451.1186
voice	-5071.356	4968.063	-1.02	0.307	-14808.58	4665.867
noviolence	-3897.586	1677.496	-2.32	0.020	-7185.417	-609.7549
goveff	-9411.874	4910.457	-1.92	0.055	-19036.19	212.4458
regqua	-2930.299	3601.981	-0.81	0.416	-9990.052	4129.455
rulelaw	10983.27	5474.066	2.01	0.045	254.2921	21712.24
nocorruption	2293.363	4588.461	0.50	0.617	-6699.854	11286.58
polity2	762.9012	1336.306	0.57	0.568	-1856.211	3382.013
durable	664.8151	341.1543	1.95	0.051	-3.834966	1333.465
inflation	-284.8652	95.3711	-2.99	0.003	-471.7891	-97.94129
rir	-133.2702	72.05149	-1.85	0.064	-274.4886	7.948072
bankz	-109.3529	144.2631	-0.76	0.448	-392.1034	173.3977
_cons	-87982.44	68586.56	-1.28	0.200	-222409.6	46444.75

```

Instruments for differenced equation
GMM-type: L(2/.)el
Standard: D.fatflist D.finrepr D.finfiu D.gdppc D.bankdeep D.innobank D.voice D.noviolence D.goveff D.regqua D.rulelaw
D.nocorruption D.polity2 D.durable D.inflation D.rir D.bankz

Instruments for level equation
Standard: _cons

```

Table 28

Arellano-Bond test for zero autocorrelation in first-differenced errors

Order	z	Prob > z
1	-1.6712	0.0947
2	1.6614	0.0966
3	-1.7213	0.0852

H0: no autocorrelation

Table 29

```

Arellano-Bond dynamic panel-data estimation Number of obs      =      94
Group variable: country                    Number of groups     =      18
Time variable: years

Obs per group:   min =      1
                  avg =  5.222222
                  max =      6

Number of instruments =      95      Wald chi2(18)        =  5.34e+08
                                          Prob > chi2         =  0.0000

One-step results
                                (Std. Err. adjusted for clustering on country)

```

el	Robust					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
el						
L1.	1.969748	.2107027	9.35	0.000	1.556778	2.382718
L2.	-.6890348	.1120448	-6.15	0.000	-.9086386	-.469431
L3.	-.4953347	.267749	-1.85	0.064	-1.020113	.0294436
gdppc	12052.74	7537.484	1.60	0.110	-2720.46	26825.94
inflation	-226.1355	89.61214	-2.52	0.012	-401.7721	-50.49893
rir	-78.76958	62.07556	-1.27	0.204	-200.4354	42.89627
bankz	-95.5717	105.3105	-0.91	0.364	-301.9765	110.8331
bankdeep	173.9614	113.8558	1.53	0.127	-49.19194	397.1147
innobank	-1217.979	557.6883	-2.18	0.029	-2311.028	-124.9304
fatflist	463.1445	1178.499	0.39	0.694	-1846.67	2772.959
finrepr	503.9649	1047.789	0.48	0.631	-1549.663	2557.593
finfiu	-2086.66	1272.507	-1.64	0.101	-4580.729	407.4084
voice	-2796.346	3794.128	-0.74	0.461	-10232.7	4640.008
noviolence	-4174.974	1839.231	-2.27	0.023	-7779.8	-570.1475
goveff	-7823.156	5270.826	-1.48	0.138	-18153.79	2507.473
regqua	-2928.356	3598.761	-0.81	0.416	-9981.797	4125.085
rulelaw	7823.403	4585.871	1.71	0.088	-1164.738	16811.54
nocorruption	-177.0264	4031.739	-0.04	0.965	-8079.09	7725.037
polity2	1529.853	1011.926	1.51	0.131	-453.4858	3513.191
durable	415.6333	259.9861	1.60	0.110	-93.93007	925.1966
_cons	-108653.6	57159.13	-1.90	0.057	-220683.4	3376.264

```

Instruments for differenced equation
GMM-type: L(2/.)el L(1/.)gdppc L(1/.)inflation L(1/.)rir L(1/.)bankz L(1/.)bankdeep L(1/.)innobank
Standard: D.fatflist D.finrepr D.finfiu D.voice D.noviolence D.goveff D.regqua D.rulelaw D.nocorruption D.polity2 D.durable
Instruments for level equation
Standard: _cons

```

Table 30

Arellano-Bond test for zero autocorrelation in first-differenced errors

Order	z	Prob > z
1	-1.6608	0.0968
2	1.6361	0.1018
3	-1.6986	0.0894

H0: no autocorrelation

Table 31

```

Arellano-Bond dynamic panel-data estimation Number of obs      =      94
Group variable: country                    Number of groups     =      18
Time variable: years

Obs per group:   min =      1
                  avg =  5.222222
                  max =      6

Number of instruments = 63          Wald chi2(17)        = 168301.87
                                      Prob > chi2           = 0.0000

One-step results
                                (Std. Err. adjusted for clustering on country)

```

ea	Robust					
	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
ea						
L1.	.6589581	.2042681	3.23	0.001	.2586	1.059316
L2.	.3096903	.0891202	3.47	0.001	.1350179	.4843626
L3.	.0729844	.0923319	0.79	0.429	-.1079829	.2539517
fatflist	-5129.142	2041.28	-2.51	0.012	-9129.978	-1128.307
finrepr	-3698.541	1820.198	-2.03	0.042	-7266.064	-131.0179
finfiu	-1597.813	1498.484	-1.07	0.286	-4534.787	1339.161
gdppc	45886.75	15865.83	2.89	0.004	14790.29	76983.21
bankdeep	7.834532	85.1225	0.09	0.927	-159.0025	174.6716
innobank	-1474.561	497.7926	-2.96	0.003	-2450.216	-498.9052
voice	-5055.832	3487.058	-1.45	0.147	-11890.34	1778.675
noviolence	-2328.291	3331.353	-0.70	0.485	-8857.623	4201.041
goveff	-1405.367	2424.237	-0.58	0.562	-6156.785	3346.051
regqua	5401.696	4412.907	1.22	0.221	-3247.443	14050.84
rulelaw	2100.407	5322.019	0.39	0.693	-8330.559	12531.37
nocorruption	3930.285	3223.625	1.22	0.223	-2387.904	10248.47
polity2	1373.315	1776.47	0.77	0.439	-2108.503	4855.133
durable	-674.0796	630.4041	-1.07	0.285	-1909.649	561.4896
inflation	-77.84363	69.36815	-1.12	0.262	-213.8027	58.11544
rir	3.723106	42.05502	0.09	0.929	-78.70322	86.14944
bankz	-221.2969	124.7854	-1.77	0.076	-465.8718	23.2779
_cons	-343001.4	120322.5	-2.85	0.004	-578829.2	-107173.6

```

Instruments for differenced equation
GMM-type: L(2/.)ea
Standard: D.fatflist D.finrepr D.finfiu D.gdppc D.bankdeep D.innobank D.voice D.noviolence D.goveff D.regqua D.rulelaw
D.nocorruption D.polity2 D.durable D.inflation D.rir D.bankz

Instruments for level equation
Standard: _cons

```

Table 32

Arellano-Bond test for zero autocorrelation in first-differenced errors

Order	z	Prob > z
1	-1.8616	0.0627
2	-.3067	0.7591
3	.55956	0.5758

H0: no autocorrelation

Table 33

```

Arellano-Bond dynamic panel-data estimation Number of obs      =      94
Group variable: country                    Number of groups     =      18
Time variable: years

Obs per group:   min =      1
                  avg =  5.222222
                  max =      6

Number of instruments =      95          Wald chi2(18)        =  4.73e+09
                                          Prob > chi2         =  0.0000

One-step results
                               (Std. Err. adjusted for clustering on country)

```

ea	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
ea						
L1.	.6810524	.210642	3.23	0.001	.2682017	1.093903
L2.	.305137	.097313	3.14	0.002	.1144071	.4958669
L3.	.0998816	.1051238	0.95	0.342	-.1061572	.3059205
gdppc	40852.98	11771.77	3.47	0.001	17780.74	63925.23
inflation	-26.04594	47.56302	-0.55	0.584	-119.2678	67.17587
rir	30.92974	38.07389	0.81	0.417	-43.6937	105.5532
bankz	-105.125	114.2746	-0.92	0.358	-329.0991	118.849
bankdeep	16.11223	58.53726	0.28	0.783	-98.61869	130.8432
innobank	-1229.64	442.061	-2.78	0.005	-2096.064	-363.2161
fatflist	-5659.119	2307.705	-2.45	0.014	-10182.14	-1136.1
finrepr	-2924.664	1393.896	-2.10	0.036	-5656.651	-192.6776
finfiu	-1065.801	1199.555	-0.89	0.374	-3416.886	1285.283
voice	-4017.086	2642.829	-1.52	0.129	-9196.935	1162.763
noviolence	-658.4439	3005.787	-0.22	0.827	-6549.678	5232.79
goveff	188.4134	2017.088	0.09	0.926	-3765.006	4141.833
regqua	2407.954	4107.603	0.59	0.558	-5642.8	10458.71
rulelaw	2768.572	4938.315	0.56	0.575	-6910.347	12447.49
nocorruption	3263.088	3204.554	1.02	0.309	-3017.722	9543.899
polity2	1307.688	1499.118	0.87	0.383	-1630.529	4245.905
durable	-513.9738	427.3598	-1.20	0.229	-1351.584	323.6361
_cons	-310938.5	91083.01	-3.41	0.001	-489457.9	-132419.1

```

Instruments for differenced equation
GMM-type: L(2/.)ea L(1/.)gdppc L(1/.)inflation L(1/.)rir L(1/.)bankz L(1/.)bankdeep L(1/.)innobank
Standard: D.fatflist D.finrepr D.finfiu D.voice D.noviolence D.goveff D.regqua D.rulelaw D.nocorruption D.polity2 D.durable
Instruments for level equation
Standard: _cons

```

Table 34

Arellano-Bond test for zero autocorrelation in first-differenced errors

Order	z	Prob > z
1	-1.9297	0.0536
2	-.041	0.9673
3	.2078	0.8354

H0: no autocorrelation



Table 35

```

System dynamic panel-data estimation      Number of obs      =      129
Group variable: country                  Number of groups   =      19
Time variable: years

Obs per group:   min =      1
                  avg =  6.789474
                  max =      8

Number of instruments =      71           Wald chi2(18)     =  15414.30
                                           Prob > chi2       =    0.0000
    
```

One-step results

etflows	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
etflows					
L1.	1.486131	.0995124	14.93	0.000	1.29109 1.681172
L2.	-.0756956	.1861622	-0.41	0.684	-.4405667 .2891756
L3.	-.245244	.1940209	-1.26	0.206	-.6255181 .13503
fatflist	-4337.204	3338.89	-1.30	0.194	-10881.31 2206.901
finrepr	-8597.589	3830.334	-2.24	0.025	-16104.91 -1090.272
finfiu	-5950.705	5167.492	-1.15	0.249	-16078.8 4177.393
gdppc	21412.36	16820.9	1.27	0.203	-11556 54380.72
bankdeep	259.3273	232.1286	1.12	0.264	-195.6365 714.2911
innobank	-3457.5	1437.651	-2.40	0.016	-6275.245 -639.7558
voice	-11771.35	12512.82	-0.94	0.347	-36296.02 12753.33
noviolence	-1633.981	7682.635	-0.21	0.832	-16691.67 13423.71
goveff	-12150.83	6343.65	-1.92	0.055	-24584.16 282.4942
regqua	4020.588	11915.15	0.34	0.736	-19332.67 27373.85
rulelaw	21174.96	13226.66	1.60	0.109	-4748.814 47098.73
nocorruption	9581.339	11581.5	0.83	0.408	-13117.99 32280.67
polity2	-1107.181	8349.744	-0.13	0.895	-17472.38 15258.02
durable	1775.695	978.5536	1.81	0.070	-142.2351 3693.624
inflation	-468.2763	283.3596	-1.65	0.098	-1023.651 87.0983
rir	-192.0181	139.898	-1.37	0.170	-466.2131 82.17695
bankz	-446.2174	460.4529	-0.97	0.333	-1348.689 456.2537
_cons	-164104.4	161893.1	-1.01	0.311	-481409.1 153200.4

Instruments for differenced equation

```

GMM-type: L(2/.)etflows
Standard: D.fatflist D.finrepr D.finfiu D.gdppc D.bankdeep D.innobank D.voice D.noviolence D.goveff D.regqua D.rulelaw
          D.nocorruption D.polity2 D.durable D.inflation D.rir D.bankz
    
```

Instruments for level equation

```

GMM-type: LD.etflows
Standard: _cons
    
```

Table 36

Arellano-Bond test for zero autocorrelation in first-differenced errors

Order	z	Prob > z
1	-1.7784	0.0753
2	.6572	0.5111
3	.83262	0.4051

H0: no autocorrelation

Table 37

```

System dynamic panel-data estimation      Number of obs      =      129
Group variable: country                  Number of groups   =      19
Time variable: years

Obs per group:   min =      1
                  avg =  6.789474
                  max =      8

Number of instruments =    151           Wald chi2(18)     =  91412.31
                                           Prob > chi2       =    0.0000
    
```

One-step results

etflows	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
etflows						
L1.	1.670684	.1445449	11.56	0.000	1.387381	1.953987
L2.	-.2242824	.1328176	-1.69	0.091	-.4846002	.0360353
L3.	-.4314388	.1813832	-2.38	0.017	-.7869433	-.0759343
bankdeep	166.4018	137.112	1.21	0.225	-102.3328	435.1364
innobank	-1595.175	838.4275	-1.90	0.057	-3238.462	48.11312
inflation	-172.6055	81.64571	-2.11	0.035	-332.6281	-12.58283
rir	-59.30575	58.48557	-1.01	0.311	-173.9354	55.32387
bankz	-39.69632	180.2864	-0.22	0.826	-393.0512	313.6585
fatflist	-7285.841	3797.045	-1.92	0.055	-14727.91	156.23
finrepr	-8589.563	3396.698	-2.53	0.011	-15246.97	-1932.157
finfiu	3202.374	2765.043	1.16	0.247	-2217.011	8621.758
gdppc	8653.445	3597.519	2.41	0.016	1602.438	15704.45
voice	1870.955	5224.021	0.36	0.720	-8367.937	12109.85
noviolence	2839.832	2408.646	1.18	0.238	-1881.027	7560.692
goveff	-3586.279	3230.14	-1.11	0.267	-9917.238	2744.679
regqua	892.6724	7833.065	0.11	0.909	-14459.85	16245.2
rulelaw	-1543.959	7161.903	-0.22	0.829	-15581.03	12493.11
nocorruption	-1892.402	2476.681	-0.76	0.445	-6746.607	2961.803
polity2	-6278.301	2965.595	-2.12	0.034	-12090.76	-465.8425
durable	214.3017	154.5248	1.39	0.165	-88.56147	517.1648
_cons	-12123.02	28782.38	-0.42	0.674	-68535.45	44289.42

Instruments for differenced equation

```

GMM-type: L(2/.)etflows L(1/.)gdppc L(1/.)bankdeep L(1/.)innobank L(1/.)inflation L(1/.)rir L(1/.)bankz
Standard: D.fatflist D.finrepr D.finfiu D.gdppc D.bankdeep D.innobank D.voice D.noviolence D.goveff D.regqua D.rulelaw
          D.nocorruption D.polity2 D.durable D.inflation D.rir D.bankz
    
```

Instruments for level equation

```

GMM-type: LD.etflows D.gdppc D.bankdeep D.innobank D.inflation D.rir D.bankz
Standard: _cons
    
```

Table 38

Arellano-Bond test for zero autocorrelation in first-differenced errors

Order	z	Prob > z
1	-1.8264	0.0678
2	2.1704	0.0300
3	.73637	0.4615

H0: no autocorrelation

Table 39

```

System dynamic panel-data estimation      Number of obs      =      129
Group variable: country                  Number of groups   =      19
Time variable: years

Obs per group:   min =      1
                  avg =  6.789474
                  max =      8

Number of instruments =      71          Wald chi2(18)     =  74398.48
                                          Prob > chi2       =   0.0000
    
```

One-step results

ea	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
ea						
L1.	.6669969	.1816612	3.67	0.000	.3109476	1.023046
L2.	.3855239	.1171566	3.29	0.001	.1559012	.6151466
L3.	-.1375594	.2216028	-0.62	0.535	-.5718929	.2967741
fatflist	-5816.448	2714.318	-2.14	0.032	-11136.41	-496.483
finrepr	-4723.272	1972.503	-2.39	0.017	-8589.306	-857.2369
finfiu	-2588.389	2665.833	-0.97	0.332	-7813.326	2636.548
gdppc	18562.28	8415.141	2.21	0.027	2068.911	35055.66
bankdeep	51.12325	76.80485	0.67	0.506	-99.41149	201.658
innobank	-1178.298	482.4503	-2.44	0.015	-2123.883	-232.7126
voice	-3515.609	4466.362	-0.79	0.431	-12269.52	5238.301
noviolence	-4201.317	3977.209	-1.06	0.291	-11996.5	3593.87
goveff	-1982.317	2873.829	-0.69	0.490	-7614.919	3650.285
regqua	11458.87	6268.852	1.83	0.068	-827.857	23745.59
rulelaw	485.8504	4893.09	0.10	0.921	-9104.43	10076.13
nocorruption	6549.528	5849.727	1.12	0.263	-4915.727	18014.78
polity2	3363.287	2427.587	1.39	0.166	-1394.696	8121.269
durable	499.4761	310.139	1.61	0.107	-108.3853	1107.337
inflation	-164.6987	119.1248	-1.38	0.167	-398.179	68.78166
rir	-22.65821	49.07978	-0.46	0.644	-118.8528	73.5364
bankz	-133.4123	166.3524	-0.80	0.423	-459.457	192.6324
_cons	-170596.9	73872.57	-2.31	0.021	-315384.5	-25809.33

Instruments for differenced equation

```

GMM-type: L(2/.)_ea
Standard: D.fatflist D.finrepr D.finfiu D.gdppc D.bankdeep D.innobank D.voice D.noviolence D.goveff D.regqua D.rulelaw
          D.nocorruption D.polity2 D.durable D.inflation D.rir D.bankz
    
```

Instruments for level equation

```

GMM-type: LD_ea
Standard: _cons
    
```

Table 40

Arellano-Bond test for zero autocorrelation in first-differenced errors

Order	z	Prob > z
1	-2.1763	0.0295
2	-1.4759	0.1400
3	1.6359	0.1019

H0: no autocorrelation

Table 41

```

System dynamic panel-data estimation      Number of obs      =      129
Group variable: country                  Number of groups   =      19
Time variable: years

Obs per group:   min =      1
                  avg =  6.789474
                  max =      8

Number of instruments =    151           Wald chi2(18)     =    8511.25
                                           Prob > chi2       =    0.0000
    
```

One-step results

ea	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
ea					
L1.	.9065495	.2233582	4.06	0.000	.4687756 1.344324
L2.	.2285892	.0903762	2.53	0.011	.0514551 .4057234
L3.	-.1531536	.1970988	-0.78	0.437	-.5394602 .233153
gdppc	3992.331	1959.903	2.04	0.042	150.9924 7833.67
bankdeep	151.1482	70.14832	2.15	0.031	13.65997 288.6363
innobank	-455.1951	309.5305	-1.47	0.141	-1061.864 151.4735
inflation	-55.93137	42.24206	-1.32	0.185	-138.7243 26.86155
bankz	38.30937	92.83065	0.41	0.680	-143.6354 220.2541
fatflist	-6844.214	3419.23	-2.00	0.045	-13545.78 -142.6472
finrepr	-3506.897	2138.775	-1.64	0.101	-7698.819 685.0247
finfiu	1227.806	1437.629	0.85	0.393	-1589.895 4045.507
voice	1439.104	3949.763	0.36	0.716	-6302.29 9180.498
noviolence	236.5538	2231.825	0.11	0.916	-4137.743 4610.851
goveff	67.13982	2390.782	0.03	0.978	-4618.707 4752.987
regqua	3623.164	3566.363	1.02	0.310	-3366.78 10613.11
rulelaw	-4911.001	3342.909	-1.47	0.142	-11462.98 1640.98
nocorruption	1232.955	1832.709	0.67	0.501	-2359.088 4824.998
polity2	-2413.739	1447.72	-1.67	0.095	-5251.218 423.74
durable	30.14852	42.92962	0.70	0.483	-53.99199 114.289
rir	-31.14387	26.71331	-1.17	0.244	-83.50099 21.21326
_cons	-13047.75	13587.04	-0.96	0.337	-39677.86 13582.37

Instruments for differenced equation

```

GMM-type: L(2/.)ea L(1/.)gdppc L(1/.)bankdeep L(1/.)innobank L(1/.)inflation L(1/.)rir L(1/.)bankz
Standard: D.fatflist D.finrepr D.finfiu D.gdppc D.bankdeep D.innobank D.voice D.noviolence D.goveff D.regqua D.rulelaw
D.nocorruption D.polity2 D.durable D.inflation D.rir D.bankz
    
```

Instruments for level equation

```

GMM-type: LD.ea D.gdppc D.bankdeep D.innobank D.inflation D.rir D.bankz
Standard: _cons
    
```

Table 42

Arellano-Bond test for zero autocorrelation in first-differenced errors

Order	z	Prob > z
1	-2.1174	0.0342
2	-.27229	0.7854
3	1.0512	0.2932

H0: no autocorrelation

Table 43

dfuller logel, lags(1) trend regress

Augmented Dickey-Fuller test for unit root      Number of obs =    62

----- Interpolated Dickey-Fuller -----

Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value
Z(t)	-2.208	-4.124	-3.173

Mackinnon approximate p-value for Z(t) = 0.4855

-----+-----

D.logel	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
logel					
L1.	-.2195112	.0994257	-2.21	0.031	-.4185334   -.020489
LD.	-.0678332	.1346521	-0.50	0.616	-.3373687   .2017022
_trend	.0016739	.0008973	1.87	0.067	-.0001222   .00347
_cons	1.436523	.6566466	2.19	0.033	.1221017   2.750944

-----

Table 44

. dfuller logea, lags(1) trend regress

Augmented Dickey-Fuller test for unit root      Number of obs =    62

----- Interpolated Dickey-Fuller -----

Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value
Z(t)	-1.949	-4.124	-3.173

MacKinnon approximate p-value for Z(t) = 0.6291

-----

D.logea	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
-----+-----					
logea					
L1.	-.1350655	.0693097	-1.95	0.056	-.2738039 .003673
LD.	-.0519041	.1314998	-0.39	0.695	-.3151296 .2113214
_trend	.0012459	.0010859	1.15	0.256	-.0009277 .0034194
_cons	.9440302	.4936064	1.91	0.061	-.0440303 1.932091

---

Table 45

. dfuller loget, lags(1) regress

Augmented Dickey-Fuller test for unit root      Number of obs =    62

----- Interpolated Dickey-Fuller -----

Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value
Z(t)	-1.380	-3.563	-2.595

Mackinnon approximate p-value for Z(t) = 0.5917

-----

D.loget	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
loget					
L1.	-.0959452	.0695108	-1.38	0.173	-.2350361 .0431456
LD.	-.0329372	.1345003	-0.24	0.807	-.3020716 .2361973
_cons	.7489709	.5379803	1.39	0.169	-.3275251 1.825467

-----

Table 46

. dfuller logea, lags(1) regress

Augmented Dickey-Fuller test for unit root      Number of obs =    62

----- Interpolated Dickey-Fuller -----				
Test	1% Critical	5% Critical	10% Critical	
Statistic	Value	Value	Value	
Z(t)	-1.677	-3.563	-2.920	-2.595

MacKinnon approximate p-value for Z(t) = 0.4430

D.logea	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
logea						
L1.	-.1111577	.0662803	-1.68	0.099	-.2437843	.0214688
LD.	-.0523073	.1318515	-0.40	0.693	-.3161416	.2115269
_cons	.8110502	.4810912	1.69	0.097	-.1516111	1.773712

---



Table 47

. dfuller d2logel, lag(2) trend regress

Augmented Dickey-Fuller test for unit root      Number of obs =      59

----- Interpolated Dickey-Fuller -----

Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value
Z(t)	-6.967	-4.130	-3.175

Mackinnon approximate p-value for Z(t) = 0.0000

-----

D.d2logel	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
d2logel					
L1.	-2.536291	.3640582	-6.97	0.000	-3.266184 -1.806398
LD.	.6721814	.2769469	2.43	0.019	.1169363 1.227426
L2D.	.2409316	.1353642	1.78	0.081	-.0304571 .5123204
_trend	.0002192	.0010015	0.22	0.828	-.0017887 .0022272
_cons	-.0016765	.0363023	-0.05	0.963	-.0744582 .0711053

-----

Table 48

. dfuller d2logea, lags(1) trend regress

Augmented Dickey-Fuller test for unit root      Number of obs =    60

----- Interpolated Dickey-Fuller -----

Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value
Z(t)	-10.709	-4.128	-3.174

MacKinnon approximate p-value for Z(t) = 0.0000

-----

D.d2logea	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
d2logea					
L1.	-2.211532	.2065103	-10.71	0.000	-2.625222 -1.797843
LD.	.4823151	.1212254	3.98	0.000	.2394714 .7251588
_trend	-.0004556	.0013114	-0.35	0.730	-.0030828 .0021715
_cons	.0136512	.0471149	0.29	0.773	-.0807313 .1080336

---

Table 49

```
. arima d2logel, arima(2,0,0)
```

ARIMA regression

Sample: 1996q3 - 2011q4                      Number of obs = 62

Wald chi2(2) = 92.83

Log likelihood = 39.26618                      Prob > chi2 = 0.0000

```
-----+-----
```

	OPG					
d2logel	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
d2logel						
_cons	.0017205	.0104665	0.16	0.869	-.0187936	.0222345
-----+-----						
ARMA						
ar						
L1.	-.7971761	.1059488	-7.52	0.000	-1.004832	-.5895203
L2.	-.2338886	.0924109	-2.53	0.011	-.4150106	-.0527665
-----+-----						
/sigma	.1277695	.0060738	21.04	0.000	.115865	.1396739
-----+-----						

Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at zero.

Table 50

. arima d2logea, arima(2,0,0)

ARIMA regression

Sample: 1996q3 - 2011q4            Number of obs   =   62

                                 Wald chi2(2)   =   70.41

Log likelihood = 22.44815            Prob > chi2   =   0.0000

```
-----
      |          OPG
d2logea |   Coef. Std. Err.   z  P>|z|  [95% Conf. Interval]
-----+-----
d2logea |
   _cons | -.0003115 .0099162  -0.03  0.975  -.0197469 .019124
-----+-----
ARMA   |
   ar   |
   L1. | -.7183172 .0914278  -7.86  0.000  -.8975123 -.5391221
   L2. | -.4658233 .0759808  -6.13  0.000  -.6147429 -.3169038
-----+-----
   /sigma | .1674372 .0071343  23.47  0.000  .1534542 .1814201
-----
```

Note: The test of the variance against zero is one sided, and the two-sided confidence interval is truncated at zero.

Table 51

. dfuller dlogbankdeep,lags(0) trend regress

Dickey-Fuller test for unit root                      Number of obs =    62

----- Interpolated Dickey-Fuller -----

Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value
Z(t)	-6.983	-4.124	-3.173

MacKinnon approximate p-value for Z(t) = 0.0000

-----  
D.dlogbank~p |    Coef.   Std. Err.    t   P>|t|   [95% Conf. Interval]

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
dlogbankdeep					
L1.	-.9072678	.1299293	-6.98	0.000	-1.167256   -0.64728
_trend	.0010211	.0005744	1.78	0.081	-.0001283   .0021706
_cons	-.0261629	.0205658	-1.27	0.208	-.0673151   .0149892

---

Table 52

dfuller d1loginnobank,lags(0) trend regress

Dickey-Fuller test for unit root                      Number of obs =    58

----- Interpolated Dickey-Fuller -----

Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value
Z(t)	-7.421	-4.132	-3.175

Mackinnon approximate p-value for Z(t) = 0.0000

-----  
D.d1loginn~k |    Coef. Std. Err.    t   P>|t|    [95% Conf. Interval]

-----+-----

d1loginnob~k						
L1.		-1.000616	.1348379	-7.42	0.000	-1.270837 - .7303945
_trend		.00012	.0013567	0.09	0.930	-.002599 .0028389
_cons		-.0072682	.046026	-0.16	0.875	-.0995063 .08497

---

Table 53

dfuller d1logbankz,lags(0) trend regress

Dickey-Fuller test for unit root                      Number of obs =    58

----- Interpolated Dickey-Fuller -----

Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value
Z(t)	-7.673	-4.132	-3.175

Mackinnon approximate p-value for Z(t) = 0.0000

D.d1logbankz	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
d1logbankz					
L1.	-1.034955	.1348782	-7.67	0.000	-1.305257 - .7646528
_trend	.0004918	.0007366	0.67	0.507	-.0009843 .001968
_cons	.0008278	.0248679	0.03	0.974	-.0490086 .0506643

---

Table 54

dfuller d1logourgdp,lags(0) trend regress

Dickey-Fuller test for unit root                      Number of obs =    62

----- Interpolated Dickey-Fuller -----

Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value
Z(t)	-8.291	-4.124	-3.173

Mackinnon approximate p-value for Z(t) = 0.0000

-----  
D.d1logour~p |    Coef.   Std. Err.    t   P>|t|   [95% Conf. Interval]

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
d1logourgdp					
L1.	-1.078363	.1300632	-8.29	0.000	-1.338619 - .8181075
_trend	.0001476	.0000832	1.77	0.081	-.0000188 .0003141
_cons	-.0026217	.0029574	-0.89	0.379	-.0085394 .0032961

---



Table 55

dfuller d1loginflation,lags(0) trend regress

Dickey-Fuller test for unit root                      Number of obs =    62

----- Interpolated Dickey-Fuller -----

Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value
Z(t)	-8.207	-4.124	-3.173

Mackinnon approximate p-value for Z(t) = 0.0000

-----+-----

D.d1loginf~n	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
d1loginfla~n					
L1.	-1.086322	.1323662	-8.21	0.000	-1.351186 - .8214576
_trend	-.0000735	.0029646	-0.02	0.980	-.0060056 .0058586
_cons	-.0086994	.1073884	-0.08	0.936	-.2235831 .2061843

---

Table 56

dfuller d1logrir,lags(0) trend regress

Dickey-Fuller test for unit root                      Number of obs =    62

----- Interpolated Dickey-Fuller -----

Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value
Z(t)	-8.566	-4.124	-3.173

Mackinnon approximate p-value for Z(t) = 0.0000

-----+-----

D.d1logrir	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
d1logrir					
L1.	-1.114859	.1301425	-8.57	0.000	-1.375274 - .854445
_trend	.0009725	.0044887	0.22	0.829	-.0080093 .0099543
_cons	-.0454328	.1626477	-0.28	0.781	-.3708902 .2800245

---

Table 57

. dfuller d1logreer,lags(0) trend regress

Dickey-Fuller test for unit root                      Number of obs =    62

----- Interpolated Dickey-Fuller -----

Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value
Z(t)	-9.839	-4.124	-3.173

MacKinnon approximate p-value for Z(t) = 0.0000

-----  
D.d1logreer |    Coef. Std. Err.    t   P>|t|   [95% Conf. Interval]

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
d1logreer					
L1.	-1.269305	.1290111	-9.84	0.000	-1.527456 -1.011154
_trend	-.0004811	.000437	-1.10	0.275	-.0013556 .0003934
_cons	.0172892	.0157991	1.09	0.278	-.0143248 .0489031

---



Table 59

ARIMA regression

Sample: 1996q3 - 2010q4                      Number of obs = 58  
   Wald chi2(3) = 52.91  
Log likelihood = 38.1618                      Prob > chi2 = 0.0000

```
-----  
      |          OPG  
d2logel |   Coef. Std. Err.   z  P>|z|   [95% Conf. Interval]  
-----+-----  
d2logel |  
d1loginnobank | .0923971 .1012792  0.91 0.362  -.1061065 .2909007  
   _cons | .0032176 .0131286  0.25 0.806  -.0225139 .0289492  
-----+-----  
ARMA   |  
   ar |  
L1. | -.7404657 .1522923 -4.86 0.000 -1.038953 -.4419783  
L2. | -.1741009 .1259797 -1.38 0.167  -.4210166 .0728147  
-----+-----  
/sigma | .1247053 .0069377 17.98 0.000  .1111077 .1383028  
-----
```

---



Table 61

ARIMA regression

Sample: 1996q3 - 2011q4                      Number of obs   =   62  
    Wald chi2(3)   =   98.50  
 Log likelihood = 39.40628                      Prob > chi2   =   0.0000

```
-----+-----
      |          OPG
d2logel |   Coef. Std. Err.   z  P>|z|   [95% Conf. Interval]
-----+-----
d2logel |
d1logourgdp | -.5969948  2.375534  -0.25  0.802  -5.252955  4.058965
   _cons | .0028586  .0114664   0.25  0.803  -.0196152  .0253323
-----+-----
ARMA   |
   ar   |
   L1. | -.7920226  .1237361  -6.40  0.000  -1.034541  -0.5495043
   L2. | -.2244325  .0997321  -2.25  0.024  -.4199038  -0.0289611
-----+-----
/sigma | .1274886  .00625  20.40  0.000  .1152388  .1397384
-----
```

Table 62

ARIMA regression

Sample: 1996q3 - 2011q4                    Number of obs = 62  
    Wald chi2(3) = 89.20  
 Log likelihood = 39.325                    Prob > chi2 = 0.0000

```
-----
```

	OPG					
d2logel	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
d2logel						
d1loginflation	.0111936	.050886	0.22	0.826	-.0885412	.1109285
_cons	.0017849	.0116861	0.15	0.879	-.0211195	.0246893
-----+-----						
ARMA						
ar						
L1.	-.7998593	.119514	-6.69	0.000	-1.034103	-.5656161
L2.	-.2360071	.0938433	-2.51	0.012	-.4199366	-.0520776
-----+-----						
/sigma	.1276437	.0062237	20.51	0.000	.1154454	.139842

---



Table 63

ARIMA regression

Sample: 1996q3 - 2011q4                      Number of obs   =   62  
    Wald chi2(3)   =   92.69  
 Log likelihood = 39.26636                      Prob > chi2   =   0.0000

```
-----+-----
      |          OPG
d2logel |   Coef. Std. Err.   z  P>|z|   [95% Conf. Interval]
-----+-----
d2logel |
d1logrir | -.0004199 .0376306  -0.01  0.991  -.0741745  .0733347
   _cons | .0017137 .0107092   0.16  0.873  -.0192759  .0227034
-----+-----
ARMA   |
   ar   |
L1. | -.7972282 .1060292  -7.52  0.000  -1.005042  -.5894149
L2. | -.2340709 .0929985  -2.52  0.012  -.4163445  -.0517973
-----+-----
/sigma | .127769 .0061413  20.80  0.000  .1157322  .1398057
-----
```

Table 64

ARIMA regression

Sample: 1996q3 - 2011q4                      Number of obs    =    62  
    Wald chi2(3)     =    95.81  
 Log likelihood = 39.39535                    Prob > chi2      =    0.0000

```

-----
      |           OPG
d2logel |   Coef. Std. Err.   z  P>|z|   [95% Conf. Interval]
-----+-----
d2logel |
d1logreer | -.1158954 .4423785  -0.26  0.793  -1.9829413  .7511505
   _cons | .0018717 .0105228   0.18  0.859  -0.0187526  .022496
-----+-----
ARMA   |
   ar   |
   L1. | -.7943965 .1218965  -6.52  0.000  -1.033309  -0.5554836
   L2. | -.2305372 .1094487  -2.11  0.035  -0.4450527  -0.0160218
-----+-----
   /sigma | .1274864 .0060925  20.93  0.000  .1155454  .1394274
-----
    
```

---

Table 65

ARIMA regression

Sample: 1996q3 - 2011q4                      Number of obs   =   62  
   Wald chi2(3)   =   61.39  
Log likelihood = 22.61049                      Prob > chi2   =   0.0000

---

-----						
	OPG					
d2logea	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
d2logea						
dlogbankdeep		-.111979	.2037646	-0.55	0.583	-.5113503 .2873922
_cons		.0002409	.012387	0.02	0.984	-.0240371 .0245189
-----+-----						
ARMA						
ar						
L1.		-.7234693	.1009915	-7.16	0.000	-.921409 -.5255295
L2.		-.4590645	.0813764	-5.64	0.000	-.6185592 -.2995697
-----+-----						
/sigma		.1670072	.0076797	21.75	0.000	.1519553 .1820591

---

Table 66

ARIMA regression

Sample: 1996q3 - 2010q4                      Number of obs   =   58  
    Wald chi2(3)   =   70.33  
 Log likelihood = 21.95042                      Prob > chi2   =   0.0000

```

-----
      |          OPG
d2logea |   Coef. Std. Err.   z  P>|z|   [95% Conf. Interval]
-----+-----
d2logea |
d1loginnobank | .002911 .2499255   0.01  0.991  - .4869339   .492756
   _cons | .0020394 .0125317   0.16  0.871  - .0225224   .0266011
-----+-----
ARMA   |
   ar   |
   L1. | -.6818413 .0859178  -7.94  0.000  - .8502371  -.5134455
   L2. | -.4455574 .0779477  -5.72  0.000  - .5983321  -.2927827
-----+-----
   /sigma | .1647416 .0069595  23.67  0.000   .1511013   .178382
-----

```

---

Table 67

ARIMA regression

Sample: 1996q3 - 2010q4                      Number of obs   =   58

   Wald chi2(3)   =   73.80

Log likelihood = 23.90179                      Prob > chi2   =   0.0000

```
-----  
      |      OPG  
d2logea |   Coef.  Std. Err.   z  P>|z|  [95% Conf. Interval]  
-----+-----  
d2logea |  
d1logbankz |  -.370419  .3060639  -1.21  0.226  -.9702933  .2294553  
  _cons |  .0076451  .0141043   0.54  0.588  -.0199988  .035289  
-----+-----  
ARMA   |  
  ar |  
L1. |  -.6914437  .0895218  -7.72  0.000  -.8669033  -.5159842  
L2. |  -.5013237  .081693   -6.14  0.000  -.6614391  -.3412083  
-----+-----  
/sigma |  .1591219  .0114002  13.96  0.000  .1367778  .1814659  
-----
```

---

Table 68

ARIMA regression

Sample: 1996q3 - 2011q4                      Number of obs   =   62  
    Wald chi2(3)   =   70.59  
 Log likelihood = 22.4556                      Prob > chi2   =   0.0000

```
-----+-----
                |       OPG
d2logea |   Coef. Std. Err.   z  P>|z|   [95% Conf. Interval]
-----+-----
d2logea |
d1logourgdp | -.1773932  1.590138  -0.11  0.911  -3.294007  2.939221
   _cons | .0000303  .0110032   0.00  0.998  -.0215356  .0215963
-----+-----
ARMA      |
   ar |
   L1. | -.7197147  .0917787  -7.84  0.000  -.8995977  -.5398317
   L2. | -.4667373  .0759896  -6.14  0.000  -.6156742  -.3178003
-----+-----
/sigma | .1674087  .0071318  23.47  0.000  .1534307  .1813867
-----
```

Table 69

ARIMA regression

Sample: 1996q3 - 2011q4                      Number of obs = 62

   Wald chi2(3) = 67.70

Log likelihood = 22.6001                      Prob > chi2 = 0.0000

```

-----
      |          OPG
d2logea |   Coef. Std. Err.   z  P>|z|   [95% Conf. Interval]
-----+-----
d2logea |
d1loginflation | -.0239773 .0625935  -0.38  0.702  -.1466582 .0987037
   _cons | -.0004067 .0104886  -0.04  0.969  -.0209641 .0201506
-----+-----
ARMA   |
   ar   |
   L1. | -.7267199 .0932884  -7.79  0.000  -.9095618 -.5438781
   L2. | -.4607245 .0783879  -5.88  0.000  -.6143621 -.307087
-----+-----
/sigma | .1670358 .0088385  18.90  0.000  .1497127 .1843589

```

---

Table 70

ARIMA regression

Sample: 1996q3 - 2011q4                      Number of obs   =   62  
    Wald chi2(3)   =   73.39  
 Log likelihood = 23.00902                      Prob > chi2   =   0.0000

```

-----
      |          OPG
d2logea |   Coef.  Std. Err.   z  P>|z|  [95% Conf. Interval]
-----+-----
d2logea |
d1logrir | .0312601  .0335865   0.93  0.352  -.0345682  .0970884
   _cons | .0002922  .0112187   0.03  0.979  -.0216959  .0222804
-----+-----
ARMA   |
   ar   |
L1. | -.7377265  .0888174  -8.31  0.000  -.9118053  -.5636476
L2. | -.444551  .0784702  -5.67  0.000  -.5983498  -.2907522
-----+-----
/sigma | .1659572  .0090981  18.24  0.000  .1481252  .1837892
-----

```





Table 72

ARIMA regression

Sample: 1996q3 - 2011q4                      Number of obs = 62  
    Wald chi2(3) = 92.03  
 Log likelihood = 39.27811                      Prob > chi2 = 0.0000

```

-----
      |          OPG
d2logel |   Coef. Std. Err.   z   P>|z|   [95% Conf. Interval]
-----+-----
d2logel |
dlistingnews | -.0168395 .167533 -0.10 0.920  -.3451982 .3115192
   _cons | .0017221 .0105148  0.16 0.870  -.0188865 .0223307
-----+-----
ARMA   |
   ar   |
L1. | -.7975703 .1056488 -7.55 0.000  -1.004638 -.5905025
L2. | -.2365181 .0920352 -2.57 0.010  -.4169037 -.0561325
-----+-----
/sigma | .1277445 .0061015 20.94 0.000  .1157859 .1397032
-----

```

Table 73

ARIMA regression

Sample: 1996q3 - 2011q4                      Number of obs = 62  
    Wald chi2(3) = 72.88  
 Log likelihood = 22.61945                      Prob > chi2 = 0.0000

```

-----
      |           OPG
d2logea |   Coef. Std. Err.   z   P>|z|   [95% Conf. Interval]
-----+-----
d2logea |
dlistingnews | -0.084665 .3882066  -0.22  0.827  -0.8455358 .6762059
   _cons | -0.0003207 .0098241  -0.03  0.974  -0.0195755 .0189341
-----+-----
ARMA    |
   ar    |
L1. | -0.7245026 .0918525  -7.89  0.000  -0.9045301 -0.5444751
L2. | -0.475238 .0742684  -6.40  0.000  -0.6208015 -0.3296745
-----+-----
/sigma | .1669394 .0070618  23.64  0.000  .1530985 .1807803
-----

```

Table 74

ARIMA regression

Sample: 1996q3 - 2011q4                      Number of obs   =   62

   Wald chi2(3)   =   91.23

Log likelihood = 39.31077                      Prob > chi2      =   0.0000

```

-----
      |           OPG
d2logel |   Coef. Std. Err.   z  P>|z|   [95% Conf. Interval]
-----+-----
d2logel |
dlistingper| .0301669 .4513418   0.07  0.947  -0.8544467 .9147805
   _cons | .0012289 .0104674   0.12  0.907  -0.0192869 .0217447
-----+-----
ARMA   |
   ar   |
L1. | -0.8015531 .1064828  -7.53  0.000  -1.010255  -0.5928507
L2. | -0.2389367 .0920205  -2.60  0.009  -0.4192937  -0.0585798
-----+-----
/sigma | .1276702 .0060763  21.01  0.000   .115761   .1395795
-----

```

Table 75

ARIMA regression

Sample: 1996q3 - 2011q4                      Number of obs    =    62  
    Wald chi2(3)    =    70.52  
 Log likelihood = 22.46082                      Prob > chi2      =    0.0000

```

-----+-----
      |          OPG
d2logea |   Coef.  Std. Err.   z  P>|z|  [95% Conf. Interval]
-----+-----
d2logea |
  dlstingper | .0207518 .4548461   0.05  0.964  -0.8707302 .9122338
   _cons | -0.0006545 .009931  -0.07  0.947  -0.020119 .0188099
-----+-----
ARMA   |
  ar |
  L1. | -0.7182093 .0912427  -7.87  0.000  -0.8970417 -0.5393769
  L2. | -0.4650659 .0760212  -6.12  0.000  -0.6140647 -0.3160671
-----+-----
/sigma | .1674018 .0071299  23.48  0.000  .1534276 .1813761

```

---

Table 76

dfuller d1el,lags(5) trend regress

Augmented Dickey-Fuller test for unit root      Number of obs =    57

----- Interpolated Dickey-Fuller -----

Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value
Z(t)	-3.755	-4.135	-3.176

Mackinnon approximate p-value for Z(t) = 0.0190

D.d1el	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
d1el					
L1.	-1.624505	.432682	-3.75	0.000	-2.494012 - .7549977
LD.	.4621306	.3880394	1.19	0.239	-.3176638 1.241925
L2D.	.5254528	.3359206	1.56	0.124	-.149605 1.200511
L3D.	.3992282	.2846592	1.40	0.167	-.1728159 .9712723
L4D.	.4463609	.2488463	1.79	0.079	-.0537145 .9464363
L5D.	.312226	.1660987	1.88	0.066	-.0215618 .6460138
_trend	.3857691	.8147705	0.47	0.638	-1.251573 2.023112
_cons	1.197235	30.75535	0.04	0.969	-60.60795 63.00242

Table 77

dfuller d1ea,lags(4) trend regress

Augmented Dickey-Fuller test for unit root      Number of obs =    58

----- Interpolated Dickey-Fuller -----

Test	1% Critical	5% Critical	10% Critical
Statistic	Value	Value	Value
Z(t)	-3.831	-4.132	-3.175

Mackinnon approximate p-value for Z(t) = 0.0151

D.d1ea	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
d1ea					
L1.	-1.554606	.4057882	-3.83	0.000	-2.36926 - .7399526
LD.	.3555256	.3568365	1.00	0.324	-.3608536 1.071905
L2D.	.2061515	.3047083	0.68	0.502	-.4055758 .8178789
L3D.	.2399939	.237114	1.01	0.316	-.2360323 .7160202
L4D.	.1149659	.163559	0.70	0.485	-.2133924 .4433243
_trend	.8116111	1.635256	0.50	0.622	-2.471303 4.094525
_cons	-10.51642	59.74457	-0.18	0.861	-130.4586 109.4258

Table 78

ARIMA regression (3,1,0)

Sample: 1996q3 - 2011q4                      Number of obs = 62

Wald chi2(3) = 71.39

Log likelihood = -376.5437                      Prob > chi2 = 0.0000

---

	OPG					
D.d1el	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
d1el						
_cons	1.790307	6.618411	0.27	0.787	-11.18154	14.76215
-----+-----						
ARMA						
ar						
L1.	-.8670932	.1148599	-7.55	0.000	-1.092214	-.6419719
L2.	-.4781598	.1195979	-4.00	0.000	-.7125675	-.2437522
L3.	-.2808275	.0963839	-2.91	0.004	-.4697365	-.0919185
-----+-----						
/sigma	104.289	5.10026	20.45	0.000	94.29268	114.2853

---





Table 80

ARIMA regression (3,1,0)

Sample: 1996q3 - 2011q4                      Number of obs   =   62

   Wald chi2(4)   =   77.39

Log likelihood = -376.3889                      Prob > chi2   =   0.0000

```

-----
      |           OPG
      |
D.d1el |   Coef. Std. Err.   z   P>|z|   [95% Conf. Interval]
-----+-----
d1el   |
      |
dlstingnews |
      |
D1. |  40.53286  106.671   0.38  0.704  -168.5384  249.6041
      |
      |
_cons |  1.771697  6.748199   0.26  0.793  -11.45453  14.99792
-----+-----

ARMA   |
      |
ar     |
      |
L1. |  -0.8573517  .1216887  -7.05  0.000  -1.095857  -0.6188463
L2. |  -0.4520059  .124656   -3.63  0.000  -0.6963271  -0.2076847
L3. |  -0.285246   .0953191  -2.99  0.003  -0.472068  -0.098424
-----+-----

/sigma |  104.0199  5.133686  20.26  0.000  93.95806  114.0817
-----

```



Table 82

ARIMA regression (3,1,0)

Sample: 1996q3 - 2011q4                    Number of obs = 62  
    Wald chi2(4) = 75.38  
 Log likelihood = -376.4901                Prob > chi2 = 0.0000

```
-----+-----
      |          OPG
D.d1el |   Coef. Std. Err.   z  P>|z|  [95% Conf. Interval]
-----+-----
d1el   |
dlistingperiod |
D1. |  31.97468  206.1902   0.16  0.877  -372.1507   436.1
      |
_cons |  1.770602  8.767567   0.20  0.840  -15.41351  18.95472
-----+-----
ARMA   |
ar     |
L1. |  -0.8655433  0.1635432  -5.29  0.000  -1.186082  -0.5450045
L2. |  -0.4797366  0.1406256  -3.41  0.001  -0.7553577 -0.2041156
L3. |  -0.2931637  0.0953578  -3.07  0.002  -0.4800616 -0.1062658
-----+-----
/sigma |  104.1772  5.320978  19.58  0.000   93.7483  114.6062
-----
```

