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A PANIC ANALYSIS OF STOCK PRICES: NEW EVIDENCE FOR INDUSTRIALIZED COUNTRIES*

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This paper presents an investigation of the time series properties of stock price indexes for a panel of 18 countries spanning from December 1969 to May 2007. Unlike previous studies in the field, we employ the PANIC procedures of Bai and Ng (2004a, b), which explicitly allow for strong forms of cross-sectional dependence and enable us to determine the source of the non-stationarity in the observed series of stock prices, i.e. whether it stems from the stochastic behavior of the common factor and/or the idiosyncratic components. Overall, there is strong evidence of non-stationarity in stock prices, which appears to be driven by a common stochastic trend. The computation of half-lives of shocks to the idiosyncratic components through impulse-response functions corroborates the findings obtained with PANIC. First, mean-reverting country-specific components suggest the existence of cross-sectional predictability of stock prices. Second, there is no evidence of time-series predictability of stock prices, since the global shock appears non-stationary in levels and exhibits an infinite half-life.

Key words: stock prices, PANIC, common factors, half-life, stock market predictability.

JEL Classification: C23, G15.

Since the pioneering work of Nelson and Plosser (1982), the examination of stochastic trends in macroeconomic variables has greatly attracted the attention of macroeconomists, applied economists and financial analysts. Discriminating between deterministic and stochastic trends is crucial for understanding the dynamic response of variables to shocks. So if a series is trend stationary,

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it follows that the series will return to its trend path over time and recurrent shocks can, at most, have long-lasting effects, since the effect vanishes as time elapses. In contrast, if a series is non-stationary, the variable will display path-dependence as its current value heavily depends on past values. In this case, recurrent shocks exert a permanent impact on the variable as the effect accumulates over time.

In this paper, we investigate the stochastic properties of the stock price indexes of 18 developed equity markets using monthly data spanning the period from December 1969 to May 2007 (before the current global financial crisis). The novelty of this article with respect to previous studies lies in the fact that it employs the recently developed Panel Analysis of Non-stationarity in Idiosyncratic and Common components (PANIC) procedure of Bai and Ng (2004a, b), which has many advantages over other panel techniques. The empirical exercise using this methodology pursues three main objectives: the decomposition of the panel of observed stock price series into common and idiosyncratic components, the investigation of the time series properties of each component using both unit root and stationarity tests at the univariate level and also for the panel as a whole, and the thorough interpretation of the results in terms of time-series and cross-sectional predictability of stock prices and the implications they have for the possibilities for an investor to diversify risk and gain long-run profits by investing abroad.

We motivate the decomposition of the observed stock price indexes into common and idiosyncratic components and the determination of their stochastic properties on the basis of their key importance for investment and diversification strategies across countries. This is because the presence of permanent idiosyncratic components in national stock price indexes implies the possibility of long-run profits from diversifying risk by investing in foreign markets. If, alternatively, the non-stationary behavior of stock prices is due to the existence of a common stochastic trend, the possibility for an investor with a long holding period to reduce risk by investing abroad vanishes, as all stocks would be driven by a common stochastic source and would move together in the long run. In addition, by using the univariate and panel statistics of Bai and Ng (2004a, b) that take, alternatively, the null hypothesis of a unit root and the null hypothesis of stationarity in both the common and idiosyncratic components, we will be able to provide confirmatory evidence of the non-stationarity properties of the different components[1].

As reviewed in Section 1 below, there are a few studies employing panel unit root statistics for testing the non-stationarity properties of stock price indexes.

(1) Henceforth, we refer to Bai and Ng (2004a) as BNG1 (for the case of testing the unit root null hypothesis) and to Bai and Ng (2004b) as BNG2 (for the case of testing the stationarity null hypothesis). The use of panel unit root tests in tandem with panel stationarity tests may allow us to draw definitive conclusions about the stochastic properties of stock prices. This is because rejection of the null hypothesis in both panel unit root and stationarity tests would indicate the existence of a mixture of stationarity and non-stationarity in the panel, while failure to reject the null hypothesis in both tests could lead to inconclusive inferences due to the poor information provided by the dataset. In addition, when we reject the null hypothesis with the panel stationarity test but not with the panel unit root test, all cross-sectional units contain a unit root; and when there is rejection with the panel unit root test but not with the panel stationarity test, all cross-sectional units may be I(0). See the discussion on this in Shin and Snell (2006, p. 136).

These include Zhu (1998), Balvers *et al*. (2000), Harris and Tzavalis (2004) and Choi and Chue (2007). However, it is remarkable that none of these studies have allowed for strong forms of cross-sectional dependence such as cross-cointegration among national stock price indexes[2]. Hence, a further advantage of the PANIC approach developed by BNG1 and BNG2 is that it allows for strong forms of cross-sectional correlation. Cross-cointegration would be present if the idiosyncratic components are stationary and the common factor is non-stationary and cointegrated with the observed stock price series. O'Connell (1998), Maddala and Wu (1999) and Banerjee *et al*. (2005) have emphasized the fact that failure to allow for cross-dependence, particularly cross-cointegration, when it is present in the data, can cause severe size distortions.

An additional advantage of using this framework is that, whereas the application of other panel unit root tests with a factor structure, such as those of Moon and Perron (2004) and Pesaran (2007), assumes that both common and idiosyncratic components have the same order of integration, the PANIC approach is flexible enough to allow for a different order of integration in the common factor(s) and idiosyncratic components. Therefore, unlike other panel unit root tests, only the PANIC procedures enable us to [1] investigate whether there is cross-sectional dependence driven by one or several common factors and [2] determine the source of non-stationarity: i.e. whether it is present in the common factors and/or in the idiosyncratic components.

Another important advantage is that the PANIC framework can be used as a cointegration test that allows us to test for the existence of stock market linkages among industrialized countries[3]. If we find a common stochastic factor driving the observed stock price indexes along with I(0) idiosyncratic components, there would be evidence of pairwise cointegration among the 18 national stock price indexes, thus implying a high degree of linkage among the stock price series involved. In addition, even though individual stock prices would be non-stationary and driven by a common stochastic trend (implying the lack of time-series predictability), the existence of pairwise cointegration would be consistent with the cross-sectional predictability of asset prices, implying the predictability of a country's stock price index relative to another's[4,5]. This implies that, whenever a coun-

(2) See the literature review in Section 1 for a detailed account of the differences between our study and that of Carrion-i-Silvestre and Villar (2011) that applies the PANIC approach to the stock returns of 21 industrialized countries from January 2004 to March 2011.

(3) As stressed by Gengenbach *et al*. (2010, p. 128), the tests of BNG1 and BNG2 can be used as cointegration statistics by testing whether there is at least one stochastic common trend and all idiosyncratic errors are stationary.

(4) Cross-sectional predictability of stock prices is associated with mean reverting behavior of the idiosyncratic components of stock price indexes (implying predictability of stock prices in one country relative to another), whereas time-series predictability is related to mean reversion in the common component to all individual stock price indexes (i.e. the common factor). From the perspective of an international risk diversification strategy, if cross-sectional predictability is present, investors will not be able to gain profits by diversifying risk through investing in foreign stocks. Likewise, lack of stock price time-series predictability in the way we defined it above (i.e. the existence of a common stochastic factor driving national stock price indexes) implies that it is impossible for

try's stock index deviates from the common trend, it should exhibit mean reversion, and periods of overperformance relative to the common trend should be offset by subsequent periods of underperformance. Under these circumstances, long-holding-period investors would not be able to diversify risk by investing abroad, as all national stock price indexes would be tightly linked in the long run.

Overall, our confirmatory PANIC analysis renders overwhelming evidence of non-stationarity in the stock price indexes, which appears to be driven by a common stochastic factor. In the case of I(0) idiosyncratic series, the evidence supports the existence of pairwise cointegration across national stock price indexes. This high degree of financial integration, in turn, implies that long-horizon investors will fail to obtain any long-term gains by diversifying in international stock markets. This might explain why there is generally a low level of international diversification by investors [Kasa (1992)].

Given that unit root tests provide incomplete information about the degree of persistence of a series as they focus exclusively on the too restrictive distinction between I(0) and I(1) processes, we also provide estimates of the half-life of a shock to both the global common factor and the level of the idiosyncratic series. For this analysis, we employ the median-unbiased method of Andrews and Chen (1994) which computes half-lives directly from impulse-response functions. To the best of our knowledge, for the analysis of the degree of persistence of stock price indexes, there is no previous attempt in the literature to estimate half-lives associated with the common factor and idiosyncratic components obtained from the decomposition of observed stock prices following the PANIC methodology[6]. Within our framework, the insights one can get from the computation of both common and idiosyncratic half-life measures of persistence are much higher than

investors to diversify risk and gain long-run profits by investing abroad since all stock price indexes would be driven by the same common stochastic trend. If the idioysincratic series are found to be I(0) (congruent with the existence of cross-sectional predictability) and that a non-stationary common factor (consistent with the lack of time-series predictability) is the driving force behind the non-stationarity in the observed stock price indexes, the above implications would find support in our results.

(5) For instance, Caporale and Pittis (1998) point out that, within a cointegrating system among N stock price series, the existence of r linearly independent cointegrating vectors implies that at least r of the N individual asset prices are predictable, whereas the rest could be unpredictable. It can also be shown that the non-stationary behavior of the N stock price series is driven by the N-r common stochastic trends. See also Granger (1986) for a proof that pairwise cointegration between asset prices is consistent with cross-sectional predictability.

(6) However, within the Purchasing Power Parity literature, only one previous study by Basher and Carrion-i-Silvestre (2013) has estimated median-unbiased half-lives not directly associated with the observed series (in that case, real exchange rates) but with the common and idiosyncratic components in which the observed series were decomposed via PANIC. In the literature dealing with the measurement of stock price persistence, there are few studies that provide estimates of half-lives of shocks to observed stock price series. These include, among others, Balvers *et al*. (2000), Chaudhuri and Wu (2004) and Gropp (2004). However, a problem with these estimates is that they are calculated using the formula $ln(0.5)/ln(\alpha)$ rather than through impulse-response functions, where α is the persistence parameter (the sum of the coefficients of the underlying AR process). This is only appropriate for AR(1) processes that decay monotonically but not for higher order AR processes for which shocks do not decay at a constant rate.

computing the half-life of a shock to the observed stock price series, since the half-life of a shock to the common factor and idiosyncratic components can provide information about the extent of time-series and cross-sectional predictability, respectively. Furthermore, this analysis enables us to measure more formally the degree of persistence of deviations from the common trend in terms of time, which can be very informative about the exact horizon over which an investor obtains short-run benefits from international risk diversification. If short-run deviations of the observed series from the common trend (i.e. the idiosyncratic series) revert very quickly, there would not be scope for gains even in the short run.

The half-life analysis appears to corroborate the findings obtained with the PANIC procedures. First, we consistently find evidence of mean-reverting country-specific components as given by finite half-lives associated with the idiosyncratic series. This, in turn, suggests the existence of cross-sectional predictability of stock price indexes. Second, there is no evidence of time-series predictability of stock prices, since the global shock given by the common factor is clearly nonstationary and exhibits an infinite half-life, which becomes finite only after applying first-differences to the common factor.

The layout of the rest of the paper is as follows. Section 1 reviews the main studies testing the unit root hypothesis in stock prices. Section 2 briefly describes the data and the panel procedures employed in the analysis and Section 3 reports the main results from the implementation of the PANIC decomposition and testing procedures. Section 4 continues the investigation of the degree of persistence of the stock price indexes by estimating half-lives of shocks to the idiosyncratic components. Section 5 puts forward some modeling implications of our results and then concludes.

1. Brief literature review

On the theoretical front, there are two areas that are modeled with cointegration methods and crucially depend on the existence of a unit root in stock price indexes. The first deals with the analysis of stock market linkages across countries, which can shed some light on the possibility for international investors to diversify and, hence, reduce risks by investing in foreign equity markets. Therefore, if country-specific stock prices exhibit a unit root and are cointegrated, the evidence would favor the existence of linkages across international equity price indexes, thus implying a high degree of financial integration. This has crucial implications for investors' trading schemes as the presence of strong linkages across international stock prices limits the possibility of obtaining benefits from risk-reduction by diversifying portfolios across national borders[7]. In this context, capital movements are expected to arbitrage away the potential gains from investing abroad beyond those caused by differences in risk and exchange premia. Studies analysing international linkages among equity prices through cointegration methods include,

(7) See Levy and Sarnat (1970) and Solnik (1991) for more explanations of the best strategies for reducing portfolio risk by investing in foreign markets.

among others, Kasa (1992), Arshanapalli and Doukas (1993), Chung and Liu (1994) and Richards (1995). Most studies have provided evidence of comovement among international stock prices[8]. As shown below in our analysis, if we end up finding a common stochastic trend driving the non-stationarity in the 18 national stock price indexes, while idiosyncratic stock price components are I(0), this would indicate the existence of pairwise cointegration across the 18 national stock markets. In that scenario, it would be impossible for investors to diversify risk by investing in foreign markets.

The second area relates to the literature of testing the empirical validity of models explaining long-run stock price behavior as a function of financial fundamentals like earnings and dividends. As noted by Crowder and Wohar (1998), the traditional present value stock price model implies that the current stock price should equal the expected discounted present value of the future stream of dividends paid on the asset. This can be expressed by $P_t = \sum_{j=1}^{\infty} (1+r)^{-j} E_t D_{t+j}$, where P_t is the stock price in period t, r is the constant discount rate, D_{t+j} is the dividend paid on the asset at $t+j$, and E_t is the expectations operator. Campbell and Shiller (1987) slightly modify the present value model to allow for the possibility of non-stationary stock prices and dividends. By subtracting D_t / r from both sides of the above equation, it yields $P_t - D_t / r = \theta \sum_{j=1}^{\infty} \delta^j E_t (D_{t+j} - D_t)$, where $\theta = 1/r$ and δ is the discount factor. Thus, Campbell and Shiller (1987) find that stock prices and dividends should be cointegrated with a cointegrating vector $[1, -\theta]'$. Through a log-linear approximation of the above model, Campbell and Shiller (1988) derive the dividend-ratio model, which shows that stock prices and dividends are cointegrated with a cointegrating vector $[1, -1]'$[9].

Early studies employing the univariate variance ratio test and/or long-horizon regressions, such as DeBondt and Thaler (1985), Fama and French (1988) and Poterba and Summers (1988), provide evidence of relatively large predictable components and mean reversion in U.S. equity markets[10]. However, Chow and Denning (1993) point out that these findings may be flawed since the univariate variance ratio technique is problematic[11]. Subsequent studies have employed traditional unit root tests like the augmented Dickey and Fuller (1979) statistic (ADF hereafter). To cite a few studies, Campbell and Shiller (1987, 1988), Kasa (1992), Arshanapalli

(8) A clear exception to this is Richards (1995) who argues that Kasa's conclusions supporting cointegration among the stock indexes of five developed countries are caused by finite-sample bias.

(9) Using quarterly stock prices and dividend data for the U.S. spanning the period 1926-1991, Crowder and Wohar (1998) find support for the log-linearized version of the present value model. Along similar lines, Lee (1995) and Lamont (1998) provide some evidence that prices and dividends are cointegrated. In contrast, Campbell and Shiller (1987), Froot and Obstfeld (1991) and Lee (1996) do not find strong support for the cointegration between stock prices and dividends.

(10) Fama and French (1988) also find some evidence of predictability in 17 other equity markets, as given by the negative serial correlation over long horizons; though they were unable to reject the random walk hypothesis with the statistical tools available at that time.

(11) See also Kim *et al.* (1991), McQueen (1992) and Richardson (1993) for studies questioning the validity and robustness of mean reversion in equity prices found in earlier studies. Lo and MacKinlay (1988) also provide evidence against mean reversion in U.S. stock prices using weekly data.

and Doukas (1993), Chung and Liu (1994), Richards (1995), Lee (1995, 1996), Choudhry (1997), Crowder and Wohar (1998), Lamont (1998) and Chaudhuri and Wu (2003), all provide evidence that stock prices are best described as a unit root process, for which shocks never die out. This result appears surprisingly robust to different sample periods, data frequencies, countries and even to the inclusion of breaks in the data generating process of the series as in Chaudhuri and Wu (2003).

Nevertheless, as stressed by Campbell and Perron (1991) and DeJong *et al*. (1992), this overwhelming evidence supporting non-stationarity in stock prices may derive from the low power of traditional unit root tests of the ADF-type, which cannot distinguish between a non-stationary process and a near unit root process. To raise statistical power, more recent studies have made use of panel data techniques which exploit the cross-sectional variability of stock price data. Focusing on a panel of annual observations for 572 U.S. companies over the period 1975-1994, Harris and Tzavalis (2004) fail to reject the non-stationarity null hypothesis for stock prices using a panel unit root test based on the Lagrange Multiplier score principle. Employing the panel unit root test of Levin *et al*. (2002) for monthly stock prices for the G7 countries over the period 1958-1996, Zhu (1998) is unable to reject the non-stationarity null hypothesis.

We also find two studies investigating the existence of a unit root in relative stock price series for a sample of 18 countries with developed stock markets[12]. Using the feasible generalized least squares panel unit root test of O'Connell (1998), Balvers *et al*. (2000) strongly reject the joint non-stationarity null hypothesis for annual relative stock price data covering the period 1969-1996. More recently, Choi and Chue (2007) have investigated the existence of a unit root in relative stock prices with monthly data over the period 1969-2002. Employing panel unit root tests which control for cross-sectional dependence through subsampling-based methods, they provide less clear-cut evidence of stationarity in relative international stock prices.

Thus far, none of the articles reviewed allow for strong forms of cross-sectional dependence, such as cross-cointegration, which can be handled with the PANIC approach. Indeed, we only find one paper by Carrion-i-Silvestre and Villar (2011) that applies PANIC but to stock returns rather than to stock prices (as we do) for a sample of 21 industrialized countries using daily frequency data spanning the period from 1 January, 2004 to 4 March, 2011. They split the time span into a pre-crisis period (1 January, 2004 to 31 July, 2007) and the financial crisis period (1 August, 2007 to 04 March, 2011). Their evidence supports the existence of two common factors that explain most of the variability in stock returns during the crisis period, thus indicating the intensification of contagion effects among industrialized countries during the current financial crisis.

Our analysis differs from this study in several respects. First, whereas our focus is on the analysis of the non-stationarity properties of stock price indexes, Carrion-i-Silvestre and Villar analyzed the first-difference of stock returns. Sec-

(12) The relative stock price series is computed as the log of each country-specific stock price relative to a reference index, which is either the Morgan Stanley Corporation International world index or the U.S. index.

ond, the nature of the studies is totally different and this fact is responsible for the differing time span investigated in each case. Whereas they concentrate their analysis of contagion effects on the period 2004-2011, paying particular attention to the current financial crisis starting in mid-2007, our focus is more on the non-stationarity properties present in stock price indexes in the long term. This explains why we go as far back in time as possible (to 1969) and, at the same time, stop the analysis just before the current financial crisis unleashed in mid-2007. This prevents the occurrence of a major structural break in stock prices during the current crisis from affecting our inferences regarding the long-term stochastic properties of stock price indexes. Not surprisingly, the results differ across studies. Whereas they find evidence of non-stationary stock returns due to the presence of a unit root in both the idiosyncratic component and in, at least, one common factor, our study provides clear-cut evidence of non-stationarity in stock price indexes but, in this case, only caused by one common stochastic factor as the idiosyncratic components of the panel appear jointly stationary.

2. Data description and econometric methodology

2.1. Data Description

We employ monthly stock price indexes expressed in U.S dollars for the period December 1969 to May 2007. By focusing on this period, we prevent our results from being affected by the current episode of global financial crisis that began in mid-2007. The source of the data is Morgan Stanley Capital International Inc. (MSCI). The dataset includes 18 countries with well-developed stock markets: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, the Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, the United Kingdom and the U.S. The observations are end-of-period value weighted indexes of a large set of companies in each country. Stock prices include reinvested dividends before withholding taxes. The data are transformed into natural logs. This is an updated version of the data employed by Choi and Chue (2007) that ended in December 2002 and which updated that of Balvers *et al*. (2000) composed of annual observations over the period 1969-1996. The advantage of using MSCI indexes over other sources is that these series are computed on a consistent basis and are thus fully comparable across countries[13].

2.2. Panel Procedures for Testing for Unit Roots

In the literature, several second-generation panel unit root tests have been proposed that allow for cross-correlation. These include the non-linear instrumental variables (IV) panel unit root test of Chang (2002), the bootstrap panel unit root

(13) Even though MSCI provides stock indexes for another five developed countries, these data are much shorter than those for the 18 countries investigated. As a matter of fact, data for Finland, Ireland, New Zealand and Portugal are available only from December 1987 and those for Greece are available from December 1998. This factor, as well as the desirability of having a relatively homogeneous sample of countries, further prevented us from including in the sample emerging markets, whose data are available from December 1987 and, in some cases, only from the early 1990s.

tests of Smith *et al*. (2004), the Breitung and Das (2005) test and the bootstrap version of the panel stationarity test of Hadri (2000). A possible shortcoming of employing the above panel tests is that they only allow for contemporaneous short-run cross-correlation, but not for stronger forms such as cross-sectional cointegration.

Breitung and Pesaran (2008) note that alternative methods such as the use of linear factor models can make some parametric assumptions on the nature of cross-sectional dependence and allow for much stronger forms of cross-dependence than the bootstrap or nonlinear IV methods. Among the panel procedures employing a factor structure to model cross-sectional dependence, we find Moon and Perron (2004), Pesaran (2007), BNG1 and BNG2. Pesaran (2007) only allows for one common factor, while Moon and Perron (2004), BNG1 and BNG2 allow for multiple common factors. Of these tests, BNG1 and BNG2 are general enough to allow for cointegration across units, which implies that the observed series can contain common stochastic trends[14]. In the event of I(0) idiosyncratic components, the observed series and the common factor would be cointegrated. Under these circumstances, the tests of Pesaran (2007) and Moon and Perron (2004) may exhibit size distortions since, in the presence of cross-cointegration, the common trends may be confused with the common factors and hence removed from the data in the defactoring process. Therefore, if the remaining idiosyncratic component is I(0) the test yields stationarity, despite the presence of non-stationary common factors[15].

BNG1 and BNG2 circumvent this shortcoming by developing the PANIC framework, which not only allows for non-stationary idiosyncratic components but also for common stochastic components. Let us model the observed data on stock price indexes expressed in log terms (denoted by P_{it}) as the sum of a deterministic part, a common component and an idiosyncratic error term:

$$P_{it} = D_{it} + \lambda'_i F_t + e_{it} \qquad [1]$$

where λ_i is an $r \times 1$ vector of factor loadings, F_t is an $r \times 1$ vector of common factors, and e_{it} is the idiosyncratic component. D_{it} can contain a constant and a linear trend. Since λ_i and F_t can only be estimated consistently when $e_{it} \sim I(0)$, we estimate a model in first-differences like $\Delta P_{it} = \lambda'_i f_t + z_{it}$, where $z_{it} = \Delta e_{it}$ and $f_t = \Delta F_t$[16]. The next step is to use principal components to estimate the common factor $\hat{f}_t$, the corresponding factor loadings $\hat{\lambda}_i$ and the residuals $\hat{z}_{it} = y_{it} - \hat{\lambda}'_i \hat{f}_t$, thereby

(14) See Gengenbach *et al*. (2010, pp. 126-129) for a detailed account of the differences and similarities between the Moon and Perron (2004), Pesaran (2007) and BNG1 panel unit root tests.

(15) See the discussion in Breitung and Pesaran (2008, pp. 301-302). See also Gengenbach *et al*. (2010, p. 134) for simulation evidence supporting the presence of large size distortions associated with the panel unit root tests of Moon and Perron (2004) and Pesaran (2007) in the scenario of non-stationary common factors and a near-unit root in the idiosyncratic component, i.e. the case of cross-unit cointegration.

(16) This representation corresponds to the factor model with a constant. In the case of a factor model with a constant and a linear trend $P_{it} = c_i + \beta_i t + \lambda'_i F_t + e_{it}$, we have $\Delta P_{it} = \beta_i + \lambda'_i \Delta F_t + \Delta e_{it}$. Letting $\overline{\Delta F} = (T-1)^{-1} \sum_{t=2}^{T} \Delta F_t$, $\overline{\Delta e_i} = (T-1)^{-1} \sum_{t=2}^{T} \Delta e_{it}$, and $\overline{\Delta P_i} = (T-1)^{-1} \sum_{t=2}^{T} \Delta P_{it}$, we proceed as follows: $\Delta P_{it} - \overline{\Delta P_i} = \lambda'_i (\Delta F_t - \overline{\Delta F}) + (\Delta e_{it} - \overline{\Delta e_i})$. This can be rewritten as $p_{it} = \lambda'_i f_t + z_{it}$, where $p_{it} = \Delta P_{it} - \overline{\Delta P_i}$, $f_t = \Delta F_t - \overline{\Delta F}$ and $z_{it} = \Delta e_{it} - \overline{\Delta e_i}$.

preserving the order of integration of F_t and e_{it}. We follow Bai and Ng (2002) by normalizing P_{it} for each cross-section unit to have a unit variance. We then recumulate the common factors and the residuals as follows: $\hat{F}_t = \sum_{s=2}^{t} \hat{f}_s$ and $\hat{e}_{it} = \sum_{s=2}^{t} \hat{z}_{is}$, which can be used to test for a unit root in the common and idiosyncratic components, respectively.

Before conducting the tests for a unit root in the common and idiosyncratic components, it is necessary to determine the number of common factors. This is done through the BIC_3 information criterion that takes the form:

$$BIC_3(k) = \hat{\sigma}_e^2(k) + k\hat{\sigma}_e^2(k_{\max})\left(\frac{(N+T-k)\ln(NT)}{NT}\right) \qquad [2]$$

where k is the number of factors included in the model, $\hat{\sigma}_e^2(k)$ is the variance of the estimated idiosyncratic components, and $\hat{\sigma}_e^2(k_{max})$ is the variance of the idiosyncratic components estimated with the maximum number of factors ($k_{max} = 5$). Note that the second argument in the loss function represents the penalty for overfitting. This term is thus intended to correct for the fact that models with a larger number of factors can fit at least as good as models with fewer common factors, but efficiency is reduced as more factor loading parameters are being estimated (see more details in Bai and Ng, 2002). We choose the optimal number of common factors $\hat{k}$ as $\text{argmin}_{0\leq k\leq 5}\ BIC_3(k)$. Our preferred criterion is BIC_3 because Bai and Ng (2002, pp. 205-207) showed that, for a sufficiently general scenario in which the idiosyncratic errors can be serially correlated and cross-correlated, the BIC_3 criterion has very good properties (see Tables VII and VIII in Bai and Ng, 2002). In addition, Moon and Perron (2007, p. 387) point out that the BIC_3 criterion "performs better in selecting the number of factors when $\min(N,T)$ is small (≤ 20), as is often the case in empirical applications". Notwithstanding, for the sake of robustness, we also compute the IC_1, IC_2 and IC_3 panel information criteria proposed by Bai and Ng (2002), which have the advantage over the PC_p counterparts that they do not depend on the maximum number of factors. The three IC_p criteria equal $\ln(\hat{\sigma}_e^2(k)) + kg(N,T)$, $g(N,T)$ being a penalty function of both T and N. This penalty function equals $\left(\frac{N+T}{NT}\right)\ln\left(\frac{NT}{N+T}\right)$, $\left(\frac{N+T}{NT}\right)\ln\left(C_{NT}^2\right)$ and $\frac{\ln C_{NT}^2}{C_{NT}^2}$ for IC_1, IC_2 and IC_3 respectively, where $C_{\text{NT}}^2 = \min(N,T)$.

To test for a unit root in the idiosyncratic components, BNG1 estimate standard ADF specifications as follows:

$$\Delta\hat{e}_{it} = \delta_{i,0}\hat{e}_{i,t-1} + \sum_{j=1}^{p_i}\delta_{i,j}\Delta\hat{e}_{i,t-j} + u_{it} \qquad [3]$$

They then employ the ADF t-statistic for testing $\delta_{i,0} = 0$, which is denoted by $ADF_{\hat{e}}^{c}(i)$ or $ADF_{\hat{e}}^{\tau}(i)$ for the cases of only a constant and a constant and a linear trend in specification [1], respectively[17]. To raise statistical power, BNG1 recom-

(17) The asymptotic distribution of $ADF_{\hat{e}}^{c}(i)$ coincides with the Dickey-Fuller distribution for the case of no constant, while that of $ADF_{\hat{e}}^{\tau}(i)$ is proportional to the reciprocal of a Brownian bridge.

mend using pooled statistics based on the Fisher-type inverse chi-square tests of Maddala and Wu (1999) and Choi (2001), only if the idiosyncratic components are assumed to be independent across cross-sectional units[18]. Letting $\pi^c_{\hat{e}}(i)$ be the p-value associated with $ADF^c_{\hat{e}}(i)$, we have[19]:

$$P^c_{\hat{e}} = -2\sum_{i=1}^{N} \log\, \pi^c_{\hat{e}}(i) \xrightarrow{d} \chi^2_{(2N)} \quad \text{for } N \text{ fixed}, T \to \infty, \qquad [4]$$

$$Z^c_{\hat{e}} = \frac{-\sum_{i=1}^{N} \log\, \pi^c_{\hat{e}}(i) - N}{\sqrt{N}} \xrightarrow{d} N(0,1) \quad \text{for } N, T \to \infty. \qquad [5]$$

To test for non-stationarity in the common factors, BNG1 employ an ADF test for the case of a single common factor ($k = 1$) or a rank test when $k > 1$. In the former case, they estimate an ADF specification for $\hat{F}_t$ with the same deterministic components as in model [1]:

$$\Delta\hat{F}_t = D_t + \gamma_0\hat{F}_{t-1} + \sum_{j=1}^{p} \gamma_j \Delta\hat{F}_{t-j} + v_{it} \qquad [6]$$

The corresponding ADF t-statistics are denoted by $ADF^c_{\hat{F}}$ and $ADF^{\tau}_{\hat{F}}$ and are characterized by the limiting distribution of the Dickey and Fuller (1979) test for the specifications with only a constant, and a constant and a trend, respectively. For the case of multiple common factors, the number of common stochastic trends in the common factors is determined using the modified rank tests labelled as the filter test MQ_f that assumes that the non-stationary components are represented by finite order vector autoregressive processes and the corrected test MQ_c that allows the unit root processes to exhibit more general dynamics.

For confirmatory purposes, BNG2 extend the PANIC procedure to the stationarity test of Kwiatkowski *et al.* (1992, KPSS hereafter). The univariate KPSS tests for the idiosyncratic components are $S^c_{\hat{e}_0}(i)$ and $S^{\tau}_{\hat{e}_0}(i)$ depending on the specification, and the tests for the common factors are $S^c_{\hat{F}}$ and $S^{\tau}_{\hat{F}}$[20]. When the common factors are I(0) stationary, the p-values associated with the univariate KPSS tests for

(18) If the observed series are correctly decomposed into the common and idiosyncratic components, the latter (i.e. the defactored data) should, by assumption, be cross-sectionally independent. More importantly, the PANIC procedure has the advantage that the common factors and indiosyncratic components are estimated consistently, irrespective of whether they are I(0) or I(1).

(19) The same holds for the case of a trend, where $\pi^{\tau}_{\hat{e}}(i)$ is the p-value associated with $ADF^{\tau}_{\hat{e}}(i)$. The pooled statistics for the trend specification are denoted as $P^{\tau}_{\hat{e}}$ and $Z^{\tau}_{\hat{e}}$. It is important to note that, under a factor structure, it is inappropriate to pool individual unit root tests for the observed series, since the limiting distribution of the test would contain terms that are common across panel members. However, as pointed out by Bai and Ng (2004a, p. 1140), "pooling of tests for $\hat{e}_{it}$ is asymptotically valid under the more plausible assumption that $\hat{e}_{it}$ is independent across i".

(20) The limiting distribution of $S^c_{\hat{F}}$ and $S^{\tau}_{\hat{F}}$ are those derived by KPSS for the cases of a constant, and a constant and a linear trend, respectively. However, the limiting distribution for testing $\hat{e}_{it}$ depends on whether $\hat{F}_i$ is I(0) or I(1). If all factors are I(0), $S^c_{\hat{e}_0}(i)$ and $S^{\tau}_{\hat{e}_0}(i)$ follow the distribution of the KPSS tests for the cases of a constant, and a constant and a trend, respectively. But if some factors are I(1), stationarity in the idiosyncratic component implies cointegration between the observed series and the I(1) common factors. In this case, we have to employ univariate cointegration tests denoted by $S^c_{\hat{e}_1}(i)$ and $S^{\tau}_{\hat{e}_1}(i)$ which have the limiting distribution of the cointegration test of Shin (1994).

the idiosyncratic components can be used to compute the pooled tests of Maddala and Wu (1999) and Choi (2001). Otherwise, pooling is not valid since the non-stationarity of the common factors, which does not vanish even asymptotically, is transmitted to the residuals under the null hypothesis of stationarity.

3. Empirical results from panic procedures

Having presented a brief description of the econometric methodology behind the panel procedures employed in our analysis, we shift the focus to report the results obtained from their application. Before conducting the unit root analysis, we carry out a formal analysis of the prevalence of cross-sectional dependence in stock price innovations by applying the tests for cross-dependence developed by Breusch and Pagan (1980) and Pesaran (2004)[21]. Remarkably, the LM test of Breusch and Pagan (1980) has values of 810.3 and 808.9 for the specifications without and with trends, and the respective values of the CD test of Pesaran (2004) are 116.0 and 115.8. In all cases, the null hypothesis of cross-sectionally independent errors is rejected at the 1% significance level. This implies that the panel unit root and stationarity tests employed in the empirical exercise must allow for cross-sectional dependence so that large size distortions in the tests are avoided.

In background work, we applied the second generation panel unit root tests of Smith *et al*. (2004), Chang (2002), Breitung and Das (2005) and the bootstrap panel stationarity test of Hadri (2000), which only allow for weak forms of cross-sectional correlation such as contemporaneous short-run cross-dependencies. The (unreported) results from these tests clearly supported the presence of a unit root in stock prices[22]. There are two reasons why we now apply the testing procedures of BNG1 and BNG2. Firstly, the testing procedures of Smith *et al*. (2004), Chang (2002), Breitung and Das (2005) and the bootstrap version of Hadri (2000) only allow for weak forms of cross-sectional dependence, which exclude, for instance, the existence of cross-sectional cointegration. Secondly, as there is preliminary evidence of a unit root in stock prices, it is necessary to establish the source of non-stationarity, i.e. whether it is present in the idiosyncratic components and/or in the common factors[23].

(21) The latter is based on the average of pair-wise correlation coefficients ($\hat{\rho}_{ij}$) of ordinary least squares (OLS) residuals obtained from standard ADF regressions for each individual. The order of the autoregressive model is selected using the *t-sig* criterion in Ng and Perron (1995), with the maximum number of lags set at $p = 4(T / 100)^{1/4}$. Pesaran's test is given by $CD = \sqrt{2T / (N(N-1))} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right) \xrightarrow{d} N(0,1)$. The CD statistic tests the null hypothesis of cross-independence, is distributed as a two-tailed standard normal distribution, and exhibits good finite-sample properties. Breusch and Pagan (1980) also test the null hypothesis of cross-sectionally independent errors via the following Lagrange Multiplier (LM) statistic $CD_{lm} = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \xrightarrow{d} \chi^2_{N(N-1)/2}$.

(22) Due to space limitations, we do not report these results, which are available in an unpublished appendix from the authors upon request.

(23) We also tested the unit root hypothesis with the tests of Pesaran (2007) and Moon and Perron (2004) and we could reject the unit root null hypothesis at the 5% level or better for the specification

Prior to testing for a unit root in the idiosyncratic series and common factors, we need to estimate the factors through principal components and then select the number of common factors present in the panel. As noted above, this is done with the BIC_3 procedure developed in Bai and Ng (2002), which appears to perform better than alternative information criteria. Setting the maximum number of factors to five, the criterion selects one common factor. The results are presented in Table 1. For the sake of robustness, Table 1 also reports the results from the three panel information criteria (IC_p) proposed by Bai and Ng (2002), which appear to favor the existence of two common factors. Since Bai and Ng (2002) found evidence that the BIC_3 criterion performed remarkably well in the presence of cross-correlations and Gengenbach *et al*. (2010, p. 134) provided simulation evidence of the superior performance of the BIC_3 criterion for short-N panels, and given the difficulty in determining the number of common factors in panels with relatively short N, we will conduct the decomposition of the stock price series into common and idiosyncratic components as if there was one common factor[24]. In addition, the application of the IPC_1, IPC_2 and IPC_3 information criteria of Bai (2004) to determine the number of *non-stationary* common factors in the panel (setting the maximum number of factors to five) clearly indicates the existence of only one common stochastic

Table 1: Information criteria

Number of factors (k)	$IC_1(k)$	$IC_2(k)$	$IC_3(k)$	$BIC_3(k)$
0	-5.4561	-5.4561	-5.4561	0.0043
1	-5.9087	-5.9064	-5.9129	0.0029*
2	-5.9872*	-5.9827*	-5.9956*	0.0030
3	-5.9748	-5.9680	-5.9873	0.0033
4	-5.9530	-5.9439	-5.9697	0.0037
5	-5.9369	-5.9255	-5.9577	0.0041

Note: * represents the lowest value of the information criteria. See the text for the equations associated with the information criteria.

Source: Own elaboration.

without trends ($t_a^* = -10.44$, $t_b^* = -5.28$, and CIPS= –2.46), whereas the null hypothesis could only be rejected with the Moon and Perron (2004) tests for the specification with trends ($t_a^* = -10.33$, $t_b^* = -5.28$, and CIPS= –2.56). As noted above, this result should not be surprising, since these panel unit root tests exhibit large size distortions in the presence of cross-cointegration (which is the result we find after applying the PANIC procedures). This occurs because the common trends are confused with the common factors and hence removed from the data in the defactoring process.

(24) Note also that, even though the information criteria for determining the optimal number of common factors work reasonably well in simulations, their practical application is difficult since they are usually found to select the maximum number of common factors permitted (Gengenbach *et al*., 2010, p. 219). However, since the four information criteria selected, at most, two common factors, which are well below the maximum allowed, we are confident that the optimal number of common factors may be correctly estimated.

factor, which coincides with the results we find below with the $ADF_{\hat{F}}^{c}$ and $ADF_{\hat{F}}^{\tau}$ statistics[25]. Therefore, if the common factor is found non-stationary, and the idiosyncratic components are I(0) stationary, there would be evidence of pair-wise cointegration among the 18 stock price indexes forming the panel.

Table 2 reports the results of the univariate and pooled ADF and KPSS tests for the idiosyncratic series in addition to the respective univariate tests for the common factor. Regarding the analysis of the common factor, the ADF test for a unit root in the common factor fails to reject the null hypothesis, while the KPSS test strongly rejects the stationarity null hypothesis. The finding of a common stochastic factor is robust to the inclusion of trends in the specification. Next, we test for a unit root in the idiosyncratic series. For the no trend specification, the univariate ADF test rejects the unit root null hypothesis at conventional significance levels in half of the countries. These are Australia, France, Germany, Italy and the United Kingdom at the 1% level, Japan and Norway at the 5% level and Canada and Sweden at the 10% level.

Given the non-stationarity in the common factor, we complement this analysis with the cointegration test of Shin (1994) applied directly to the idiosyncratic series. The Shin statistic tests for cointegration between the observed series and the common factor, which is tantamount to testing for stationarity in the idiosyncratic series. The Shin statistic fails to reject the null hypothesis of cointegration between the observed series and the I(1) common factor for seven countries (Austria, Germany, Hong Kong, the Netherlands, Norway, Sweden and the United Kingdom). Therefore, there is confirmatory evidence of stationary idiosyncratic series for Germany, Norway, Sweden and the United Kingdom for the specification without trends. In addition, we find non-stationary idiosyncratic series for Belgium, Denmark, Singapore, Spain, Switzerland and the U.S. For the rest of the series, there is inconclusive evidence which may stem from the poor performance associated with univariate statistics.

For the trend specification, the ADF test rejects the null hypothesis of a unit root in the idiosyncratic series for all but seven countries (Austria, Canada, Japan, the Netherlands, Spain, Switzerland and the U.S.), while the Shin test rejects the cointegration null hypothesis for all countries at conventional significance levels. Hence, there is confirmatory evidence of non-stationary idiosyncratic series for Austria, Canada, Japan, the Netherlands, Spain, Switzerland and the U.S., while the evidence is inconclusive for the rest. Again, this inconclusive evidence may derive from the poor performance of univariate unit root and stationarity tests. Therefore, we try to raise statistical power by pooling the ADF statistics associated with individual idiosyncratic series through the Fisher-type inverse Chi-squared tests of Maddala and Wu (1999) and Choi (2001). By doing so, we are now able to strongly reject the joint non-stationarity null hypothesis, irrespective of the inclu-

(25) Unlike the information criteria to determine the optimal number of common factors (stationary and non-stationary) in BNG1 and BNG2 that were applied to data in first-differences, the IPC_p panel information criteria to determine the number of *non-stationary* common factors proposed by Bai (2004) is applied to level data. In addition, the consistency of Bai (2004)'s information criteria requires the idiosyncratic component to be I(0), which we will find below to be the case.

sion of linear trends. Since the common factor was found non-stationary, it is not appropriate to pool the univariate Shin statistics. Therefore, from this analysis, we can infer the joint stationarity of the idiosyncratic components of the panel[26].

Direct testing for a unit root in the observed data provides clear-cut evidence of non-stationarity with the univariate ADF and KPSS statistics for the specification without a trend, since the null hypothesis of a unit root cannot be rejected for any of the observed stock price series with the ADF statistics while the null hypothesis of stationarity can be strongly rejected with the KPSS statistic at the 1% level. For the specification with a deterministic trend, the evidence appears to favor non-stationarity in stock prices in all countries expect for Canada where the stock price is I(0) and Denmark and Singapore for which the evidence is inconclusive[27]. The above decomposition of the original series into the idiosyncratic and common components indicates that the source of non-stationarity is primarily a common stochastic trend which drives the non-stationarity in the observed series. This, coupled with the existence of jointly stationary idiosyncratic components, provides evidence of pairwise cointegration across the 18 national stock price indexes considered. We can interpret this evidence as a significant degree of international stock market linkages. This finding stands in support of previous evidence provided by studies analyzing international linkages among stock prices of different countries. For instance, Kasa (1992), Arshanapalli and Doukas (1993) and Chung and Liu (1994) all find some evidence of long-run international linkages among stock prices of different countries, which include OECD countries, Latin American countries and South-East Asian countries.

In column 12 we show the ratio of the standard deviation of the idiosyncratic component to the standard deviation of the observed data (both expressed in first-differences). This statistic helps us determine the relative importance of the idiosyncratic component. If the ratio is close to one, country-specific variations would prevail vs. the common component. In relative terms, this appears to be the case for Austria, Italy and Japan, which are mainly driven by idiosyncratic variations while other countries' stock prices are more largely affected by external common factors.

All in all, our thorough analysis of the stochastic properties of our panel of stock prices appears to be strongly supportive of the unit root hypothesis. In addition, the PANIC procedures show that the source of non-stationarity in the observed data is a common stochastic factor. It is worth highlighting that this evidence is obtained employing both unit root and stationarity tests that complement each other by taking alternative null hypotheses. This reinforces the view that international stock prices are best described as non-stationary processes, which appear to be driven by a common stochastic factor[28].

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(26) The evidence of I(0) idiosyncratic stock price components is consistent with the production-based asset pricing model of Lucas (1978) that relates asset returns to output growth, thereby implying that transitory productivity differences entail transitory differences in stock price indexes.

(27) As noted in footnote 19, the factor structure of the panel prevented us from pooling individual statistics associated with the observed stock price series.

(28) Following the suggestion of one of the referees, we tried to check whether our baseline results of a non-stationary common factor along with joint stationarity in the idiosyncratic components

At this point, we note that it is not our content to derive any conclusion on the basis of our findings regarding the Market Efficiency Hypothesis (MEH)[29]. In fact, even if the common component were found to be I(0), this would suggest time series predictability globally. This in turn may mean that either global risk or risk premia are varying over time, and need not imply market inefficiency. Besides, stationarity in the idiosyncratic component entails the predictability of stock prices in one country relative to another. Arguably, this constitutes a more serious challenge for market efficiency (easily "arbitraged"), but it could be due to differences in systematic risk across countries.

Our findings appear to be in line with previous studies employing univariate unit root tests of the ADF-type as well as with some studies like Zhu (1998) and Harris and Tzavalis (2004) that employed panel unit root tests. Our results apparently contrast with those by Balvers *et al*. (2000) who analyzed a panel of relative stock price series for the same set of countries as ours using annual data covering the period 1969-1996[30]. However, it is worth noting that Balvers *et al*. (2000) employed relative stock price series rather than stock prices themselves, where the reference country is acting as a common factor. So the data contain a common factor by construction. This implies that if both a country's stock price and that of the reference country are non-stationary and cointegrated with each other (as the literature on international stock market linkages has demonstrated), the relative stock price series would exhibit stationarity. Our analysis, indeed, appears to provide some evidence of pairwise cointegration among the stock indexes since the observed stock price series are found to cointegrate with the common stochastic factor. Hence, our results do not contradict previous findings from studies showing non-stationarity in stock price indexes and stationarity in relative stock prices. On these grounds, researchers could take the non-stationarity property for stock prices as a stylized fact when modeling international stock market linkages and long-run stock price behavior with cointegration techniques.

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hold when we split the time span to allow for structural change. Since, for the implementation of the PANIC approach, we need a balanced panel, we try to find the most likely common structural shift that is affecting all the series simultaneously. The avenue we take for this is to test for structural instability in the common stochastic trend that is driving all country-specific stock price series. Given the trending behavior of the common stochastic trend, we allow for both a mean and a slope shift. We would have liked to allow for more than one structural break, but the poor performance in terms of statistical power of univariate unit root and stationarity tests for short time spans prevented us from doing so. To identify the break location, we follow the procedure of Bai and Perron (1998) which is based upon the global minimization of the sum of squared residuals using a trimming parameter of 0.15. The break appears to be located at December 1985. Therefore, we repeat the PANIC analysis fully for both subsamples: December 1969 - December 1985 and January 1986 - May 2007. As shown in the unpublished appendix, the results clearly point to the existence of one common factor for both subsamples using the BIC_3 procedure. Besides, the PANIC analysis renders clear-cut evidence of a non-stationary common factor along with jointly stationary idiosyncratic series for the panel as a whole for both subperiods, just as we found for the whole time span.

(29) The MEH implies that prices respond quickly to all relevant and publicly available information. If that occurs, the returns associated with an asset are unpredictable from the past behavior of price changes.

(30) Choi and Chue (2007) provide less clear-cut evidence for non-stationarity in relative stock prices for the same panel of countries over the period 1969-2002.

Table 2: PANEL ANALYSIS OF NON-STATIONARITY IN IDIOSYNCRATIC AND COMMON COMPONENTS OF STOCK PRICES

No Trend Specification					
Country	k	$ADF_y^c(i)$	$ADF_{\hat{e}}^c(i)$	$S_y^c(i)$	$S_{\hat{e}_1}^c(i)$
Australia	0	0.818	-3.416***	4.980***	0.310*
Austria	5	-0.188	-1.486	4.607***	0.203
Belgium	7	-0.283	-1.162	4.990***	0.297*
Canada	6	0.110	-1.874*	4.971***	0.497**
Denmark	7	-0.400	-1.339	5.025***	0.248*
France	3	-0.177	-3.772***	5.007***	0.275*
Germany	7	-0.506	-3.318***	4.993***	0.129
Hong Kong	1	-1.241	-1.021	4.949***	0.201
Italy	6	-0.215	-3.594***	4.618***	0.326**
Japan	3	-2.234	-2.139**	4.275***	1.147***
Netherlands	0	-0.196	-0.830	5.074***	0.223
Norway	4	-0.248	-2.019**	4.840***	0.142
Singapore	1	-1.807	-0.785	4.580***	0.560***
Spain	7	0.259	-1.595	4.544***	0.817***
Sweden	6	-0.292	-1.694*	5.039***	0.118
Switzerland	5	-0.213	-1.258	5.049***	0.592***
United Kingdom	3	-0.414	-2.826***	5.029***	0.223
United States	5	-0.158	-0.696	5.071***	0.513**
Critical Values					
1%		-3.430	-2.580	0.743	0.536
5%		-2.860	-1.950	0.463	0.324
10%		-2.570	-1.620	0.343	0.235
		$P_{\hat{e}}^c$	120.887***		N.A.
		$Z_{\hat{e}}^c$	10.004***		N.A.

Common Factor Analysis		Critical Values		
	Statistic	1%	5%	10%
$ADF_{\hat{F}}^c$	-0.237	-3.430	-2.860	-2.570
$S_{\hat{F}}^c$	5.045***	0.743	0.463	0.343

Note: The augmented autoregressions employed in the ADF analysis select the optimal lag-order with the t-sig criterion of Ng and Perron (1995), setting a maximum lag-order equal to $p = 4(T/100)^{1/4}$. The stationarity tests are based on 12 lags of the Quadratic spectral kernel. The information criterion BIC_3 has chosen an optimal rank of 1 for the tests of Bai and Ng (2004a,b). $P_{\hat{e}}$ is distributed as χ^2_{36}, with 1%, 5% and 10% critical values of 58.620, 51.000 and 47.212, respectively. $Z_{\hat{e}}$ is distributed as N(0,1) with 1%, 5% and 10% critical values of 2.326, 1.645, and 1.282.

***, ** and * imply rejection of the null hypothesis at 1%, 5% and 10%, respectively.

Source: Own elaboration.

Table 2: Panel analysis of non-stationarity in idiosyncratic and common components of stock prices (continuation)

Trend Specification						
Country	k	$ADF_y^{\tau}(i)$	$ADF_{\hat{e}}^{\tau}(i)$	$S_y^{\tau}(i)$	$S_{\hat{e}_1}^{\tau}(i)$	$\frac{\sigma(\Delta\hat{e}_{it})}{\sigma(\Delta y_{it})}$
Australia	0	-2.994	-3.064**	0.224***	0.309***	0.562
Austria	1	-1.991	-1.872	0.252***	0.190***	0.706
Belgium	1	-2.085	-2.690**	0.383***	0.305***	0.461
Canada	0	-3.227*	-1.643	0.101	0.520***	0.507
Denmark	0	-4.098***	-3.695***	0.155**	0.260***	0.595
France	0	-2.695	-3.820***	0.336***	0.286***	0.441
Germany	0	-2.934	-3.725***	0.350***	0.129**	0.441
Hong Kong	0	-2.981	-3.091**	0.377***	0.201***	0.568
Italy	6	-2.955	-3.429***	0.311***	0.333***	0.674
Japan	3	-1.826	-1.674	1.011***	1.129***	0.696
Netherlands	0	-1.819	-2.146	0.524***	0.197***	0.320
Norway	4	-2.767	-3.477***	0.193**	0.131**	0.511
Singapore	1	-3.323*	-3.047**	0.621***	0.564***	0.545
Spain	0	-1.660	-1.564	0.589***	0.822***	0.588
Sweden	0	-2.810	-3.548***	0.331***	0.106*	0.506
Switzerland	2	-2.541	-2.163	0.327***	0.571***	0.425
United Kingdom	5	-2.170	-3.174***	0.469***	0.219***	0.460
United States	0	-2.085	-2.233	0.440***	0.470***	0.514
Critical Values						
1%		-3.960	-3.167	0.215	0.185	
5%		-3.410	-2.577	0.149	0.122	
10%		-3.120	-2.314	0.120	0.098	
		$P_{\hat{e}}^{\tau}$	138.227***		N.A.	
		$Z_{\hat{e}}^{\tau}$	12.048***		N.A.	

Common Factor Analysis			Critical Values		
		Statistic	1%	5%	10%
	$ADF_{\hat{F}}^{\tau}$	-2.363	-3.960	-3.410	-3.120
	$S_{\hat{F}}^{\tau}$	0.405***	0.215	0.149	0.120

Note: The augmented autoregressions employed in the ADF analysis select the optimal lag-order with the t-sig criterion of Ng and Perron (1995), setting a maximum lag-order equal to $p = 4(T/100)^{1/4}$. The stationarity tests are based on 12 lags of the Quadratic spectral kernel. The information criterion BIC_3 has chosen an optimal rank of 1 for the tests of Bai and Ng (2004a,b). $P_{\hat{e}}$ is distributed as χ^2_{36}, with 1%, 5% and 10% critical values of 58.620, 51.000 and 47.212, respectively. $Z_{\hat{e}}$ is distributed as N(0,1) with 1%, 5% and 10% critical values of 2.326, 1.645, and 1.282.

***, ** and * imply rejection of the null hypothesis at 1%, 5% and 10%, respectively.

Source: Own elaboration.

4. Persistence of shocks to stock prices

In this section, we complement the previous analysis with the use of median unbiased estimates of the half-life of a shock to the common and idiosyncratic components in which the original stock price series were decomposed[31]. This, in turn, will allow us to shed some light on the predictability of stock price indexes along the time-series and cross-sectional dimensions, respectively. The half-life of a shock measures the number of years for a unit impulse to dissipate by one half. For AR(1) processes, the half-life is computed using the formula $HL = \ln(0.5)/\ln(\alpha_{MU})$, where α_{MU} is the median unbiased estimate of the persistence parameter[32]. For autoregressive processes of order greater than one, the series do not decay monotonically and the estimate of α_{MU} must be approximately derived from the impulse-response function. In this regard, we follow the suggestion of Cheung and Lai (2000) who obtain point estimates and confidence intervals of the half-life of a shock directly from the impulse-response function. We also provide 90% confidence intervals of the point estimates[33].

In what follows, we try to frame the interpretation of the half-lives of shocks to both the common and idiosyncratic components in terms of time-series and cross-sectional predictability of stock price indexes. Considering a model like [1] in Section 2.2 above, we employ $\hat{F}_t$ and $\hat{e}_{it}$ to compute the half-lives of shocks to the common factor and idiosyncratic components in which the logarithm of the observed stock price indexes (P_{it}) are decomposed.

The idea is to compute the half-life associated with the global shocks as well as with the country-specific idiosyncratic shocks. Note, however, that we focus on the persistence of shocks to the idiosyncratic components, because the common factor was found to be non-stationary and its half-life is, by definition, infinite, as we corroborate empirically. Hence, beforehand, we can assure that the results do not support the existence of time series predictability[34]. Since the idiosyncratic series reflect deviations of the observed stock price indexes from the common trend, the measurement of the half-life of a shock to the idiosyncratic series is of parti-

(31) The median-unbiased procedure, originally proposed by Andrews (1993) for AR(1) processes and later extended by Andrews and Chen (1994) for autoregressive processes of order greater than one, can correct for the downward bias associated with the OLS estimates of the persistence parameter. This (median) bias is caused by the skewness to the left in the distribution of the estimators of the persistence parameter in autoregressions. In addition, median-unbiased estimates of half-lives and confidence intervals are crucial in addressing the low power of univariate unit root tests since they can inform about whether failure to reject the unit root null hypothesis is caused by low power or is due to the existence of a high degree of uncertainty about the true value of the persistence parameter.

(32) The median-unbiased property characterizing the point estimates of the persistence parameter carries over to any scalar measure of persistence calculated from them, as is the case for the half-life point estimates.

(33) The order of the autoregressive process is the one found when estimating the ADF specifications for testing for a unit root in the common factor and in the idiosyncratic components.

(34) Though not reported, the half-life associated with the common factor is found to be infinite and the 90% confidence interval equals [21.17, ∞]. When we first-difference it, the evidence indicates the occurrence of automatic adjustment in response to any shock hitting the first-differenced common factor.

cular economic relevance since, in the event of half-lives measured in decades, investors with finite horizons might well neglect the existence of a common stochastic trend and pursue possible short-run gains from international diversification. On the contrary, if an investor has a long holding period, the presence of a common factor will prevent her from seeking potential gains from diversifying across the set of countries sharing a common stochastic trend.

In order to have a precise measure of how persistent transitory fluctuations can be, Table 3 presents the point estimates of the half-life of shocks to the idiosyncratic component and their respective 90% confidence intervals for each of the 18 national stock markets investigated. Since our results are essentially the same regardless of the inclusion or not of a linear trend, the exposition focuses on those obtained from a specification with a trend[35].

As expected, given the fact that all idiosyncratic series were previously found to be jointly stationary, the analysis shows that all country-specific components of stock prices display finite half-lives. Notwithstanding, we observe that there is considerable variation in the degree of persistence in the country-specific component of stock price indexes across national stock markets, though in most cases the half-life point estimate is well below 10 years. There are only five countries with half-lives greater than 10 years: Belgium, Denmark and the Netherlands with half-lives within the range between 10 and 20 years, and Singapore and the U.S. exhibiting the highest persistence with half-lives of 27 and 35 years, respectively. This implies that, for the country with the highest persistence (i.e. the U.S.), it takes 425 months for a unit impulse on the country-specific component to dissipate by half, which is a rather long horizon from the perspective of a financial investor. For Singapore and the U.S., there would be scope for gains from international risk diversification for a relatively long period, as deviations from the common stochastic trend are long-lasting and require many years to vanish. In addition, there are seven countries (Austria, Hong Kong, Japan, Norway, Spain, Sweden and Switzerland) with half-lives between 6 and 10 years. Finally, we find six countries (Australia, Canada, France, Germany, Italy and the U.K.) with half-lives equal to or below three years.

To have a measure of the persistence of shocks for the whole panel of idiosyncratic components, we compute the median half-life for the 18 countries. The median half-life equals 6.8 years, which implies a speed of convergence of about 9.7% per year. In addition, the median lower bound of the 90% confidence interval for half-lives is 3.2 years, which implies that shocks to the idiosyncratic components of stock prices decay at an approximate rate of 19.7% per year[36]. In addition, with the exception of Australia, Canada, France, Germany, Italy and the United Kingdom, the upper bound of the confidence interval is infinite. For the 12 countries with an infinite upper bound, the width of the confidence intervals asso-

(35) In our analysis we consider that, if after 40 years (480 months) shocks have not vanished by half, the half-life is assumed to be infinite. Graphs depicting the impulse response for each country to a unit shock in both the common and idiosyncratic components along with 90% confidence intervals are available from the authors upon request.

(36) The average half-life point estimate is 9.9 years with a speed of convergence of 6.8% per year, and the average lower bound is 3.5 years.

ciated with the half-life point estimates indicates that there is some degree of uncertainty in half-life estimation, as they are consistent with a wide range of degrees of persistence.

Table 3: HALF-LIVES OF SHOCKS TO THE IDIOSYNCRATIC COMPONENT OF STOCK PRICES

	No Trend Specification		Trend Specification	
Country	HL_{IRF}	$90\% - CI_{HL}$	HL_{IRF}	$90\% - CI_{HL}$
Australia	1.83	[1.25, 3.75]	1.83	[1.25, 3.75]
Austria	5.25	[2.75, ∞]	6.92	[3.00, ∞]
Belgium	12.25	[5.08, ∞]	13.17	[5.25, ∞]
Canada	3.17	[1.75, 19.50]	3.17	[1.75, 18.33]
Denmark	9.83	[4.50, ∞]	19.92	[5.50, ∞]
France	1.17	[0.75, 2.08]	1.17	[0.83, 2.08]
Germany	1.92	[1.33, 3.33]	1.92	[1.17, 5.33]
Hong Kong	6.92	[2.75, ∞]	6.58	[2.67, ∞]
Italy	2.17	[1.58, 3.83]	2.17	[1.58, 3.83]
Japan	6.67	[3.58, ∞]	6.67	[3.58, ∞]
Netherlands	19.00	[6.42, ∞]	19.00	[6.42, ∞]
Norway	6.25	[3.08, ∞]	6.25	[3.08, ∞]
Singapore	27.08	[6.25, ∞]	27.08	[6.25, ∞]
Spain	7.17	[3.58, ∞]	7.75	[3.58, ∞]
Sweden	6.17	[3.08, ∞]	7.58	[3.25, ∞]
Switzerland	9.17	[3.83, ∞]	9.17	[3.83, ∞]
United Kingdom	2.08	[1.33, 5.17]	2.17	[1.33, 5.92]
United States	26.42	[7.83, ∞]	35.42	[8.17, ∞]

Note: The degree of augmentation of the ADF regression is selected with a general to specific criterion setting a maximum lag-order of $p = 4(T/100)^{1/4}$. The value is the one provided in Table 2. We use 2,000 iterations in our numerical simulations in order to generate quantile functions of $\hat{\alpha}$. The entries in columns 2 and 4 are the median-unbiased half-life point estimates and those in columns 3 and 5 the 90% confidence intervals of the half-life of a shock. Half-lives are measured in years and are computed directly from the impulse-response functions.

Source: Own elaboration.

Overall, the half-life analysis appears to corroborate the findings obtained with the PANIC procedures. On the one hand, there is consistent evidence of transitory or mean-reverting country-specific components, thus suggesting the existence of cross-sectional predictability of stock price indexes. On the other, the overwhelming evidence of a common stochastic factor indicates that there is no evidence of time-series predictability of stock prices, since the global shock exhibits an infinite half-life, which turns finite only after first-differencing the common factor.

It is important to point out that it is beyond the scope of the present paper to establish the factor causing the cross-sectional predictability of stock prices in different countries. As noted by Richards (1995), such predictability can result from fads, investors' overreaction and speculative bubbles, or other types of irrationality. It may also be caused by time-varying risk factors (as changes in stock prices bring changes in leverage and risk) within an equilibrium framework as well as by market segmentation due to regulatory constraints. In Kim *et al*. (2001), mean reversion could mask the behavior implicit in the historical timing of stock market volatility (risk) and expected returns on a market portfolio. Finally, Malliaropulos and Priestley (1999) associate cross-sectional predictability in Southeast Asian stocks with the existence of time-varying risk exposure and risk price as well as from partial integration of the local market into world stock markets.

5. Conclusions

This paper has investigated the stochastic properties of stock price indexes for a sample of 18 countries with well-developed stock markets over the period 1969-2007, prior to the current global financial crisis. We have employed the PANIC procedures of BNG1 and BNG2, which explicitly allow for strong forms of cross-sectional dependence. Unlike previous studies in this field, we have conducted a formal investigation of the prevalence of strong forms of error cross-sectional correlation. All in all, we have found overwhelming evidence that the stock prices of our sample of 18 countries are best described as non-stationary processes. The PANIC analysis has provided strong evidence that the idiosyncratic series are I(0) and a common stochastic factor appears to be the driving force behind the non-stationarity in the observed series.

As a complement to that analysis, we have computed median-unbiased estimates of the half-lives of shocks to both the idiosyncratic and common components and their associated 90% confidence intervals, all obtained directly from impulse-response functions. Overall, the half-life analysis appears to corroborate the findings obtained with the PANIC procedures. First, we consistently find evidence of mean-reverting country-specific components, as given by finite half-lives associated with the idiosyncratic series. This, in turn, suggests the existence of cross-sectional predictability of stock prices. Second, in line with the non-stationarity in the common factor found in the PANIC analysis, there is no evidence of time-series predictability of stock price indexes, since the global shock exhibits an infinite half-life, which becomes finite only after first-differencing the common factor.

Our results carry far-reaching implications for the empirical modelling of international stock market linkages and long-run stock price behavior with cointegration methods. First, if national stock prices exhibit a unit root and are cointegrated, then there is evidence of international linkages across stock prices, thus supporting the existence of a high degree of financial integration. Since our analysis has supported the existence of pairwise cointegration among international stock prices due to a common stochastic factor combined with I(0) idiosyncratic series, this can be interpreted as a significant degree of international stock price linkages. This indicates that investors with long holding periods may have little

chance of obtaining benefits from risk-reduction by diversifying portfolios across borders. Second, testing, with cointegration techniques, the empirical validity of models explaining long-run stock price behavior as a function of fundamentals hinges on the presence of a unit root in stock prices and their cointegration with dividends and earnings. Since we found evidence of a common stochastic trend in stock prices, it would be interesting to explore whether dividends or other fundamentals also exhibit similar stochastic properties over long horizons.

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RESUMEN

Este artículo investiga las propiedades estocásticas de los índices bursátiles para un panel de 18 países durante el periodo que va de diciembre de 1969 a mayo de 2007. A diferencia de los estudios previos en este campo, empleamos las técnicas PANIC propuestas por Bai y Ng (2004a, b), que explícitamente permiten la existencia de dependencia transversal en sentido fuerte además de determinar la fuente de la no estacionariedad de las series observadas de índices bursátiles, es decir, si procede de la no estacionariedad del factor común y/o de los componentes idiosincráticos. En general, encontramos evidencia clara de no estacionariedad en los índices bursátiles debido a la existencia de una tendencia estocástica común. El cómputo de la vida media de las perturbaciones asociadas a los componentes idiosincráticos mediante funciones impulso-respuesta corrobora los resultados obtenidos con las técnicas PANIC. En primer lugar, la existencia de componentes idiosincráticos que revierten a su senda de largo plazo sugiere la presencia de predictibilidad transversal en las series de índices bursátiles. En segundo lugar, no existe evidencia clara de predictibilidad de los índices bursátiles en la dimensión temporal, dado que el factor común es no estacionario en niveles y exhibe una vida media infinita.

Palabras clave: precios bursátiles, PANIC, factores comunes, vida media, predictibilidad de los mercados financieros.

Clasificación JEL: C23, G15.