Determinants of Initial Public Offerings: A European Time-Series Cross-Section Analysis

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1 Introduction

With the financial systems of continental European countries traditionally dominated by banks mainly for institutional reasons, debt financing has been playing a more prominent role than equity finance, causing the debt-to-equity ratios to be relatively high. The capital structure of a firm, in turn, influences its probability of default: higher leverage increases bankruptcy risk. Since a company tends to reduce its leverage when going public, as evidenced by a number of empirical studies for European countries (see, among others, Pagano et al., 1998), initial public offerings (IPOs) might be seen as reducing bankruptcy risk as they increase the equity ratio and reduce leverage. This reduction in bankruptcy risk, especially in combination with a potential systemic relevance of corporations going public, may have a positive effect on aggregate financial stability, given that banks benefit from lower credit risks and firms may gain more room for maneuver insofar as the money raised should theoretically enable them to optimize their business strategies under fewer restrictions than before. Most research carried out to date on IPO-related issues was devoted to the underpricing and underperformance of stocks issued. Relatively little – notably empirical – work, however, has been done to establish why and when companies go public, and what consequences public offerings typically have (a differentiation difficult to make). Given the considerable implications IPOs have for many internal and external company issues (the tendency to reduce leverage being only one, though the critical example for this work) this is particularly surprising. Moreover, many of the studies that have been undertaken were related to the U.S. market. Therefore, the mostly very different IPO cultures in Europe deserve further investigation.

A detailed discussion at the micro (individual firm) level was undertaken by Pagano et al. (1998), who investigated a comprehensive data set of Italian companies. The authors infer determinants of the decision to go public from corporate characteristics ("ex ante influences") as well as from the consequences public offerings have for investment and financial behavior. For independent companies (as opposed to carve-outs), they find the most important determinants of IPOs to be, first, company size (the larger the company, the higher the probability) and, second, the industry market-to-book ratio (which measures the stock market valuation of firms in a given industry for their shareholders). A typical Italian company launching an IPO is eight times as large and six times as old as a U.S. firm. With respect to consequences for investment and financial behavior, the authors' main conclusions about Italian IPOs are as follows: going public makes borrowing cheaper, and corporations use IPOs to rebalance their accounts after a period of high investment and growth rather than to finance subsequent investment and growth. In the United States, in contrast, companies usually undergo a considerable growth process after listing.

There are also relatively few papers which, even as an aside, undertake a macroeconomic analysis of factors that may prompt a company to going public, one example being the work by Loughran et al. (1994). This article reviews the timing of IPOs by analyzing data from 15 countries and modeling the number of issues in relation to inflation-adjusted stock price indexes as well as gross national product (GNP) growth rates. The results exhibit a positive relationship between IPO activity and stock price levels, but no correlation with business cycle movements. Another study on cross-country data was carried out by Rydqvist and Högholm (1995). The authors use data from 11 European countries for the period 1980 to 1989 (in the case of Sweden, for the period 1970 to 1991), regressing the number of IPOs separately on, inter alia, GNP growth rates and relative changes in the stock price level. They find unlagged stock price returns to have significant explanatory power for IPOs. In contrast, GNP growth appears to demonstrate no significant explanatory power for IPO activity across the whole European sample. Mirroring the findings mentioned above, further results show that the average European firm going public is quite old (more than 40 years for the sample analyzed), and that IPOs are made mainly because the original stockholders wish to reallocate their portfolios and not because they have investment or growth intentions. Empirical results for Germany (Ljungqvist, 1995) suggest that high IPO frequencies are positively associated with both high stock index levels and good business conditions and tend to follow phases of extensive IPO underpricing. Rees (1997), concentrating on UK data, also examines the incentives for going public. The results again suggest that both the number and value of IPOs are significantly positively associated with the level of the stock market, the introduction of the Unlisted Securities Market in Great Britain, and, in the case of the number of IPOs, significantly positively associated with a business cycle indicator. No significant link is apparent between the number of IPOs and interest rates.

This paper intends to study the explanatory power of selected macroeconomic factors for IPOs. As the analysis is aimed at identifying IPO patterns in continental European economies, the sample area is limited to that region. We focus on a data set of annual observations of IPO volumes for six continental European countries over a period of 18 years (1980 to 1997). Due to the structural changes seen at European stock markets over the past few years, we decided not to extend our sample period beyond 1997. With investors continuing to rush into stocks despite inflated stock valuations and companies adapting their fund-raising behavior consequently, followed by scenarios of heavy price erosion, loss of investor confidence and finally (as one unavoidable consequence) readaption of IPO patterns, the past few years are likely to be viewed as a transition period. We think that analyses of the most recent, in a sense, consolidated period might deliver helpful indications for the next more stable state to come. Even though we are fully aware that any attempt at a final analysis will have to combine results from both micro- and macroeconomic considerations, we explicitly excluded microeconomic aspects in order to keep the problem formulation manageable. Concerning the composition of the data set no previous paper has, to our knowledge, used either a homogeneous cross-country data set or cross-country IPO volume data. We consider both criteria to be important and have therefore tried to incorporate them accordingly. After all, homogeneity is a precondition for pooling data across the countries included in the sample. And unlike IPO numbers, IPO volumes (being monetary data) can appropriately reflect the extent to which the primary market was actually tapped – information that cannot be simply deduced from the number of IPOs. This study applies panel data analysis, which can be expected to be an appropriate statistical approach given existing database features. Overall, we analyze the explanatory power of the following macroeconomic factors for national annual

IPO volumes: stock index returns, changes in savings deposits, gross domestic product (GDP) growth and interest rates.

The principal results obtained in this paper are: For stock index returns, all pooled procedures yield significantly positive parameter estimates, while individual country regressions working with untransformed IPO volumes tend not to generate significant parameter estimates. In contrast, logarithmic transformation of IPO volumes leads to persistently significant estimates for both pooled and individual country regressions. Across all specifications tested, neither savings deposit changes nor GDP growth are found to exhibit any significant influence on IPO volumes. Interest rates do not perceivably influence demand for raising equity through IPOs, either.

The rest of this paper is structured as follows: Section 2 describes the data set we use, specifies the models evaluated and sketches the applied methodology. Section 3 presents the empirical results, analyzes and interprets them, and section 4 concludes.

2 Data Set, Model Specifications and Applied Methodology

2.1 Data Set

The following table gives an overview of the variables used for our analyses:

Dependent Variable: Annual IPO Volumes (First Differences or ln)

Explantory Variables	Data Sources	Calculation	Expected Sign
stock index return	IFS and MEI	annual growth rates (using yearly closing dates)	+
% change savings			–
% change GDP			+
interest rates		ten-year government bond yields	+

IPO data: The IPO data underlying the empirical analysis undertaken in this paper are national annual volume figures denominated in the respective local currency. National volumes are defined here as a product of the first listed price times the number of stocks included in the IPO, summed up across all IPOs per country and year. We obtained these data for six continental European states (Austria, Belgium, Denmark, Finland, France, and the Netherlands) over a time period of 18 years (1980 to 1997) from the main stock exchange in each of the above countries. The macroeconomic factors used as explanatory variables (stock index returns, changes in savings deposits, GDP growth and interest rates) as well as exchange rates were taken from the International Financial Statistics (IFS) and the Main Economic Indicators (MEI) databases. Stock index returns, changes in savings deposits and changes in GDP are calculated as annual growth rates by reference to yearly closing dates, with the U.S. dollar used as numeraire. As the annual evolution of the time series should not be distorted by DC/USD_{it} (exchange rate of the domestic currency of country i against the U.S. dollar for period t) exchange rate fluctuations, we calculate the average value of the DC/USD_{it} exchange rates over the whole observation period and apply the result (DC/USD_i) as a conversion factor (which is constant for each country and thus preserves the required continuity).

Stock index return: In the context of IPOs, stock index levels and stock index returns (unlike savings deposits) are among the most frequently analysed explanatory variables. The results obtained for stock index levels and stock index returns in previous studies seem to concur in that they all detect a significantly positive influence of stock index levels (see, for example, Loughran et al., 1994; Ljungqvist, 1995; and Rees, 1997) and stock index returns (see, for instance, Rydqvist and Högholm, 1995) on the number of IPOs. Rees (1997), who also includes monetary values, likewise finds these factors to have a significantly positive influence on the volume of IPOs. The approach of Pagano et al. (1998) differs from the above studies in that, among other things, they analyze the probability of IPOs at the micro level and use industry-specific indicators, including the relationship between industry market value to book value as an explanatory variable. They find this relationship to have a significantly positive effect on the probability of IPOs. Preliminary analyses carried out in the context of this paper, however, generated ambivalent results in that, unlike previous studies, they did not identify an unambiguously significant dependence of IPO volumes on stock index returns. Thus the question arose whether we were about to produce results partly contradicting previous papers or whether previous investigations had not taken into account certain functional and interactive aspects, the nonconsideration of which might cause unstable results. Following a closer examination, we defined the problem outline as follows: If one assumes that companies make the timing of their IPOs dependent on the level of the national stock index (in order to maximize the value they obtain for their stocks), then the actors' behavior exactly fits the empirically established significantly positive influence of stock index levels on IPO activity. From a demand-side perspective one might, alternatively, assume that stock market returns have a positive effect on IPO volumes on the grounds that higher profit potentials in the form of higher returns should induce increased buying interest. Closer examination reveals that successful efforts to optimally time an IPO with respect to the stock price are not compatible with a significantly positive homogeneous parameter across all stock price levels for stock index returns. This can most clearly be seen from the fact that price-maximizing behavior causes many IPOs to be launched during stock market highs, when stock price returns have decreased dramatically already or even turned negative. And even for those stock price levels which exhibit a positive influence of stock price returns on IPO volumes, this effect will be much weaker for low stock price levels than for high ones. Considering the need for problem segmentation, the question we want to address here is: are there stable indications that yearly IPO volumes depend on stock index returns for what we call consolidated periods, i.e. periods not characterized by extreme (positive or negative) market sentiments?

Changes in savings deposits: Percentage changes in savings deposits are included as an explanatory variable in order to identify possible flows of funds between savings deposits and investment in stocks (in this context, investment in IPOs), and to establish whether a reduction in one of the aggregates is accompanied by an increase in the other. Savings deposits themselves could be used as an indicator of monetary assets potentially available for alternative purposes (e.g., for investment in stocks). This idea addresses the nature of savings deposits as a reservoir that can be tapped for new investment. The higher these liquid reserves, the more reasonable it will be to assume that some part will be made available for new uses, in this case for investment in stocks; in other words, savings deposits are an indicator of potential. But as untransformed savings deposits are not stationary, they have to be transformed accordingly – in this paper into percentage changes in savings deposits. To our knowledge, our analysis is the first to consider savings deposits as a possible explanatory variable for IPO volumes.

GDP growth: At first sight, previous investigations show no consistent results regarding the explanatory power of GDP and GNP growth for IPOs. On closer inspection, research results are divergent only when analyses of short-term GDP and GNP growth rates are compared with analyses of long-term GDP growth or absolute level figures. The research done by Loughran et al. (1994) and by Rydqvist and Högholm (1995) falls into the former category. Both articles analyze the influence of GNP growth rates on the number of IPOs, but do not find any significant influence. The paper of La Porta et al. (1997) falls into the latter category. Although the authors are more interested in the influence of economic conditions (as expressed in the respective legal systems) on the numbers of IPOs than in the influence of GDP per inhabitant, the findings in their cross-sectional study are interesting in this context. They show that the quality of law enforcement, which is highly correlated with the level of GDP per capita, has a strong positive effect on the number of IPOs. In addition, the authors identify a statistically significant influence of long-term GDP growth rates, i.e. average annual percentage growth of per capita GDP for the period 1970 to 1993, on IPOs. Complementary to these existing empirical results (suggesting a positive influence of both long-term GDP growth and GDP level on IPOs while not having identified any impact of short-term growth) we want to test the explanatory power of short-term GDP growth rates for IPO volumes for our sample. As we do not carry out a cross-sectional analysis with a sufficiently high number of cross-sectional units, we had to refrain from dealing with long-term GDP growth or with GDP levels as explanatory variables.

Interest rates: Interest rates used are ten-year government bond yields, the average of 12 monthly observations in order to give a representative indication of debt financing costs. As this information was not available for Finland, we considered the Finland Base Middle Rate instead. But on closer examination and when comparing the Finland Base Middle Rate with the Finland Interbank Fixing 3M Offered Rate as a sort of control measure, we found the latter lying up to 900 basis points above the former during the late 1980s and at the beginning of the 1990s before the two time series started converging from 1993 on. Therefore, the Finnish data available for interest rate analyses are – obviously partly due to the Finnish banking crisis – not appropriate. Thus, we eventually had to remove Finland from the data set for the interest rate analyses, although it might have been interesting to further investigate the years with extremely high divergences between the Finland Base Middle Rate and the Finland Interbank Fixing 3M Offered Rate, as the highest (out-of-sample period) Finnish IPO activity falls into this period.

2.2 Model Specifications

The models for which estimation results are presented in this paper are specified as follows:

$$IPO_{it} = \alpha + \beta_1 IPO_{it-1} + \beta_2 SR_{it-1} + \beta_3 SG_{it-1} + \beta_4 GDPG_{it} + u_{it} \qquad I$$

Where the variables are defined as stated below (for u_{it} see section 2.3):
$IPO_{it} = (\sum_{j=1}^{p} FLP_j * NB_j)$ (million) $*DC/USD_i$
$j =$ index of IPOs for country i in period t
$p =$ number of IPOs in country i for period t
$FLP_j =$ first listed price of IPO j
$NB_j =$ number of stocks of IPO j

$SR_{it} = \frac{SP_{it}-SP_{it-1}}{SP_{it-1}} * 100$
with: $SP_{it} =$ overall stock price index of country i for period t

$SG_{it} = \frac{SD_{it}-SD_{it-1}}{SD_{it-1}} * 100$
with: $SD_{it} =$ amount of savings deposits in country i for period t

$GDPG_{it} = \frac{GDP_{it}-GDP_{it-1}}{GDP_{it-1}} * 100$
with: $GDP_{it} =$ gross domestic product of country i for period t (million)

We also test this model formulation by taking first differences, as the IPO series is not unambiguously stationary whereas first differences of IPOs are. Therefore, estimations are carried out for both alternatives.

$$ln\left(\frac{IPO_{it}}{GDP_{it}}\% * 100\right) = \alpha + \beta_1 ln\left(\frac{IPO_{it-1}}{GDP_{it-1}}\% * 100\right) + \beta_2 SR_{it-1} + \\ + \beta_3 SG_{it-1} + \beta_4 GDPG_{it} + u_{it} \qquad II$$

The idea behind the model II specification was, first, to put IPO volumes into proportion with GDP so that country-specific effects do not have to absorb differences in IPO volumes resulting from the varying sizes of the economies included in the sample. And second, we wanted to investigate our assumption that a nonlinear (specifically a logarithmic) relationship could possibly better model any dependence of IPO volumes on included independent variables than a linear one. Model II is tested with and without including the first lag of the dependent variable as an explaining variable. Zero observations on IPO volumes were approximated by replacing $ln\left(\frac{IPO_{it}}{GDP_{it}}\% * 100\right) = 0$ with 0.00001 and, alternatively (to make a sensitivity check), with 0.0000001 – an approximation which we consider to be economically negligible.

$$\Delta IPO_{it} = \alpha + \beta_1 GBY_{it} + u_{it} \qquad III$$

with: $GBY_{it} =$ government bond yield for country i in period t per cent

As we had to exclude Finland from the sample set (see section 2.1), analyses for interest rates were carried out separately from the investigations under equations I and II in order to avoid unnecessary downsizing of our overall sample size.

2.3 Methodology

To estimate the model coefficients we used a panel data approach. In the following we briefly discuss the methodological aspects relevant for the investigations carried out in this paper. Equation (1) represents a basic model for panel data regressions which has to be specified and modified into different directions depending on the data set investigated and on the purpose of the respective analysis:

$$y_{it} = \alpha + x_{it}^T\beta + u_{it} \qquad\qquad i = 1, ..., N;\ t = 1, ..., T \tag{1}$$

with i identifying cross-sectional units and t denoting time periods or time points. α should be a scalar, β a $K \times 1$ vector, x_{it} the it-th observation vector on K explanatory variables, and u_{it} the random error term (for the following see Baltagi, 2001; Hsiao, 1990). For economic research, panel data sets are very valuable and have several important advantages over conventional cross-sectional or time-series data sets: They provide a large number of data points, which helps to improve the efficiency of econometric estimates as degrees of freedom are increased and collinearities between explaining variables are reduced. Panel data also allow to study important economic issues that may be difficult or impossible to analyze exclusively on the basis of cross-sectional or time-series data sets (e.g., dynamic effects, precise estimates of dynamic coefficients, to better control for the effects of missing or unobserved variables).

One possibility to take account of heterogeneity across cross-sectional units and/or through time is to use variable-intercept models. The main assumption underlying variable-intercept models in general is that, conditional on the observed explanatory variables, the effects of all omitted (or excluded) variables are driven by three types of variables: individual-variant time-invariant, individual-invariant time-variant, and individual-variant time-variant variables.[1])

One-way error component models: The first generalization of a constant-intercept constant-slope model for panel data is to either introduce dummy variables to account for those omitted variables that are specific to individual cross-sectional units but stay constant over time, or to introduce dummy variables for the effects that are specific to each time period but are the same for all cross-sectional units at a given point in time – thereby forming a variable-intercept model with a one-way error component. The illustrations presented in the following are focused on individual-specific (in this context, country-specific) effects, though equally applicable to time-specific effects. The model therefore can be formulated as

$$\begin{bmatrix} y_1 \\ \vdots \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} e_T \\ 0 \\ \vdots \\ 0 \end{bmatrix} \alpha_1^* + \begin{bmatrix} 0 \\ e_T \\ \vdots \\ 0 \end{bmatrix} \alpha_2^* + ... + \begin{bmatrix} 0 \\ 0 \\ \vdots \\ e_T \end{bmatrix} \alpha_N^* + \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_N \end{bmatrix} \beta + \begin{bmatrix} v_1 \\ \vdots \\ \vdots \\ v_N \end{bmatrix}$$

1 *If the assumption that regression parameters take the same values for all cross-sectional units in all time periods, as it would be in the case of a single (constant) parameter pair (α, β), is not valid, the pooled least-squares estimates may lead to false inferences. Thus, in a first step, we had to test whether / which parameters characterizing the random outcome of variable y stay constant across all i and t. For a detailed description of the tests to be carried out on data poolability we refer to Hsiao (1990).*

$$\text{where } y_i = \begin{bmatrix} y_{i1} \\ y_{i2} \\ \vdots \\ y_{iT} \end{bmatrix}; \quad X_i = \begin{bmatrix} x_{1i1} & x_{2i1} & \dots & x_{Ki1} \\ x_{1i2} & x_{2i2} & \dots & x_{Ki2} \\ \vdots & \vdots & \dots & \vdots \\ x_{1iT} & x_{2iT} & \dots & x_{KiT} \end{bmatrix}; \; i = 1, ..., N. \quad (2)$$

Furthermore, $v_i^T = (v_{i1}, ..., v_{iT})$, $\mathrm{E}v_i = 0$, $\mathrm{E}v_i v_i^T = \sigma_v^2 I_T$, and $E\mathbf{v}_i v_j = 0$ if $i \neq j$. I_T should denote the T x T identity matrix and e_T is a vector of ones of dimension T. In addition, we have $\alpha_i^* = \alpha + \mu_i$, a 1 x 1 constant scalar. The error term v_{it} comprises the effects of omitted variables that are characteristic to both the individual units and time periods and can be represented by an IID random variable with mean zero and variance σ_v^2. Model (2) is also known as the analysis of covariance model. Given the above stated properties of $\mathbf{v}_{it}$, it is known that the ordinary-least-squares (OLS) estimator of (2) is the best linear unbiased estimator. The OLS estimators of α_i^* and β are:

$$\hat{\beta}_{CV} = \left[\sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)^T \right]^{-1} \left[\sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)(y_{it} - \bar{y}_i) \right] \quad (3)$$

$$\hat{\alpha}_i^* = \bar{y}_i - \beta^T \bar{\mathbf{x}}_i \quad i = 1, ..., N; T = 1, ..., T \quad (4)$$

where $\bar{y}_i = \frac{1}{T} \sum_{t=1}^{T} y_{it}$ and $\bar{x}_i = \frac{1}{T} \sum_{t=1}^{T} x_{it}$.

One can also obtain the least-squares dummy variables (LSDV) estimator from (2) via premultiplying the model by a T x T idempotent transformation matrix Q (in order to eliminate the α_i^* by using $Qe_T \alpha_i^* = 0$): $Qy_i = QX_i\beta + Qv_i$, with $Q = I_T - \frac{1}{T} e_T e_T^T$. Applying OLS to this latter equation leads to

$$\hat{\beta}_{CV} = \left[\sum_{i=1}^{N} X_i^T Q X_i \right]^{-1} \left[\sum_{i=1}^{N} X_i^T Q y_i \right]. \quad (5)$$

As (2) is also named analysis of covariance model, the LSDV estimator of β is sometimes called the covariance estimator – or the within-group estimator, as only the variation within each group is utilized in forming this estimator. The covariance (CV) estimator $\hat{\beta}_{CV}$ is unbiased and also consistent when either N or T or both tend to infinity. Whereas the estimator for the intercept (4), though being unbiased, is consistent only when T$\to \infty$.

Another possibility of generalization is to include the individual-specific effects as random variables, like v_{it}, assuming that the residual u_{it} can be described by $u_{it} = \mu_i + v_{it}$. Furthermore, $E\mu_i = Ev_{it} = 0$, $E\mu_i v_{it} = 0$, $E\mu_i x_{it}^T = Ev_{it}\, x_{it}^T = 0$, as well as

$$E\mu_i\mu_j = \begin{matrix} \sigma_\mu^2 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{matrix} \quad \text{and} \quad Ev_{it}v_{js} = \begin{matrix} \sigma_v^2 & \text{if } i = j, t = s \\ 0 & \text{otherwise.} \end{matrix}$$

The variance of y_{it} conditional on x_{it} is consequently $\sigma_y^2 = \sigma_\mu^2 + \sigma_v^2$, with the variances σ_μ^2 and σ_v^2 called variance components – the latter also constituting the reason for this kind of model being known as variance-components (or error-components) model. The model specification can then be represented by

$$y_i = Z_i\delta + u_i \qquad i = 1, ..., N \tag{6}$$

where $Z_i = (e_T, X_i), \delta^T = (\alpha, \beta^T), u_i^T = (u_{i1}, ..., u_{iT})$, and $u_{it} = \mu_i + v_{it}$. As the residuals of (6) are correlated (u_{it} and u_{is} both contain μ_i), GLS has to be applied in order to obtain efficient estimates for $\delta^T = (\alpha, \beta^{\mathbf{T}})$. The normal equations for the GLS estimators are given by[1])

$$\left[\sum_{i=1}^{N} Z_i^T \Omega_i^{-1} Z_i\right] \hat{\delta}_{GLS} = \left[\sum_{i=1}^{N} Z_i^T \Omega_i^{-1} y_i\right] \tag{7}$$

Two-way error component models: The next broader generalization are two-way error component models

$$y_{it} = \alpha + x_{it}^T\beta + \mu_i + \lambda_t + v_{it} \qquad i = 1, ..., N; t = 1, ..., T \tag{8}$$

where α is a constant, μ_i an unobserved individual effect, λ_t an unobserved time effect, v_{it} an unobserved remainder, and u_{it} (as it will be used later) $= \mu_i + \lambda_t + v_{it}$. First we assume that μ_i and λ_t are unknown but fixed parameters such that $\sum_{i=1}^{N} \mu_i = 0$ and $\sum_{t=1}^{T} \lambda_t = 0$. The v_{it} are random such that $Ev_{it} = 0$ and $Ev_{it}v_{js} = \sigma_v^2$ if $i = j$ and $t = s, 0$ otherwise. Then, the best linear unbiased estimator of β will be

$$\hat{\beta} = (X^T Q_F X)^{-1} X^T Q_F y \tag{9}$$

where $Q_F = I_N \otimes I_T - I_N \otimes \bar{J}_T - \bar{J}_N \otimes I_T + \bar{J}_N \otimes \bar{J}_T$, with I_N (I_T) being an identity matrix of dimension N (T), with $J_T(J_N)$ as a matrix of ones of dimension T (N), and $\bar{J}_T(\bar{J}_N) = \frac{J_T}{T}\left(\frac{J_N}{N}\right)$.

Next we assume that all the components μ_i, λ_t, and v_{it} are random such that $E\mu_i = 0, E\mu_i\mu_j = \sigma_\mu^2$ if $i = j, 0$ if $i \neq j; E\lambda_t\lambda_s = \sigma_\lambda^2$ if $t = s, 0$ if $t \neq s$; $Ev_{it} = 0, Ev_{it}\ v_{js} = \sigma_v^2$ if $i = j$ and $t = s$, 0 otherwise; μ_i, λ_t, and v_{it} are independent of each other and, furthermore, $T > K, N > K$ and the variances σ_μ^2, σ_λ^2, and σ_v^2 are unknown. True GLS would be the BLUE for this setting, but variance components are usually not given and have to be estimated. Feasible GLS estimators, however, are in principle asymptotically efficient. The resulting two-stage GLS estimator is then given by $\hat{\beta} = \left(X^T\tilde{\Omega}^{-1}X\right)^{-1} X^T\tilde{\Omega}^{-1}y.$[2])

Fixed-effects versus random-effects: Whether the effects are considered fixed or random (for the following see Hsiao, 1990) can result in remarkable differences in parameter estimates. One way to unify the fixed-effects and the random-effects models might be to assume as starting point that the effects are random. While the fixed-effects model can be considered as one in which investigators make inferences conditional on the effects that are in the sample, the random-effects model can be seen as one in which investigators make unconditional or marginal inferences with respect to the population of all effects. Thus it should depend on the features of the respective paper whether inference will be made with respect to the population characteristics or only with respect to the effects that are in the sample. When inferences are restricted to the effects in the

1 *For estimation details regarding the variance-covariance matrix we refer to Baltagi (2001).*

2 *For presentation of estimation procedures when variance components are unknown (as it is the case in this work) we refer to Baltagi (2001).*

sample, the effects are appropriately considered fixed. If, however, inferences will be made about the whole population, effects should be treated random. In formulating the latter type of models the important issue is to find out if the conditional distribution of μ_i given x_i equals the unconditional distribution of μ_i. If in the linear regression framework μ_i is correlated with x_i, treating μ_i as fixed-effects leads to the same estimator of β as would be obtained when such correlation were explicitly allowed for in the construction of the estimator. One possibility to find out whether having to work with a fixed-effects or a random-effects model is to test for misspecification of (6), where μ_i is assumed random, by using the Hausman (1978) test statistic

$$m = \hat{q}^T \hat{V}ar(\hat{q})^{-1} \hat{q} \tag{10}$$

where $\hat{q} = \hat{\beta}_{CV} - \hat{\beta}_{GLS}$ and $\hat{V}ar(\hat{q}) = Var(\hat{\beta}_{CV}) - Var(\hat{\beta}_{GLS})$. The null hypothesis $\mathrm{E}(\mu_i \mid X_i) = 0$ is tested against the alternative $\mathrm{E}(\mu_i \mid X_i) \neq 0$. Under H_0 (μ_i and $\mathbf{x}_i$ are uncorrelated), this statistic will be asymptotically central chi-square distributed, with K degrees of freedom. Under H_1(μ_i and x_i are correlated), it exhibits a noncentral chi-square distribution with non-centrality parameter $\bar{q}^T Var(\hat{q})^{-1} \bar{q}$, where $\bar{q} = plim(\hat{\beta}_{CV} - \hat{\beta}_{GLS})$.

Dynamic models: Panel data offer the advantage of being better able to analyze dynamic economic relationships. Such dynamic relationships are characterized by the presence of a lagged dependent variable among the regressors,

$$y_{it} = \gamma y_{i,t-1} + x_{it}^T \beta + \mu_i + v_{it} \quad i = 1, ..., N;\ t = 1, ..., T \tag{11}$$

where γ is a scalar. For illustration purposes we assume the model to be a one-way error component model. In the fixed effects case (see Baltagi, 2001), the LSDV estimator will be biased of $\mathrm{O}\left(\frac{1}{T}\right)$ and its consistency depends on the dimension of T. Random effects, on the other hand, where we assume $\mu_i \sim IID(0, \sigma_\mu^2)$ and $v_{it} \sim IID(0, \sigma_v^2)$, independent of each other and among themselves, cannot simply and sufficiently be dealt with by GLS error-component techniques. They can alternatively be modelled by fixed effects procedures. But as it is well known that the LSDV estimator is inconsistent for finite T and $N \to \infty$; Kiviet (1995) introduced an approximation to the small-sample bias (finite N *and* finite T) for the LSDV estimator and demonstrated the construction of a bias-corrected LSDV estimator which compares with other consistent ($N \to \infty$, fixed T) estimators. From Kiviet's Monte Carlo experiments it follows that in many circumstances a bias-corrected version of the (in principle inconsistent) LSDV estimator is unexpectedly efficient compared to established consistent estimation methods. The remaining errors of the presented approach are $\mathrm{O}\left(N^{-1}T^{-\frac{3}{2}}\right)$. We did the suggested bias corrections, but found that for our results they were negligible.

3 Empirical Results

For each of the variables we tested lagged versions as well as synchronous ones and chose those generating the most significant results for presentation in tables 1 to 6.

3.1 Results for Specification I

We started our investigations with the unmodified IPO series denominated in USD (for estimation results see table 1). Single-country regressions were additionally carried out in national currencies. The main points that can be seen from table 1 are: For all pooled estimations, the only significant (at the 1% level) parameters are those for the first lag of IPOs. At the same time, no significant dependence of IPO volume on stock index returns could be identified apart from the weak dependence in the individual country regressions for Austria and Finland. Furthermore, neither changes in savings deposits nor GDP growth exhibit a significant influence on IPO volume. These results are accompanied by relatively high R^2 figures of 0.492 for the pooled OLS regression, 0.560 for the one-way fixed-effects model, and 0.359 for one-way random effects.

However, on closer examination the pooled estimations turned out to be unstable. Our attempts to improve stability led us to exclude the Netherlands from the data set. The reason therefore were considerable swings in Dutch IPO volumes compared with the rest of the sample countries (for illustration purposes please refer to charts 1 to 6), supported by the value of its parameter estimate (–18.87) as well as its t-statistic (–0.26). With the Netherlands removed from the data set, pooled estimations (see table 2) produced, first, stable results and, second, highly significant parameter estimates for stock index returns, while estimates for the IPO lag stayed significant, though in a less pronounced manner. Obviously, the swings in Dutch IPO volumes were too large to be effectively captured by country-specific effects and therefore caused problems in the estimation process. Another point to be made is that only pooled estimation procedures generate significant parameter estimates while single-country analyses hardly do so (except for Austria and Finland). This might be interpreted in favor of pooled approaches and their ability of extracting relevant information from cross-sectional observations.

As already mentioned, the unmodified IPO series is not unambiguously stationary. Therefore, the next step was to investigate first differences of IPO volumes for all sample countries but the Netherlands (because the above-discussed problem affected this constellation as well). Again, the first lag of the dependent variable turned out to be highly significant, as did stock index returns. For example, pooled OLS regression (R^2: 0.24) generated a parameter estimate for the stock index return of 5.74 combined with a t-value of 2.79, and one-way fixed-effects (R^2: 0.25) produced an estimate of 5.88 with a t-value of 2.78. On the other hand, estimates for the first lag of first differences are not only highly significant but also persistently negative – both for pooled estimations and single-country regressions. Pooled OLS, again, yields a parameter estimate of –0.46 in combination with a t-value of –4.45, and one-way fixed effects an estimate of –0.46 with a t-value of –4.39. The highest single-country significance can be observed for France with a parameter estimate of –0.67 and a t-value of –2.75. A supposition arising from this latter empirical observation might be the assumption of a mean-reverting tendency for the whole IPO process within the sample period.

Neither for changes in savings deposits nor for GDP growth could we identify any significant influence on unmodified IPO series or on first differences. The single occurrence of a t-value of 1.47 for GDPG in the case of the Netherlands (see table 1) does not seem to deserve further attention.

3.2 Results for Specification II

In model II we tried to incorporate the empirical observations made under model I analyses. This means, first of all, to put IPO volumes into proportion with GDP so that country-specific effects do not have to absorb differences in IPO volumes resulting from varying economy sizes. And, second, we wanted to investigate our assumption – additionally fostered by individual country results from model I – that a nonlinear (specifically a logarithmic) relationship could possibly better model any dependence of IPO volumes on included independent variables than a linear one. Again, this latter consideration refers to a period not characterized by pronounced fluctuations. Estimation results for model II are presented in tables 3 to 6.

Zero observations on IPO volumes were approximated by replacing $ln(\frac{IPO_{it}}{GDP_{it}}\% * 100) = 0$ with 0.00001 and, alternatively (to make a sensitivity check), with 0.0000001. Table 3 exhibits estimation results for model II when all six countries are included and $ln(\frac{IPO_{it}}{GDP_{it}}\% * 100) = 0$ is approximated with 0.0000001. What we can see from the results are predominantly significant estimates for the first lag of the dependent variable as well as for stock index return. But, in contrast to model I specifications, here also individual country regressions (apart from Belgium and the Netherlands) exhibit significant positive parameter estimates for stock index returns. This might be an indication that the functional form tested under model II is superior to the linearity assumption implied by model I.

Turning from pooled estimations including all sample countries to estimations excluding the Netherlands, we can hardly detect any effect on parameter estimates for stock index returns. Both the first lag of the dependent variable and the stock index return are characterized by highly significant estimates (the exception of two-way fixed-effects models may well result from some sort of overfitting). Also R^2-values are on average rather similar, irrespective of whether the Netherlands are included or excluded. In other words, working with IPO-to-GDP ratios appears to sufficiently absorb economy size effects.

The next point was to carry out a sensitivity check with respect to the approximation of $ln(\frac{IPO_{it}}{GDP_{it}}\% * 100) = 0$. Therefore we tested exactly the same model specification as presented in table 4 except for approximation details (table 4: 0.0000001). Table 5 contains estimation results when approximation is done with 0.00001. Notwithstanding minor changes, the deviations are insubstantial for the purpose of this paper. Our last step in testing the stability of model II estimation results was to exclude the first lag of the dependent variable as an explanatory variable (see table 6). Estimation and test results for stock index returns were hardly affected by this reduction. The only remarkable as well as expected consequence was a significant drop in R^2 – in the case of pooled OLS, for example, from 0.25 to 0.09, for one-way fixed-effects from 0.46 to 0.39, or for one-way random-effects from 0.23 to 0.12.

Again, across all specifications tested neither changes in savings deposits nor GDP growth exhibit any significant influence on IPO volume. With regard to changes in savings deposits (included in order to identify possible flows of funds between savings deposits and investment in stocks) the results therefore seem to contradict any significant effect of a liquidity supply via savings reductions on IPO volumes. The significant results in case of two-way specifications for GDP growth may well stem from an overfitting tendency arising from the additional inclusion of time effects, but do not seem to deserve further attention.

3.3 Results for Specification III

Model III was designed to test the potential influence of interest rates on IPO volumes, with interest rates indicating the price of a competing financing form. The analyzed data series were first differences of IPO volumes. Due to the difficulties with respect to Finnish government bond yield data, elaborated under section 2.1, analyses had to be restricted to the four remaining countries. Estimates for the influence of government bond yields on IPOs turned out to be highly insignificant, both for individual country analyses and for pooled estimations. R^2, without having included the first lag of the dependent variable as an explanatory variable, was close to zero throughout. The indication of these results is therefore: The price of competing financing does not perceivably influence demand for raising equity through IPOs.

4 Conclusion

Only few empirical studies have been carried out to establish why and when companies go public, and what consequences IPOs have, which is particularly surprising given the considerable implications for many internal and external issues. This paper investigates the explanatory power selected macroeconomic factors have for IPOs by analyzing a data set of annual IPO volumes for six continental European countries over a time period of 18 years. Microeconomic aspects are explicitly excluded in order to keep the problem formulation manageable. The main results obtained in this work are: In order to study the influence of stock index returns on IPOs volumes we see a necessity for problem segmentation with respect to stock market levels, given that, on closer examination, successful efforts to optimally time an IPO with respect to the stock price level cannot evidently be accompanied by a significantly positive homogeneous parameter for stock index return across all stock price levels. Hence, we investigated the question if there are stable indications that IPOs depend on stock index returns for what we termed consolidated periods. While all pooled procedures yielded significantly positive parameter estimates, individual country regressions working with untransformed IPO volumes did not generate significant parameter estimates (except for Finland and Austria). In contrast, logarithmic transformation of IPO volumes (representing our supposition of a nonlinear relationship between IPO volumes and stock index returns) leads to persistently significant estimates for both pooled and individual country regressions. Across all specifications tested, the hypothesis that percentage changes in savings and GDP growth have explanatory power for IPO volumes could not be supported by empirical evidence; neither of the two factors exhibits any significant influence. The same holds for interest rates (indicating the price of competing financing sources), which have not been found to perceivably influence demand for raising equity through IPOs.

One possible direction of future research on the questions addressed in this paper would be, first, to extend the data set underlying the investigation – evaluations on the basis of a broader (but still homogeneous) sample could increase the degree of representativeness. And second, analyses of periods characterized by extreme market sentiments, either positive or negative, would complement and enrich the discussion.

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Following abbreviations are used throughout:
OLSp: OLS regression pooled over all countries and all time periods
OLS-BL, OLS-DK, OLS-FL, OLS-FR, OLS-NL, and OLS-AT characterize country-specific OLS regressions carried out separately for Belgium, Denmark, Finland, France, the Netherlands, and Austria
FE1W / FE2W: fixed-effects one-way / two-way error component model
RE1W / RE2W: random-effects one-way / two way error component model evaluated by applying LSDV-residuals
***, **, and * mark coefficients as being significant at the 1 per cent, 5 per cent, and 10 per cent level respectively.

$$IPO_{it} = \alpha + \beta_1 IPO_{it-1} + \beta_2 SR_{it-1} + \beta_3 SG_{it-1} + \beta_4 GDPG_{it} + u_{it} \qquad I$$

Table 1

Estimation Results for Model I (a)

Lag 1 of dependent variable as explanatory; pooled results: 6 countries

Method	R^2	x_1 = Dep. V.-lag 1		x_2 = SR-lag 1		x_3 = SG-lag 1		x_4 = GDPG	
		Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value
OLSp.	0.492	0.7330	9.5081***	5.3140	0.6301	– 6.8994	–0.4914	– 21.2106	–0.3374
OLS-BL	0.051	–0.0125	–0.0411	2.1465	0.5671	– 0.8782	–0.3300	– 17.2288	–0.5277
OLS-DK	0.158	0.0049	0.0145	– 0.1205	–0.0314	– 4.8791	–1.2562	0.2219	0.0077
OLS-FL	0.321	0.2313	0.9187	2.2467	1.4914*	0.4626	0.1476	– 0.4738	–0.0448
OLS-FR	0.211	–0.1859	–0.6523	3.4901	0.5301	33.9448	0.7867	– 72.2531	–1.7211
OLS-NL	0.441	0.4134	1.7617**	–18.8725	–0.2605	–448.2796	–1.3208	1,136.3743	1.4689*
OLS-AT	0.385	0.4147	1.7434**	7.2957	1.8094**	– 28.9314	–0.5807	63.1408	0.5504
FE1W	0.560	0.5462	6.1630***	3.3910	0.4191	– 5.4492	–0.3904	24.9731	0.3988
RE1W	0.359	0.6119	7.3122***	4.0679	0.5033	– 5.9558	–0.4313	8.5601	0.1384
FE2W	0.659	0.5098	4.9573***	– 4.4912	–0.4468	– 3.4133	–0.2300	112.3377	1.2250
RE2W	0.339	0.5901	6.9360***	1.5046	0.1787	– 5.1069	–0.3765	31.9909	0.4717

Source: OeNB.
Pooled results are based on 102 observations, each of the single country regressions uses 17 oberservations.

Table 2

Estimation Results for Model I (b)

Lag 1 of dependent variable as explanatory; pooled results: 5 countries (excl. NL)

Method	R^2	x_1 = Dep. V.-lag 1		x_2 = SR-lag 1		x_3 = SG-lag 1		x_4 = GDPG	
		Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value
OLSp	0.210	0.3740	3.6424***	4.3417	2.4527***	−1.0133	−0.3567	−16.8043	−1.2644
FE1W	0.344	0.1718	1.5746*	4.8559	2.9240***	−0.2987	0.1082	−18.8606	−1.4808
RE1W	0.150	0.2297	2.1706**	4.7112	2.8321***	−0.5139	−0.1875	−18.2581	−1.4385
FE2W	0.489	0.0931	0.7075	3.9825	1.9052**	1.3010	0.4261	− 3.0757	−0.1511
RE2W	0.121	0.1989	1.8508**	4.6141	2.7009***	0.1109	0.0408	−16.3117	−1.1813

Source: OeNB.
Pooled results are based on 85 observations, each of the single country regressions uses 17 oberservations.

$$ln\left(\frac{IPO_{it}}{GDP_{it}}\% * 100\right) = \alpha + \beta_1 ln\left(\frac{IPO_{it-1}}{GDP_{it-1}}\% * 100\right) + \beta_2 SR_{it-1} + \\ + \beta_3 SG_{it-1} + \beta_4 GDPG_{it} + u_{it} \qquad II$$

Table 3

Estimation Results for Model II (a)

Lag 1 of dependent variable as explanatory; pooled results: 6 countries

Method	R^2	x_1 = Dep. V.-lag 1		x_2 = SR-lag 1		x_3 = SG-lag 1		x_4 = GDPG	
		Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value
OLSp	0.166	0.0287	3.3902***	0.0729	2.1643**	−0.0630	−1.1252	0.1142	0.4553
OLS-BL	0.142	0.2026	1.0838	0.0525	0.3213	−0.0538	−0.4684	0.4213	0.2991
OLS-DK	0.344	−0.0210	−0.2793	0.1719	2.1766**	0.0648	0.7957	−1.0953	−1.9043
OLS-FL	0.517	0.1675	1.4380*	0.1943	2.6339***	−0.0777	−0.5037	−0.1607	−0.3105
OLS-FR	0.376	−0.0352	−0.5654	0.0214	1.6791*	0.0785	0.9539	−0.1669	−2.1492
OLS-NL	0.276	0.0288	2.0359**	0.0532	0.3425	−0.1281	−0.1798	−0.5701	−0.3428
OLS-AT	0.378	0.0483	1.5061*	0.0507	1.4163*	−0.5389	−1.2281	0.1177	0.1159
FE1W	0.389	0.0313	3.4647***	0.0845	2.8433***	−0.0441	−0.8596	0.0232	0.1008
RE1W	0.819	0.0307	3.5202***	0.0825	2.7662***	−0.0475	−0.9291	0.0414	0.1806
FE2W	0.705	0.0142	1.6737**	0.0104	0.3557	−0.0558	−1.2980*	1.0860	4.0191***
RE2W	0.215	0.0235	2.9299***	0.0415	1.4709*	−0.0542	−1.2374	0.5878	2.4525***

Source: OeNB.
Pooled results are based on 102 observations, each of the single country regressions uses 17 oberservations (zero approximation with 0.0000001 [see section 2.2]).

Table 4

Estimation Results for Model II (b)

Lag 1 of dependent variable as explanatory; pooled results: 5 countries (excl. NL)

Method	R^2	x_1 = Dep. V.-lag 1		x_2 = SR-lag 1		x_3 = SG-lag 1		x_4 = GDPG	
		Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value
OLSp	0.209	0.1128	3.5425***	0.0714	2.1567**	−0.0634	−1.1958	0.1399	0.5667
FE1W	0.441	0.0843	2.2896***	0.0828	2.8892***	−0.0438	−0.9195	0.0647	0.2970
RE1W	0.200	0.0898	2.8255***	0.0810	2.8171***	−0.0469	−0.9867	0.0755	0.3463
FE2W	0.677	0.0197	0.5681	0.0223	0.7195	−0.0472	−1.0425	0.8880	2.8543***
RE2W	0.168	0.0585	1.8939**	0.0504	1.779**	−0.0460	−1.0573	0.4215	1.6991**

Source: OeNB.
Pooled results are based on 85 observations (zero approximation with 0.0000001 [see section 2.2]).

Table 5

Estimation Results for Model II (c)

Lag 1 of dependent variable as explanatory; pooled results: 5 countries (excl. NL)

Method	R^2	x_1 = Dep. V.-lag 1		x_2 = SR-lag 1		x_3 = SG-lag 1		x_4 = GDPG	
		Estimate	t-value	Estimate	t-value	Estimate	t-value	Estimate	t-value
OLSp	0.245	0.0782	3.9799***	0.0510	2.4935***	−0.0364	−1.1113	0.0625	0.4103
OLS-BL	0.129	0.1172	1.0057	0.0355	0.3489	0.0330	−0.4610	0.2444	0.2782
OLS-DK	0.301	−0.0023	−0.0453	0.1010	1.8857**	0.0336	0.6051	−0.6115	−1.5585
OLS-FL	0.547	0.1032	1.4811*	0.1238	2.8070***	−0.0406	−0.4404	−0.1053	−0.3400
OLS-FR	0.376	−0.0352	−0.5654	0.0214	1.6791*	0.0785	0.9539	−0.1669	−2.1492
OLS-AT	0.462	0.0391	1.9023**	0.0398	1.7308*	−0.3807	−1.3510*	0.1532	0.2348
FE1W	0.459	0.0581	2.8728***	0.0579	3.2523***	−0.0256	−0.8643	0.0215	0.1588
RE1W	0.233	0.0621	3.1493***	0.0568	3.1775***	−0.0274	−0.9265	0.0275	0.2027
FE2W	0.704	0.0177	0.8462	0.0209	1.1140	−0.0256	−0,9338	0.5285	2.1800***
RE2W	0.200	0.0413	2.1920**	0.0375	2.1688**	−0.0253	−0.9565	0.2485	1.6321*

Source: OeNB.
Pooled results are based on 85 observations, each of the single country regressions uses 17 oberservations (zero approximation with 0.00001 [see section 2.2]).

Table 6

Estimation Results for Model II (d)

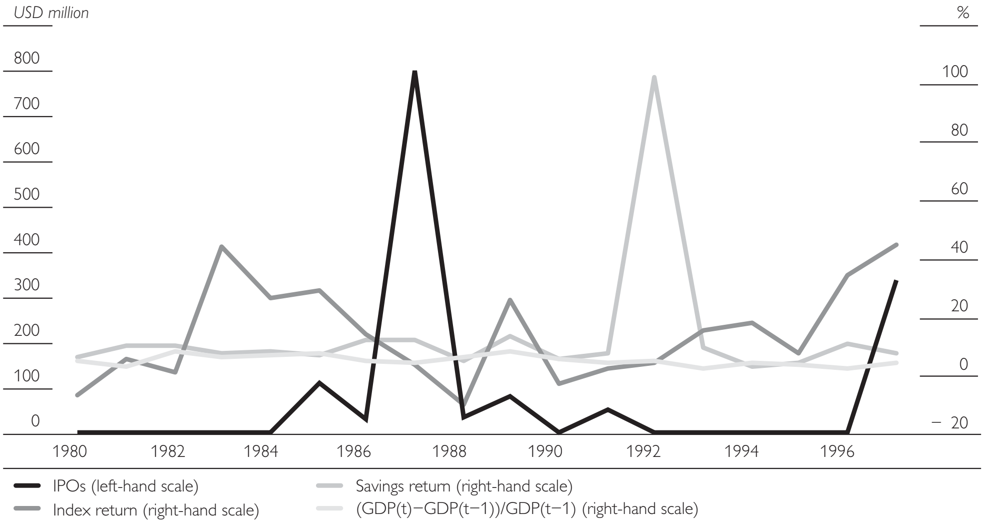
Lag 1 of dependent variable excluded; pooled results: 5 countries (excl. NL)

Method	R^2	x_1 = SR-lag 1		x_2 = SG-lag 1		x_3 = GDPG	
		Estimate	t-value	Estimate	t-value	Estimate	t-value
OLSp	0.085	0.0777	2.1988**	−0.0674	−1.1900	0.0730	0.2776
OLS-BL	0.058	0.0300	0.1841	−0.0512	−0.4428	0.7151	0.5139
OLS-DK	0.340	0.1599	2.4435**	0.0629	0.8039	−1.0127	−2.1295
OLS-FL	0.433	0.2029	2.6529***	−0.0196	−0.1268	−0.1621	−0.3010
OLS-FR	0.359	0.0203	1.6552*	0.0777	0.9698	−0.1586	−2.1364
OLS-AT	0.260	0.0528	1.4094*	−0.5928	−1.2939*	−0.1120	−0.1064
FE1W	0.391	0.0878	2.9618***	−0.0448	−0.9084	0.0431	0.1911
RE1W	0.121	0.0865	2.9060***	−0.0478	−0.9688	0.0473	0.2093
FE2W	0.675	0.0210	0.6836	−0.0473	−1,0510	0.9402	3.1814***
RE2W	0.134	0.0489	1.7052**	−0.0460	−1.0471	0.5077	2.0303**

Source: OeNB.
Pooled results are based on 85 observations, each of the single country regressions uses 17 oberservations (zero approximation with 0.00001 [see section 2.2]).

Figure 1

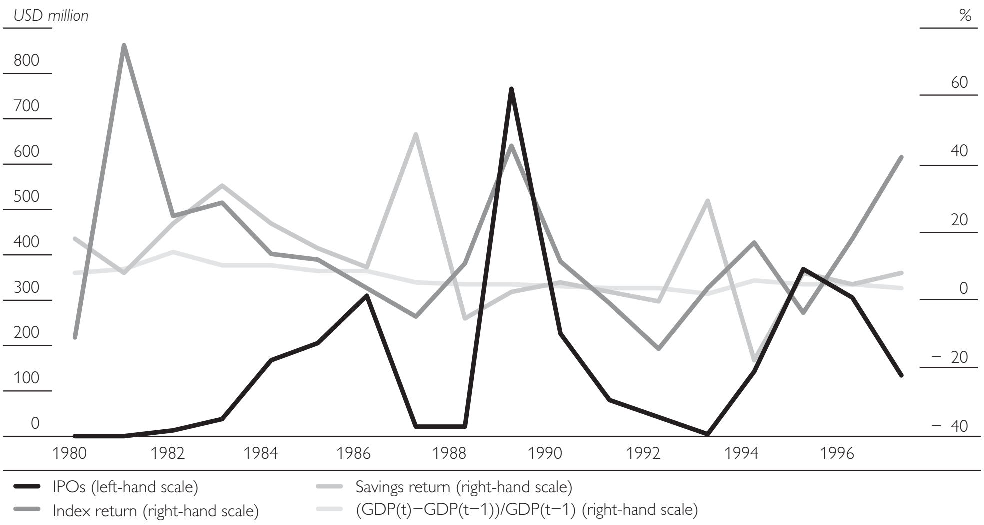
Belgium



Source: Main stock exchange, IMF, OECD.

Figure 2

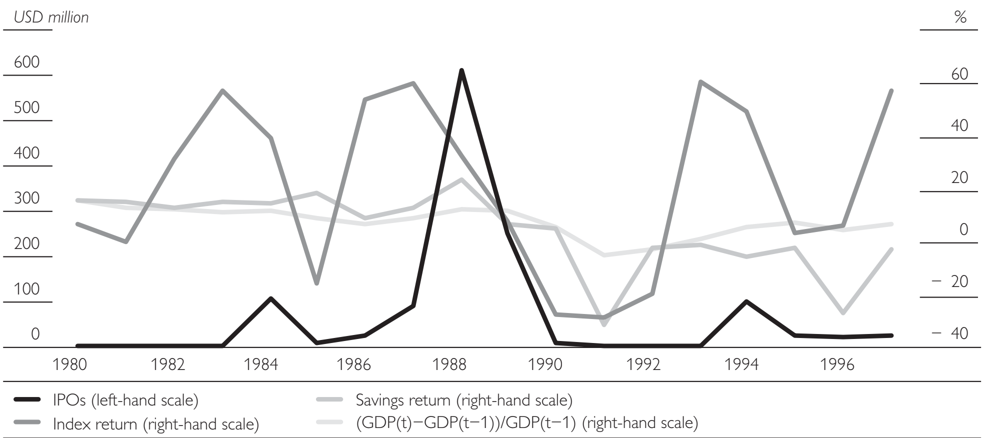
Denmark



Source: Main stock exchange, IMF, OECD.

Figure 3

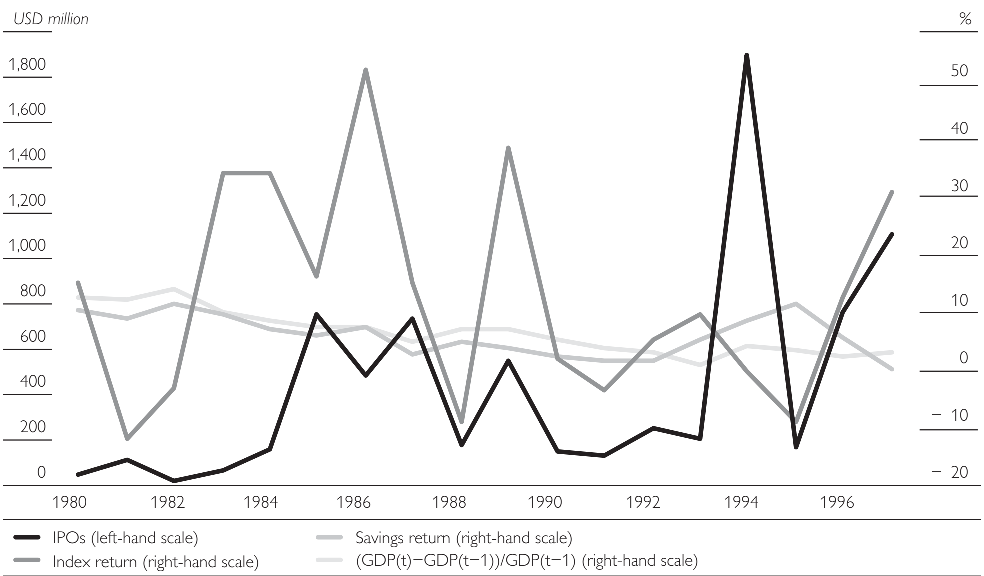
Finland



Source: Main stock exchange, IMF, OECD.

Figure 4

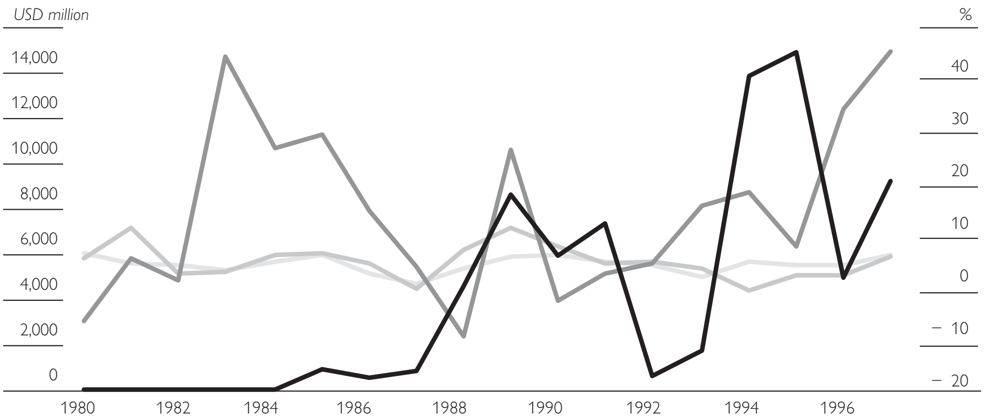
France



Source: Main stock exchange, IMF, OECD.

Figure 5

Netherlands

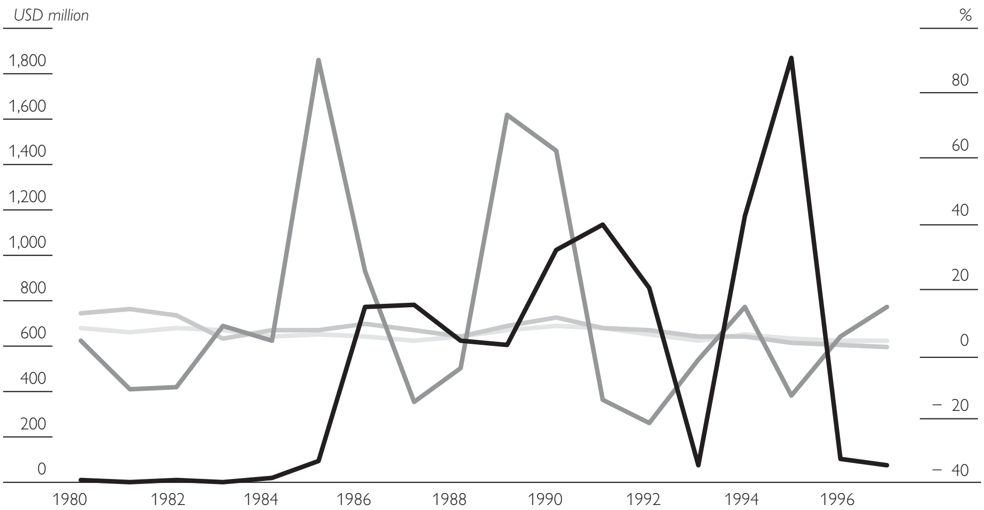


IPOs (left-hand scale) Savings return (right-hand scale)
Index return (right-hand scale) (GDP(t)–GDP(t–1))/GDP(t–1) (right-hand scale)

Source: Main stock exchange, IMF, OECD.

Figure 6

Austria



IPOs (left-hand scale) Savings return (right-hand scale)
Index return (right-hand scale) (GDP(t)–GDP(t–1))/GDP(t–1) (right-hand scale)

Source: Main stock exchange, IMF, OECD.