Do European Capital Flows Comove?*

Silvio Contessi
Federal Reserve Bank of St. Louis

Pierangelo De Pace
Johns Hopkins University

March 2009

Abstract

We study the cross-section correlations of net, total, and disaggregated capital flows for the major source and recipient European Union countries. We seek evidence of changes in these correlations since the introduction of the euro to understand whether the European Union can be considered a unique entity with regard to its international capital flows. We make use of Ng's (2006) "uniform spacing" methodology to rank cross-section correlations and shed light on potential common factors driving international capital flows. We find that a common factor structure is suitable for equity flows disaggregated by sign but not for net and total flows. We only find mixed evidence that correlations between types of flows have changed since the introduction of the euro.

JEL Classification: F32, F34, F36

Keywords: capital flows volatility, foreign direct investment, foreign portfolio investment, uniform spacings, group effects

*We thank Serena Ng for providing the MATLAB codes, Ariel Weinberger for capable research assistance, Andrew Hughes Hallett for helpful discussion, and the participants in The Implications of European Integration conference organized by the Federal Reserve Bank of St. Louis for their comments. Silvio Contessi: Federal Reserve Bank of St. Louis, Research Division, P.O. Box 442, St. Louis MO 63166-0442. Pierangelo De Pace (corresponding author): Johns Hopkins University, 3400 N. Charles Street, Baltimore MD 21218, pierangelo.depace@jhu.edu.

1 Introduction

The volatility of capital flows and the effects of financial liberalization on growth have been at the heart of the policy debate for many countries at least over the past two decades. The recent literature has increasingly considered the different second-moment properties (covariances, correlations) of capital flows at the aggregate (Kaminsky, Reinhart, and Vegh, 2004, Rothenberg and Warnock, 2006) and at the disaggregate level (Neumann, Penl, and Tanku, 2006) and studied how different types of capital flows affect risk sharing (Devereux and Sutherland, forthcoming). Empirical evidence shows that not only do net and gross flows have different second-moment properties, but also that they differ in terms of persistence and correlation with macroeconomic variables once they are disaggregated by type and sign (Levchenko and Mauro, 2007; Smith and Valderrama, forthcoming; Contessi, De Pace, and Francis, 2008).

These findings and new developments in the open economy macroeconomic literature allow to take dynamic stochastic general equilibrium models with complex financial structures to the data, to calibrate and estimate them with the ultimate objective of assisting policy analysis. Recent developments in computing solutions for dynamic stochastic general equilibrium models with country portfolios or borrowing constraints (Devereux and Sutherland, 2006, 2008; Tille and van Wincoop, 2008; Smith and Valderrama, forthcoming) now allow to study the dynamics of models with a realistic financial structure, that is, where agents and countries can hedge against risk by using a wide range of financial instruments, yet assuming market incompleteness.

Despite these theoretical results, many empirical issues remain. For example, consider the problem of calibrating a two-country model with country portfolios similar to that described by Devereux and Sutherland (2006). Clearly, the United States can be treated as a unique entity when considered as the source and destination of international financial flows, because intrastate risk sharing mirrors almost perfect capital mobility and the rest of the world is clearly defined (Ekinci, Kalemli-Ozcan, and Sorensen, 2008). But, can the European Union (EU), taken as a whole, be assumed to be a *country* when it comes to the study of the cyclical properties of its inward and outward capital flows? Is there a common capital flows cycle that responds to EU-specific shocks? Has the introduction of the euro reinforced or weakened the comovement of capital flows originating in and entering these countries?

In this paper we attempt to answer these questions. In the first part, we use Ng (2006)'s "uniform spacings" method to determine whether the comovement of disaggregated capital flows has increased with the introduction of the euro in 1999. Although the breakpoint date could have been estimated, rather than exogenously imposed, we choose to use an exogenous breakpoint that looks natural for European economies. In related research , we show that the conditional variance of the cyclical component of individual capital flows exhibits a structural break between the first quarter of 1998 and the second quarter of 1999 in most cases (Contessi, De Pace, and Francis, 2008).

We analyze disaggregated capital flows organized in 11 panels, assess the extent of their cross-section correlation, and find that a common factor structure is suitable for equity flows disaggregated by sign but not for net and total flows. Hence, as suggested by recent theoretical contributions (Devereux and Sutherland, 2006, 2008; Tille and van Wincoop, 2008), the analysis of countries' gross assets and liabilities and their breakdown into different types might be important when capital flows are interpreted as adjustments to country portfolios.

In the second part of our paper, we examine changes in correlation between different types of flows for each country over the two subperiods 1990-1998 and 1999-2006. We measure these correlations and formally test for changes over the two subperiods using a statistical approach originally suggested by Doyle and Faust (2005) and later revisited by De Pace (2008). We find mixed evidence of significant changes and no systematic pattern.

The structure of the paper is as follows. Section 2 describes the data, Section 3 explains the methodologies we use to detect the presence of common factors in European capital flows and to test for correlation changes. In Section 4 we present the results, followed by our conclusions in Section 5.

2 International Capital Flows

Most of the literature on international capital flows focuses on net flows, often defined as the difference between aggregate inflows and outflows. Recent empirical contributions, such as those of Lipsey (1999), Rothenberg and Warnock (2006), and Kose, Prasad, and Terrones (forthcoming), have pointed out that disaggregated flows data contain relevant information that helps understand aggregate net flows. In addition to how they are classified in the balance of payments, the economic characteristics of each type of capital flow are quite different. Transactions such as bank loans, government securities, bonds, and equity are conducted and observed in markets populated by many buyers and sellers, standardized contracts, and publicly available prices. On the contrary, foreign direct investment (FDI) is the result of financial and industrial decisions that are internal to the firm, not market-mediated. In the case of emerging economies, an empirical case for separately examining inflows and outflows is made by Rothenberg and Warnock (2006), who look at gross flows and show that about half of the observed sudden stops (retreat of global investors) are actually episodes of sudden flight of local investors.

In two recent theoretical exceptions, Tille and van Wincoop (2008) and Devereux and Sutherland (forthcoming) develop a novel solution for two-country DSGE models with country portfolios and stress the importance of distinguishing between gross and net flows. In a small open economy setting, Smith and Valderrama (forthcoming) discuss the cyclical properties of different types of flows to a group of emerging countries using data recorded at the quarterly frequency. Unlike previous open economy macroeconomic models that stylize international financial linkages in terms of net foreign assets and the current account, these papers consider the fact that the data show huge cross-country gross asset and liability positions in assets whose value might change radically over short periods, even if the trade balance barely moves (Lane and Milesi Ferretti, 2007). The size of such gross asset positions suggests the need of understanding the determinants of portfolio choice and their effects on macroeconomic dynamics. For example, fluctuations of the nominal exchange rate alter capital gains and losses for gross positions, with potentially large effects on the value of net foreign assets (depending on the composition of countries' portfolios). However, they do not necessarily imply changes in net export.

We interpret different types of capital flows as adjustments to country positions of FDI, foreign portfolio investment (FPI), and debt stocks. We focus on quarterly data on capital flows, disaggregated by sign and type. Complete series are available for the period 1990:Q1 through 2006:Q4 for the major countries in the EU (France, Germany, Italy, Finland, the Netherlands, Portugal, Spain, the United Kingdom, and Sweden).[1] International capital flows are reported as assets (outflows) and liabilities (inflows), separately for each country.

We collect 11 panels organized as follows. (i) Inward foreign direct investment (iFDI) is *direct investment in the reporting economy*, (ii) outward foreign direct investment (oFDI)

[1]Source: *International Financial Statistics* (IFS), published by the International Monetary Fund (IMF), various issues.

is *direct investment abroad*. Both types of investment include equity capital, reinvested earnings, other capital, and financial derivatives associated with various intercompany transactions with affiliated companies, as discussed in IMF (2007). Inward and outward portfolio investment includes financial securities of any maturity, including corporate securities, bonds, notes, and money market instruments other than those parts of direct investment or reserve assets. Because IFS data combine debt and equity portfolio investment, we separate Equity Securities from Debt Securities. According to our definition, (iii) inward (iFPI) and (iv) outward equity securities (oFPI) include only shares, stock participation, and similar equity investments (e.g., American Depository Receipts and Global Depository Receipts). Debt securities assets and liabilities include bonds, debentures, notes, and money market or negotiable debt instruments. We combine these series with other investment assets and liabilities (i.e., all the financial transactions not covered in direct investment, portfolio investment, financial derivatives, or other assets, such as trade credits, loans, transactions in currency and deposits, and other assets/liabilities). We define these aggregates as (v) inward debt (iDebt) and (vi) outward debt (oDebt). Total equity flows are calculated as equity securities plus foreign direct investment for both inflows and outflows and labelled (vii) total equity liabilities (iEqu) and (viii) total equity assets (oEqu). Total equity flows plus total debt flows are summed as (ix) total inflows liabilities (iTot) and total outflows assets (oTot). The difference between oTot and iTot is (xi) net outward flows (noTot). Table 1 summarizes the classification of capital flows.

We study the levels of the quarterly series of nominal capital flows. A few series exhibit occurrences of negative values or zero entries. In some cases, negative values may be due to either underreporting or large disinvestment; the latter is often caused by repatriation of previous investment (for example, negative FDI inflows). Given the nature of our dataset, using the log of capital flows to reduce the weight of observations with particularly large quarter-specific values is not always viable, because some entries in the series may be negative or zero. A semi-logarithmic transformation would deal with zero entries, but would not solve the issue of negative observations. We use the solution described in Levy-Yeyati, Panizza, and Stein (2007) and opt for the transformation

$$Flow_t^* = sign\,(Flow_t) \times \log\left(1 + |Flow_t|\right) \tag{1}$$

where $Flow_t$ can be any of the capital flow series previously described. This manipulation of the data still allows the application of conventional filtering methods to the transformed variables without distorting standard interpretations. We detrend the transformed capital flow series using a standard Hodrick-Prescott filter.

3 The Econometric Framework

In this section, we briefly describe the theoretical framework developed in Ng (2006) to test for cross-section correlations and briefly refer to De Pace (2008) for a formal test on correlation changes based on bootstrap methods.

3.1 Cross-Section Correlations: Ng's Uniform Spacings Methodology

We test for the significance of cross-section correlations in 11 panels of data on international capital flows, organized by type and sign, and treated as previously described.

Our adoption of Ng's (2006) methodology is motivated by the observation that the majority of tests for cross-section correlation in panels of data are based on the null hypothesis that all the units exhibit no correlation against the alternative hypothesis that the correlation is different from zero for some units.[2] Such statistical tests provide no guidance on the assessment of the extent of correlation in the panel if the null is rejected. On the contrary, the application of Ng (2006)'s uniform spacings methodology allows the determination of whether at least some (not necessarily all) countries in the sample have correlated capital flows. Furthermore, we can identify those countries clearly. Formally, for the panel of a specific capital flow, let M be the number of countries in the sample and T the number of time-series observations (quarters herein). The number of unique elements above (or below) the diagonal of the sample correlation matrix is denoted by $N = \frac{M(M-1)}{2}$.[3] Let $\overline{\rho} = (|\widehat{\rho}_1|, |\widehat{\rho}_2|, ..., |\widehat{\rho}_N|)'$ be the vector of the absolute sample correlation coefficients: the absolute values of the estimates of the population correlations in the vector $\rho = (\rho_1, \rho_2, ..., \rho_N)'$. Then sort the elements in $\overline{\rho}$ from the smallest to the largest in the ordered series $\left(\overline{\rho}_{[1:N]}, \overline{\rho}_{[2:N]}, ..., \overline{\rho}_{[N:N]}\right)'$. Finally, define $\overline{\phi}_j = \Phi\left(\sqrt{T}\overline{\rho}_{[j:N]}\right)$, where

[2] An assessment of the extent of cross-section correlation in the errors has significant implications for estimation and inference. Andrews (2005) showed that ordinary least squares applied to cross-section data can be inconsistent unless the errors, conditional on the common shock, are uncorrelated with the regressors.

[3] The application of the testing strategy requires the correlation coefficients to be ordered from the smallest to the largest. We do not directly test whether the sample correlations (jointly or individually) are zero. Instead, as we describe later, the goal is to test whether the probability integral transformation of the ordered correlations, $\overline{\phi}_j$, is uniformly distributed.

Φ is the cumulative distribution function of a standard normal distribution.[4] Given that $\overline{\rho}_{[j:N]} \in [0,1]\ \forall j$, then $\overline{\phi}_j \in [0.5,1]$, from which Ng (2006) shows that the null hypothesis of $\rho_j = 0$ is equivalent to the null of $\overline{\phi}_j \sim U\,(0.5,1)$. The q-order uniform spacings are simply defined as $\left\{\left(\overline{\phi}_j - \overline{\phi}_{j-q}\right)\right\}_{j=1}^{N}$.[5]

We partition the N absolute sample correlations into two groups: S for *small* (containing the smaller absolute correlations) and L for *large* (containing the larger absolute correlations), with $\theta \in [0,1]$ being the fraction of the sample contained in S. θ is estimated through maximum likelihood using a standard breakpoint analysis. The S group has size $\widehat{K}$, whereas the L group has size $\left(N-\widehat{K}\right)$. It may happen that the $\left(N-\widehat{K}\right)$ correlations in L are not statistically different from the $\widehat{K}$ correlations in S. In that case, the strategy is to test whether the $\widehat{K}$ correlations in S are zero. If the small correlations are statistically different from zero, then the correlations in L must also be different from zero by construction. Ng (2006) proposes a standardized spacings variance-ratio (SVR) test based on a statistic, $SVR\,(\eta)$, that asymptotically follows a standard normal distribution under the null of no correlation in the subsample of size η.[6]

The SVR test can be applied to the full sample, to S, or to L, with $\eta = N$, $\eta = \widehat{K}$, or $\eta = \left(N-\widehat{K}\right)$, respectively. The SVR test is based on the spacings, which are exchangeable. This fact implies that the test can be performed on any subset of the ordered correlations. It can be shown that, if the data are uncorrelated, the $\overline{\phi}_j$ all lie along a straight line. This allows to use any partition of the full sample to test the slope. If the uniformity hypothesis on the $\overline{\phi}_j$ is rejected in S, testing whether the same hypothesis holds in L becomes noninformative.[7] In principle, we can reapply the breakpoint estimator to the partition S (*second split*) to obtain two further subsamples, SS and SL.[8] Then we

[4]Note that because $\left\{\overline{\rho}_{[j:N]}\right\}_{j=1}^{N}$ is ordered, then $\left\{\overline{\phi}_j\right\}_{j=1}^{N}$, a set of monotonic transformations of ordered absolute correlations, is also ordered.

[5]Ng (2006) also provides details explaining why, if the underlying correlations are 0, the uniform spacings, $\left(\overline{\phi}_j - \overline{\phi}_{j-q}\right)$, represent a stochastic process with easily testable properties.

[6]This is an asymptotic result that holds true when the the number, N, of unique correlations approaches infinity. Ng (2006) shows that the method is also reliable in small samples.

[7]For further details, the reader is referred again to Ng (2006). Here we note that, for each group, we test whether the variance of $\left(\overline{\phi}_j - \overline{\phi}_{j-q}\right)$ is a linear function of q, which turns the problem of testing the cross-section correlation into a problem of testing uniformity and nonstationarity of a transformation of the sample correlations. A q-q plot of the $\overline{\phi}_j$ may provide information about the extent of cross-section correlation in the data. If all correlations are nonzero, then the q-q plot will be shifted upward and its intercept will be larger than 0.5. If there is homogeneity in a subset of the correlations, then the q-q plot will be flat over a certain range. The more prevalent and the stronger the correlation, the further away are the $\overline{\phi}_j$ from the straight line with slope $\frac{1}{2(n+1)}$.

[8]Note that failing to reject the null of no correlation in a group is not evidence of no correlation, because the test may simply have low power. Given the characteristics of the testing strategy, it may happen that we reject the null in the S

can perform the SVR test to determine whether the observations in the subsample SS are uncorrelated.[9]

Notice that, to isolate cross-section correlation from serial correlation, we apply the testing strategy on the correlation coefficients of the residuals from the regressions of each capital flows series on a constant term and its own first lag (conditional correlations).[10]

3.2 Testing for Sample Correlation Changes of Disaggregated Capital Flows

We now abandon the definition of cross-section correlation and seek for statistical evidence of simple correlation changes between types of capital flows within each country. We follow the bootstrap techniques described in De Pace (2008) and, given the nature of the data, we resort to the standard independent bootstrap – and to an iterated version of it – to test for correlation changes in time-series pairs. More specifically, we bootstrap the difference between correlation coefficients over two subsequent subsamples. The breakpoint, Br is exogenously given by the introduction of the euro in the first quarter of 1999.[11]

4 Empirical Results

We report results for nine major EU countries (EU9) using conditional correlations (Table 2), that is, the testing method is applied to the residuals of a regression of each detrended flow on a constant and the variable's lag. This is designed to separate serial from cross-section correlation in a fashion similar to that used by Herrera, Murtazashvili, and Pesavento (2008). Furthermore, we analyze correlation changes between flows within each country.

4.1 Cross-Section Correlations

We look at (i) the longest period – between 1990:Q1 and 2006:Q4 (see the top of the Table 2) – and at two subperiods, (ii) 1990:Q1-1998:Q4 and (iii) 1999Q1-2006:Q4, corresponding to the quarters available before and after the introduction of the euro on January 1, 1999.

group, but not in the L group. In such a case, we reject the null of no correlation for the entire sample.

[9]Two main caveats are implicit to the sequential application of this testing strategy. First, if there are too few observations in S, then the subsample SS may be too small to make the test precise. Second, if the SVR is applied to the SS subsample after the S sample rejects uniformity, then the sequential nature of the test should be considered when making inference.

[10]We do not use more than one lag in these regressions, because detrended capital flow series exhibit very low serial correlation for most countries in the sample.

[11]Further details on the procedure are described in the Appendix.

The columns of Table 2 report the following measures: the SVR, for each considered sample of ordered absolute correlations; the estimated fractions, $\widehat{\theta}$, of correlation pairs in S or SS; the number of correlations, η, in S or SS; and the SVR values for S, L, and SS. We have nine countries for each flow and time period, hence $N = 36$ correlation pairs. The SVR statistic is used to test the null of no correlation, or, more precisely, of uniformity in any given set of correlations. A large value of SVR suggests the rejection of H_0.[12]

In some cases, we are able detect significant cross-section correlations by running the test directly over the full sample. For example, this happens with iFPI for the period 1990-2006. In other cases, such correlations are revealed only by sequentially testing over the subsamples, e.g., iFDI over the 1999-2006 period.

Tests over the Entire Period (1990:Q1-2006:Q4). If we look at total flows (iTot, oTot), we find no significant evidence of cross-section correlation on the full sample of country pairs. Instead, for the equity and FPI series, the pervasiveness of cross-section correlation over the full sample is evident. Both inward and outward equity flows show significant correlation in the 36 country pairs. Some significant cross-correlation regards inward FDI in 13 out of 36 pairs.

Tests over the Two Subperiods. There are signs of cross-section correlation for inward total flows over both subperiods, but we find no indication of correlation for outward flows. We do not detect significant correlation for net and outward flows. Disaggregating the flows by type, we are able to detect the presence of a common factor structure for some flows only. We reject the null for inward and outward equity in both periods, and for inward FDI and outward debt in the second subperiod only. No evidence of significant correlations is found in all the other cases.

Histograms (Figures 1 to 3). Histograms in Figures 1 and 2 show conditional correlations over the two subperiods for inward and outward flows, respectively. Figure 3 depicts conditional correlations for net flows. An informal inspection of the plots over the 1990:Q1-1998:Q4 period reveals that bilateral point conditional correlations are mainly positive for iFPI, oFDI, oFPI, oDebt, and oTot (basically all the outward flows series, in addition to inward FPI). If we consider the period 1999:Q1-2006:Q4, we find that positive pairwise conditional correlations prevail for iFPI, iEqu, iDebt, oFDI, oFPI, oEqu, oDebt, oTot, and noTot. For each capital flow series, a nonnegligible proportion of pairwise correlations

[12] One asterisk indicates significance at the 10 percent level, two asterisks significance at the 5 percent level, and three asterisks significance at the 1 percent level.

change sign from one period to the other.

The potential existence of common factors driving capital flows at the EU level, which we can detect with Ng's statistical procedure, is due to the magnitude of absolute correlations between the flows of pairs of countries. The larger these correlations, the more likely the existence of such a common factor. The histograms indicate which pairs of countries contribute (and how much) to the rejection of the null of no cross-section correlations in the considered samples.

Ordered Absolute Correlations (Figures 4 and 5). Figures 4 and 5 provide a graphical representation of the ordered absolute correlation pairs for EU countries and for each capital flow. As in the previous analysis, the full sample (1990:Q1-2006:Q4) is split into two disjoint subsamples. If the curve connecting absolute correlations lies above the 45-degree line passing through the origin of the axes, absolute correlations have increased from the first to the second subsample. This indicates that also the likelihood that capital flows are driven by a common factor at the EU level has increased. The larger the distance from the 45-degree line, the greater the likelihood. Curves below the 45-degree line have an opposite interpretation.

A graphical inspection of the plots shows that absolute correlations have likely increased for oTot, noTot, oEqu, oFDI, oFPI, and probably for oFDI. In the other cases, absolute correlations seem to be fairly stable over the subperiods. Of note, conclusions from this informal investigation cannot be definite. Instead, they are more informative if combined with the formal inference on the spacings described earlier. For instance, pointwise positive changes in absolute correlations may still not be enough to justify the claim of emergence of a common factor on statistical grounds.

Correlation Changes

We try to establish whether the introduction of the euro in 1999 has been accompanied by correlation changes between types of capital flows within each country in the sample. We report descriptive statistics and inference for the two subperiods in Tables 3 through 5.

Results basically show no systematic pattern. Previous empirical evidence suggests that iFDI and iDebt are negatively correlated for emerging countries (Smith and Valderrama, forthcoming), and that iFDI and iFPI are negatively correlated during times of crisis (Acharya, Shin, and Yorulmazer, 2007). In our dataset, most couples of gross flows have mixed correlation signs.

Inward Flows. Correlations range widely from approximately minus 0.2 to 0.2 for the couple iFPI-iDebt to almost minus 0.4 to 0.4 for the couple iDebt-iEqu. Some of the correlations experience wide swings between periods. Unlike the large variations, which are more likely to be detected as significant by our bootstrap-based tests, small shifts are more challenging. We are able to detect only eight significant changes out of 36 using the test based on the iterated bootstrap, 13 using the noniterated version of it. As for the correlations between the two types of equity flows, we have two negative shifts (Finland and Italy) and two positive shifts (France and Germany). Significant changes between iFDI and iDebt are both negative (Finland and the Netherlands), whereas they are mixed in sign between iFPI and iDebt. The only cases of significant correlation changes between iDebt and iEqu occur in Finland (down by 0.56) and Italy (down by 0.78), findings similar to those in Smith and Valderrama (forthcoming) for emerging countries.

Outward Flows. Table 4 shows results for outward flows. The magnitudes and ranges of correlations are generally similar to those observed for inward flows. Swings between periods are somewhat smaller, except for the United Kingdom. A majority of countries shows positive correlations between outward portfolio flows and oDebt. On the other hand, outcomes for the other flows look mixed. Our test delivers significant changes only for a handful of countries: twice when the iterated bootstrap is applied and four times (out of 36) when the noniterated bootstrap is run. We find a statistically significant decrease in correlations between outward FDI and FPI only for Italy and Sweden, whereas correlation shifts are significantly positive only for the United Kingdom (outward FDI and FPI, and outward FPI and debt).

Inward and Outward Flows by Type of Flow and Country. In Table 5 we report results coming from tests run between inward and outward series for each type of flow. The range of correlations is definitely larger than in the two previous tables and a ranking of the magnitude of correlations is clearer. Inward and outward debt flows are almost always negatively correlated, with larger negative correlations reaching the value of minus 0.9, as in the United Kingdom. Other flows are less correlated, with values similar to those in the previous tables, and their signs are mixed. This finding may be consistent with the fact that debt flows respond to interest rate differentials, whereas FDI and FPI are less likely to react to changes in nominal returns. This result reinforces our belief that looking at net flows might only lead to incorrect conclusions and that it is ultimately worth looking at disaggregated flows. Correlations between inward and outward total flows are positive and large, mostly dominated by the dynamics of debt flows. We detect significantly negative changes between iFDI and oFDI (Italy and Portugal), and iDebt and oDebt (Finland and Portugal). The signs of significant changes between total flows are mixed, positive for France, Germany, and the Netherlands, negative for Italy, Portugal, Sweden and the United Kingdom. Also note that, in a majority of instances, point estimates of absolute correlations increase from one subperiod to the next.

5 Conclusions

In this paper we study the cross-section correlation of net, total, and disaggregated capital flows for nine major source and recipient European Union countries. Our aim is to determine whether it is reasonable to model the EU as an integrated economic entity when observed as the source and destination of capital flows, for example as a counterpart of the United States in two-country DSGE models with international portfolios. We first use Ng (2006)'s uniform spacing method to establish the extent of cross-section correlations and to determine which flows comove more. We find that a common factor structure is suitable for equity flows and little evidence that a common factor drives the other flows, except for inward total flows, inward FDI, and outward debt during the euro years. Hence – as suggested by recent theoretical contributions – the analysis of countries' gross assets and liabilities and their disaggregation into different types might be useful, when capital flows are interpreted as adjustments to country portfolios.

We also study whether the correlations between types of flows have changed since the introduction of the euro. We find mixed evidence of significant changes, but we notice that, in a majority of cases, point estimates of absolute correlations increase from one subperiod to the next. This finding is consistent with the claim that EU capital flows are possibly driven by a common factor.

References

Acharya, Viral V., Hyun Song Shin, and Tanj Yorulmazer (2007): "Fire-Sale FDI," CEPR Discussion Paper No. 6319.

Andrews, Donald W.K. (2005): "Cross-section Regression with Common Shocks," *Econometrica*, 73(5), 1551–1585.

Contessi, Silvio, Pierangelo De Pace, and Johanna Francis (2008): "The Cyclical Properties of Disaggregated Capital Flows," Federal Reserve Bank of St. Louis, manuscript.

De Pace, Pierangelo (2008): "Currency Union, Free-Trade Areas, and Business Cycle Synchronization," Johns Hopkins University, manuscript.

Devereux, Michael, and Alan Sutherland (2006): "Solving for Country Portfolios in Open Economy Macro Models," CEPR Discussion Paper No. 5966.

——— (forthcoming): "A Portfolio Model of Capital Flows to Emerging Markets," *Journal of Development Economics*.

DiCiccio, Thomas J., Michael A. Martin, and G. Alastair Young (1992): "Fast and Accurate Approximate Double Boostrap Confidence Intervals," *Biometrika*, 79(2), 285–295.

Doyle, Brian, and John Faust (2005): "Breaks in the Variability and Co-Movement of G-7 Economic Growth," *Review of Economics and Statistics*, 87(4), 721–740.

Ekinci, Mehmet Fatih, Sebnem Kalemli-Ozcan, and Bent E. Sorensen (2008): "Integration within EU Countries: The Role of Institutions, Confidence, and Trust," in *NBER International Seminar on Macroeconomics 2007*, ed. by F. G. Clarida, Richard. University of Chicago Press.

Herrera, Ana Maria, Irina Murtazashvili, and Elena Pesavento (2008): "The Comovement in Inventories and in sales: Higher and Higher," *Economics Letters*, 99(1), 155–158.

IMF (2007): *International Financial Statistics of the International Monetary Fund*. Washington D.C.: International Monetary Fund.

Kaminsky, Graciela L., Carmen M. Reinhart, and Carlos A. Vegh (2004): "When it Rains, it Pours: Procyclical Capital Flows and Macroeconomic Policies," in *NBER Macroeconomics Annual 2004*, ed. by M. Gertler, and K. Rogoff. Cambridge, MA: The MIT Press.

Kose, Ayhan M., Eswar S. Prasad, and Marco E. Terrones (forthcoming): "Does Financial Globalization Promote Risk Sharing?," *Journal of Development Economics*.

Lane, Philip, and Gian-Maria Milesi Ferretti (2007): "The External Wealth of Nations Mark II: Revised and Extended Estimates of Foreign Assets and Liabilities," *Journal of International Economics*, 73(November), 223–250.

Levchenko, Andrei, and Paolo Mauro (2007): "Do Some Forms of Financial Flows Help Protect from Sudden Stops?," *World Bank Economic Review*, 21(3), 389–411.

Levy-Yeyati, Eduardo, Ugo Panizza, and Eduardo Ernesto Stein (2007): "The cyclical nature of North-South FDI flows," *Journal of International Money and Finance*, 26(1), 104–130.

Lipsey, Robert E. (1999): "The Role of FDI in International Capital Flows," in *International Capital Flows*, ed. by M. Feldstein. Chicago: University of Chicago Press.

Neumann, Rebecca, Ron Penl, and Altin Tanku (2006): "Volatility of capital flows and financial liberalization: Do specific flows respond differently?," University of Wisconsin-Milwakee Working Paper No. 06-202.

Ng, Serena (2006): "Testing Cross-Section Correlation in Panel Data Using Spacings," *Journal of Business and Economic Statistics*, 24(January), 12–23.

Rothenberg, Alexander, and Francis E. Warnock (2006): "Sudden Flight and True Sudden Stops," NBER Working Paper No. 12726.

Smith, Katherine, and Diego Valderrama (forthcoming): "The composition of capital flows when emerging market firms face financing constraints," *Journal of Development Economics.*

Tille, Cedric, and Eric van Wincoop (2008): "International Capital Flows," University of Virginia, manuscript.

Appendix - Bootstrap Tests for Correlation Changes

Let ρ be the unconditional correlation coefficient between two time series, ρ_1 the unconditional correlation over the first sample, and ρ_2 the unconditional correlation over the second sample. We are interested in testing whether the parameter shift, $\Delta\rho = (\rho_2 - \rho_1)$, is statistically significant and formally consider the statistical test with size $(1-\alpha) \in (0,1)$:

$$\begin{cases} H_0 : \Delta\rho = (\rho_2 - \rho_1) = 0 \\ H_1 : \Delta\rho = (\rho_2 - \rho_1) \neq 0 \end{cases} .$$

Our inference is based on the construction of two-sided α-level confidence intervals from the bootstrap distribution of $\widehat{\Delta\rho}$.[13] This allows us to test for significant breaks and directly infer the direction of the shift. We apply bootstrap techniques to the data and also use bootstrap iteration to estimate confidence intervals with potentially improved accuracy. Namely, we derive iterated bootstrap percentile confidence intervals and iterated bias-corrected (BC) percentile confidence intervals (as described in DiCiccio, Martin, and Young, 1992). We interpret significant shifts at the 5 percent or 10 percent level as signs of parameter instability over the sample.

Constructing Bootstrap Distributions

In the simple case of two capital flows series for two countries, A and B, let $X_{A,t} = \{X_{A,s}\}_{s=1}^{T}$ and $X_{B,t} = \{X_{B,s}\}_{s=1}^{T}$ denote the two observed time series, with Br being an exogenous breakpoint. Each series is split into two subsamples, $X_{A,t}^1 = \{X_{A,s}\}_{s=1}^{Br}$, $X_{B,t}^1 = \{X_{B,s}\}_{s=1}^{Br}$, $X_{A,t}^2 = \{X_{A,s}\}_{s=Br+1}^{T}$, and $X_{B,t}^2 = \{X_{B,s}\}_{s=Br+1}^{T}$. Let $I_1, I_2, \ldots$ be a

[13] We refer to two-sided equal-tailed confidence intervals. They are equal-tailed because they attempt to place equal probability in each tail.

stream of random numbers uniform on the integers $1, ..., Br$. The algorithm that generates two bootstrap time series replicates over the first subsample, $X^{1*}_{A,t}$ and $X^{1*}_{B,t}$, runs as follows: (i) set $X^{1*}_{A,t} = X^{1}_{A,I_1}$, $X^{1*}_{B,t} = X^{1}_{B,I_1}$, and $j = 1$; (ii) while $length\left(X^{1*}_{A,t}\right) < Br$, increment j by 1 and redefine $X^{1*}_{A,t}$ and $X^{1*}_{B,t}$ as $X^{1*}_{A,t} := X^{1*}_{A,t} \cup X^{1}_{A,I_j}$ and $X^{1*}_{B,t} := X^{1*}_{B,t} \cup X^{1}_{B,I_j}$. We repeat this scheme N^B times for both the first and the second subsamples. At each complete resample of the original data, we estimate and collect $\widehat{\Delta\rho}^* = \left\{\widehat{\rho}\left(X^{2*}_{A,t}, X^{2*}_{B,t}\right) - \widehat{\rho}\left(X^{1*}_{A,t}, X^{1*}_{B,t}\right)\right\}$ to compose the bootstrap distribution of $\widehat{\Delta\rho}$.[14]

Estimating Accurate Confidence Intervals

Let $X_{A,t}$ and $X_{B,t}$ be two variables and $I_0\left(\alpha; X_{A,t}, X_{B,t}; X^{*}_{A,t}, X^{*}_{B,t}\right)$ the uncorrected bootstrap percentile confidence interval of nominal coverage probability α for $\Delta\rho$. $X^{*}_{A,t}$ and $X^{*}_{B,t}$ are two generic resamples with replacement from $X_{A,t}$ and $X_{B,t}$. The bootstrap confidence interval, I_0, is constructed from sample and resample information. In empirical applications, the coverage probability of I_0, $P(\alpha) = Prob\left\{\Delta\rho \in I_0\left(\alpha; X_{A,t}, X_{B,t}; X^{*}_{A,t}, X^{*}_{B,t}\right)\right\}$, usually differs from α. However, there exists a real number, ϱ_α, such that $P(\varrho_\alpha) = \alpha$.

Let $I_0\left(\alpha; X^{*}_{A,t}, X^{*}_{B,t}; X^{**}_{A,t}, X^{**}_{B,t}\right)$ be a version of $I_0\left(\alpha; X_{A,t}, X_{B,t}; X^{*}_{A,t}, X^{*}_{B,t}\right)$ computed using information from $X^{*}_{A,t}$, $X^{*}_{B,t}$, $X^{**}_{A,t}$, and $X^{**}_{B,t}$, where $X^{**}_{A,t}$ and $X^{**}_{B,t}$ are resamples with replacement of $X^{*}_{A,t}$ and $X^{*}_{B,t}$. $P(\alpha)$ can be estimated as

$$\widehat{P}(\alpha) = Prob\left\{\widehat{\Delta\rho} \in I_0\left(\alpha; X^{*}_{A,t}, X^{*}_{B,t}; X^{**}_{A,t}, X^{**}_{B,t} | X_{A,t}, X_{B,t}\right)\right\}.$$

Let N^B_O be the number of bootstrap replications at the outer level of resampling. Then $\widehat{P}(\alpha)$ can be easily calculated as

$$\widehat{P}(\alpha) = \frac{\sum_{n^B_O=1}^{N^B_O} 1\left\{\widehat{\Delta\rho} \in I_{0,n^B_O}\left(\alpha; X^{*}_{A,t}, X^{*}_{B,t}; X^{**}_{A,t}, X^{**}_{B,t}\right)\right\}}{N^B_O}.$$

Because information on the distribution of $X^{**}_{A,t}$ and $X^{**}_{B,t}$ given $X^{*}_{A,t}$ and $X^{*}_{B,t}$ is unavailable, an inner level of independent resamples (say, N^B_I resamples for each outer resample,

[14] When we apply the standard bootstrap with no iteration, $N^B = 10,000$.

n_O^B) from $X_{A,t}^*$ and $X_{B,t}^*$ is executed to outline the features of that distribution.[15] The bootstrap estimate for ϱ_α is the solution, $\widehat{\varrho}_\alpha$, to the equation $\widehat{P}(\varrho_\alpha) = \alpha \therefore \widehat{\varrho}_\alpha = \widehat{P}^{-1}(\alpha)$.[16] The iterated bootstrap confidence interval for $\Delta\rho$ is then $I_1\left(\widehat{\varrho}_\alpha; X_{A,t}, X_{B,t}; X_{A,t}^*, X_{B,t}^*\right)$.

[15] We use $1,000$ replications for the outer bootstrap; 500 for the inner bootstrap. Note the presence of a serious trade-off between the number of resamples, which affects the overall accuracy of estimations, and computation time.

[16] With discrete bootstrap distributions, an exact solution for this equation cannot always be found, unless we use smoothing techniques. We choose the smallest value $\widehat{\varrho}_\alpha$ such that $\widehat{P}(\widehat{\varrho}_\alpha)$ is as close as possible to α, that is, such that $\left|\widehat{P}(\varrho_\alpha) - \alpha\right|$ is minimized over a grid of values and additional conditions defining tolerance are satisfied. Refer to De Pace (2008) for further information on the algorithm and other estimation procedures adopted in this paper.

Table 1: Classification of Capital Flows

Type	Component	
Foreign Direct Investment	FDI [iFDI, oFDI]	Total Equity [iEqu, oEqu]
Foreign Portfolio Investment	Equity [iFPI, oFPI]	
	Debt	Total Debt [iDebt, oDebt]
Other Investment	Other Debt	
Total Flows	[iTot, oTot, noTot]	

Table 2: EU(9): Ng's Test for Conditional Correlations

		Full Sample SVR	N	First split $\widehat{\theta}$	First split η	First split SVR for S	First split SVR for L	Second split $\widehat{\theta}$	Second split η	Second split SVR for SS
iTot	1990:Q1-2006:Q4	0.239	36	0.583	21	0.655	0.046	0.238	5	0.891
oTot	1990:Q1-2006:Q4	1.351	36	0.806	29	0.524	1.707*	0.897	26	0.357
noTot	1990:Q1-2006:Q4	-0.880	36	0.750	27	-0.985	0.310	0.741	20	-0.937
iFDI	1990:Q1-2006:Q4	1.497	36	0.639	23	-1.525	2.822***	0.261	6	-1.047
oFDI	1990:Q1-2006:Q4	0.030	36	0.528	19	-0.692	1.471	0.263	5	0.873
iFPI	1990:Q1-2006:Q4 ◁	2.834***	36	0.806	29	3.998***	0.140	0.241	7	2.448**
oFPI	1990:Q1-2006:Q4 ◁	3.146***	36	0.389	14	-0.067	0.000	0.857	12	3.327***
iEqu	1990:Q1-2006:Q4 ◁	2.765***	36	0.667	24	-0.232	2.297**	0.208	5	-0.419
oEqu	1990:Q1-2006:Q4 ◁	2.924***	36	0.361	13	-0.923	1.902*	0.846	11	1.483
iDebt	1990:Q1-2006:Q4	1.530	36	0.472	17	-0.584	0.599	0.882	15	-0.340
oDebt	1990:Q1-2006:Q4	1.360	36	0.583	21	-1.308	-0.147	0.857	18	-0.278
iTot	1990:Q1-1998:Q4 ◁	-1.406	36	0.167	6	2.013**	-1.742*	0.833	5	-0.727
	1999:Q1-2006:Q4 ◁	1.875*	36	0.778	28	0.622	2.211*	0.750	21	0.419
oTot	1990:Q1-1998:Q4	1.564	36	0.806	29	0.763	2.306**	0.862	25	0.546
	1999:Q1-2006:Q4	0.784	36	0.722	26	0.674	1.747*	0.385	10	-0.520
noTot	1990:Q1-1998:Q4	0.221	36	0.861	31	0.806	0.334	0.290	9	-0.796
	1999:Q1-2006:Q4	-0.037	36	0.444	16	-0.351	0.850	0.500	8	-1.264
iFDI	1990:Q1-1998:Q4	0.648	36	0.667	24	0.634	-0.419	0.500	12	-0.498
	1999:Q1-2006:Q4 ◁	1.384	36	0.167	6	3.211***	0.964	0.500	3	-1.732*
oFDI	1990:Q1-1998:Q4	0.892	36	0.472	17	-1.035	1.784*	0.118	2	—
	1999:Q1-2006:Q4	0.469	36	0.472	17	0.480	-0.135	0.353	6	-0.494
iFPI	1990:Q1-1998:Q4	-0.680	36	0.611	22	-0.524	0.805	0.773	17	-0.158
	1999:Q1-2006:Q4	-0.497	36	0.556	20	-0.407	-0.087	0.200	4	-1.547
oFPI	1990:Q1-1998:Q4	1.142	36	0.611	22	1.401	-0.871	0.636	14	-1.163
	1999:Q1-2006:Q4	0.584	36	0.556	20	0.284	-0.410	0.750	15	0.127
iEqu	1990:Q1-1998:Q4 ◁	0.536	36	0.139	5	1.083	0.277	0.800	4	-1.941*
	1999:Q1-2006:Q4 ◁	1.301	36	0.583	21	-0.545	0.271	0.762	16	-2.026**
oEqu	1990:Q1-1998:Q4 ◁	-1.685*	36	0.750	27	-2.588***	1.480	0.852	23	-2.045**
	1999:Q1-2006:Q4 ◁	1.683*	36	0.583	21	1.039	-0.263	0.571	12	0.093
iDebt	1990:Q1-1998:Q4	1.250	36	0.417	15	1.249	0.789	0.267	4	-0.271
	1999:Q1-2006:Q4	1.614	36	0.444	16	-0.760	1.554	0.250	4	-0.652
oDebt	1990:Q1-1998:Q4	0.695	36	0.806	29	0.240	-1.518	0.690	20	-0.276
	1999:Q1-2006:Q4 ◁	1.171	36	0.750	27	1.442	0.644	0.111	3	-1.732*

NOTE: N is the total number of pairwise correlations and θ is the proportion of correlations in the subsample with smaller correlations; η is the number of correlations in the subsample with smaller correlations. H_0: no correlation in the sample. We indicate the rejection of the null over the full sample by a triangle. One asterisk denotes significance at the 10 percent level, two asterisks significance at the 5 percent level, and three asterisks significance at the 1 percent level.

Table 3: Correlations of Inward Flows by Country

		iFDI iFPI	iFDI iDebt	iFPI iDebt	iDebt iEqu		iFDI iFPI	iFDI iDebt	iFPI iDebt	iDebt iEqu
ρ_{90-98}	Finland	0.172	0.333	0.054	0.281	Portugal	-0.055	0.217	-0.011	-0.058
ρ_{99-06}		-0.221	-0.274	-0.274	-0.274		-0.152	0.153	-0.365	-0.134
$\Delta\rho$		-0.393	-0.607	-0.328	-0.556		-0.097	-0.064	-0.354	-0.075
test 1		D	D	D	D		d	d	d	d
test 2		D	D	D	D		d	d	D	d
ρ_{90-98}	France	-0.085	0.084	-0.316	-0.211	Spain	0.023	-0.137	0.020	-0.024
ρ_{99-06}		0.234	0.163	0.163	0.169		-0.199	-0.049	0.131	-0.047
$\Delta\rho$		0.319	0.080	0.479	0.380		-0.222	0.088	0.111	-0.023
test 1		u	u	U	u		d	u	u	d
test 2		U	u	U	u		d	u	u	d
ρ_{90-98}	Germany	-0.269	-0.066	-0.212	-0.160	Sweden	-0.099	0.179	-0.172	-0.063
ρ_{99-06}		0.203	0.084	0.053	-0.032		0.205	0.173	-0.218	0.140
$\Delta\rho$		0.472	0.150	0.266	0.127		0.305	-0.007	-0.046	0.203
test 1		u	u	u	u		u	d	d	u
test 2		U	u	u	u		u	d	d	u
ρ_{90-98}	Italy	0.287	0.116	0.455	0.398	United Kingdom	-0.042	-0.120	-0.175	-0.091
ρ_{99-06}		-0.131	0.346	-0.303	-0.380		-0.158	-0.160	0.192	0.021
$\Delta\rho$		-0.418	0.230	-0.758	-0.777		-0.116	-0.041	0.367	0.112
test 1		d	u	D	D		d	d	u	u
test 2		D	u	D	D		d	d	U	u
ρ_{90-98}	Netherlands	-0.039	0.102	0.033	-0.213					
ρ_{99-06}		-0.140	-0.263	0.137	-0.108					
$\Delta\rho$		-0.101	-0.365	0.104	0.105					
test 1		d	D	u	u					
test 2		d	D	u	u					

Note: Tests of statistical significance on $\Delta\rho$. Test 1 is run using iterated bootstrap techniques. Test 2 is run using noniterated bootstrap techniques. u: positive correlation change; d: negative correlation change; U: significantly positive correlation change; D: significantly negative correlation change.

Table 4: Correlations of Outward Flows by Country

		oFDI oFPI	oFDI oDebt	oFPI oDebt	oDebt oEqu		oFDI oFPI	oFDI oDebt	oFPI oDebt	oDebt oEqu
ρ_{90-98}	Finland	0.020	-0.358	0.120	-0.314	Portugal	-0.100	-0.233	0.112	-0.105
ρ_{99-06}		-0.174	-0.223	0.181	-0.160		-0.189	-0.012	0.167	0.064
$\Delta\rho$		-0.194	0.135	0.062	0.154		-0.089	0.221	0.055	0.169
test 1		d	u	u	u		d	u	u	u
test 2		d	u	u	u		d	u	u	u
ρ_{90-98}	France	0.016	-0.179	0.114	-0.161	Spain	-0.182	-0.120	0.129	-0.177
ρ_{99-06}		0.120	-0.037	0.096	-0.032		-0.139	0.009	0.106	0.020
$\Delta\rho$		0.104	0.142	-0.018	0.128		0.042	0.129	-0.022	0.197
test 1		u	u	d	u		u	u	d	u
test 2		u	u	d	u		u	u	d	u
ρ_{90-98}	Germany	0.057	0.262	-0.233	-0.171	Sweden	0.180	0.155	0.015	0.100
ρ_{99-06}		0.008	0.243	-0.104	0.291		-0.218	0.196	0.187	0.361
$\Delta\rho$		-0.048	-0.019	0.129	0.462		-0.399	0.040	0.172	0.261
test 1		d	d	u	u		D	u	u	u
test 2		d	d	u	u		D	u	u	u
ρ_{90-98}	Italy	0.154	0.023	-0.101	-0.004	United Kingdom	-0.041	-0.055	-0.340	-0.206
ρ_{99-06}		-0.157	-0.137	0.188	0.109		0.371	-0.102	0.052	0.054
$\Delta\rho$		-0.311	-0.160	0.289	0.113		0.412	-0.047	0.392	0.260
test 1		D	d	u	u		u	d	u	u
test 2		D	d	u	u		U	d	U	u
ρ_{90-98}	Netherlands	-0.038	-0.152	-0.259	-0.302					
ρ_{99-06}		-0.288	0.085	-0.349	-0.369					
$\Delta\rho$		-0.249	0.237	-0.089	-0.068					
test 1		d	u	d	d					
test 2		d	u	d	d					

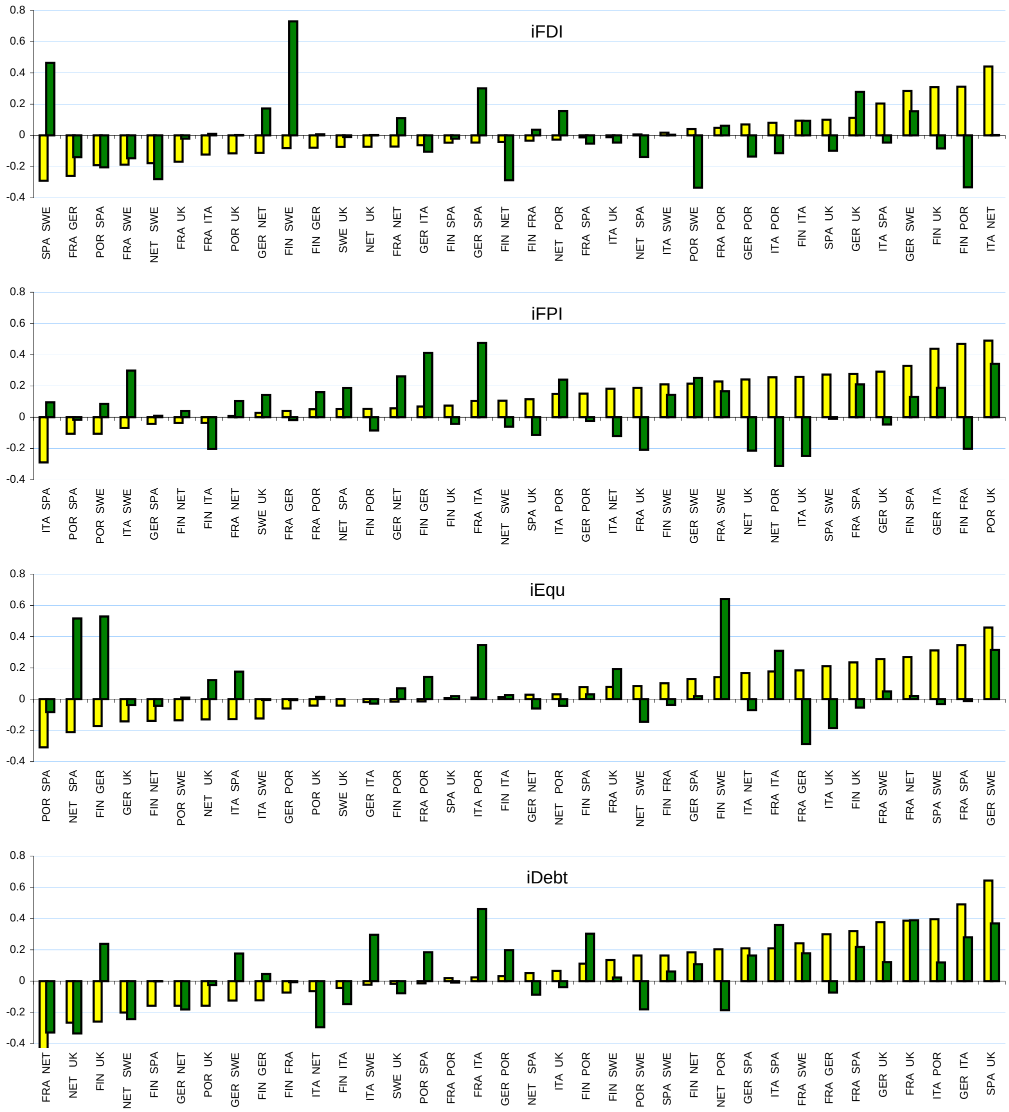
Note: Tests of statistical significance on $\Delta\rho$. Test 1 is run using iterated bootstrap techniques. Test 2 is run using noniterated bootstrap techniques. u: positive correlation change; d: negative correlation change; U: significantly positive correlation change; D: significantly negative correlation change.

Table 5: Correlations of Inward and Outward Flows by Country

		iFDI oFDI	iFPI oFPI	iDebt oDebt	iEqu oEqu	iTot oTot		iFDI oFDI	iFPI oFPI	iDebt oDebt	iEqu oEqu	iTot oTot
ρ_{90-98}	Finland	-0.086	-0.201	-0.444	-0.200	-0.495	Portugal	0.194	-0.049	-0.135	0.050	-0.022
ρ_{99-06}		-0.420	-0.155	-0.723	-0.605	-0.773		-0.162	0.061	-0.785	-0.200	-0.768
$\Delta\rho$		-0.335	0.046	-0.278	-0.404	-0.279		-0.357	0.110	-0.650	-0.251	-0.746
test 1		d	u	d	d	d		D	u	D	d	D
test 2		d	u	D	d	d		D	u	D	d	D
ρ_{90-98}	France	-0.123	-0.138	-0.821	-0.267	-0.989	Spain	-0.185	0.197	-0.549	-0.104	-0.742
ρ_{99-06}		-0.312	-0.512	-0.324	-0.380	-0.414		-0.199	-0.023	-0.343	-0.204	-0.967
$\Delta\rho$		-0.190	-0.373	0.497	-0.112	0.576		-0.015	-0.220	0.206	-0.100	-0.225
test 1		d	d	u	d	u		d	d	u	d	d
test 2		d	d	U	d	U		d	d	u	d	d
ρ_{90-98}	Germany	-0.090	0.119	-0.403	0.133	-0.670	Sweden	-0.240	0.112	-0.561	-0.095	-0.331
ρ_{99-06}		-0.186	0.016	-0.457	0.092	-0.082		0.005	0.501	-0.815	-0.159	-0.858
$\Delta\rho$		-0.096	-0.102	-0.053	-0.041	0.587		0.245	0.388	-0.254	-0.064	-0.527
test 1		d	d	d	d	u		u	U	d	d	D
test 2		d	d	d	d	U		u	U	d	d	D
ρ_{90-98}	Italy	-0.032	-0.196	-0.666	-0.049	-0.772	United Kingdom	0.013	-0.324	-0.821	-0.010	-0.424
ρ_{99-06}		-0.758	0.043	-0.511	-0.047	-0.994		0.037	0.073	-0.900	0.059	-0.998
$\Delta\rho$		-0.726	0.239	0.155	0.002	-0.221		0.024	0.397	-0.079	0.069	-0.574
test 1		D	u	u	u	d		u	U	d	u	D
test 2		D	u	u	u	D		u	U	d	u	D
ρ_{90-98}	Netherlands	0.265	0.178	-0.776	-0.011	-0.480						
ρ_{99-06}		-0.121	-0.009	-0.730	-0.119	-0.235						
$\Delta\rho$		-0.386	-0.187	0.046	-0.108	0.245						
test 1		d	d	u	d	U						
test 2		d	d	u	d	U						

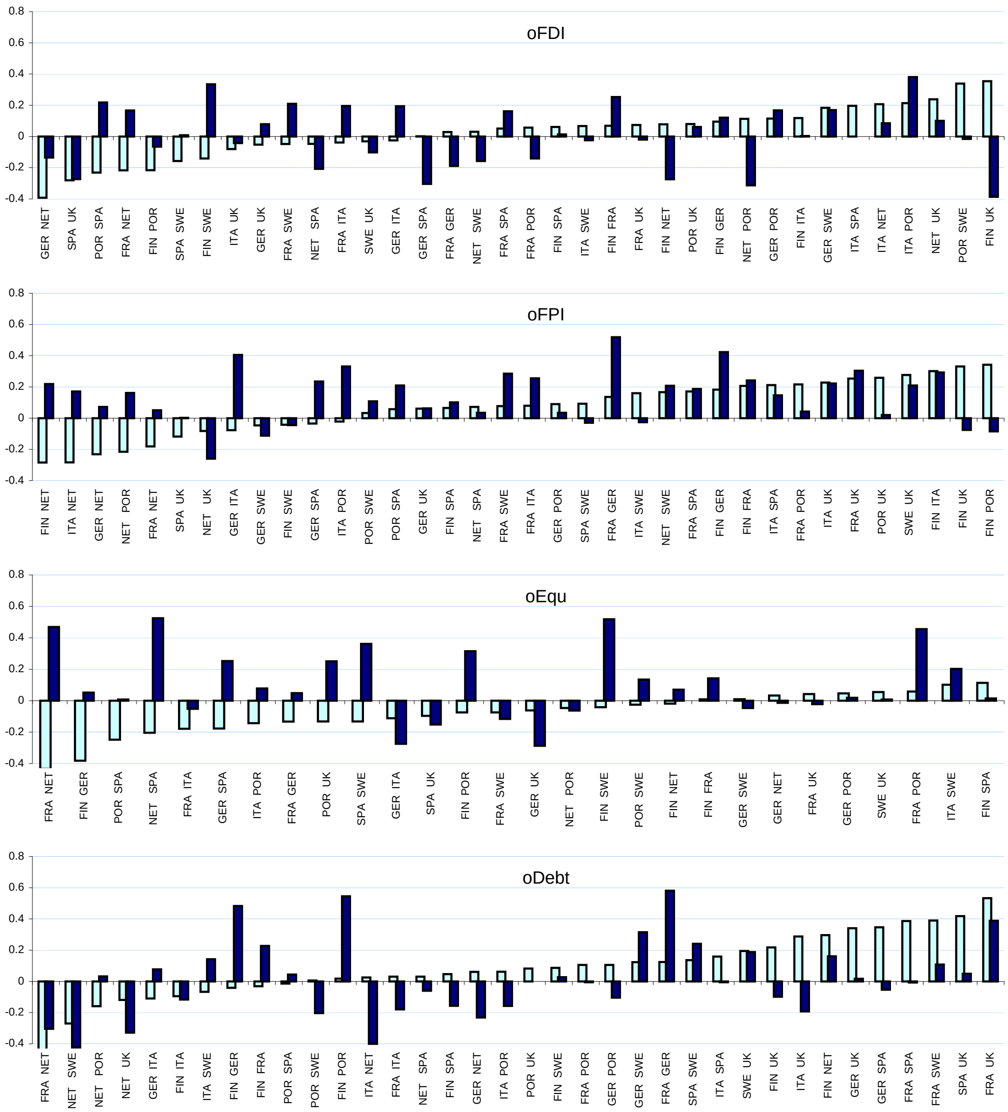
Note: Tests of statistical significance on $\Delta\rho$. Test 1 is run using iterated bootstrap techniques. Test 2 is run using noniterated bootstrap techniques. u: positive correlation change; d: negative correlation change; U: significantly positive correlation change; D: significantly negative correlation change.

Figure 1: Conditional correlations by type of inward flow



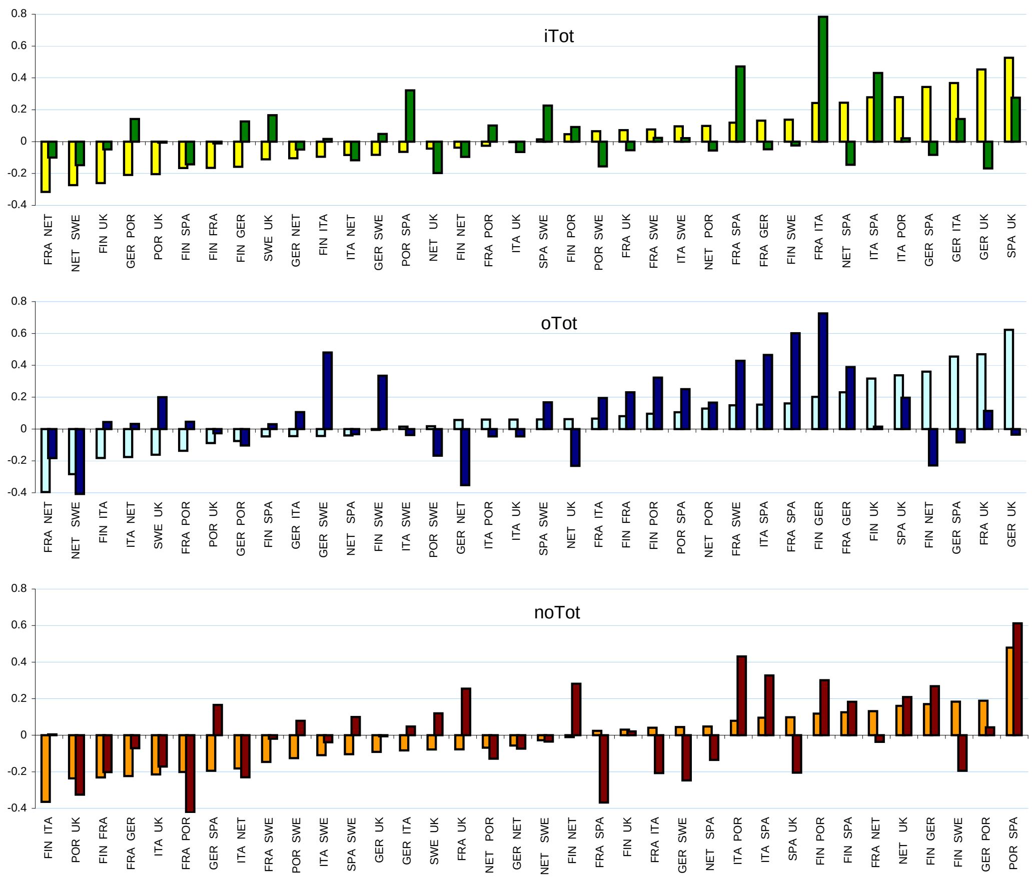
Note: 1990:Q1-1998:Q4 (open bars) and 1999:Q1-2006:Q4 (solid bars)

Figure 2: Conditional correlations by type of outward flow



Note: 1990:Q1-1998:Q4 (open bars) and 1999:Q1-2006:Q4 (solid bars)

Figure 3: Conditional correlations of net total outward flows



Note: 1990:Q1-1998:Q4 (open bars) and 1999:Q1-2006:Q4 (solid bars)

Figure 4: Ordered correlation pairs before and after the introduction of the euro, total flows.

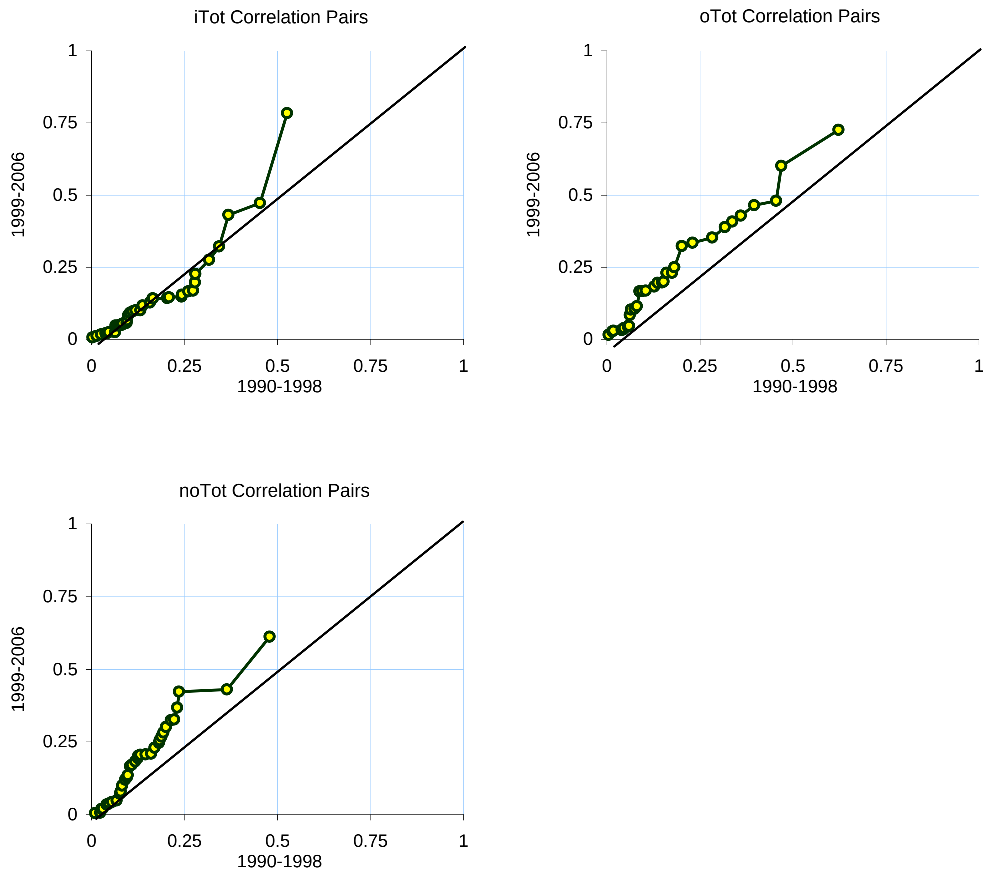


Figure 5: Ordered correlation pairs before and after the introduction of the euro, disaggregated flows.