International Equity Flows and the Predictability of U.S. Stock Returns

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Abstract

We examined the link between international equity flows and U.S. stock returns. Based on the results of tests of in-sample and out-of-sample predictability of stock returns, we found evidence of a strong positive (negative) link between international equity flows and contemporaneous (one-month-ahead) stock returns. Our results also indicate that an investor, in real time, could have used information on the link between international equity flows and one-month-ahead stock returns to improve the performance of simple trading rules.

Keywords: International equity flows, predictability of stock returns, performance of trading rules, the United States

JEL classification: E44, F32, G11

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1. Introduction

A key manifestation of the globalization of the world's economy and the international integration of financial markets is the significant increase in international capital flows since the mid-1990s. Much of the increase in international capital flows has been due to cross-border financial flows in equities (Eichengreen and Fishlow 1998). The increasing importance of international equity flows has spurred the interest of researchers in the question whether international equity flows affect stock returns. International equity flows may affect stock returns through momentum trading of foreign investors, price-pressure and liquidity effects, a potential broadening in the investor base, and changes in the cost of capital (see Stulz 1999, for a survey). Empirical evidence for a link between stock returns and international equity flows has been reported by Brennan and Cao (1997), Froot et al. (2001), and Bekeart et al. (2002), to name just a few.

Interesting and yet unanswered questions are whether international equity flows help to predict stock returns, and how much an investor can gain from accounting for the link between international equity flows and stock returns. We provide answers to these questions by analyzing the implications of international equity flows for the predictability of stock returns. We used in-sample tests, out-of-sample tests, and the recursive modeling approach developed by Pesaran and Timmermann (1995, 2000) to study whether international equity flows help to forecast stock returns. The recursive modeling approach developed by Pesaran and Timmermann has the key advantage of allowing an investor's real-time portfolio-allocation problem to be analyzed. Because the recursive modeling approach captures how an investor's information on international equity flows changes over time, it renders it possible to gauge whether an investor can use this information to forecast stock returns in real time and to set up profitable trading rules.

In order to analyze whether international equity flows help to forecast stock returns, we used monthly data for the recent period 1985–2005 on net purchases of U.S. stocks by foreign investors. Our empirical results can be summarized as follows. First, the results of in-sample tests of stock-return predictability reveal a strong positive (negative) link between international equity flows and contemporaneous (one-month-ahead) stock returns. Second, the results of out-of-sample tests of stock-return predictability indicate that international equity flows help to predict one-month-ahead stock returns. Third, the results of the recursive modeling approach show that an investor could have used real-time information on international equity flows to set up profitable trading rules, and for market-timing purposes.

We organize the remainder of this paper as follows. In Section 2, we lay out the data on international equity flows, the stock-market data, and the other macroeconomic and financial data we used in our empirical analyses. In Section 3, we report the results of in-sample and out-of-sample tests of stock-return predictability based on international equity flows. In Section 4, we describe our recursive modeling approach and how we analyzed the performance of trading rules in real time. Furthermore, we present the results of implementing the recursive modeling approach, and we report the results of tests of market timing. In Section 5, we offer some concluding remarks.

2. The Data

Our source of monthly data on net international equity flows to the United States is the U.S. Treasury International Capital (TIC) reporting system. We used monthly data on net purchases of U.S. stocks by foreign investors for the period of time 1985/1–2005/6. The TIC data have been used by many other authors to study international equity flows (Tesar and Werner 1993, Bekaert et al. 2002). The TIC data are published with a lag of one and a half months. For this reason, we accounted for a publication lag of two months in our empirical analyses. We did so in order to account for the fact that an investor can only use historical and contemporaneous information to forecast stock returns. An investor cannot use information becoming available later on. Figure 1 shows our data on international equity flows. It can be seen that international equity flows started increasing significantly at around 1995, and that international equity flows were quite volatile. Moreover, international equity flows were large and positive at the end of the 1990s when stock prices significantly increased. International equity flows became smaller and turned negative after 2000 when stock prices started decreasing. This suggests that there was a close comovement of stock returns with international equity flows. For an investor, this raises the question whether this comovement implies that international equity flows could have been used to forecast stock returns in the United States.

— Insert Figure 1 about here. —

In order to answer this question, we collected data on a number of macroeconomic and financial variables. The main source of our data is Thomson Financial Datastream. We give the Datastream codes in parentheses when we introduce a variable for the first time to enable a reader to replicate our results. In the case of our stock market data, we used daily data to extract end-of-month data. The reason for this is that Datastream provides start-of-month data in the case of monthly data. Our list of macroeconomic and financial variables contains the following variables:

1) Stock returns. We used the MSCI performance index for the United States (MSUSANL(RI)) to measure the development of the stock market. We computed stock returns as the change in the natural logarithm of this index. We then subtracted from stock returns a short-term interest rate to compute excess stock returns. To this end, we used the three months Treasury bill rate (USI60C..).

2) The stochastically detrended short-term interest rate (RTB). We used the three months Treasury bill rate as our short-term interest rate. As in Rapach et al. (2005), we computed RTB as the difference between the short-term interest rate and its 12-month backward-looking moving average.

3) The term spread (TSP). TSP is defined as the difference between the long-term government bond yield (USI61...) and the three-month Treasury bill rate. TSP has been considered by, for example, Campbell (1987), Chen et al. (1986), and Chen (1991) as a predictor of stock returns.

4) A dummy variable (DMA150) that assumes the value one if the difference between the stock market index and its six-month backward-looking moving average is smaller than one percent, and zero otherwise. We considered DMA150 as a predictor for stock returns because moving-average rules have been studied in the literature on technical-trading rules (Brock et al. 1992).

5) The inflation rate (INF). INF is defined as the 12-month backward-looking moving average of the change in the natural logarithm of the consumer price index (USI64...F). The publication lag for INF is two months. The inflation rate can be used as a measure of monetary conditions and business-cycle fluctuations. It has been used as a variable to forecast stock returns, for example, by Chen et al. (1986) and Fama (1981).

6) The growth rate of industrial production (DIPA). DIPA is defined as the 12-month backward-looking moving average of the change in the natural logarithm of industrial production (USI66..IG). The publication lag for DIPA is two months. Various studies of return predictability using macroeconomic variables have focused on industrial production as a measure of the stance of the business cycle (Chen et al. 1986, Rapach et al. 2005, to name just a few).

7) The consumption-wealth ratio (CAY). We used data on CAY compiled by Lettau (2005). The publication lag for CAY is two months. Lettau and Ludvigson (2001) provide a detailed description of how CAY can be calculated. They have reported that quarterly changes in CAY predict U.S. excess stock returns. In order to convert the quarterly CAY data to a monthly frequency, we treated CAY as constant within a quarter.

8) The change in the natural logarithm of the trade-weighted real effective exchange rate (RER). The source of our RER data is the International Financial Statistics of the IMF (111..RECZF...). Several authors have argued that there may be evidence for the link between exchange rate movements and stock returns (Bartov and Bodnar 1994, Williamson 2001).

9) The lagged stock returns (RETLAG). We used the lagged stock returns as a regressor to take into account that return predictability may arise because stock returns may follow a first-order autoregressive process, not because international capital flows have predictive power for stock returns.

3. Tests of Predictability of Stock Returns

This section comes in two parts. In the first part, we report the results of in-sample tests of predictability of stock returns. In the second part, we report the results of out-of-sample tests of predictability of stock returns.

3.1 In-Sample Tests of Predictability of Stock Returns

In Table 1, we report results of regressions of stock returns on contemporaneous international equity flows and other macroeconomic and financial variables. To generate the results summarized in Table 1, we neglected any publication lags. We report estimation results for the full sample 1985–2005 (Panel A) and for a subsample that covers the period of time 1995–2005 (Panel B). The subsample covers the recent period of large and volatile international equity flows. Regarding the estimation results for the full sample, international equity flows help to explain contemporaneous stock returns in only one equation. This result is consistent with the results reported by Brennan and Cao (1997), who have reported that the link between international equity flows to the U.S. from developed countries and contemporaneous stock returns is insignificant. The coefficient of international equity flows, however, is statistically significant and positive in a broader sense in seven out of the ten equations. Furthermore, the coefficients of the variables DMA150 and RER are statistically significant. Regarding the subsample, the coefficient of international equity flows is statistically significant and positive in eight out of the ten equations. In the other two equations, the coefficient is significant at a marginal level of significance of 11 percent and 15 percent. The list of other variables that help to explain contemporaneous stock returns includes the variables CAY, DMA150, TSP, RER, and RETLAG.

For an investor who wants to forecast stock returns, the results reported in Table 1 are informative. However, more relevant for an investor are results on the link between international equity flows and future stock returns. We, therefore, report in Table 2 regression results that answer the question whether international equity flows help to predict one-month-ahead stock returns. In order to produce the results summarized in Table 2, we accounted for publication lags. (The results we obtained when we neglected publication lags are similar and can be obtained from the authors upon request.) As regards the estimation results for the full sample, international equity flows are always highly significant. Their coefficient is always negative. Other important variables are CAY, TSP, and DMA150. As regards the estimation results for the subsample, international equity flows are highly significant in all regression equations. Other variables that had predictive power for stock returns are the variables TSP, DIPA, and RER.

Our result of a positive (negative) link between international equity flows and contemporaneous (one-month-ahead) stock returns is consistent with results reported in earlier empirical studies. Our result could be interpreted, for example, in terms of an overshooting of stock returns in response to international equity flows. An overshooting implies that international equity flows have a large effect on contemporaneous stock prices that is gradually reversed in later months. Another interpretation of our results could be based on the widespread belief that local investors have better information about local assets than foreign investors. If this is the case, foreign investors would have to trade against potentially better informed U.S. investors who know better when to sell and when to buy. One way for foreign investors to deal with this informational asymmetry would be to buy U.S. stocks when the price is high and to sell stocks later on when the price is low. This could give rise to the link between international equity flows and one-month-ahead stock returns we found in our empirical analysis.

We do not want to stretch the interpretation of our result too far for two reasons. First, it is important to note that both international equity flows and stock returns are endogenous. Both variables are the result of investors' portfolio-allocation decisions. For this reason, any theoretical interpretation of our results would require a more structural empirical model than the one we used in our analyses. For example, to obtain a theoretical interpretation of our results, it would be useful to differentiate between expected and unexpected international equity flows (Clark and Berko 1997, Bekaert et al. 2002). Second, an investor who examines whether information on international equity flows can be used to predict stock returns might not be interested too much in a structural theoretical interpretation of our results. An investor needs a model that allows the predictive content of international equity flows for future stock returns to be traced out. For an investor, the estimation results summarized in Table 2 are useful because they provide a first hint that international equity flows may have predictive content for one-month-ahead stock returns. The usefulness of the results for an investor, however, is limited insofar as our results only document the in-sample predictability of stock returns based on international equity flows.

3.2 Out-of-Sample Tests of Predictability of Stock Returns

We used Theil's U statistic, the MSE-F test developed by McCracken (2004), and the ENC-NEW test developed by Clark and McCracken (2001) to examine the out-of-sample predictability of one-month-ahead stock returns based on international equity flows. To this end, we defined a benchmark model for forecasting stock returns and an alternative model, where the benchmark model is nested within the alternative model.

Theil's U statistic is defined as the ratio of the square roots of the mean-squared forecasting errors of the alternative model and the benchmark model. If

Theil's U statistic is smaller than one, then the forecasts based on the alternative model are superior to the forecasts of the benchmark model. The null hypothesis of the MSE-F test is that the mean-squared forecasting error of the benchmark model is smaller than or equal to that of the alternative model. The one-sided alternative hypothesis is that the alternative model has a lower mean-squared error than the benchmark model. The null hypothesis of the ENC-NEW test is that the forecasts derived from the benchmark model encompass all the information on one-month-ahead stock returns. The one-sided alternative hypothesis is that the forecasts derived from the alternative model contain additional information. Both the MSE-F test and the ENC-NEW test have nonstandard asymptotic distributions. We, therefore, used a bootstrap simulation experiment to compute the p-values for the MSE-F and the ENC-NEW tests. We used 1,000 bootstrap simulations to compute the p-values.

In order to implement the MSE-F and the ENC-NEW tests, we followed Lettau and Ludvigson (2001) and defined two benchmark models. The first benchmark model is an autoregressive model. This autoregressive model describes stock returns in terms of a constant and lagged stock returns. The second benchmark model is a constant-expected returns model that describes stock returns in terms of a constant only. We compared our benchmark models to an alternative model that contains either international equity flows or one of the other macroeconomic and financial variables described in Section 2.1 as a further explanatory variable. We first estimated both models using data for the period of time 1985/1–1994/12. We then produced two series of one-step-ahead forecasts of stock returns by recursively estimating both models, adding data for one month at a time. We compared the one-step-ahead forecasts of stock returns with realized stock returns to compute the mean-squared forecasting errors of both the benchmark and the alternative models.

The results summarized in Table 3 show that both Theil's U statistic and the statistically significant MSE-F test indicate that the forecasts of stock returns derived from the alternative model that features international equity flows are more accurate than the forecasts of stock returns derived from the benchmark models. The ENC-NEW test is significant only in a broader sense with p-values of

0.19 and 0.20, respectively. As regards the other macroeconomic and financial variables, only the forecasts derived from an alternative model that features the variable TSP seems to contain some useful information with regard to stock returns not already contained in the forecasts derived from the benchmark models. Theil's U statistic in general exceeds unity in the case of the other macroeconomic and financial variables. Moreover, the MSE-F and the ENC-NEW tests are not statistically significant. Thus, to sum up, the overall impression that emerges is that international equity flows contain significant information that can be used by an investor to forecast one-month-ahead stock returns. The usefulness of the other macroeconomic and financial variables is limited.

4. A Recursive Modeling Approach

We describe the recursive modeling approach that we used to analyze whether an investor, in real time, could have forecasted stock returns based on information on international equity flows in four steps. In a first step, we describe how we implemented the recursive modeling approach. In a second step, we lay out how we used the recursive modeling approach to analyze the performance of simple trading rules. In a third step, we report our empirical results. In a fourth step, we report the results of tests of market timing.

4.1 Recursive Forecasting of Stock Returns in Real Time

We considered an investor whose problem, in every month, is to decide on how to combine the then available information on macroeconomic and financial variables to predict one-month-ahead stock returns. In every month, the investor must reach a decision under uncertainty about the optimal model for forecasting stock returns. In order to reach a decision, the investor applies a recursive modeling approach as developed by Pesaran and Timmermann (1995, 2000). According to this recursive modeling approach, the investor attempts to identify the optimal forecasting model by searching, in every month, over a large number of different models that feature different macroeconomic and financial variables. As time progresses and new data on international equity flows and the other macroeconomic and financial variables become available, the investor recursively restarts the search for the optimal forecasting model.

We assumed that the investor identifies the optimal forecasting model by searching over all possible permutations of international equity flows and the other macroeconomic and financial variables considered as candidates for forecasting stock returns. This implies that the investor must search in every month over a large number of different models. Because the investor must conduct this search in an efficient and timely manner, we followed Pesaran and Timmermann (1995, 2000) and assumed that the investor only considers linear regression models. The investor estimates the vector of parameters of the regression models by the ordinary least squares technique, where we assumed that the vector of regressors always includes a constant. Furthermore, we assumed that, in order to set up the recursive modeling approach, the investor considers the period of time 1985/1–1994/12 as a training period.

In order to identify the optimal forecasting model among the large number of forecasting models being estimated in every month, the investor needs a model-selection criterion. The model-selection criteria we considered are the Adjusted Coefficient of Determination (ACD), the Akaike Information Criterion (AIC, Akaike 1973), and the Bayesian Information Criterion (BIC, Schwarz 1978). The ACD, AIC, and BIC model-selection criteria have the advantage that an investor can easily compute these criteria in real time. Moreover, these model-selection criteria are widely used in applied research, and they were readily available to investors at the beginning of our sample period. This is an advantage because we plan to simulate the real-time investment decisions of an investor, implying that we must ensure that the investor bases investment decisions only on information which were available in the months in which these decisions had to be reached.

4.2 Measuring the Performance of Trading Rules

In each period of time, the investor selects three models: one model that maximizes the ACD model-selection criterion, and two models that minimize the AIC and BIC model-selection criteria, respectively. This yields three sequences of optimal one-step-ahead stock-return forecasts. Every single one of these sequences of stock-return forecasts can be used by the investor to set up a trading rule. Depending on the trading rule chosen by the investor, the financial wealth of the investor changes over time.

The trading rules that we analyzed require that the investor switches between shares and bonds. To this end, our investor can use information on the optimal one-step-ahead stock-return forecasts extracted from the optimal forecasting models which have been selected on the basis of one of the three model-selection criteria. The investor only invests in shares, not in bonds, when the optimal one-step-ahead stock-return forecasts are positive. By contrast, the investor only invests in bonds, not in shares, when the optimal one-step-ahead stock-return forecasts are negative. When reaching an investment decision our investor does not make use of short selling, nor does our investor use leverage. Furthermore, we assume that trading in stocks and bonds is connected with transaction costs that are (i) constant through time, (ii) the same for buying and selling stocks and bonds, and (iii) proportional to the value of a trade.

Our trading rules require that the investor switches between domestic shares and domestic bonds. Our choice of trading rules is in line with the results of much empirical research that, despite the recent growth in international equity flows, a strong domestic bias in investors' equity portfolios continues to exist (French and Poterba 1991, Tesar and Werner 1995, Lewis 1999). This so-called "home bias" implies that, as compared to the predictions of international asset pricing models, investors allocate too little of their wealth to foreign stocks. Investors, therefore, do not fully share risk with foreigners, and they do not fully take advantage of the gains from international diversification.

We measured the performance of the different trading rules available to our investor in terms of Sharpe's ratio (Sharpe 1966). We computed Sharpe's ratio as $SR = \bar{r} / SD$, where SR denotes Sharpe's ratio, $\bar{r}$ denotes the average excess portfolio returns from the first month after the training period to the end of the sample, and SD denotes the standard deviation of excess portfolio returns. In addition to Sharpe's ratio, we also computed investor's wealth at the end of the sample period under the different trading rules.

4.3 Empirical Results

The results reported in Panel A of Table 4 summarize how often an investor would have included international equity flows and the other macroeconomic and financial variables in the optimal forecasting model for stock returns. We report results for the ACD, the AIC, and the BIC model-selection criterion. Panel B of Table 4 summarizes the corresponding results we obtained when we dropped international equity flows from the set of variables used by the investor to forecast stock returns.

— Insert Table 4 about here. —

The results indicate that, irrespective of the model-selection criterion being used, international equity flows are very often included in the optimal forecasting model. This confirms the results of the in-sample and out-of-sample tests of return predictability that we reported in Section 3. Other variables often included in the optimal forecasting model are the variables DMA150, CAY, and TSP. The variables DIPA, RTB, and RER are important predictors of stock returns only under the ACD model-selection criterion. As one would have expected, under the BIC criterion, the investor would have selected a very parsimonious forecasting model containing only two variables, international equity flows and DMA150.

When international equity flows are dropped from the list of variables considered by the investor to be of potential importance for forecasting stock returns, the importance of the variable CAY increases. The variable CAY is now often included in the optimal forecasting model under the BIC model-selection criterion. Moreover, when information on international equity flows is not used to forecast stock returns, the variables DIPA and RTB are often selected as predictors of stock returns under the AIC model-selection criterion. Under the ACD model-selection criterion, there are hardly changes as compared to the model in which international equity flows are considered as a potentially relevant variable for forecasting stock returns.

In Table 5, we summarize results on the performance of the investor's trading rules under the different model-selection criteria in terms of Sharpe's ratio and investor's terminal wealth. We report the results that we obtained when we used international equity flows as a candidate for forecasting stock returns, and the results that we obtained when we neglected international equity flows. We also report results for zero, medium-sized, and high transaction costs. In order to calibrate transaction costs, we followed Pesaran and Timmermann (1995). They assumed medium-sized (high) transaction costs of 0.5 and 0.1 of a percent (0.1 of a percent and 1 percent) for shares and bonds, respectively.

— Insert Table 5 about here. —

The key result conveyed by Table 5 is that the performance of trading rules that account for information on international equity flows dominates the performance of trading rules that neglect this information. Sharpe's ratio and investor's terminal wealth are higher when international equity flows are not considered to be relevant for forecasting stock returns only when transaction costs are high and the investor uses the BIC model-selection criterion to identify the optimal forecasting model. As expected, Sharpe's ratio and investor's terminal wealth are the lower, the higher are transaction costs.

We ran a bootstrap simulation experiment to analyze the statistical significance of the improvement in the performance of the investor's trading rules that we found when we used international equity flows as a candidate for forecasting stock returns. In order to reduce the computing time needed to run this experiment, in a first step, we selected four core variables: international equity flows, DMA150, CAY, and TSP. As documented in Table 4, these four core variables are often included in the optimal forecasting model. In a second step, we resampled with replacement from our core variables in a way such that the contemporaneous correlation between stock returns, international equity flows, and the other core variables is preserved. In a third step, we implemented our recursive modeling approach and computed Sharpe's ratio and investor's terminal wealth. In a fourth step, we dropped international equity flows from our list of core variables and applied again our recursive modeling approach. Finally, in a fifth step, we computed the differences in Sharpe's ratio and in investor's terminal wealth between the model that features international equity flows and the model that does not. We repeated this process 1,000 times, giving us sampling distributions of the differences between models with regard to Sharpe's ratio and investor's terminal wealth. We used the sampling distributions to compute critical values for the differences between models as regards Sharpe's ratio and investor's terminal wealth.

— Insert Tables 6 and 7 about here. —

Table 6 summarizes the results for the core model in terms of Sharpe's ratio and investor's terminal wealth. The results confirm those documented in Table 5. Using information on international equity flows yields a higher Sharpe ratio and increases investor's terminal wealth. This suggests that our results are robust to changes in the set of variables the investor considers to be of potential relevance for forecasting stock returns. In order to analyze the statistical significance of the increases in Sharpe's ratios and investor's terminal wealth that results when the investor uses information on international equity flows, Table 7 summarizes the results of our bootstrap simulation experiment. The results reveal that, under the ACD and the AIC model-selection criteria, using international equity flows for forecasting stock returns results in a significant increase in Sharpe's ratio and in investor's terminal wealth. We obtained this result when we assumed that transaction costs are zero or medium-sized. For large transaction costs, in contrast, the differences in Sharpe's ratios and in investor's terminal wealth are not statistically significant. An investor who had used the BIC model-selection criterion would not have benefited from using information on international equity flows for forecasting stock returns. Thus, the results differ across model-selection criteria. Notwithstanding, the results of our bootstrap simulation experiment indicate that there is empirical evidence that an investor could have used information on international equity flows to improve the performance of simple trading rules.

4.4 Tests of Market Timing

The empirical results reported in Section 4.3 suggest that information on international equity flows should affect an investor's market-timing ability. We, therefore, used the forecasts of stock returns implied by our recursive modeling approach to analyze the implications of our results for market timing. We used the tests developed by Cumby and Modest (1987) and by Pesaran and Timmermann (1992) to test for market timing.

In order to implement the Cumby-Modest test, we defined a dummy variable that assumes the value one when the forecasts of stock returns are positive, and zero otherwise. We then regressed one-month-ahead stock returns on a constant and this dummy variable. If the coefficient of the dummy variable is statistically significantly different from zero, there is evidence of market timing. The Pesaran-Timmermann test is a nonparametric test of market timing. The null hypothesis of this test is that there is no information in the forecasts of stock returns over the sign of subsequent realizations of stock returns. The Pesaran-Timmermann test has a standardized normal distribution in large samples.

— Insert Table 8 about here. —

The Cumby-Modest test and the Pesaran-Timmermann test yield similar results (Table 8). The results of the Cumby-Modest test are significant under the ACD and AIC model-selection criteria when information on international equity flows are used to forecast stock returns. The test results under the BIC model-selection criterion are significant in a broader sense at a marginal significance level of 17 percent. Under the ACD model-selection criterion, the Pesaran-Timmermann test also provides evidence of market timing when information on international equity flows are used to forecast stock returns. Under the AIC model-selection criterion, the result of the Pesaran-Timmermann test is significant at a marginal significance level of 18 percent. The results of the Pesaran-Timmermann test are insignificant under the BIC model-selection criterion. For both the Cumby-Modest and the Pesaran-Timmermann tests, there is only rather weak evidence of market timing when information on international equity flows are not used to forecast stock returns. Thus, the results of the tests indicate that using information on international equity flows improves an investor’s market-timing ability.

5. Conclusions

While our results suggest that international equity flows help to predict U.S. stock returns, much more research needs to be done before investors can use our results to solve real-world portfolio-allocation problems. For example, it would be interesting to use a forecasting approach other than the recursive modeling approach we used in this paper to analyze the link between international equity flows and stock returns (Avramov 2002; Aiolfi and Favero 2005). Moreover, we have focused in our empirical analysis on the implications of international equity flows for forecasting stock returns. In future research, it would be interesting to study in more detail the potentially complex links between international equity flows, stock market volatility, and the correlations between international stock markets. Moreover, it would be interesting to compare our results with results on the link between international equity flows and stock returns for countries other than the United States. Finally, while we have studied an investor who seeks to forecast one-month-ahead stock returns, it could be useful to analyze in future research the forecasting power of international equity flows for stock returns at longer horizons.

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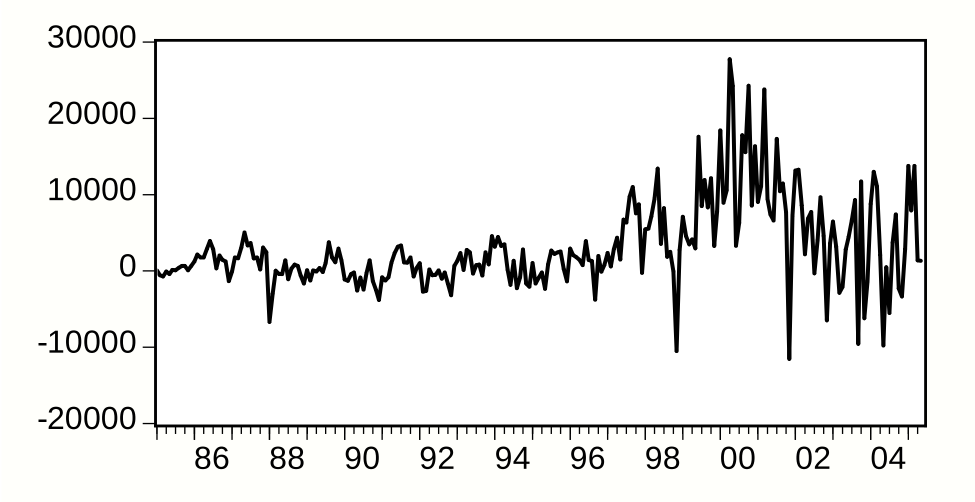
Figures and Tables

Figure 1 – Net international equity flows to the United States, 1985–2005



Note: The data are at a monthly frequency. Negative (positive) international equity flows indicate net sales (purchases) by foreign investors to (from) U.S. residents. Net international capital flows are measured in millions of dollars.

Table 1 – International equity flows and contemporaneous stock returns

Panel A: Full sample, 1985–2005

Constant	FLOWS	CAY	TSP	RTB	DMA150	DIPA	INF	RER	RETLAG	Adj. R^2
0.77	0.71									0.01
2.31**	1.38									
0.70	0.84	7.79								0.01
1.72*	1.32	0.39								
1.19	0.59		-0.20							0.01
1.64*	1.08		-0.69							
0.78	0.71			0.03						0.01
2.29**	1.38			0.09						
0.94	0.73				-2.01					0.02
2.67***	1.48				-3.12***					
0.70	0.71					0.30				0.01
1.60	1.38					0.22				
0.69	0.72						0.30			0.01
0.65	1.34						0.08			
6.47	1.06							-0.06		0.03
2.62***	1.96**							-2.24**		
0.77	0.71								-0.00	0.01
2.14	1.40								(-0.01)	
11.53**	0.96	-15.47	-0.10	-0.18	-2.13	-1.02	-2.83	-0.10	-0.04	0.05
2.56**	1.52	-0.63	-0.29	-0.37	-2.94***	-0.52	-0.58	-2.42**	(-0.50)	

Panel B: Subsample, 1995–2005

Constant	FLOWS	CAY	TSP	RTB	DMA150	DIPA	INF	RER	RETLAG	Adj. R^2
0.37	0.95									0.02
0.70	1.61									
0.34	1.22	22.40								0.03
0.64	1.76*	0.88								
0.51	0.92		-0.08							0.02
0.49	1.43		-0.19							
0.42	0.95			0.50						0.03
0.82	1.62*			0.97						
0.55	0.96				-1.80					0.04
0.98	1.68*				-2.25**					
-0.37	1.02					2.67				0.05
-0.53	1.77*					1.76*				
1.14	1.02						-3.97			0.02
0.64	1.77*						-0.49			
17.42	1.65							-0.18		0.14
4.32***	2.62***							-4.01***		
0.38	0.96								-0.01	0.02
0.69	1.62*								-0.12	
39.48	2.37	-64.48	0.75	-1.30	-2.62	-0.87	-9.40	-0.41	-0.27	0.27
4.51***	3.20***	-1.64*	1.78*	-1.54	-2.65***	-0.33	-1.04	-4.37***	-2.38**	

Note: The regression equations were estimated by means of the ordinary least squares technique. t-statistics that were computed by using heteroskedasticity consistent standard errors are reported below the coefficients. Asterisks * (**, ***) denote significance at the 10 (5, 1) percent level, respectively. Coefficients of international equity flows were multiplied by 1,000.

Table 2 – International equity flows and one-month-ahead stock returns

Panel A: Full sample, 1985–2005

Constant	FLOWS	CAY	TSP	RTB	DMA150	DIPA	INF	RER	RETLAG	Adj. R^2
1.45	-1.58									0.04
4.85***	-3.07***									
1.28	-1.24	20.15								0.04
3.37***	-2.00**	1.05								
2.49	-1.87		-0.50							0.05
4.02***	-3.58***		-1.88*							
1.48	-1.59			0.13						0.04
4.68***	-3.06***			0.38						
1.29	-1.57				1.80					0.05
4.13***	-3.04***				1.99**					
1.10	-1.57					1.55				0.05
2.79***	-3.05***					1.28				
1.56	-1.59						-0.42			0.04
1.64*	-3.02***						-0.12			
2.74	-1.50							-0.01		0.04
1.29	-2.90***							-0.60		
1.50	-1.63								-0.03	0.04
4.23***	-3.10***								-0.36	
0.44	-1.41	51.91	-0.74	-0.50	2.03	2.38	-3.19	0.02	-0.04	0.09
0.14	-2.30**	2.05**	-2.08**	-1.13	2.12**	1.54	-0.76	0.80	-0.54	

Panel B: Subsample, 1995–2005

Constant	FLOWS	CAY	TSP	RTB	DMA150	DIPA	INF	RER	RETLAG	Adj. R^2
1.89	-1.87									0.08
4.41***	-3.30***									
1.85	-1.44	36.15								0.10
4.25***	-2.20**	1.53								
3.09	-2.17		-0.66							0.10
4.15***	-3.91***		-1.85**							
1.97	-1.87			0.64						0.09
4.62***	-3.26***			1.26						
1.77	-1.87				1.41					0.09
3.89***	-3.27***				1.20					
1.04	-1.79					3.09				0.12
1.80*	-3.14***					2.09**				
0.87	-1.96						5.23			0.09
0.46	-3.53***						0.60			
11.53	-1.41							-0.10		0.12
2.90***	-2.43***							-2.35**		
2.06	-2.03								-0.09	0.09
4.43***	-3.74***								-0.90	
5.09	-1.53	46.23	-0.44	-0.21	1.81	2.64	-1.89	-0.03	-0.13	0.17
0.65	-2.48**	1.21	-0.83	-0.20	1.49	0.85	-0.19	-0.33	-1.41	

Note: The regression equations were estimated by means of the ordinary least squares technique. t-statistics that were computed by using heteroskedasticity consistent standard errors are reported below the coefficients. Asterisks * (**, ***) denote significance at the 10 (5, 1) percent level, respectively. Coefficients of international equity flows were multiplied by 1,000.

Table 3 – Results of out-of-sample tests of predictability of stock returns

Panel A: Autoregressive model for stock returns is the benchmark model

	DIPA	INF	RTB	TSP	DMA150	CAY	RER	FLOWS
Theil's U	1.01	1.01	1.00	1.00	1.04	1.02	1.00	0.99
MSE-F	-2.46	-1.40	-0.47	0.24	-9.92	-5.71	-0.88	1.23
p-value	0.73	0.47	0.23	0.12	1.00	0.90	0.54	< 0.00
ENC-NEW	-0.85	-0.62	-0.06	0.55	-0.67	-0.65	-0.34	2.04
p-value	0.81	0.69	0.38	0.21	0.81	0.62	0.63	0.19

Panel B: Constant-expected returns model is the benchmark model

	DIPA	INF	RTB	TSP	DMA150	CAY	RER	FLOWS
Theil's U	1.01	1.01	1.00	1.00	1.03	1.03	1.00	0.99
MSE-F	-2.66	-1.49	-0.54	-0.07	-7.80	-6.12	-1.02	1.03
p-value	0.79	0.50	0.25	0.16	0.99	0.93	0.59	< 0.00
ENC-NEW	-0.88	-0.66	-0.07	0.41	-0.08	-0.78	-0.38	1.95
p-value	0.85	0.72	0.35	0.24	0.38	0.69	0.67	0.20

Note: Theil's U is defined as the ratio of the square roots of the mean-squared errors of the alternative model and the benchmark model. The alternative model is a model that, in addition to the benchmark model, contains the variables shown in the first rows of Panel A and Panel B as regressors. We add the variables in the first rows of Panel A and Panel B one at a time to the benchmark model. The benchmark model is either a first-order autoregressive model for stock returns (Panel A) or a model that only contains a constant (Panel B). The column labeled MSE-F gives the results of the out-of-sample test of McCracken (2004). The null hypothesis of the MSE-F test is that the mean-squared forecasting error of the benchmark model is smaller than or equal to that of the alternative model. The column labeled ENC-NEW gives the results of the out-of-sample test of Clark and McCracken (2001). The null hypothesis of the ENC-NEW test is that the forecasts derived from the benchmark model encompass all the information for one-month-ahead stock returns. We used 1,000 bootstrap simulations to compute the p-values.

Table 4 – Inclusion of variables in the forecasting models (in percent)

PANEL A: Models with international equity flows

Variables	ACD	AIC	BIC
RETLAG	1.60	0.00	0.00
DIPA	72.80	15.20	0.00
INF	17.60	0.00	0.00
RTB	72.80	15.20	0.00
TSP	94.40	50.40	0.00
DMA150	100.00	95.20	48.00
CAY	100.00	27.20	0.00
RER	52.00	0.00	0.00
FLOWS	56.00	48.00	52.00

PANEL B: Models without international equity flows

Variables	ACD	AIC	BIC
RETLAG	0.00	0.00	0.00
DIPA	74.40	39.20	0.00
INF	18.40	0.00	0.00
RTB	74.40	39.20	0.00
TSP	94.40	52.00	0.80
DMA150	100.00	97.60	57.60
CAY	100.00	52.80	41.60
RER	56.00	0.80	0.00

Note: For definitions of variables, see Section 2. ACD denotes the Adjusted Coefficient of Determination, AIC denotes the Akaike Information Criterion, and BIC denotes the Bayesian Information Criterion.

Table 5 – Performance of trading rules

	With international equity flows	Without international equity flows	With international equity flows	Without international equity flows
	Sharpe's ratio		Terminal wealth	
Zero transaction costs				
ACD	0.26	0.22	349.19	307.84
AIC	0.31	0.21	452.08	304.86
BIC	0.21	0.17	330.97	309.02
Medium-sized transaction costs				
ACD	0.21	0.18	285.21	261.99
AIC	0.26	0.18	371.46	264.43
BIC	0.17	0.17	280.24	303.50
High transaction costs				
ACD	0.17	0.16	245.20	234.50
AIC	0.23	0.16	317.75	239.09
BIC	0.14	0.17	242.15	298.95

Note: In each period of time, the investor selects three optimal forecasting models according to the ADC, AIC, and BIC model-selection criteria. For switching between shares and bonds, the investor uses information on the optimal one-step-ahead stock-return forecasts implied by the optimal forecasting models. When the optimal one-step-ahead stock-return forecasts are positive (negative), the investor only invests in shares (bonds), not in bonds (shares). The investor does not make use of short selling, nor does the investor use leverage when reaching an investment decision. Initial wealth is 100. We assumed medium-sized (high) transaction costs of 0.5 and 0.1 of a percent (0.1 of a percent and 1 percent) for shares and bonds, respectively.

Table 6 — Performance of trading rules based on the core model

	With international equity flows	Without international equity flows	With international equity flows	Without international equity flows
	Sharpe's ratio		Terminal wealth	
Zero transaction costs				
ACD	0.33	0.21	488.24	319.61
AIC	0.33	0.20	496.52	319.80
BIC	0.21	0.18	330.97	309.02
Medium-sized transaction costs				
ACD	0.27	0.19	386.22	293.40
AIC	0.26	0.18	398.28	293.36
BIC	0.23	0.17	280.24	303.50
High transaction costs				
ACD	0.21	0.18	317.30	275.20
AIC	0.17	0.17	330.55	276.15
BIC	0.14	0.17	242.15	298.95

Note: This table summarizes the results for a core model that features CAY, TSP, DMA150, and international equity flows as candidate variables for forecasting stock returns. In each period of time, the investor selects three optimal forecasting models according to the ADC, AIC, and BIC model-selection criteria. For switching between shares and bonds, the investor uses information on the optimal one-step-ahead stock-return forecasts implied by the optimal forecasting models. When the optimal one-step-ahead stock-return forecasts are positive (negative), the investor only invests in shares (bonds), not in bonds (shares). The investor does not make use of short selling, nor does the investor use leverage when reaching an investment decision. Initial wealth is 100. We assumed medium-sized (high) transaction costs of 0.5 and 0.1 of a percent (0.1 of a percent and 1 percent) for shares and bonds, respectively.

Table 7 — Sharpe's ratio and investor's terminal wealth based on the core model

Panel A: Differences in Sharpe's ratio

	Differences in Sharpe's ratios			95% critical values			90% critical values		
	Transaction costs			Transaction costs			Transaction costs		
	zero	medium-sized	high	zero	medium-sized	high	zero	medium-sized	high
ACD	0.12**	0.09*	0.05	0.11	0.10	0.10	0.08	0.08	0.07
AIC	0.13**	0.09**	0.06	0.10	0.09	0.09	0.08	0.07	0.07
BIC	0.03	0.00	-0.03	0.11	0.10	0.09	0.09	0.08	0.07

Panel B: Differences in terminal wealth

	Differences in terminal wealth			95% critical values			90% critical values		
	Transaction costs			Transaction costs			Transaction costs		
	zero	medium-sized	high	zero	medium-sized	high	zero	medium-sized	high
ACD	168.63*	93.83	42.10	170.53	130.19	108.80	133.61	102.21	82.63
AIC	176.76**	104.92*	54.40	161.37	125.84	105.69	119.48	88.73	73.81
BIC	21.95	-23.25	-56.79	169.44	124.46	99.40	127.29	92.04	72.65

Note: This table summarizes the results of a bootstrap simulation experiment. The results are based on 1,000 bootstrap simulations of a core model that features CAY, TSP, DMA150, and international equity flows as candidate variables for forecasting stock returns. For the core model, we computed Sharpe's ratio and terminal wealth under different model-selection criteria and different assumptions regarding the magnitude of transaction costs. We also simulated a modified core model under the assumption that an investor does not use information on international equity flows to forecast stock returns. For the modified core model, we also computed Sharpe's ratio and terminal wealth. Finally, we computed the differences between Sharpe's ratios and terminal wealth implied by the core model and the modified core model, respectively. Asterisks * (**) denote significance at the 10 (5) percent level, respectively.

Table 8 — Tests of market timing

Panel A: Cumby-Modest test without international equity flows

	ACD	AIC	BIC
Constant	0.04	0.04	-0.68
	0.07	0.06	-0.59
Dummy	1.45	1.28	1.61
	1.80*	1.50	1.32

Panel B: Cumby-Modest test with international equity flows

	ACD	AIC	BIC
Constant	-0.20	-0.91	-0.34
	-0.32	-1.26	-0.35
Dummy	1.86	2.67	1.48
	2.30**	3.12***	1.38

Panel C: Pesaran-Timmermann tests of market timing

	With international equity flows	Without international equity flows
ACD	1.99**	1.38*
AIC	0.96	0.03
BIC	0.50	0.92

Note: In Panels A and B, we present results of a test of market timing developed by Cumby and Modest (1987). In Panel A (Panel B), we report the results we obtained when we neglected (used) information on international equity flows to forecast stock returns. The Cumby-Modest test requires estimating a regression of realized stock returns on a constant and a dummy variable that assumes the value one if the forecast of stock returns is positive, and zero otherwise. t-statistics that were computed by using heteroskedasticity consistent standard errors are reported below the coefficients. In Panel C, we report results of nonparametric tests for market timing developed by Pesaran and Timmermann (1992). The Pesaran-Timmermann test has asymptotically a standard normal distribution. Asterisks * (**, ***) denote significance at the 10 (5, 1) percent level, respectively.