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# Dynamic Adjustment of Stock Prices to the Fundamental Value

## An Error Correction Approach

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## Abstract

This thesis analyses the long term dynamic adjustment of stock prices to the fundamental value process. Whereas most research on relative mean reversion is based on crude measures of the fundamental value, such as dividends and earnings, we model various proxies of the fundamental value process which explicitly take into account *expected* future cash flows instead of realised cash flows. First, we consider the ability of the simple mean reversion model, the two step Error Correction Model (ECM) and the single equation ECM to account for the dynamics of the mean reversion process. It is found that the single equation ECM, which takes into account both the short- and long term effect of changes in the fundamental value on the stock price, as well as changes in the co-integrating relation between these two variables over time, is the preferred model specification. When the single equation ECM is estimated at country level, we find significant evidence of mean reversion, unlike previous studies on relative mean reversion. Secondly, we estimate the single equation ECM within 2 panel datasets: one long dataset from 1922 to 2009 including 3 countries and one broad dataset from 1973 to 2009 including 13 countries. In the first dataset we find a significant positive speed of mean reversion with a half-life ranging between 8.5 and 18.8 years, depending on the proxy included in the model. For our second dataset, we do not find significant estimates of the speed of mean reversion, which underlines the importance of obtaining sufficiently long time series to find evidence in favour of mean reversion. Using rolling window estimation, we find large fluctuations in the speed of mean reversion over time, and in a substantial number of periods no mean reversion is found at all.

*Keywords: Mean reversion, Fundamental value, Error Correction Model.*

## Index

## Introduction

The late 90s saw an unprecedented rise in stock prices, followed by a rapid decline during the recent financial crisis. In 2000, the Price-to-Dividend (PD) ratio for the S&P 500 index reached a level of 85, against a historical average of approximately 25. This extreme behaviour of valuation ratios has led to a revival of the debate between efficient market theorists and proponents of behavioural finance theory on the long-run behaviour of stock markets. One of the most controversial issues within this debate is the question whether stock prices revert to their mean in the long run. A considerable body of research indicates that stock prices exhibit mean reverting behaviour over long horizons, whereby a slowly decaying component causes prices to return to their mean in the long run. This observation may be explained either by the persistence of investment risk across time horizons, or by long temporary swings of stock prices away from their fundament value.

According to the efficient market theory stock prices can not deviate from their fundamental value since any deviation will immediately be traded away by rational investors. Instead, the rapid increase in stock prices can be explained by changes in fundamental economic factors. It is argued that the increasing integration of financial markets has removed barriers to diversification, which has led to a decrease in the risk premium, and hereby the required rate of return on stocks. Consequently, the lower discount rate applied by investors to future payoffs on stocks has led to an increase in stock prices. Behavioural finance theorists oppose this rational view, and claim that changes in fundamental economic factors are not large enough to account for the large increase in stock prices of the late 90's. Campbell and Shiller (2001) argue that in an economy where rational and irrational investors interact, irrationality can have a substantial and long-lasting impact on prices. Even when an asset is wildly mispriced due to the irrational trading behaviour of some investors, strategies designed to correct the mispricing can be both risky and costly, rendering them unattractive.[1] As a consequence, stock prices can persistently deviate from their fundamental value. However, since the fundamental value of stocks as well as the discount rate is unobserved, it has proven to be highly complicated to confirm these theoretical views empirically.

Whether stock prices have a mean reverting component is of high interest to investors, since existence of mean reversion would suggest that long-horizon investment is probably less risky than short-horizon investment.[2] This implies that the longer the horizons, the more investors benefit from investing in equity, a strategy which Jorion (2003) has termed time-diversification.[3] In addition, Gropp (2004) finds that parametric contrarian investment strategies (selling past winners and buying past losers), which exploit mean reversion, outperform buy-and-hold and standard contrarian strategies. These investment strategies may be especially interesting for pension funds due to the long-term nature of promised pension benefits. Ponds (2003) argues that pension funds have a strong belief that they are able to improve the long-run trade-off between return and mismatch risk due to mean reverting properties of risky assets (stocks and long bonds). Vlaar (2005) indicates that mean-reversion strongly increases the attractiveness of equity investments for pension funds. Even moderate mean reversion may sufficiently reduce long-run stock market volatility to increase the optimal share of stock market investment. In addition, mean reversion may stimulate pension funds to invest in equity after a downfall of the stock market, since low returns are expected to be followed by higher future returns.

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[1] Summers (1986)
[2] Chen (2005)
[3] Jorion (2003): 1

The empirical evidence on mean reversion is mixed though, and has been highly debated. Initially research focused on absolute mean reversion, whereby the mean value remained unspecified. Hereby mean reversion is equated to negative autocorrelation in stock returns, caused by a stationary component in stock prices (Fama and French (1988a), Poterba and Summers (1988), Gropp (2004) a.o.). But consistent evidence of absolute mean reversion is lacking due to small sample sizes and statistical tests that lack power. In the meantime a new branch of research has been developed, which focuses on relative mean reversion. Hereby the fundamental value process around which stock prices are expected to mean revert is specified, which may substantially improve the estimation accuracy of mean reversion. The assessment of relative mean reversion introduces the problem of specifying an accurate proxy for the fundamental value though.

This thesis addresses several issues in existing research on relative mean reversion. First of all, the specification of the fundamental value process is improved by comparing various proxies based on variables related to company fundamentals. Instead of using realised dividends and earnings as a proxy, we model the *expected* value of future cash flows, whereby the discount rate is explicitly taken into account. Secondly, the simple model of mean reversion, which is commonly used to estimate the speed of mean reversion, is extended to a single equation Error Correction model (ECM), which accounts for both short and long term effects, as well as changes in the assumed co-integrating relation between stock prices and the fundamental value process over time. Whereas most research on relative mean reversion is based on a limited number of observations from the US market, our dataset is extended to multiple countries, including a long dataset of the US, Sweden and Denmark from 1922 to 2009, as well as a broad dataset of 13 developed countries from 1973 to 2009. The use of panel data increases the number of observation which increases the power of our tests and enables us to examine the variation of mean reversion over time, using a rolling window estimation.

The thesis is organised as follows: chapter 1 reviews the large amount of literature on mean reversion, whereby a distinction is made between absolute and relative mean reversion; chapter 2 provides an overview of the economic theory and the empirical evidence on the specification of the fundamental value of stocks; followed by an outline of the empirical evidence on the relation between stock prices and measures of the fundamental value in chapter 3; chapter 4 specifies the single equation Error Correction Model; chapter 5 provides a description of the dataset; the research findings, as well as the fluctuations of the mean reversion process over time are discussed in chapter 6; after which we conclude on the consequences of the research findings for investment strategies, and the application of a mean reversion parameter by pension funds in particular.

# 1 Long term mean reversion

The existence of mean reversion of stock prices is subject to much controversy. Despite numerous studies on this topic, no conclusive empirical evidence on mean reversion has been found up to date. Fama and French (1988a) and Poterba and Summers (1988) were the first to provide empirical evidence of the reversion of stock prices to a trend path over long horizons. Their research is based on the hypothesis that stock prices contain a slowly decaying stationary component. Whereas this stationary component may not be observable over short horizons, the behaviour of stock returns over long horizons can provide evidence of the importance of this mean-reverting price component. The basic model of mean reversion provided by Summers (1986) and Fama and French (1988a) defines a mean reverting price process $p_t$ to be composed out of a permanent component $q_t$ and a temporary component $u_t$:

$$p_t = q_t + u_t \tag{1.1}$$

Hereby the temporary component $u_t$ can be modelled as a stationary AR (1) process:

$$u_t = \alpha u_{t-1} + v_t \tag{1.2}$$

The error term $v_t$ is assumed to be white noise. Any shock to the permanent component at time t is incorporated completely in the future stock price. A price shock to the temporary component is expected to slowly decay towards zero, whereby $\alpha$ is expected to be close to one, resulting in long-run mean reversion of stock prices. This model is just one way of representing a combination of a random walk and a stationary price component.[4] The more general hypothesis underlying the model is that stock prices are nonstationary processes in which the permanent gain from each price shock is less than one.[5]

As mentioned, there are two competing economic theories which attempt to explain the empirical evidence on mean reversion:

- The slowly decaying price component may be explained from the point of view of an efficient market. The efficient market hypothesis (EMH) holds that all available information is reflected in the value of a stock. Any deviations from the stock value will immediately be traded away by rational investors, hereby ensuring that stock prices are always in line with the fundamental value of the stock. Proponents of the efficient market view have attempted to explain mean reversion from the point of view of time varying risk, whereby changes in the degree of risk aversion of investors leads to variation in the returns expected by investors over time. This time varying equilibrium expected return may be mean reverting.[6]
- Behavioural finance has countered this time varying risk-explanation; according to behavioural finance theory long term mean reversion is a consequence of the

[4] Poterba and Summers (1987) find positive autocorrelation of stock returns over short intervals which implies that the AR (1) specification of the temporary component is inappropriate. Instead, they develop an approach which does not require them to specify a process for the temporary component.
[5] Fama and French (1988a): 249
[6] Another explanation in line with the EMH holds that consumption smoothing motives may generate mean reversion (Cechetti, Lam and Mark 1990, Basu and Vinod 1994, Caporale and Gil-Alana 2002). Drobetz and Wegmann (2002) argue that mean reversion is a natural result to be expected under rational asset pricing; given that consumption is cyclical and investors attempt to smooth consumption over time, stock returns must be negatively serially correlated.

speculative process itself.[7] In an irrational market, stock prices may take long temporary swings away from their fundamental values, resulting in temporary price components which cause the mean reverting behaviour of stock prices. Based on this view, the initial model of Summers (1986) and Fama and French (1988a) is slightly reformulated, to include both the fundamental value of the stock $(p_t^*)$ and a non-fundamental price component ($u_t$). The deviation of stock prices from the fundamental value can be captured by the following simple model:[8]

$$p_t = p_t^* + u_t \tag{1.3}$$

$$u_t = \alpha u_{t-1} + v_t \tag{1.4}$$

Obviously, the structure of this model is the same as the model summarized in equation (1.1) and (1.2), whereby the permanent price component is defined as the fundamental value of the stock.

Since we do not observe the permanent price component, its existence and properties have to be inferred from the behaviour of stock returns. Two approaches are suggested in the literature to test the stationarity of process $u_t$ :

- Absolute mean reversion does not specify the permanent price component ($q_t$). Instead, the empirical tests focus on the fact that the temporary price component ($u_t$) implies negative autocorrelation of stock returns.[9] This branch of research attempts to estimate the size of $\alpha$ by regressing stock returns on lagged returns.
- Relative mean reversion attempts to specify the fundamental value process $(p_t^*)$ , hereby deriving the estimate of $\alpha$ directly from equation (1.4).

Both approaches test the zero hypothesis that $\alpha$ equals one, which is in line with a random walk of stock prices, against the alternative hypothesis that $\alpha$ is smaller than one, which implies mean reversion of stock prices. Finding empirical evidence of mean reversion has proven to be difficult. Both price components are unobserved which complicates tests for mean reversion. In addition, Summers (1986) argues that $u_t$ requires a long time to revert to zero, which implies that large datasets, over long time horizons, are needed to provide evidence of mean reversion. These complications are at the core of the large body of research on long term mean reversion.

## 1.1 Absolute mean reversion

The research on absolute mean reversion has attempted to model the behaviour of stock prices without regard to the underlying fundamental value process. Hereby mean reversion is equated to negative autocorrelation in stock returns, caused by a stationary component in stock prices. Alternatively, when stock returns would be entirely unpredictable from past returns because of arbitrage, stock prices could be characterized as a random walk, in line with the efficient market view. Initially, no economically significant evidence of the autocorrelation of stock returns was found

[7] Cutler et al (1991)
[8] Summers (1986): 594
[9] Fama and French (1988a) show how the mean reversion of the stationary price component causes negative autocorrelation in stock returns.

since only short horizon returns (daily of weekly) were used.[10] Following the suggestion of Summers (1986) that mean reversion of stock prices only takes place in the long run, research started to focus on long-horizon returns. Fama and French (1988a) examine the negative autocorrelation of stock returns using several time horizons between one and ten years. When regressing multi-period returns on lagged values of multi-period returns, using monthly and early US data, the strongest evidence of mean reversion is found at the 3- to 5-year horizon. At these horizons, 25 to 40 percent of the variation of returns is predictable by past returns.

Poterba and Summers (1988) examine a specific property of the random walk process to find evidence of mean reversion. If the logarithm of the stock price, including cumulated dividends, follows a random walk, then the return variance should be proportional to the return horizon. Mean reversion implies that his will not be the case, since the presence of a temporary component which generates negative autocorrelation will result in a variance ratio below one. The variance-ratio test of Cochrane (1988) is used to test for mean reversion. Hereby, Poterba and Summers (1988) find significant evidence that over long horizons, return variance rises less than proportional with time, which implies mean reversion over long horizons. This tendency for mean reversion is even more pronounced in less broad-based and sophisticated equity markets than the US market.

The findings of Poterba and Summers (1988) and Fama and French (1988) have been reviewed extensively in later years, whereby researchers have focused on the statistical properties of the tests which were applied as well as the robustness of the findings on mean reversion. The main criticism concerns the corrections for small sample bias which were applied in both articles. The evidence on absolute mean reversion in stock prices is based on long horizon returns. Unfortunately, the sample of independent observations reduces as the return horizon increases. Both papers use monthly overlapping data to increase the sample size and the power of the test statistics. The use of overlapping data results in severely autocorrelated errors though, causing biased and inconsistent estimates of the standard error.[11] Hansen and Hodrick (1980) develop a consistent estimator which corrects the residual serial correlation. This estimator is based on asymptotic distribution theory though, which is unlikely to hold given the small sample size. Several attempts have been made to solve this small sample problem, including better asymptotic approximations in Lo and MacKinlay (1988) and Richardson and Stock (1989). Nevertheless, Chen (2005) argues that the majority of studies on mean reversion draw statistical inference using asymptotic results, assuming that the power of these tests is maintained in finite samples. 'Finite sample tests that are potentially more reliable are largely unavailable in the literature.'[12]

Another problem is posed by the heteroskedasticity of stock returns which results from periods of high volatility in stock prices. McQueen (1992) attempts to correct for heteroskedasticity in stock returns by using weighted least squares (WLS), which gives a lower weight to observations with a higher variability. He finds that periods of high volatility have a stronger mean reverting tendency, which causes the general evidence of mean reversion to be overstated. This finding is supported by results of Kim, Nelson and Startz (1991), who find that there is mean reversion in 3- and 4 year US stock returns only during the highly volatile 1926–1946 period. Thus, the period which is included in the sample may heavily influence the mean reversion results, a conclusion which was already drawn by Fama and French (1988a), who stated that: 'Although a tendency toward negative autocorrelation is always

[10] Fama (1970) provides an overview of the literature on autocorrelation in stock returns over short horizons.
[11] McQueen (2009)
[12] Chen (2005): 2

observed, sub period results suggest that the strong negative autocorrelation of the 1926-85 period may be largely due to the first 15 years.' 'Stationary price components may be less important after 1940, or perhaps prices no longer have such temporary components. Resolution of this issue will require more powerful statistical techniques.'[13]

Most of the evidence on mean reversion has been based on about 80 years of US data. Jorion (2003) indicates that, besides the low statistical power of tests due to the lack of independent observations over long horizons, there may also be a serious survivorship bias with respect to US data. 'It is no coincidence that the longest time series available for equities is also that of the most successful capitalist system in the world.' [14] Even though Poterba and Summers (1988) find mean reversion in other markets than the US market, Jorion (2003) finds no evidence of mean reversion based on variance ratio tests on a sample of 31 countries including the US, covering the period from 1921 to 1996. He concludes that mean reversion may be 'an artifact of survival', and evidence of mean reversion must be evaluated considering the survival of the market.

## 1.2 Relative mean reversion

Due to the statistical difficulties involved in testing for negative autocorrelation in stock returns, as well as the lack of a sufficiently large datasets, the empirical evidence on absolute mean reversion remains inconclusive. Spierdijk, Bikker and van den Hoek (2010) indicate that the variation of the error term $u_t$ may be substantially reduced by replacing the permanent component $q_t$ in equation (1.1) by a proxy for the fundamental value $p_t^*$. Hereby the mean reversion of stock prices can be assessed relative to a specified mean. A general formulation of such a process is: [15]

$$p_{t+1} - p_t = \alpha + \lambda\,(p_{t+1}^* - p_t) + \varepsilon_{t+1} \qquad (1.5)$$

where $p_t$ represents the natural logarithm of the stock price, so that $p_{t+1} - p_t$ equals the continuously compounded return which an investor realizes in period t+1; $p_t^*$ indicates the natural logarithm of the fundamental value of the stock at time t, which is unobserved; $a$ is a positive constant and $\varepsilon_{t+1}$ is a zero mean stationary shock term. The parameter $\lambda$ measures the speed of reversion, whereby a significant finding of $\lambda > 0$ is needed to confirm mean reversion empirically.

Finding empirical evidence of relative mean reversion is complicated by the correct specification of the fundamental value $p_t^*$. Fama (1970) points to the 'joint-hypothesis problem': '(…) in order to claim that the price of a security differs from its properly discounted future cash flows, one needs a model of 'proper' discounting. Any test of mispricing is therefore inevitable a joint test of mispricing and a model of discount rates, making it difficult to provide definitive evidence of inefficiency.'[16] A similar logic applies to a test for relative mean reversion; since we can not observe the fundamental value of stocks, any test of relative mean reversion will inevitably

[13] Fama and French (1988a): 266
[14] Jorion (2003): 3
[15] As indicated by Spierdijk et al (2010) equation (1.5) is directly derived from the two component model of equation (1.3); see Annex II.
[16] Constantinides et al (2003): 1061

consist of a joint test of mean reversion of stock prices to the fundamental value, as well as the proxy used to specify the fundamental value.

Thus, the evidence on relative mean reversion depends highly on the correct specification of the mean. Empirical tests of relative mean reversion may give rise to invalid outcomes when the fundamental value is not correctly specified. Nevertheless, when a good proxy can be found, based on reliable economic arguments, the power of the test for mean reversion can be increased, and more accurate results may be obtained than is the case with tests of absolute mean reversion. In order to define an accurate proxy for the fundamental value process, the following chapter provides a discussion of the available theory and empirical evidence on the fundamental value of stocks.

## 2 The fundamental value of stocks

Specification of the fundamental value of stocks has received broad attention in finance literature.[17] Initially, the fundamental value of a stock was defined in line with the efficient market view, based on equilibrium asset pricing models. A lack of empirical evidence in favour of asset pricing models led to a relaxation of the strict assumptions underlying these models in recent years. In order to correctly specify the fundamental value process, this chapter provides a discussion of the economic theory and empirical evidence on asset pricing, followed by an overview of empirical evidence on the relation between stock prices and various measures of the fundamental value in chapter 3. Based on these findings, we develop a number of proxies of the fundamental value, which will be assessed within a dynamic mean reversion model in chapter 4.

### 2.1 Basic economic theory

A stock is a type of security that signifies ownership in a corporation (equity) and represents a claim on part of the corporation's assets and earnings. The size of the ownership is determined by the number of shares owned by the stockholder relative to the number of shares outstanding. The owner of a stock is entitled to the payment of dividends by the corporation. Dividends are the portion of corporate profits paid out to the stockholders, whereby the remaining profits are retained and reinvested in the corporation. The amount of dividends paid to the stockholders depends both on the size of earnings as well as the dividend payout-policy of the corporation.

Investors hold stock in order to obtain these dividend payments, as well as possible capital gains from an increase in the stock price. Thus, the value of a stock to investors is determined by the expected future cash flows, as well as the way in which investors value these future cash flows. The valuation of future cash flows compared to current cash flows is captured by the discount rate, which represents the opportunity cost of holding the stock from now until the time when income is received. Since individuals prefer to receive income sooner rather than later, investors will demand more than a dollar in the future to give up a dollar of current income. In addition, investors will demand a higher expected return from a risky asset than from a safe asset. Thus, when investors are more impatient or more risk averse, the discount rate which they apply to future cash flows will be higher.[18]

### 2.2 Equilibrium asset pricing models

In line with neoclassical financial theories, the fundamental value of a stock can be defined as the present value with constant discount rate of optimally forecasted future real dividend payments.[19] This definition is based on the Efficient Market Hypothesis (EMH)[20], which holds that financial markets are informationally efficient.[21]

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[17] For an extensive overview of asset pricing models, see for example Constantinides et al. ( 2003) or Cochrane (2000)
[18] Balke and Wohar (2001): 24
[19] Shiller (2001): 8
[20] The Efficient Market Hypothesis was first formulated by Eugene Fama; subsequent research on this hypothesis has been conducted by Samuelson, Paul Cootner, Harry Markowitz, James Tobin, Franco Modigliani, Merton Miller, Fisher Black, Myron Scholes, Eugene Fama, William Sharpe and Robert Merton a.o.
[21] This strong version of the EMH can only hold if all available information is costless to obtain, which is not in line with empirical findings. A weaker but more realistic version of the EMH holds 'that prices reflect information up to the point where the marginal benefits of acting on the information (the expected profits to be made) do not exceed the marginal costs of collecting it'. Beechey et al (2000): 2

According to this view security prices fully reflect all available information under the precondition of zero trading and information costs.[22] As a consequence, prices should always be consistent with 'fundamentals'; since all investors rationally calculate the same expected future value of the stock based on the available information, a deviation from the fundamental value will immediately be traded away through arbitrage. Therefore, only the expected future dividends and the discount factor play a role in determining the stock price. This definition of the fundamental value is captured by the Present Value model:[23]

$$P_t = E_t\left[\frac{1}{1+r_{t+1}}\right](P_{t+1} + D_{t+1}), \tag{2.1}$$

where $P_t$ is the price of the stock at the end of period t, $D_{t+1}$ is dividend paid during period (t+1) and $r_{t+1}$ is the required rate of return at time (t+1). $E_t(.)$ indicates the expectation based on the information available at time t. When the law of iterated expectations is applied we obtain the following equation:

$$P_t = E_t\left[\sum_{j=1}^{T}\left(\prod_{i=1}^{j}\frac{1}{1+r_{t+i}}\right)D_{t+i}\right] + E_t\left[\prod_{i=1}^{T}\frac{1}{1+r_{t+i}}P_{t+T}\right], \tag{2.2}$$

This equation indicates that the present value of the stock, when we hold the stock for T periods, is equal to the expected discounted value of the dividends and the expected discounted value of the price for which the stock is sold to another investor. When we assume that the asset price increases at a lower rate than the discount factor, the terminal price eventually becomes of negligible importance as viewed from today; this assumption of an infinite planning horizon is termed the transversality condition.[24]

$$\lim_{T\to\infty} E_t\left[\prod_{i=1}^{T}\frac{1}{1+r_{t+i}}P_{t+T}\right] = 0, \tag{2.3}$$

When this condition holds and $T \to \infty$, the stock price becomes equal to the expected discounted value of the future dividend payments, whereby $P_t^*$ is termed the fundamental value of the stock:

$$P_t^* = E_t\left[\sum_{j=1}^{T}\left(\prod_{i=1}^{j}\frac{1}{1+r_{t+i}}\right)D_{t+i}\right], \tag{2.4}$$

Thus, the fundamental value will only change when dividend payments change or when new information arises which changes the forecasts about future dividends.[25] When the dividend growth rate is defined as $D_{t+1} = (1+g_{t+1})D_t$, the fundamental value is given by:

$$P_t^* = E_t\left[\sum_{j=1}^{T}\left(\prod_{i=1}^{j}\frac{1+g_{t+i}}{1+r_{t+i}}\right)D_t\right] \tag{2.5}$$

[22] Fama (1991): 1575
[23] Manzan (2003): 2
[24] Stiglitz (1990): 14
[25] Shiller (2001): 72

This model was further simplified by Gordon (1959), whereby it is assumed that the discount rate remains constant over time, and dividends grow at a constant rate in perpetuity. Under this assumption, the stock value is given by:

$$P^* = D\frac{1+g}{r-g} \quad \text{and} \quad \frac{P^*}{D} = \frac{1+g}{r-g} \tag{2.6}$$

This basic Gordon model predicts that the price-dividend (P/D) ratio should remain constant over time. When dividends are assumed to be a linear function of earnings, and a constant payout ratio (q) is applied, also the P/E ratio is expected to remain constant over time:[26]

$$D = qE \quad \text{and} \quad \frac{P^*}{E} = q\left(\frac{1+g}{r-g}\right) \tag{2.7}$$

The validity of these equilibrium asset pricing models as a correct approximation of the fundamental value of stocks has become the subject of considerable debate though. Obviously, the rapid increase in the P/D and P/E ratios during the 1990s is not in line with the predictions of the simple Gordon model. But even the less restrictive present value model of equation (2.4) is not fully supported by empirical evidence.

## 2.3 Empirical evidence on equilibrium asset pricing models

Initial tests of the present value model as outlined in equation (2.4) were based on variance bound tests, which assess whether changes in price reflect news about future dividends (LeRoy and Porter 1981, Shiller 1981). These tests found that stock prices are too volatile to result solely from the changes in the expected discounted value of dividends. This conclusion has been questioned by several authors though. Flavin (1983) argues that in small samples the tests are biased toward finding excess volatility. Marsh and Merton (1986) note that researchers will find stock price to be too volatile given the practice of dividends smoothing by management, whereby the smoothing lowers the variance of detrended real dividends. Ackert and Smith (1993) find no excess volatility when measuring cash flows broader by including not only ordinary cash dividends but also share repurchases and takeover distributions. Kleidon (1986) argues that the use of ex-post dividends series to test the present value model is incorrect, since demand for a stock depends on expected future dividends, and realised dividends is only one of many possible realizations. In addition, Kleidon (1986) notes that the results of variance bound tests have been overstated since price and dividend series are non-stationary and these tests are quite sensitive to transformations that attempt to achieve stationarity.

In response to this criticism, Campbell and Shiller (1987) suggested an alternative test which accounts for the non-stationarity of dividend and price time series, by subtracting $D_t / r$ from both sides of equation (2.4):

$$P_t - D_t r^{-1} = r^{-1} E_t\left[\sum_{i=0}^{\infty}\left(\frac{1}{1+r}\right)\Delta D_{t+i}\right] \tag{2.8}$$

where $\Delta$ denotes the difference operator ($\Delta D_t = D_t - D_{t-1}$). If dividends contain a unit root, equation (2.8) implies that stock prices and dividends are co-integrated, which indicates that the relation between the stock price and dividends should be

[26] Balke and Wohar (2001): 24

stationary over time. Based on this model, tests of the present value model have involved tests of the co-integration between real prices and real dividends.

Since stock returns are likely to vary over time though, Campbell and Shiller (1987) provide a log-linear approximation of model (2.8), which does not assume constant expected stock returns:

$$d_t - p_t = E_t \sum_{i=0}^{\infty} \rho^{-i} \left[ r_{t+i} - \Delta d_{t+i} \right] \tag{2.9}$$

where $d_t \equiv \log(D_t)$, $p_t \equiv \log(P_t)$, $\rho$ is a discount factor, and $r_t$ is the log stock return, defined as $\log(P_t + D_t) - \log(P_{t-1})$. Equation (2.9) implies that stock prices and dividends are co-integrated with the co-integrating vector of the log dividend yield if both stock returns and dividend growth are stationary.[27] In addition, this equation indicates that stock returns can be predicted by the dividend yield.[28] When the discount rate and the dividends growth rate are stationary, the dividend yield will be stationary, which implies that the natural logarithm of dividends and prices are co-integrated. The statistical analysis of equation (2.9) therefore involves testing the stationarity of the log dividend-price ratio.

The results of the tests of equation (2.8) and (2.9) have been mixed. Crowder and Wohar (1998) find that a long-run relationship equilibrium exists between the natural logarithm of real stock prices and the log of real dividends, as implied by equation (2.9). Campbell and Shiller (1987), Froot and Obstfeld (1991) and Lee (1996) do not find strong evidence that dividends and prices are co-integrated, while Lamont (1998) rejects the null hypothesis that prices and dividends are not co-integrated.[29] In response to the mixed empirical evidence in favour of equilibrium asset pricing models, three alternative explanations have been developed to account for the variance of the dividend yield:[30]

### *2.3.1 Misspecification of the valuation model*

Since asset-pricing models tie discount rates to observables, a rejection of the dividend discount model may indicate that other variables than dividends should be included in the model. Francis et al (2000) find that other valuation models, such as the accounting-based residual income model, perform better in explaining the variation in stock prices than the dividend discount model. Fama (1991) argues that the present value model (PVM) should be augmented by time-varying expected inflation to more adequately account for actual stock price behaviour. Several studies find that the explanatory power of the present value model can be improved by including earnings in the model (Lee 1996, Lamont 1998). They find that stock prices, dividends and earnings are co-integrated, and hence earnings have explanatory power to stock returns in addition to dividends. However, Shiller (2001) indicates that earnings may be relevant to the pricing of shares, but only insofar as earnings are indicators of future dividends.[31]

[27] Notice that the left hand side of the equation is equal to the natural logarithm of the dividend yield:

$$d_t - p_t = \log(D_t) - \log(P_t) = \log\left(\frac{D_t}{P_t}\right)$$

[28] Pan (2007): 537

[29] Pan (2007): 537

[30] Cochrane (1992): 246

[31] Shiller (2001): 117

### *2.3.2 Unobserved discount rate processes*

Alternatively, a rejection of the dividend discount models may indicate that there is no observable discount rate process which can explain the variance of the dividend yield. Since the extreme price movements observed in reality can not be accounted for within asset pricing models with a constant or a stationary discount rate, a new branch of asset pricing models has been developed, which allow for more extreme variation in the discount rate over time. These models still rest on the neoclassical assumption that asset markets do not permit the presence of arbitrage opportunities, which ensures that price equals the fundamental value. However, the original definition of the fundamental value is stretched out to include a stochastic discount factor.[32] Shiller (2001) notes regarding equation 2.4 that 'If we modify the model to allow real discount rates to vary without restriction through time, then the model becomes untestable.(…) Regardless of the behaviour of $P_t$ and $D_t$ there will always be a discount rate series that makes the equation hold identically.'[33]
Despite this theoretical possibility of extreme movements in discount rates over time, it is questionable whether such time-varying required returns could be reconciled with the observed mean of ex-post excess returns. Poterba and Summers (1988) assess whether time-varying required returns, generated by risk factors, can account for the observed variance in dividend yield. They construct an expression which indicates the variation in required returns needed to generate a transitory components of a given size. However, it is found that the standard deviation of the discount rate which is needed to reconcile the observations with the present-value model is too high.[34] 'It is difficult to think of risk factors that could account for such large variations in required returns.'[35]

### *2.3.3 Persistent deviations from the fundamental value*

An alternative explanation of the variance of the dividend yield has been developed by behavioural finance theorists, who argue that there is no discount rate process which can rationalize the variance of the dividend yield.[36] The present value model depends crucially on the tranversality condition to ensure a unique price, namely the fundamental stock price. When the tranversality condition does not hold, there are an infinite number of solutions to the present value model.[37] In this case, the price of the stock is determined by the expected discounted value of the dividends and the expected discounted value of the price for which the stock will be sold to another investor (the capital gain). Thus, rational investors may base their investment decision not only on the fundamental value of the stock, whereby the stock price is a reflection of the information about future dividends, but also on the rational expectation that the stock can be sold to another investor at a higher price. As a result the stock price deviates from its 'fundamental value', as originally defined by Neoclassical financial theory, and the equilibrium asset pricing models will no longer provide an accurate estimation of the fundamental value of the stock. Within this line of reasoning equation (2.4) is extended by a non-fundamental component, which captures deviations of the stock price from the fundamental value.

The theoretical debate on asset pricing models complicates the correct definition of the fundamental value of stocks. As mentioned in chapter 1, mean reversion can be explained both by time-varying expected returns as well as non-fundamental components, whereas empirically, these two explanations may be indistinguishable.

[32] Campbell (2000): 1517
[33] Shiller (2001): 118
[34] Idem
[35] Poterba and Summers (1988): 29
[36] Cochrane (1992): 247
[37] McMillan (2009): 5

Consequently, attempts have been made within both theoretical views to relate measures of the fundamental value, such as dividends and earnings, to stock price movements. The following chapter provides an overview of the empirical findings on the long run behaviour of stock prices and fundamentals. Based on these findings we develop various proxies for the fundamental value, which will be assessed within a dynamic mean reversion model in chapter 4.

# 3 Empirical evidence on relative mean reversion

The lack of conclusive evidence on absolute mean reversion has led to attempts to relate the long-run behaviour of stock prices to various measures of the fundamental value, including earnings and dividends. Initially, research focused mainly on the behaviour of valuation ratios whereby the underlying fundamental value process remained largely unspecified. These valuation ratios are based on realised company fundamentals, and therefore can not capture expectations regarding future cash flows which influence the fundamental value. In order to obtain an accurate estimate of the speed of mean reversion, the fundamental process should be explicitly modelled based on company fundamentals, including a measure of the *expected* future return.

## 3.1 Forecasting returns with valuation ratios

The tests on absolute mean reversion of Fama and French (1988a) and Poterba and Summers (1988) all suffer from statistical power failure. Fama (1991) argues that tests for return predictability can be enhanced if one can identify forecasting variables that are better proxies for expected returns than past returns. 'There is a simple way to see the power problem. An autocorrelation is the slope in a regression of the current return on past return. Since variation through time in expected returns is only part of the variation in returns, tests based on autocorrelation lack power because past realized returns are noisy measures of expected returns.'[38]

Consequently, a large amount of literature has been developed which attempts to forecast stock returns using regressions of stock returns on lagged valuation ratios.[39] Initially attempts were made to relate expected inflation as well as the level of short term interest rates to monthly stock returns, whereby the implied variation in expected returns was found to be only a very small part (less than 3% for monthly returns) of the variance of returns.[40] More recent tests have demonstrated that, in line with the empirical evidence on absolute mean reversion, the predictable variation becomes a larger part of return variances when the return horizon is increased.

Fama and French (1988b) find that dividend yield (D/P) explains only small fractions of monthly and quarterly return variances. When the return horizon is increased to 2- to 4-year returns, fractions of the explained variance increase to 25%. Campbell and Shiller (1988) find that dividends per share (DPS), dividend growth and earnings per share (EPS), especially when earnings are averaged over 10 to 30 years, are significant in explaining stock price returns for long investment horizons, whereby long term EPS explains the majority of the variability of returns. The increased explanatory power of valuation ratios over longer return horizons leads several authors to conclude that valuation ratios tend to remain stable around a historical mean in the long run (Fama and French 1988b, Chiang et al 1997).

This conclusion is challenged by Torous et al (2004), who claim that '(…)the previous evidence reported at long horizons simply reflects that conventional statistics overreject the null hypothesis of no predictability when the persistent behavior of the

[38] Fama (1991): 1582

[39] Note that this research is based on the general formulation of a mean reverting process, as outlined in equation (1.5): $p_{t+1} - p_t = \alpha + \lambda\ (p^*_{t+1} - p_t) + \varepsilon_{t+1}$

whereby, for example: $(p^*_{t+1} - p_t) = (\log(D_{t+1}) - \log(P_t)) = \log(\frac{D_{t+1}}{P_t})$

resulting in a regression of dividend yield on stock returns: $r_{t+1} = a + \lambda(\frac{d_{t+1}}{p_t}) + \varepsilon_{t+1}$

[40] Fama (2002): 1583

explanatory variables is not explicitly taken into account.'[41] Thus, when the stochastic explanatory variable of a predictive regression is nonstationary the evidence of return predictability at long horizons may not be statistically significant. Since stock price, earnings and dividend data are commonly found to be non-stationary, it is likely that predictive regressions for stock returns lead to spurious regressions. In addition, Cutler et al (1991) estimate equation (1.5) for 13 countries, and find that the predictive power of the dividend yield over long return horizons is much weaker when corrections for small sample bias are made (given that the sample size decreases when the return horizon is increased). Also, a much weaker relation is found in other markets than the US market.

### 3.2 Mean reversion of valuation ratios

The inconclusive evidence on the predictive power of valuation ratios for long return horizons, whereby it is *assumed* that valuation ratios are mean reverting, has led to more explicit research on the timeseries behaviour of valuation ratios. Hereby it is examined whether valuation ratios revert to a historical mean in the long run. When stock prices are high compared to company fundamentals, such as dividends and earnings, it is expected that either stock prices or the fundamentals adjust the ratios in order to bring them back to an equilibrium level. This line of research initially focused on the reversion of valuation ratios towards one constant historical mean. However, Coakley et al (2006) indicate that standard linear time-series models of valuation ratios are not able to capture changes in investor sentiments over time. In order to test for mean reversion or persistence a standard unit root test is often used. The null hypothesis of a unit root test is that the time series is a random walk (possibly with a drift) the alternative is that the series is (trend-) stationary, and reverts to a constant mean or a linear trend line. This type of test loses power when structural breaks are not taken into account. Thus, when no empirical evidence is found of stationarity, this may well be due to the presence of structural breaks in the time series instead of the absence of mean reversion. [42] In order to accurately test for mean reversion a more flexible framework is needed to capture the changes in economic fundamentals and investor sentiments over time.

#### *3.2.1 Mean reversion of valuation ratios around a broken trend*

Attempts to develop such a flexible framework include the research on mean reversion around a broken trend. Hereby models are developed which allow for structural breaks in the time series behaviour of valuation ratios. This approach brings along the problem of defining how many structural breaks have occurred, and when these breaks have occurred.

Manzan (2003) assumes a break in the equity premium around 1950 in analyzing the behaviour of price–dividend ratios. He bases his assumption on the finding of Fama and French (2002) that '(…) until the mid 1950s the stock price is most of the time below the value predicted by the Gordon model whereas after it is mostly above it. This suggests that the average PD ratio might have shifted upward due to a structural decrease in the discount rate of an increase in the average growth rate of dividends.' Manzan (2003) attempts to capture this regime switch by allowing for a shift in the discount rate, which is used to calculate the Gordon model, in 1950.

Carlson et al (2002) argue that the plot of P/E ratios reveal that the series can not be approximated with just one or two structural changes. In addition, the series does not seem to follow abrupt changes in levels. 'Instead, through continuous changes, sometimes spontaneous or gradual, the series moves around different levels, while

[41] Torous et al (2004): 964
[42] Carlson et al (2002): 2

taking long cycles.'[43] Carlson et al (2002) use two different approaches to allow for multiple structural breaks: a unit root test with structural changes and a regime switching model. This latter model allows the data generating process to switch between two different processes without the need to specify when the breaks occurred, as they are determined endogenously from the data. Based on the outcomes of both methodologies it is concluded that, conditional on the structural breaks, the time-series process of P/R ratios is stationary, and thus mean-reverting.[44]

Coakley et al (2006) use a similar approach by developing a dynamic framework which allows for the non-linear evolution of valuation ratios during bull and bear market phases. A non-linear adjustment model of valuation ratios is developed, whereby the reversion of the valuation ratios to a time-varying mean is examined. They find that during bull market phases fundamentals carry less weight and deviations from fundamentals last longer. On the other hand, evidence is found of reversal or significant adjustment towards equilibrium values in bear markets. Coakley et al (2006) conclude that the short run evolution of stock prices reflects unobserved behavioural factors such as market sentiments, while the long run behaviour of stock prices is consistent with fundamentals.[45]

### 3.3 Reversion of stock prices to the fundamental value

Even though the research on the timeseries behaviour of valuation ratios provides valuable insights in the relation between fundamentals and stock prices, the underlying fundamental value process remains largely unspecified. Reversion of the valuation ratio to a (time-varying) historical mean may be attributed both to changes in the numerator and the denominator of the valuation ratio. Campbell and Shiller (2001) observe that prices rather than fundamentals (dividends or earnings) do most of the adjustment in bringing the price-earnings (P/E) and price-dividend (P/D) ratios back towards their long-run equilibrium levels. However, the exact timeseries behaviour of the numerator and denominator of the valuation ratio often remains largely unspecified.

In addition, earnings and dividends seem very crude approximations of the fundamental value process. Gropp (2004) argues that valuation ratios are inherently flawed, because information on company fundamentals cannot be compared to stock prices due to the delay in adjustment. Expected future dividends and earnings influence the fundamental value, which cannot be captured by the current dividend yield or price-earnings ratio. Since anticipated increases in the growth rate of earnings or dividends raise the fundamental value, but not its proxy, these measures must be flawed, which causes the estimate of $\lambda$ in equation (1.5) to be inconsistent and have a downward bias of unknown size.[46] Thus, in order to gain insight in the speed of reversion of stock prices to the fundamental value, the mean reversion process should be explicitly modelled, including an accurate proxy for the fundamental value process.

#### *3.3.1 A benchmark of stock prices*

Balvers et al (2000) avoid the problem of specifying a proxy for the fundamental value by using a benchmark of stock prices. Hereby national stock price indices are considered relative to a reference index, assuming that the difference between the intrinsic value of one country's stock price index and that of a reference index is stationary, and that the speed of mean reversion in different countries is similar.

[43] Carlson et al (2002): 8
[44] Carlson et al (2002): 19
[45] Coakley et al (2006): 2327
[46] Balvers et al (2002): 748

Based on a sample of 18 countries during the period 1969 tot 1996, strong evidence is found of mean reversion in relative stock index prices. Spierdijk et al (2010) build on this approach, and analyze mean reversion in international stock markets based on the annual data of 17 OECD countries in the period of 1900 to 2008, hereby almost doubling the length of the time series used by Balvers et al (2000). They find large fluctuations in the speed of mean reversion over time, and in a substantial number of periods no significant mean reversion is found at all, which indicates that the choice of sample period is crucial in finding evidence of mean reversion.

The approach of Balvers et al (2000) and Spierdijk et al (2010) rests crucially on the assumption of a continuous stationary relation between the fundamental value of the country stock price indices and the fundamental value of the reference index. This assumption can not be tested empirically since these fundamental values are both unobserved. The assumption is justified based on the finding of Barro and Sala-i-Martin (1995) that real per capita GDP across the 20 OECD countries displays absolute convergence. '(..) any country specific productivity advancement is eventually mimicked by other countries so that the innovating country's relative advantage disappears and GDPs per capita converge.'[47] Since the values of firms converge in these countries, so should the fundamental value of the stock market, leading Balvers et al (2000) to conclude that the differences in slowly converging fundamental stock prices across countries should be stationary.[48]

Consequently, the fundamental values of both the country indices and the reference index can be removed from the regression equation. Since the assumption of continuous co-integration between the fundamental value of the country stock price indices and the fundamental value of the reference index can not be tested in practice, it may well be that the strength of the co-integrating relation varies over time though, which could seriously influence the estimation of the speed of mean reversion. Thus, even though it seems beneficial to exclude a proxy for the fundamental value from the equation, it also eliminates the possibility to examine the assumptions underlying the research approach. In addition, valuable information on the variation in the fundamental value process may be lost when a proxy for the fundamental value is excluded from the equation, and only information on the difference between the stock index and a benchmark index is used to estimate the speed of mean reversion.[49]

## 3.4 Improvements on previous research

In order to obtain a more accurate estimate of the speed of mean reversion we will explicitly model the fundamental value process based on variables related to company fundamentals. Instead of using realised dividends and earnings as a proxy, we model the *expected* value of future cash flows, whereby the discount rate is explicitly taken into account.
The simple model of mean reversion, which is commonly used to estimate the speed of mean reversion, is extended to a single equation Error Correction model (ECM), which accounts for both short and long term effects, as well as changes in the co-

[47] Balvers and Wu (2006): 27

[48] This assumption is probably only valid in OECD countries. Balvers et al (2000) note that Barro et al (1991) find *conditional* convergence for a larger group of 98 countries whereby real per capita GDP only converged to the same steady state after adjusting for differences in human capital. Since differences in human capital across OECD countries are relatively minor the assumption of convergence of absolute convergence may hold.

[49] Balvers et al (2002) note that, if the speed of mean reversion is constant across countries, and the assumption of stationary differences in slowly converging fundamental stock prices across countries holds, any country index should be able to serve as a benchmark index. However, in finite samples different estimates of the speed of mean reversion are obtained when a different reference index is used.

integrating relation between stock prices and the fundamental value process over time. Instead of assuming the existence of such a relation, we will explicitly test for the presence of a unit root in both stock prices and our proxies of the fundamental value process, as well as co-integration between these variables.
Whereas most research on relative mean reversion is based on a limited number of observations from the US market, our dataset is extended to multiple countries, including a long dataset of the US, Sweden and Denmark from 1922 to 2009, as well as a broad dataset of 13 developed countries from 1973 to 2009. Based on this extension of the amount of observations we can examine the variation of mean reversion over time, using rolling window estimation.

The dynamic mean reversion model, as well as the various proxies which we use to approximate the fundamental value process, are outlined in the next chapter. The data is described in detail in chapter 5, after which we apply the model to the datasets, and report the empirical findings in chapter 6.

## 4 A dynamic model of relative mean reversion

Since the influential paper of Campbell and Shiller (1987) it has been well established in the literature that US stock prices and dividends are linked by a long-run relationship. Later research has found that also accounting earnings have a co-integrating relation with dividends and stock prices (Lee, 1996). These findings indicate that, whereas stock prices may deviate from company fundamentals in the short run, in the long run stock prices are expected to return to these crude measures of the fundamental value, either due to investor behaviour or market forces.

The adjustment towards the long-run equilibrium is often assumed to be linear. There are however good reasons to expect the dynamic adjustment process of the stock price to the fundamental value to be asymmetric and non-linear. Kim et al (1991) find that mean reversion has been a phenomenon of the 1926-1946 period, which includes the Great Depression and World War II, when the stock market was highly volatile. On the contrary, the post-war period has been characterised by mean *aversion*.[50] 'We interpret these findings as evidence that the behaviour of stock returns changed at the end of World War II, perhaps because of the resolution of major uncertainties about the survival of the U.S. economy.'[51] McQueen (1992) finds that the Depression and World War II observations both have large error variances and stronger mean-reverting tendencies; a pattern of mean-reverting stock prices is found only in individual 3- and 4-year returns and only during the highly volatile 1926 to 1946 period. Spierdijk et al (2010) suggest that '(…) expected returns diverge away from their long-term value and converge back to this level relatively quickly during periods of high economic uncertainty (…). When the economic uncertainty dissolves, expected returns are likely to show a substantial increase in value during a relatively short time period, which could account for such high mean reversion speed.' [52]

The non-linear adjustment process has often been interpreted as a lack of co-integration, possibly due to collapsing bubbles in prices which may temporarily interrupt the adjustment process (Froot and Obstfeld, 1991). Psaradakis et al (2004) indicate that 'when prices and dividends are co-integrated (…), periods during which prices appear to deviate persistently from the long-run value implied by the underlying fundamentals can be thought of as representing either periods during which co-integration fails (and there is no short-run adjustment to departures from the long-run equilibrium relationship) or periods where adjustment takes place at different rates.'

Since most research on relative mean reversion has been based on the simple model as outlined in equation (1.5), the possible changes in the co-integrating relationship over time have often not been incorporated in the model. In addition, the simple model of mean reversion does not take into account the short run dynamics of the adjustment process. The restrictive assumptions underlying the simple mean reversion model is likely to bias the estimate of the speed of mean reversion.[53] In order to capture both short- and long term dynamics of the adjustment process, as well as changes in the co-integrating relation over time, we use a Single Equation Error Correction Model (ECM) to estimate the speed of mean reversion.

[50] Kim et al (1991): 526
[51] Kim et al (1991): 527
[52] Spierdijk et al (2010): 15
[53] De Boef et al (2006) provide a detailed overview of the consequences of restricting the general Error Correction Model, when the restrictions implied by these specifications are not explicitly tested.

## 4.1 The Single Equation Error Correction model

We consider the stock market indices of N countries, observed over T years. We assume a mean reverting process for each country i: [54]

$$\Delta p_t^i = \alpha_0^i + \beta_0^i \Delta p_t^{*i} + \beta_1^i (p_{t-1}^i - \beta_2^i p_{t-1}^{*i}) + \psi_t^i \qquad (4.1)$$

Where $p_t^i$ is the natural logarithm of the stock index of country i at time t, $p_t^{*i}$ is the natural logarithm of the intrinsic value of the stock index of country i at time t , $\alpha_0^i$ is a country specific constant and $\Delta$ denotes first differences. The error term $\psi_t^i$ is assumed to be a country specific stationary process with unconditional mean zero. Note that $\Delta p_t^i$ equals the continuously compounded capital gain when we first difference the natural logarithm of the price index, and $\Delta p_t^i$ equals the continuously compounded total return when we first-difference the natural logarithm of the return index. [55]

The coefficients of equation (4.1) can be interpreted as follows:

- $\beta_1^i (p_{t-1}^i - \beta_2^i p_{t-1}^{*i})$ is the error correction (EC) component of the model, which measures the speed at which prior deviations from the equilibrium are corrected.
  - When EC= 0, $p_{t-1}^i$ and $p_{t-1}^{*i}$ are in their equilibrium state;
  - When EC>0, $p_{t-1}^i$ is above its equilibrium value; in order to restore equilibrium $\Delta p_t^i$ must be negative;
  - When EC<0, $p_{t-1}^i$ is below its equilibrium value; in order to restore equilibrium $\Delta p_t^i$ must be positive.
- $\beta_0^i$ estimates the short term effect of an increase in $P_t^{*i}$ on $P_t^i$ ;
- $\beta_1^i$ estimates the speed of return to equilibrium after a deviation;
- $\beta_2^i$ estimates the long term effect of a one percent increase in $P_t^{*i}$ on $P_t^i$ . This long term effect will be distributed over future time periods according to the rate of error correction $\beta_1^i$ . If $\beta_2^i = 1$, a 1% increase in $P_t^{*i}$ will lead $P_t^i$ to increase by 1% in the long run, which implies a fully co-integrating relation between both variables. When the long-run multiplier $\beta_2^i$ is higher than 1, a 1% increase in the fundamental value leads to more than a 1% increase in the stock price in the long run, which indicates that there is no stable co-integrating relation between the fundamental value and the stock price.

Our main interest lies in $\beta_1^i$ , which estimates the speed of reversion of the stock price to the fundamental value, or alternatively, the fraction of the deviation of the price from the fundament value which is eradicated over a 1-year horizon. Given the Error Correction-mechanism described above, $\beta_1^i$ should be negative. If the current stock price is one percent below the fundamental value, then the return over the next year

[54] This model can be derived directly from the static model of equation (1.1) and (1.2), as outlined in Annex II.

[55] The research findings reported in chapter 6 are based on regressions including capital gain as the dependent variable.

will be higher by -100* $\beta_1^i$ percent (ceteris paribus). Thus, the process in equation (4.1) contains a mean-reverting process if $-1 < \beta_1^i < 0$. If $\beta_1^i = -1$ a full adjustment occurs in the next period, when $\beta_1^i = 0$ no error correction takes place and when $\beta_1^i > 0$ mean aversion occurs.

In order to demonstrate the consequences of applying overly restrictive models to the dynamic mean reverting process, we compare our estimates of the speed of mean reversion based on equation (4.1) to two frequently applied models:[56]

1) The general mean reverting process based on equation (1.5):
$r_{t+1}^i = \alpha^i + \lambda^i (p_{t+1}^{i*} - p_t^i) + \varepsilon_{t+1}^i$
where $r_{t+1}^i$ equals the continuously compounded return of the stock index of country i between time t and t+1. This model assumes that $\beta_0^i = 0$ and $\beta_2^i = 1$, which indicates that there is no short-run effect, and $P_t$ and $P_t^*$ are fully co-integrated over time. Whereas the ECM models require a significant finding of $\beta_1^i < 0$ to confirm mean reversion, this model requires a significant finding of $\lambda^i > 0$.

2) The Engle and Granger Two-Step ECM, whereby:
- First an estimate of $\xi_t^i$ is obtained by regressing $p_t^i$ on $p_t^{*i}$;
- The lagged residuals of this regression are used as a measure of the error correction term in the following model:
  $\Delta p_t^i = \alpha_0^i + \beta_0^i \Delta p_t^{*i} + \beta_1^i \xi_{t-1}^i + \psi_t^i$

This model assumes that $\beta_2^i = 1$, which implies that $P_t$ and $P_t^*$ are fully co-integrated over time.

Empirically, to confirm mean reversion within equation (4.1), we need a significant finding of $\beta_1^i < 0$ . Hereby we are confronted with two practical problems:
- Since mean reversion, if it exists, is likely to occur slowly, it can only be detected within long time series. Sufficiently long time series are hard to come by in practice. We use the additional information of cross-country comparisons to increase the power of the mean reversion test.
- To estimate the various parameters of equation (4.1) we have to specify the fundamental value process $P_t^{*i}$. Since the fundamental value is unobserved, we need to identify a measurable variable which can serve as a suitable proxy. The issue of constructing a suitable proxy is outlined in §4.2.

### *4.1.1 Testing for unit roots and co-integration*

As mentioned in §2.3 the non-stationary behaviour of both price and dividend time series gives rise to spurious regression. Traditional approaches to handling non-stationary time series have included detrending, which leads to invalid estimates when the series are I(1), and differencing. First-differencing is sensitive to short-term noise components though, and gives biased estimates when series have a long-run equilibrium relationship. Engle and Granger (1987) proposed to use an Error Correction Model in case of a co-integrating relation between I(1) time series. Since all the variables in the ECM are stationary, the ECM has no spurious regression

[56] See Annex II for the derivation of both models from the basic mean reversion model of equation (1.1) and (1.2).

problems. See Annex III for a detailed overview of the theory on co-integration and ECM's.

Ever since the influential paper of Engle and Granger (1987) the Error Correction Model (ECM) has been closely linked to co-integration theory. The Single Equation ECM is appropriate for both co-integrated as well as long-memoried, but stationary data though. [57] Thus, even when we find one of our variables to be stationary, we can still apply the ECM. We test for a unit root as well as co-integration to examine the time-series properties of the variables under consideration. At country level, we use the Augmented Dickey-Fuller test (ADF) to investigate the order of integration of each variable. When the variable is found to be I(1), we test for stationarity of the variable following first-differencing. The Engle-and Granger bivariate co-integration analysis is used to examine whether the dependent and the indepent variable under consideration are co-integrated. For the panel datasets we use the unit root tests of Im, Pesaran and Shin (1997). We test for co-integration with the bivariate Engle-Granger methodology in combination with the IPS test. The test results are reported in Annex V.

### *4.1.2 Removing serial correlation*

If the disturbance term $\psi_t^i$ of equation (4.1) is serially uncorrelated, we can use the Ordinary Least Squares (OLS) estimator to run the regression, and the t-statistics could be used to test the null hypothesis of no mean reversion ($\beta_1^i = 0$) against the alternative hypothesis of mean reversion ($\beta_1^i < 0$). When serial correlation of $\psi_t^i$ is present though, we should add lagged values of returns to equation (4.1) as additional regressors, resulting in the following equation:

$$\Delta p_t^i = \alpha_0^i + \beta_0^i \Delta p_t^{*i} + \beta_1^i (p_{t-1}^i - \beta_2^i p_{t-1}^{*i}) + \sum_{j=1}^{k} \varphi_j^i (\Delta p_{t+k-j}^i) + \omega_t^i \qquad (4.2)$$

The serial correlation of $\psi_t^i$ is removed when the right number of lagged returns are chosen. If returns are persistent, i.e. values in the far past are still affecting today's values, more lags will be needed. But when too many lags are added, the forecast error will go up. We determine the right number of lags based on the Bayesian Information Criterium (BIC). Following this adaptation, the residuals of equation (4.2) are only correlated across countries, but not within countries. Consequently, for each country we consider the error term $\omega_t^i$ to be a white noise process with a time-invariant country specific variance $\sigma_i$ . Following the adjustment for autocorrelation by adding lagged returns to the equation, only correlation between countries remains. At panel level we use the Generalised Least Squares estimation to adjust for correlation between panels.[58]

[57] Pesaran and Shin (1999) demonstrate that Autoregressive Distributed Lag (ARDL) Models, which are appropriate for stationary data, are in fact equivalent to ECMs, which indicates that ECM's can be applied to both stationary and non-stationary data.

[58] The software which we use, Stata 11, provides the option to adjust for correlation between countries when a Generalised Least Squares Estimation is applied to panel data. The efficiency of these estimates could be improved by applying a Seemingly Unrelated regression (SUR), which adjusts explicitly for the correlation structure between seemingly independent systems of equations. This econometric technique is beyond the scope of this thesis though.

### *4.1.3 Generalized Least Squares estimation*

An additional problem is posed by heteroskedasticity of the error term. When the variance of the error term is not constant over time, the OLS estimates are unbiased and consistent, but they are not efficient; other unbiased estimators will be better in minimizing the variance. In addition, the standard errors are biased when heteroskedasticity is present, which leads to bias in test statistics and confidence intervals. Robust standard errors are commonly used to provide more accurate test statistics. This method is only applicable to large samples though. Considering our small samples, a better option is to use Generalized Least Squares (GLS) to correct for heteroskedasticity. The OLS method gives the same weight to observations coming from populations with more variability than observations coming from populations with less variability. Since observation with a larger error variance contain less information on the position of the true regression line, these observations are considered less reliable, and are therefore given less weight by the GLS method. In this way, more efficient estimators are produced, which can be considered the Best Linear Unbiased Estimates (BLUE). McQueen (1992) indicates regarding the use of GLS that: "This extension is critical since the Depression/World War II period exhibits the strongest mean-reverting tendencies, and this same period, due to its relatively high volatility, receives inordinate weight in OLS regressions."

Whereas OLS minimizes the sum of squared regression residuals, assuming that the error variances are the same for all observations, GLS minimizes the *weighted* sum of squared residuals by dividing each squared residual by the error variance. In the hypothetical case where the error variances $(\sigma_i)$ would be known, the GLS estimator could be constructed by dividing each variable by $\sigma_i$. Since the error variances are unobserved, Zellner (1962) suggests constructing a feasible GLS estimator by using the residuals of an OLS estimation of $\lambda^i / \beta_1^i$ as an estimator of the unknown error variances. Hereby the theoretical distribution of the error term is approximated by the empirical distribution of a set of residuals. We apply feasible GLS both to the country- and the panel data estimations.[59]

## 4.2 Proxies of the fundamental value process

The relation between the fundamental value $P^*$ and the proxy variable $\tilde{P}$ can be modelled as follows:

$$P^* = \delta_0 + \delta_1 \tilde{P} + \nu$$

Hereby $\nu$ is the error term resulting from the differences between the proxy and the fundamental value. The observed variable $\tilde{P}$ can only be considered a suitable proxy when the parameter $\delta_1 > 0$. Incorrect specification of the fundamental value will result in an incorrect estimate of the speed of mean reversion. Since we can not estimate the relation between the unobserved fundamental value and the proxy variable, we will have to rely on economic theory in order to find a suitable proxy. The possibility of finding a suitable proxy is constrained by the availability of data on company fundamentals over sufficiently long time horizons. In line with economic

[59] When GLS is applied to estimate equation (4.2) normality of the residuals is assumed. This assumption holds asymptotically, but is unlikely to hold for finite samples. Balvers et al (2000) adjust for small sample bias by using Monte Carlo simulation and Spierdijk et al (2010) apply a bootstrapping procedure to the standard errors. These econometric techniques are beyond the scope of this thesis though.

theory and the empirical evidence on the long run relation between stock prices and company fundamentals, we compare the following proxies of the fundamental value:

1. Dividends
2. Smoothed earnings
3. The perfect foresight price
4. The hindsight price
5. The Gordon model

*Dividends*
Dividends is the most commonly used measure of the fundamental value, and is found to have strong predictive value of stock returns, especially over long horizons. We include dividends as a measure of the fundamental value in order to compare its behaviour to the other proxies.

*Smoothed earnings*
As mentioned in §3.1 Campbell and Shiller (1988) find that data on accounting earnings, measured as a long moving average over several years, help to predict the present value of future dividends. In addition, the E/P ratio and earnings-per-share are found to be powerful predictors of the return on stock, especially over long horizons. When earnings are available within the dataset (see Annex I) we use smoothed earnings as a proxy for the fundamental value, whereby for the long dataset we take an average over 30 years, and for the short dataset over 10 years.[60] In line with Campbell and Shiller (1988) the 10-year and the 30-year moving average of real earnings are calculated as follows:

Smoothed earnings (10): $\widetilde{P}_t = E_t^{10} = (e_t + e_{t-1} .... + e_{t-10})/10$

Smoothed earnings (30): $\widetilde{P}_t = E_t^{30} = (e_t + e_{t-1} .... + e_{t-30})/30$

*Perfect foresight price*
Since dividends measure the realised cash flow in the present, while stock prices are determined by expected cash flows in the future, the perfect foresight price is likely to provide a better estimate of future expected dividends than realised dividends. The ex-post value or perfect-foresight price is defined by Shiller (2001) as the value of an investment in the asset, taking into account the actual future dividends that the investor will receive. This measure should be contrasted with the economic or investment value of an asset, which is the value we place on an asset given only the information available about it today. If we would have perfect information about the future dividends, than the economic value should be equal to the ex-post value. Due to imperfect information ex-post value is not known today, but it can be computed later after dividends become known. We can use the perfect foresight price to estimate the fundamental value of a stock. Since cash flows that are further away are discounted at a higher rate, the present value of these cash flows becomes decreasingly significant in determining the ex-post value.[61] Koller et al. (2005) claim that the value of a company can be approximated by the cash flows during the next five years, sufficiently. Thus, we will use dividends of the next five years as an estimator of the ex-post value:

$$\widetilde{P}_t = \frac{Div_{t+1}}{1+r_{t+1}} + \frac{Div_{t+2}}{(1+r_{t+2})^2} + \frac{Div_{t+3}}{(1+r_{t+3})^3} + \frac{Div_{t+4}}{(1+r_{t+4})^4} + \frac{Div_{t+5}}{(1+r_{t+5})^5}$$

[60] We do not use a moving average of dividends as a proxy for the fundamental value, since the perfect foresight price and the hindsight price are basically a long moving average of dividends when the discount rate is held constant during the sample period.
[61] Shiller (2001): 78

Shiller (2001) assumes that, at the end of the time period, the present value of future real dividends is equal to the price of the stock. Capital gains or losses from selling the share to another investor are not taken into account, since the ex-post value only includes the payoffs that the investment itself produces. 'If the efficient market theory is right, these capital gains or losses are just reflections of changes in, or of changing information about, ex-post value.'[62]

*Hindsight price*
The perfect foresight price, based on actual future dividends, is compared to the hindsight price, which takes into account the dividends realised in the near past. Hereby it is assumed that investors base their expectations regarding future cash flows on historical information. More distant dividend streams are considered to have less predictive value for future dividend streams, and are thus discounted at a higher rate:

$$\widetilde{P}_t = \frac{Div_{t-1}}{1+r_{t-1}} + \frac{Div_{t-2}}{(1+r_{t-2})^2} + \frac{Div_{t-3}}{(1+r_{t-3})^3} + \frac{Div_{t-4}}{(1+r_{t-4})^4} + \frac{Div_{t-5}}{(1+r_{t-5})^5}$$

*The Gordon model*
The Gordon model, as outlined in equation (2.6) is frequently used in the literature to approximate the present value of stocks. Manzan (2003) uses the static Gordon model to approach the fundamental value in a mean reversion process. Hereby he first considers the ability of static and dynamic versions of the Gordon model to account for the dynamics of the annual stock prices of the S&P 500 from 1871 to 2003. He finds that the static Gordon model, with constant dividend growth and ex ante return, is unable to capture the dynamics of the P/D ratio (which should remain constant within this model). Consequently, Manzan (2003) uses a dynamic Gordon model, whereby the required rate of return and the dividend growth rate are allowed to vary over time. Since the required rate of return is unobserved, Manzan (2003) assumes that the ex-ante return is given by the risk-free real interest rate and a constant risk premium. This model does not add significant explanatory power compared to the static model, which leads Manzan (2003) to conclude that both asset pricing models are unable to account for the short-run dynamics of stock prices, although they tend to explain their long-run behaviour. Thus, Manzan (2003) decides to use the static Gordon model to estimate the fundamental value (i.e. the P/D ratio), whereby a structural break in the discount rate and the dividend growth rate is applied in the 1950's. In line with the findings of Manzan (2003) we use the static Gordon model to approximate the fundamental value. It should be noted that, when the natural logarithm of the Gordon model is used as a proxy for the fundamental value, whereby the dividend growth rate and the discount rate are held constant over time, the variation in this proxy is in fact equal to the natural logarithm of dividends:[63]

$$\widetilde{P}_t = mD_t \qquad m = \frac{1+g}{r-g} \tag{2.6}$$

When the multiplier m is allowed to vary over time, for example by applying a structural break or a stochastic discount factor, the discount rate (r) and dividend growth rate (g) determine the dynamics of the P/D ratio.

[62] Shiller (2001): 72
[63] Visual inspection of the Gordon model vis-a-vis the stock price seems to suggest that the Gordon model provides a more accurate approximation of the fundamental value than dividends, since it follows the price process much more closely. However, when we estimate the speed of mean reversion we incorporate the natural logarithm of the Gordon model or dividends into the model as a proxy of the fundamental value. When r and g are assumed to remain constant over time both proxies follow the same process, and provide the same estimation results.

## 4.3 Defining the discount rate

The appropriate discount rate can be determined based on an estimate of the expected return on equity. Correctly specifying the expected return is of high importance since slight differences in the time value of money over long horizons can result in very different conclusions.[64] Unfortunately, the expected return is unobserved, and opinions differ on the correct approximation method. Fama and French (2002) indicate that: 'Financial economists typically use the average return on a broad portfolio of stocks to estimate the expected market return.' This approach assumes a constant and unique discount rate, an assumption which seems unlikely since expectations vary over time, and different investors may have different expectations and valuations of the risks involved in equity investments. [65] An alternative approach is the use of forecasts by security analysts; these forecasts are only available for short sample periods though.[66] In order to allow for time-varying expected returns, the equity premium, which can be defined as the extra return that the overall stock market or a particular stock must provide over the risk free rate to compensate for market risk, is increasingly predicted with the help of valuation models.[67] Fernández (2006) clarifies this discussion by making a distinction between the Historical Equity Premium (HEP) and the Expected Equity Premium (EEP):

*1) The historical equity premium (HEP)*
The HEP is defined as the historical differential return of the stock market over treasuries.[68] Different estimates of the HEP arise since authors have used different time frames, market indices, instruments for the risk free rate, calculations of return (based on %-change or log-changes) and averages (arithmetic or geometric).[69] In addition, the data from the 19th century and the first part of the 20th century is often quite poor, which influences the estimates of the sample average return on stocks. The lack of reliable long time series data influences the reliability of the findings.[70]

*2) The expected equity premium (EEP)*
The EEP is defined as the expected differential return of the stock market over treasuries. Fernández (2006) indicates that: 'Estimates of the EEP based on historical analysis presume that the historical record provides an adequate guide for future expected long-term behaviour. However, the HEP changes over time, and it is not clear why capital market data from 19th century of the first half of the 20th century may be useful in estimating expected returns in the 21st century.'[71] Fernández argues that the error from using the HEP as an estimator of the EEP is substantial. Survivorship bias is likely to lead the observed returns (HEP), conditional on survival, to overestimate the unconditional expected return (EEP).[72]

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[64] Jorion (1999): 4
[65] Fernández (2006): 34
[66] Fama and French (2002): 1
[67] Hereby the cost of equity is defined as the risk free rate of return + the premium expected for risk
[68] Fernández ( 2006): 5
[69] Fernández (2006) gives a detailed overview of various estimates of the HEP, both for the US and other markets. A discussion of the use of the arithmetic versus the geometric average is provided by Jacquier, Kane and Marcus (2003).
[70] Jorion (1999) indicates that, due to the volatility of stock returns, a very large number of observations is needed to establish that growth is positive with statistical confidence. A market with a 6% average growth rate and a standard deviation of 20 percent requires at least 44 observations (N) to establish a positive growth rate at a 5% confidence level, using a standard t-test, requiring a t-statistic which is approximately greater than 2: $t = \frac{\hat{\mu}}{\hat{\sigma}/\sqrt{N}} = \frac{0.06}{0.20/\sqrt{N}}$
[71] Fernández (2006): 12
[72] Many authors consider the equity premium to be a stationary process, which would make the HEP and unbiased estimate of the EEP. Survivorship bias, which applies not only to the stocks within the market but also to stock markets themselves, is likely to cause the observed return to overestimate the expected return.

This opinion is supported by research of Fama and French (2002) on the equity premium of the US market. They compare estimates of the equity premium for the 1872 -1999 period based on realized returns and the Gordon model. For the 1872 – 1949 period, similar estimates of the equity premium are found. For 1950–1999, the Gordon estimate is only about forty percent of the estimate from realized returns though. Fama and French (2002) argue that the estimate provided by the Gordon model is likely to be closer to the EEP.[73] In order to assess the consequences of assuming different discount rates, we use two different estimates of the discount rate to calculate the perfect foresight price, the hindsight price, and the Gordon model:

- The geometric mean of the total return
- The geometric mean of the Gordon estimate

In line with most research on equity premia, we use the geometric instead of the arithmetic mean to calculate the average total return and the Gordon estimate (based on real values in US dollars).[74] These estimates are compared to the estimates of the equity premium provided by Jorion (1999) and Dimson et al (2002). In addition, for the countries included in dataset 1, we assess whether a structural break should be applied in line with the findings of Fama and French (2002) for the US market; we do not find a clear structural break for Sweden and Denmark. Since dataset 2 only covers the 1973 to 2009 period we assume that no structural break is included in this time period. Both datasets are described in Annex I, and Annex IV provides a detailed overview of the estimation of the discount rate. The discount rates applied to the proxies are summarized in Table I, whereby the first version of each proxy includes a discount rate based on total return, and the second based on the Gordon estimate. Especially in the case of Sweden these estimates of the discount rate differ substantially, which allows us to examine the consequences of applying different discount rates to the proxies for our estimation results.

[73] Fama and French (2002) indicate that 'If the stock return and the dividend growth rate are stationary (mean reverting) the dividend yield is also stationary. Then, over long estimation periods, the averages of the sample dividend yields and the sample dividend growth rate provide good estimates of the long-term expected values, and the Gordon estimate provides an approximately unbiased estimate of the long-term (unconditional) expected stock return.'

[74] Jacquier, Kane and Marcus (2003) argue that for typical investment horizons the proper discount rate is in fact between tbe arithmetic and the geometric mean. A weighted average of the arithmetic and the geometric sample mean should be used as a discount rate. Since our estimates of the arithmetic mean are much higher than the estimates of Jorion (1999) and Dimson et al (2002), especially for the short period included in the second dataset, we prefer to use the geometric mean.

**Table 1 Discount rates applied to the proxies**

*Dataset 1*

| | United States (%) | Denmark (%) | Sweden (%) |
|---|---|---|---|
| Perfect foresight price1 | 7 | 5% | 7% |
| Perfect foresight price 2 | 8.07% before 1950<br>4.74% after 1950 | 5% | 12.43% |
| Hindsight price 1 | 7% | 5% | 7% |
| Hindsight prices 2 | 8.07% before 1950<br>4.74% after 1950 | 5% | 12.43% |
| Gordon model 1 | r=7%<br>g=1.37% | r= 6.17%<br>g=2.65% | r=7%<br>g=4.63% |
| Gordon model 2 | r: 8.07% before 1950<br>4.73% after 1950<br>g: 2.74% before 1950<br>1.05% after 1950 | r= 6.17%<br>g=2.65% | r=12.43%<br>g=4.63% |

*Dataset 2*

| | Perfect foresight price 1<br>Hindsight price 1<br>Gordon 1 (%) | Perfect foresight price 2<br>Hindsight price 2<br>Gordon 2 (%) |
|---|---|---|
| Australia | 6.49 | 17.14 |
| Belgium | 5.44 | 14.54 |
| Canada | 7.81 | 16.29 |
| Denmark | 7.43 | 11.00 |
| France | 8.09 | 18.00 |
| Germany | 7.74 | 11.61 |
| Ireland | 10.48 | 17.50 |
| Japan | 5.09 | 9.37 |
| Netherlands | 8.93 | 11.86 |
| South Africa | 7.04 | 11.90 |
| Switzerland | 10.61 | 14.72 |
| UK | 7.35 | 14.39 |
| USA | 8.56 | 10.94 |

## 5 Data description

In order to examine mean reversion of equity indices over long horizons we use annual data instead of the more frequently sampled monthly data, for a number of reasons: [75]

- Fama and French (1988a) find that mean reversion based on monthly returns is concentrated in January. By using yearly data these seasonal effects can be avoided.
- The power of unit root tests depends primarily on the time span of the sample, rather than the number of observations. Therefore higher frequency data provide little addition information for detecting a slowly decaying component in stock prices.
- Since dividends are paid out at different times during the year, price indices vary based on infrequent dividend distributions, whereas return indices assume dividends to be received on a continuous basis. Using annual data avoids variations in monthly index data caused by the assumptions regarding dividend payout policies.

Very few of the studies on mean reversion have been based on data from outside the US, primarily since the long time series which are required are unavailable for most countries. Jorion and Goetzmann (1999) indicate that 'Markets have been closed or suspended due to financial crises, wars, expropriations, or political upheaval.' The US market, which is today's largest stock market, is one of the few markets with a continuous time history. Monthly stock market indices for the US market have been constructed by Standard and Poor's and, prior to 1926, by Alfred Cowles (1939) going back into the 1870s. For the non-US data, a variety of data sources must be combined to construct uninterrupted long time-series.
Dimson et al (2002) have constructed the indices of 17 countries with historically well developed economies and financial markets, which jointly account for 91% of the global market value in 2006.[76] This database is not suitable for research on relative mean reversion though, as no data is included which could be used to construct a reliable proxy for the fundamental value process.[77]
Jorion and Goetzmann (1999) have constructed a database which includes stock returns with and without dividends for multiple countries. The database covers 16 markets from 1970 to 1995 based on Morgan Stanley Capital International Perspective (MSCIP) data, as well as 6 long-term markets from approximately 1920 to 1995 obtained from various sources.[78] Unfortunately this dataset is not publicly available, and only summary statistics of the data are provided in the article of Jorion and Goetzmann (1999).

Instead, we use data obtained from Datastream for 13 countries from 1973 to 2009, which includes the stock price index, the total return index, market value, P/E multiples and dividend yield. In addition to this 'broad' dataset, we obtain three 'long'

[75] Balvers et al (2002): 751
[76] The data of Dimson et al (2002) covers the stock indices of the following 17 countries: Australia, Belgium, Canada, Denmark, France, Germany, Ireland, Italy, Japan, The Netherlands, Norway, South Africa, Spain, Sweden, Switzerland, United Kingdom and the United State.
[77] The data of Dimson et al (2002) includes yearly total return indices, which incorporates the reinvested dividends into the index. Since no data is provided on the capital gain, the dividend data can not be isolated from this index in order to construct a proxy for the fundamental value. Combining this data with MSCI data of the capital gain gives inaccurate results of the dividend yield, due to differences in the methods used to calculate the yearly stock indices.
[78] The data of Jorion and Goetzmann (1999) covers the following markets:
1970 – 1995: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, UK, US
+/- 1921 – 1995: Denmark, Germany, Sweden, Switzerland, UK, US

datasets from various sources, including yearly total stock returns and dividend yields of Denmark (1922 – 2009) and Sweden (1919-2006) as well as stock prices, earnings and dividends from the United States (1871-2009). To increase the power of our statistics these three national databases are combined to a cross-section database including observation from 1922 to 2009.
Each dataset is combined with the inflation rates and the exchange rates provided by Dimson et al (2002) in order to obtain real stock prices, dividends and earnings in US dollars. In this way we correct for large fluctuations in the inflation rates in some countries, as well as price fluctuations due to exchange rate movements. By applying the model to each dataset we ensure that we make maximum use of the length and breadth of the available data. A detailed overview of the variables included in the different datasets and the calculations applied to the data is provided in Annex I.

Table 2.1 provides the summary statistics of the continuously compounded capital gain, which is calculated based on the price index (PI):
Capital gain = $\log(PI_{t+1}^{i}) - \log(PI_{t}^{i})$
For each country we report both the arithmetic and the geometric mean, as well as the standard deviation, skewness and excess kurtosis. Table 2.2 provides the same statistics for the continuously compounded total return, which is calculated based on the return index (RI):
Total return = $\log(RI_{t+1}^{i}) - \log(RI_{t}^{i})$
The statistics of the total return are very similar to the statistics of the capital gain, especially for the second dataset. The mean and the standard deviation of both the capital gain and the total return are sensitive to the exclusion of outliers, which indicates that our estimates of the mean are influenced by periods of highly volatile stock returns included in both samples.[79] We do not exclude the outliers from our sample though, since these observations are likely to contain important information on the mean reversion process.[80]
Both the geometric and the arithmetic mean are much higher for the short period covered by the second dataset, which stresses the importance of using a sufficiently long time period when estimating the discount rate, as discussed in the previous chapter. With the exception of Switzerland the skewness of the capital gain and the total return is negative in all countries, which indicates more volatility in negative returns. The excess kurtosis indicates the deviation of the kurtosis from three. If the excess kurtosis is zero, the tails of the return distribution are comparable to those of a normal distribution. When the excess kurtosis is much larger than zero, the return distribution exhibits fat tails. Notice that in dataset 1 the United States, which is the most frequently studied market, has the lowest excess kurtosis of 0.58. In the second dataset, both the skewness (-2.0089) and the excess kurtosis (6.2234) of the capital gain and the total return are quite extreme for the Netherlands. The statistics for the other countries vary from lows of a skewness of -1.198 for the US and an excess kurtosis of -0.939 for South Africa, to highs of a skewness of 0.004 for Switzerland and an excess kurtosis of 2.738 for the UK.

[79] When we exclude the most extreme observations in our two datasets, the means shift substantially, which indicates that the outliers affect the normality of the distribution of our observations. Woolridge (2009) indicates that the decision to keep or drop such extreme observations is a difficult one, since outlying observations can provide important information by increasing the variability in the (in-)dependent variables, whereas on the other hand outliers may influence the OLS estimates, especially in small sample sizes.
[80] Instead we correct for the heteroskedasticity resulting from the inclusion of these outliers by applying Generalised Least Squares (GLS), as described in §4.1.3.

**Table 2.1 Summary statistics of the continuously compounded capital gain**

*Dataset 1 1922 - 2009*

| | Arithmetic mean | Geometric mean | Standard deviation | Skewness | Excess kurtosis |
|---|---|---|---|---|---|
| United States | 0.026 | 0.005 | 0.194 | -0.740 | 0.581 |
| Sweden | 0.060 | 0.026 | 0.232 | -0.878 | 2.239 |
| Denmark | 0.048 | 0.020 | 0.228 | -0.060 | 1.708 |

Dataset 2 1973 – 2009

| | Arithmetic mean | Geometric mean | Standard deviation | Skewness | Excess kurtosis |
|---|---|---|---|---|---|
| Australia | 0.115 | 0.065 | 0.282 | -0.912 | 1.152 |
| Belgium | 0.109 | 0.054 | 0.274 | -0.992 | 2.562 |
| Canada | 0.105 | 0.078 | 0.213 | -1.130 | 2.697 |
| Denmark | 0.117 | 0.074 | 0.267 | -1.003 | 1.353 |
| France | 0.122 | 0.080 | 0.283 | -0.406 | 0.149 |
| Germany | 0.103 | 0.077 | 0.229 | -0.127 | 1.511 |
| Ireland | 0.123 | 0.105 | 0.378 | -0.454 | 1.226 |
| Japan | 0.085 | 0.051 | 0.268 | -0.006 | -0.382 |
| The Netherlands | 0.130 | 0.089 | 0.228 | -2.009 | 6.223 |
| South Africa | 0.124 | 0.070 | 0.326 | -0.340 | -0.939 |
| Switzerland | 0.124 | 0.106 | 0.196 | 0.004 | 0.454 |
| UK | 0.124 | 0.073 | 0.278 | -1.056 | 2.738 |
| US | 0.104 | 0.085 | 0.187 | -1.198 | 1.316 |

**Table 2.2 Summary statistics of the continuously compounded total return**

*Dataset 1 1922 - 2009*

| | Arithmetic mean | Geometric mean | Standard deviation | Skewness | Excess kurtosis |
|---|---|---|---|---|---|
| United States | 0.086 | 0.068 | 0.194 | -0.145 | -0.090 |
| Sweden | 0.097 | 0.064 | 0.231 | -0.980 | 2.451 |
| Denmark | 0.089 | 0.062 | 0.225 | -0.177 | 2.102 |

*Dataset 2 1973 – 2009*

| | Arithmetic mean | Geometric mean | Standard deviation | Skewness | Excess kurtosis |
|---|---|---|---|---|---|
| Australia | 0.115 | 0.065 | 0.282 | -0.912 | 1.152 |
| Belgium | 0.109 | 0.054 | 0.274 | -0.992 | 2.562 |
| Canada | 0.105 | 0.078 | 0.213 | -1.130 | 2.697 |
| Denmark | 0.117 | 0.074 | 0.267 | -1.003 | 1.353 |
| France | 0.122 | 0.080 | 0.283 | -0.406 | 0.149 |
| Germany | 0.103 | 0.077 | 0.229 | -0.127 | 1.511 |
| Ireland | 0.123 | 0.105 | 0.378 | -0.454 | 1.226 |
| Japan | 0.085 | 0.051 | 0.268 | -0.006 | -0.383 |
| The Netherlands | 0.130 | 0.089 | 0.228 | -2.009 | 6.223 |
| South Africa | 0.123 | 0.070 | 0.326 | -0.340 | -0.939 |
| Switzerland | 0.124 | 0.106 | 0.196 | 0.004 | 0.454 |
| UK | 0.124 | 0.074 | 0.278 | -1.056 | 2.738 |
| US | 0.104 | 0.086 | 0.187 | -1.198 | 1.316 |

## 6 Empirical results

The single equation ECM is applied to both datasets to examine the dynamic adjustments process of the stock price to the various proxies for the fundamental value. The estimates of the single equation ECM are compared to the estimates based on the simple mean reversion model and the Engle and Granger two-step ECM, in order to examine the consequences of applying the restrictive assumptions underlying these latter models. It is found that the assumption of no short-run effect and continuous co-integration do not hold, which indicates that the two-step ECM is the preferred specification of our model. The results reported in this chapter are all based on the price index; for a comparison of these results to the findings based on the total return index see Annex VI.

### 6.1 Individual countries

For the three long datasets of the US, Sweden and Denmark, we first estimate the speed of mean reversion at country level. We use the continuously compounded capital gain (based on the price index) as the dependent variable, and estimate all equations with FGLS, whereby in some cases lagged capital gains are added to the equation to purge the model from autocorrelation. The estimates and the t-statistics are reported in table 3.

Whereas Spierdijk et al (2010) do not find significant evidence of mean reversion when the countries are considered separately, despite a dataset which is similar in length to our three long datasets, we find evidence of mean reversion in all three countries. [81] When the hindsight price is included in the regression, no significant results are obtained for any of the three models. The other proxies, however, all provide significant estimates of the speed of mean reversion when the single equation ECM is applied. Note that dividend and the Gordon model provide the same estimate when no structural break is applied. Furthermore, when we apply a different discount rate to the perfect foresight price and the hindsight price, this does not seem to have a very large influence on the estimated speed of mean reversion.[82]

The performance of the simple mean reversion model is much less convincing than the single equation ECM. For the Swedish dataset, no significant results are obtained when this model is applied, and in Denmark only dividends and the Gordon model provide a significant estimate of the speed of mean reversion. When the simple model is extended by including the short term effect, resulting in the two step ECM, all proxies except the hindsight price give a significant estimate of the speed of mean reversion. Since the short term effect is positive and significant in many of the regressions, the assumption that $\beta_0^i = 0$ does not seem accurate.[83] When the two step ECM is extended to the single equation ECM, hereby relaxing the assumption that $P_t$ and $P_t^*$ are fully co-integrated over time, it becomes clear that the estimate of

[81] We can not say with certainty whether the increase in signifance is caused by the use of proxies related to company fundamentals instead of a benchmark of stock prices, or by the extension of the simple model to the single equation ECM.

[82] This is mainly caused by the way in which the perfect foresight price and the hindsight price have been modelled. Since only 5 time-periods are considered, changes in the discount rate have only a minor impact on the fundamental value process. If a proxy could be modelled which takes into account an infinite investment horizon the effect of applying a slightly different discount rate would be much larger.

[83] In some cases the short term effect is negative, which seems counterintuitive. But since the estimate is insignificant in these cases we do not provide an economic explanation for the negative sign of the estimate.

$\beta_2^i$ is often not equal to one.[84] When the long-run multiplier $\beta_2^i$ is higher than 1, a 1% increase in the fundamental value leads to more than a 1% increase in the stock price in the long run, which indicates that the co-integrating relation between the stock price and the fundamental value is unstable.[85] Even though our estimates of $\beta_0^i$ and $\beta_1^i$ , as well as the significance of our results only change slightly by including $\beta_2^i$ in the equation, the single equation ECM seems the preferred specification of our model, for various reasons:

- The two step ECM assumes endogeneity between the co-integrating time series, whereby no clear distinction is made between the dependent and the independent variable. Since our aim is to estimate the speed of reversion of the stock price to the fundamental value, and empirical evidence suggests that it is usually the stock price which adjusts to measures of the fundamental value (see § 3.3), we prefer a specification which assumes exogeneity;
- The two step ECM is only appropriate when the variables are truly co-integrated. Since the power of unit root tests is low, especially in small samples, and the co-integrating relationship may vary over time, as confirmed by our estimates of $\hat{\beta}_2^i$, we are likely to draw faulty inferences from the two-step ECM.
- The ADF-test results (see Annex V) indicate that not all variables contain a unit root. Since the single equation ECM is appropriate for both co-integrated and long-memoried data, these stationary variables do not pose any problems to our estimation results.

Thus, we apply the single equation ECM to estimate the speed of mean reversion in a panel data model, whereby a constant speed of reversion across countries is assumed.[86]

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84 The long run multiplier $\beta_2^i$ and its standard error are determined by applying a Bewley transformation regression. This method provides an approximation of the variance, since instruments are used to estimate the model.

85 In some cases our estimates of the long run multiplier are very large, with a positive or a negative sign. See table 3.2: Sweden, hindsight price 1 ($\hat{\beta}_2^i$ = 7.604) and table 4.4: hindsight price 1 ($\hat{\beta}_2^i$ = -7.998) , hindsight price 2 ($\hat{\beta}_2^i$ = -5.103). There seems to be no plausible economic explanation for these findings. Since the estimates of the speed of mean reversion are insignificant in all of these cases though, we will not attempt to find an economic explanation for these results.

86 This seems like a reasonable assumption given that our estimates of the speed of mean reversion within the single equation ECM range between 0.086 and 0.264.

**Table 3.1 United States (1871 – 2009)**

*Simple mean reversion model*

| Proxy: | $\hat{\lambda}_o^i$ | 95% C.I $\hat{\lambda}_o^i$ | $P > \|t\|$ |
|---|---|---|---|
| Dividend / Gordon 1 | 0.106 | (0.031, 0.180) | 0.006*** |
| Smoothed earnings (30) | 0.087 | (0.015, 0.160) | 0.019** |
| Perfect foresight price 1 | 0.145 | (0.069, 0.221) | 0.000*** |
| Perfect foresight price 2 | 0.156 | (0.079, 0.233) | 0.000*** |
| Hindsight price 1 | 0.054 | (-0.020, 0.127) | 0.149 |
| Hindsight price 2 | 0.064 | (-0.014, 0.143) | 0.108 |
| Gordon 2 | 0.182 | (0.096, 0.269) | 0.000*** |

* = significant at 10% c.l.
** = significant at 5% c.l.
***= significant at 1% c.l.

*Two step ECM*

| Proxy (log) | $\hat{\beta}_0^i$ | $\hat{\beta}_1^i$ |
|---|---|---|
| Dividend/ Gordon 1 | 0.889<br>(8.21)*** | -0.140<br>(-3.06)*** |
| Smoothed earnings (30) | 2.862<br>(3.50)*** | -0.110<br>(-2.91)*** |
| Perfect foresight price 1 | -0.366<br>(-1.31) | -0.255<br>(-5.93)*** |
| Perfect foresight price 2 | -0.3429<br>(-1.24) | -0.261<br>(-5.83)*** |
| Hindsight price 1 | -0.280<br>(-0.78) | -0.045<br>(-0.88) |
| Hindsight price 2 | -0.197<br>(-0.57) | -0.061<br>(01.19) |
| Gordon 2 | 0.733<br>(6.83)*** | -0.126<br>(-2.95)*** |

*Single equation ECM*

| Proxy (log) | $\hat{\beta}_0^i$ | $\hat{\beta}_1^i$ | $\hat{\beta}_2^i$ |
|---|---|---|---|
| Dividend/ Gordon 1 | 0.784<br>(6.88)*** | -0.129<br>(-2.82)*** | 1.674<br>(57.48)*** |
| Smoothed earnings (30) | 2.906<br>(3.55)*** | -0.110<br>(-2.87)*** | 1.138<br>(41.65)*** |
| Perfect foresight price 1 | -0.356<br>(-1.29) | -0.262<br>(-5.83)*** | 1.673<br>(48.11)*** |
| Perfect foresight price 2 | -0.333<br>(-1.21) | -0.264<br>(-5.72)*** | 1.517<br>(48.15)*** |
| Hindsight price 1 | -0.284<br>(-0.80) | -0.045<br>(-0.78) | 0.968<br>(19.30)*** |
| Hindsight price 2 | -0.200<br>(-0.58) | -0.061<br>(-1.18) | 1.118<br>(28.43)*** |
| Gordon 2 | 0.738<br>(6.76)*** | -0.123<br>(-2.90)*** | 1.248<br>(58.32)*** |

### Table 3.2 Sweden (1919 – 2009)

*Simple mean reversion model*

| Proxy (log) | $\hat{\lambda}_o^i$ | 95% C.I $\hat{\lambda}_o^i$ | $P > \|t\|$ |
|---|---|---|---|
| Dividend / Gordon 1/ Gordon 2 | 0.0481 | (-0.019, 0.115) | 0.158 |
| Perfect foresight price 1 | 0.028 | (-0.052, 0.108) | 0.493 |
| Perfect foresight price 2 | 0.028 | (-0.052, 0.107) | 0.489 |
| Hindsight price 1 | -0.004 | (-0.070, 0.063) | 0.911 |
| Hindsight price 2 | -0.004 | (-0.071, 0.063) | 0.904 |

* = significant at 10% c.l.
** = significant at 5% c.l.
***= significant at 1% c.l.

*Two step ECM*

| Proxy (log) | $\hat{\beta}_0^i$ | $\hat{\beta}_1^i$ |
|---|---|---|
| Dividend/ Gordon 1/ Gordon 2 | 0.845<br>(5.35)*** | -0.079<br>(-1.84)** |
| Perfect foresight price 1 | 0.178<br>(0.40) | -0.133<br>(-2.84)*** |
| Perfect foresight price 2 | 0.108<br>(0.23) | -0.131<br>(-2.82)*** |
| Hindsight price 1 | -0.200<br>(-0.43) | -0.017<br>(-0.32) |
| Hindsight price 2 | -0.138<br>(-0.30) | -0.020<br>(-0.38) |

*Single equation ECM*

| Proxy (log) | $\hat{\beta}_0^i$ | $\hat{\beta}_1^i$ | $\hat{\beta}_2^i$ |
|---|---|---|---|
| Dividend/ Gordon 1/ Gordon 2 | 0.943<br>(5.81)*** | -0.086<br>(-2.32)** | 1.428<br>(82.55)*** |
| Perfect foresight price 1 | -0.795<br>(-1.89)* | -0.094<br>(-2.01)** | 1.813<br>(57.01)*** |
| Perfect foresight price 2 | -0.251<br>(-0.56) | -0.113<br>(-2.43)** | 1.651<br>(63.26)*** |
| Hindsight price 1 | -0.422<br>(-0.84) | -0.004<br>(-0.08) | 7.604<br>(23.47)*** |
| Hindsight price 2 | -0.278<br>(-0.55) | 0.027<br>(0.51) | 0.795<br>(21.07)*** |

**Table 3.3 Denmark (1922 – 2009)**

*Simple mean reversion model*

| Proxy (log) | $\hat{\lambda}_o^i$ | 95% C.I $\hat{\lambda}_o^i$ | $P > \lvert t \rvert$ |
|---|---|---|---|
| Dividend / Gordon | 0.115 | ( 0.037, 0.194) | 0.005*** |
| Perfect foresight price | 0.057 | (-0.034, 0.148) | 0.218 |
| Hindsight price | 0.000 | (-0.081, 0.082) | 0.993 |

* = significant at 10% c.l.
** = significant at 5% c.l.
***= significant at 1% c.l.

*Two step ECM*

| Proxy (log) | $\hat{\beta}_0^i$ | $\hat{\beta}_1^i$ |
|---|---|---|
| Dividend/ Gordon | 0.544<br>(7.52)*** | -0.127<br>(-2.90)*** |
| Perfect foresight price | -0.610<br>(-2.34)** | -0.157<br>(-3.28)*** |
| Hindsight price | 0.058<br>(0.19) | -0.023<br>(-0.41) |

*Single equation ECM*

| Proxy (log) | $\hat{\beta}_0^i$ | $\hat{\beta}_1^i$ | $\hat{\beta}_2^i$ |
|---|---|---|---|
| Dividend/ Gordon | 0.595<br>(9.14)*** | -0.109<br>(-2.31)** | 1.572<br>(66.98)*** |
| Perfect foresight price | -1.033<br>(-4.04)*** | -0.150<br>(-3.64)*** | 2.005<br>(49.41)*** |
| Hindsight price | -0.081<br>(-0.23) | -0.086<br>(-1.30) | 2.271<br>(39.89)*** |

## 6.2 Panel data

In order to gain test power, the sample size is increased by combining the datasets of the United States, Denmark and Sweden. The single equation Error Correction Model is applied to this enlarged dataset, which ranges from 1922 to 2009. In addition, we apply the single equation ECMl to the second dataset, which includes 13 countries and covers the 1973 to 2009 period.

*Dataset 1: US, Denmark and Sweden (1922-2009)*

For each proxy, with the exception of the hindsight price, we find evidence of co-integration with the logarithm of the price index, which is in line with our findings at country level. See Annex V for the test results. We first estimate the single equation ECM with Fixed Effects (FE) or Random Effects (RE), depending on the outcomes of the Hausman specification test (see table 4.1). The autocorrelation within panels is corrected by adding lags of the dependent variables based on the Bayesian Information Criterium (BIC). The residuals between panels may still be correlated though. In addition, Fixed Effect and Random Effect regressions do not correct for heteroskedasticity. In order to adjust the biased estimates obtained by FE/ RE, we apply a panel data Generalised Least Squares (GLS) estimation which corrects for cross-section correlation and the heteroskedastic error structure.[87] The estimates are reported in table 4.2.

With the exception of the regression including the hindsight price, we find significant evidence of mean reversion at a 5% confidence level. Now that we have combined the three datasets, even the estimate based on the hindsight price is significant at a 10% confidence level, and the estimates are lower than the estimates obtained at country level.[88] The estimated size of the speed of mean reversion ranges between 0.036 and 0.078. For each significant estimate $\hat{\beta}_1^i$ we also report the half-life of the mean reversion process, as well as the corresponding 95% confidence interval. The half-life measures slowness of the mean reversion process; i.e. the time it takes for 50% of a shock to the stock price to be offset by the mean reversion process. Thus, when the speed of mean reversion is higher, the half-life will be shorter.[89]

Our results are quite similar to the estimates obtained by Spierdijk et al (2010), who find an estimate of $\hat{\lambda}^i$ of 0.0668 when the world index is used as a benchmark, and an even lower estimate of 0.0491 when a Seemingly Unrelated Regression (SUR) and bootstrapped standard errors are applied to improve the efficiency of the estimators and correct for small sample bias. These results are much lower than the speed of mean reversion found by Balvers et al (2002), who find an estimate of $\hat{\lambda}^i$ of 0.182 when the world index is used as a benchmark, correcting for small sample bias using Monte Carlo simulation. This estimate implies a half-life of 3.5 years, whereby the

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[87] As mentioned in Chapter 4, the efficiency of this GLS estimation could be further improved by applying a Seemingly Unrelated Regression (SUR) to correct for cross-sectional correlation, as well as bootstrapped standard errors to account for the small sample bias of the GLS-estimates. These econometric techniques are likely to lower the estimates which we obtain, but are beyond the scope of this thesis.

[88] Strangely, the regression including the perfect foresight price 1 & 2 gives a significant negative short term effect; there seems to be no economic explanation for this result.

[89] The half-life of the stationary process in equation (1.1) is calculated by $\frac{\ln(0.5)}{\ln(\alpha)}$. As demonstrated in Annex II, $\alpha = 1 - \lambda$ and $\lambda = -\beta_2$ Therefore, the half-life is calculated by $\frac{\ln(0.5)}{\ln(1+\beta_2)}$.

90% confidence interval ranges between 2.4 and 5.9 years. Spierdijk et al (2010) find a half-life of 13.8 years with a 95%-confidence interval ranging between 10.1 and 21.1 years. Our 95% confidence interval for the half-life is slightly larger than the findings of Spierdijk et al (2010) when the perfect foresight price is used as a proxy. Since the lower confidence bound of $\hat{\beta}_1^i$ is very close to zero when the Gordon model and dividends are used as a proxy, the upper confidence bound of the confidence interval of the half-life is magnified in these cases. These findings indicate that the estimates of the speed of mean reversion depend crucially on the time interval included in the sample. In addition, the perfect foresight price may provide a shorter 95% confidence interval, and hereby more certain estimates, than when dividends is used as a proxy.

**Table 4.1 Dataset 1: FE or RE estimation**

Reported statistics FE: t
Reported statistics RE: P>|z|

| | $\hat{\beta}_0^i$ | $\hat{\beta}_1^i$ | $\hat{\beta}_2^i$ | Estimation method |
|---|---|---|---|---|
| Dividend/ Gordon 1 | 0.609<br>(10.47)*** | -0.102<br>(-3.75)*** | 1.558<br>(125.08)*** | FE |
| Perfect foresight price 1 | -0.687<br>(-3.56)*** | -0.156<br>(-5.48)*** | 1.730<br>(96.09)*** | FE |
| Perfect foresight price 2 | -0.666<br>(-3.49)*** | -0.161<br>(-5.58)*** | 1.710<br>(96.58)*** | FE |
| Hindsight price 1 | -0.237<br>(0.300) | -0.015<br>(0.502) | 1.900<br>(0.000)*** | RE |
| Hindsight price 2 | -0.193<br>(0.394) | -0.018<br>(0.440) | 1.758<br>(0.000)*** | RE |
| Gordon 2 | 0.609<br>(10.53)*** | -0.103<br>(-3.75)*** | 1.526<br>(125.28)*** | FE |

* = significant at 10% c.l.
** = significant at 5% c.l.
***= significant at 1% c.l.

**Table 4.2 Dataset 1: GLS estimation**

Reported statistics: P>|z|

| | $\hat{\beta}_0^i$ | $\hat{\beta}_1^i$ | $\hat{\beta}_2^i$ |
|---|---|---|---|
| Dividend | 0.525<br>(0.000)*** | -0.043<br>(0.018)** | 0.971<br>(0.000)*** |
| Gordon 1 | 0.522<br>(0.000 )*** | -0.036<br>(0.034)** | 0.802<br>- |
| Perfect foresight price 1 | -0.448<br>(0.009)*** | -0.068<br>(0.002)*** | 1.120<br>(0.000)*** |
| Perfect foresight price 2 | -0.436<br>(0.010)** | -0.078<br>(0.001)*** | 1.134<br>(0.000)*** |
| Hindsight price 1 | -0.112<br>(0.535) | -0.038<br>(0.087)* | 1.267<br>(0.000)*** |
| Hindsight price 2 | -0.078<br>(0.657) | -0.043<br>(0.068 )* | 1.270<br>(0.000)*** |
| Gordon 2 | 0.531<br>(0.000)*** | -0.038<br>(0.022)** | 1.042<br>- |

*Estimated half-life in years*

| | $\hat{\beta}_1^i$ | Half-life | 95% C.I. |
|---|---|---|---|
| Dividend | -0.0426** | 15.9 | ( 8.6, 93.6 ) |
| Gordon 1 | -0.0363** | 18.8 | ( 9.6, 245.9 ) |
| Perfect foresight price 1 | -0.0675 *** | 9.9 | ( 6.0, 26.8 ) |
| Perfect foresight price 2 | -0.0780*** | 8.5 | ( 5.3, 20.3 ) |
| Gordon 2 | -0.0376** | 18.1 | ( 9.6, 128.4) |

*Dataset 2: 13 countries (1973-2009)*

For each proxy, with the exception of the hindsight price, we find evidence of co-integration. The IPS-test indicates that some panels are stationary, but as mentioned this does not pose a problem for the application of the single equation ECM. See Annex V for the test results. Also for this dataset we first estimate our model with Fixed Effects or Random Effects, which results in very high and very significant estimates of $\hat{\beta}_1^i$. However, when we correct for cross-section correlation and heteroskedasticity by using Generalized Least Squares, our estimates become very small and insignificant. Only when we include Earnings (10) in the regression we obtain a significant finding of $\hat{\beta}_1^i$, but in this case the co-integrating relation become negative, which seems highly unlikely. The estimates are reported in table 4.3 and 4.4.

These results stress the importance of obtaining sufficiently long time series in order to find significant estimates of the speed of mean reversion. Each panel in the second dataset contains only 37 yearly observations, and an additional 5 observations are lost when we model the perfect foresight price and the hindsight price. Even though the number of panels in the second dataset is much larger than in the first dataset, which leads to a considerable increase in sample size, this does not seem to compensate for the lack of yearly observations. This outcome suggests that the number of yearly observations per panel is of more importance in finding significant estimates of the speed of mean reversion than the number of panels included in the dataset, especially considering that we already find significant estimates of $\hat{\beta}_1^i$ at country level.[90]

[90] However, Cutler et al (1991) cover an even shorter time period from 1960 to 1988 for 13 countries. They estimate the simple mean reversion model including dividends as a proxy for the fundamental value, whereby Newey-West standard errors are applied to adjust for heteroskedasticity and Monte Carlo simulation to adjust for small sample bias. For a 1-year return horizon, a speed of mean reversion of 0.14 on average is found, with a p-value of 0.01. When the speeds of mean reversion are constrained to be equal across all countries using a SUR-regression, a value of 0.16 is found. These findings suggest that the information contained in a broad cross-section database with a limited number of yearly observations could be used more efficiently by applying other econometric techniques, such as SUR regression, which are beyond the scope of this thesis.

**Table 4.3 Dataset 2: FE or RE estimation**

Reported statistics FE: t
Reported statistics RE: P>|z|

| | $\hat{\beta}_0^i$ | $\hat{\beta}_1^i$ | $\hat{\beta}_2^i$ | Estimation method |
|---|---|---|---|---|
| Earnings (10) | 1.506 (21.80)*** | -0.492 (-16.11)*** | 0.550 (110.30)*** | FE |
| Dividend/ Gordon | 0.612 (9.94)*** | -0.238 (-6.21)*** | 0.704 (75.33)*** | FE |
| Perfect foresight price 1 | -0.308 (-2.18)** | -0.385 (-11.28)*** | 0.845 (86.39)*** | FE |
| Perfect foresight price 2 | -0.254 (-1.79)*** | -0.388 (-11.19)*** | 0.846 (86.39)*** | FE |
| Hindsight price 1 | -0.388 (-2.17)** | -0.134 (-3.39)*** | 0.570 (40.98)*** | FE |
| Hindsight price 2 | -0.326 (-1.85 )* | -0.138 ( -3.44)*** | 0.574 (41.31)*** | FE |

* = significant at 10% c.l.
** = significant at 5% c.l.
***= significant at 1% c.l.

**Table 4.4 Dataset 2: GLS estimation**

Reported statistics: P>|z|

| | $\hat{\beta}_0^i$ | $\hat{\beta}_1^i$ | $\hat{\beta}_2^i$ |
|---|---|---|---|
| Earnings (10) | 0.862 (0.000)*** | -0.010 (0.016)** | -0.395 (0.000)*** |
| Dividend/ Gordon | 0.418 (0.000)*** | -0.000 (0.931) | -10.188 - |
| Perfect foresight price 1 | 0.180 (0.032)** | -0.008 (0.151) | 0.115 (0.000)*** |
| Perfect foresight price 2 | 0.216 (0.009)*** | -0.008 (0.131) | 0.183 (0.000)*** |
| Hindsight price 1 | -0.447 (0.000)*** | -0.001 (0.795) | -7.998 (0.000)*** |
| Hindsight price 2 | -0.4053 (0.000)*** | -0.002 (0.703) | -5.103 (0.000)*** |

## 6.3 Time-varying mean reversion

As mentioned in chapter 4, the speed of mean reversion is likely to vary over time. Spierdijk et al (2010) apply a rolling window estimation to the cross-section dataset whereby time intervals of 27 years are used, resulting in 83 estimates for the 1900 to 2008 period. For 24 of the 83 intervals (28.9%), no significant speed of mean reversion is found. Figure 1 depicts the rolling window estimates found by Spierdijk et al (2010).

We compare our estimates of the speed of mean reversion to the findings of Spierdijk et al (2010). Since our findings are already significant at country level, we first apply a rolling window estimation to the US dataset, which is the longest dataset available. We use a 27 year interval to be able to compare our findings to the results of Spierdijk et al (2010). Since the US dataset covers the 1871 to 2009 period, the midyear of each time interval ranges between 1884 and 1996, whereby the first interval covers the 1871 to 1897 period, and the last interval covers the 1983 to 2009 period. Figure 2 represents the rolling window estimates using perfect foresight price 1, smoothed earnings and dividends as a proxy. Our estimates of the speed of mean reversion for the full time period (see Table 3.1) indicated that the use of the perfect foresight price as a proxy gives the most significant finding of $\hat{\beta}_1^i$. Indeed, the lower bound of the 95% confidence interval is above zero most often when we use perfect foresight price 1 as a proxy. For 16 of the 113 time intervals (14.15%) a significant speed of mean reversion is found, which is quite an improvement compared to the results of Spierdijk et al (2010). In addition, the period around 1900 is now also included in our estimates. This period has a very high speed of mean reversion, much higher than any of the other periods. The period between 1920 and 1940 also includes a peak in the speed of mean reversion, which is in line with the rolling-window estimates of Spierdijk et al (2010). Most of the *in*significant estimates are concentrated in the period around 1950 and after 1990. Spierdijk et al (2010) find peaks in the speed of mean reversion in these periods.

Given the insignificance of our findings in these periods, we apply the rolling window estimation to the cross-section dataset of Sweden, Denmark and the US, in order to improve the power of our test for these periods. As demonstrated in figure 3, all insignificant estimates, 12 out of 62 time intervals (19.35%), are now concentrated in the final period covering the midyears of 1984 to 1995. In addition, the variation in the mean reversion process is much smoother when we apply the rolling window estimation to panel dataset 1, resulting in only one clear peak in the speed of mean reversion around 1970. We expect that the efficiency of these estimates could be improved by applying a Seemingly Unrelated Regression (SUR) with bootstrapped standard errors. In addition, expanding the number of national stock indices to more than only three countries may lead to more accurate panel data estimates. Thus, even though the percentage of significant findings is increased compared to the rolling window estimation of Spierdijk et al (2010), we can not confirm their conclusion that the speed at which stocks revert to the fundamental value is higher in periods of high economic uncertainty, caused by major economic and political events. Nevertheless, our findings do confirm the conclusion that the estimated speed of mean reversion depends crucially on the sample period. In addition, the mean reversion parameter is very small, and even turns out insignificant during some periods.

**Figure 1** **Rolling window estimates of Spierdijk et al (2010)**

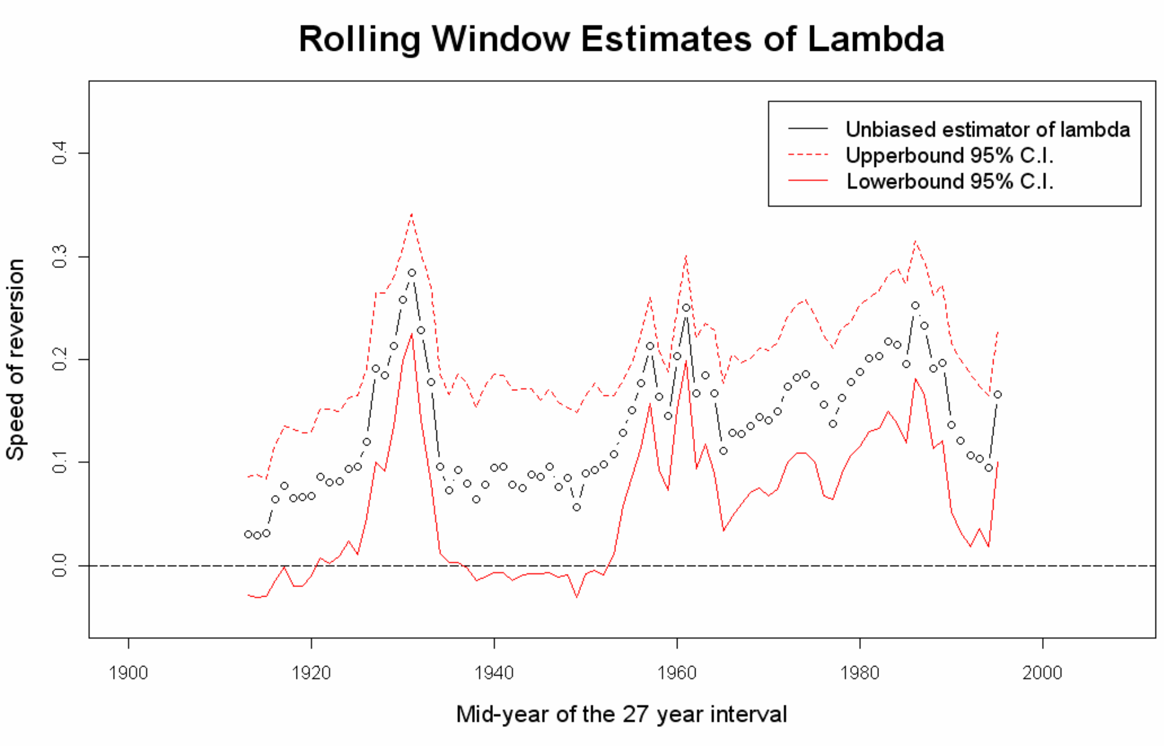
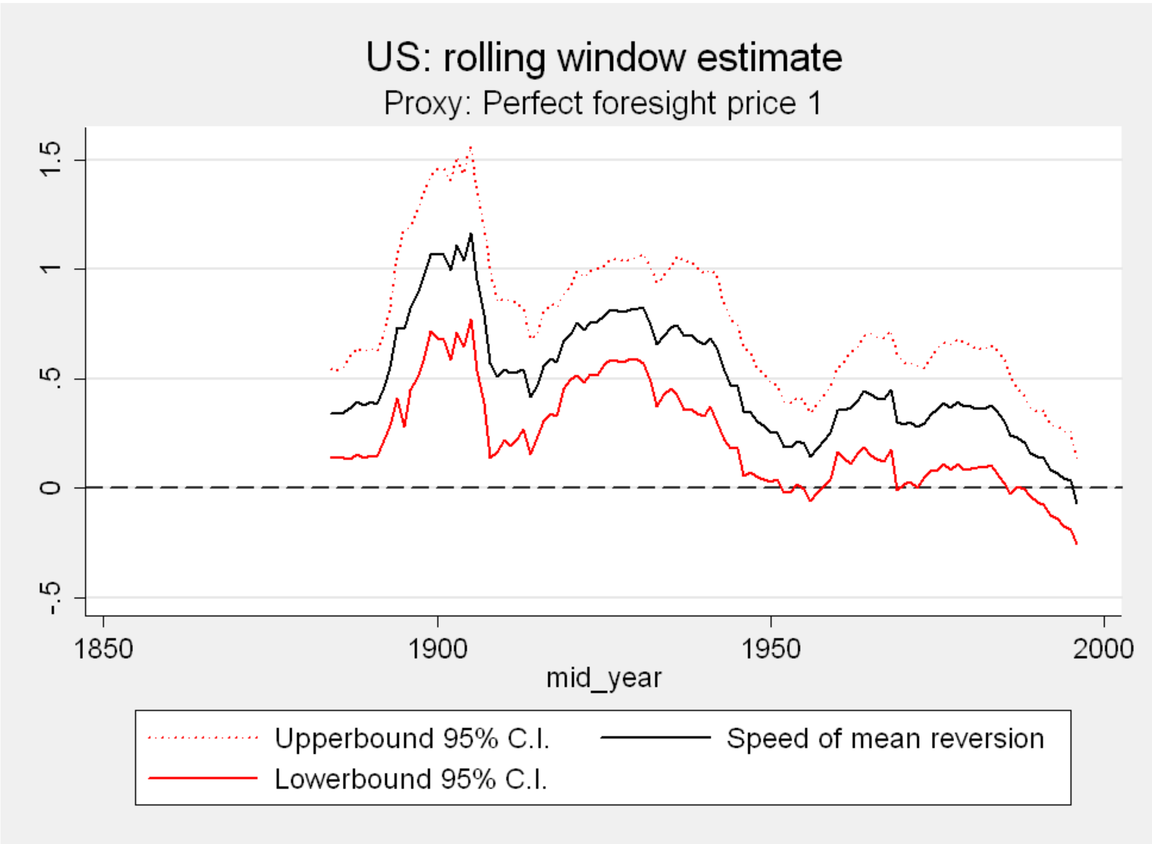
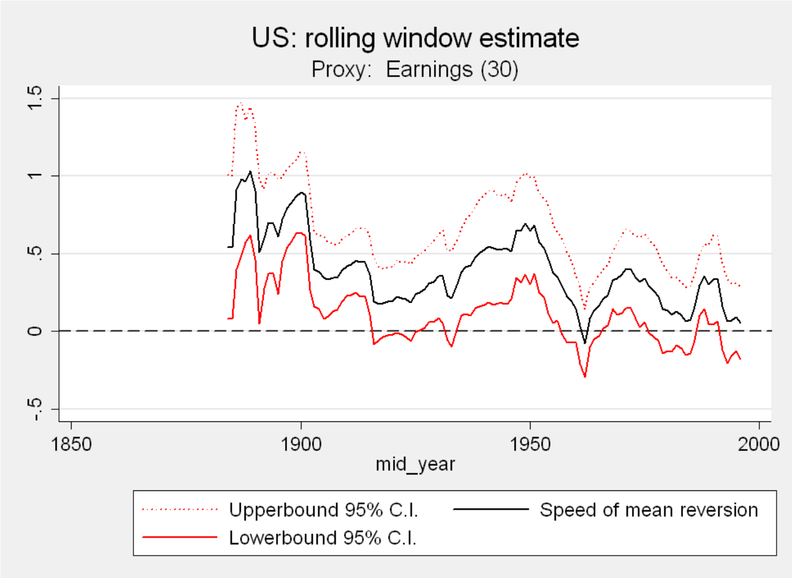



**Figure 2** **Rolling window estimates at country level**





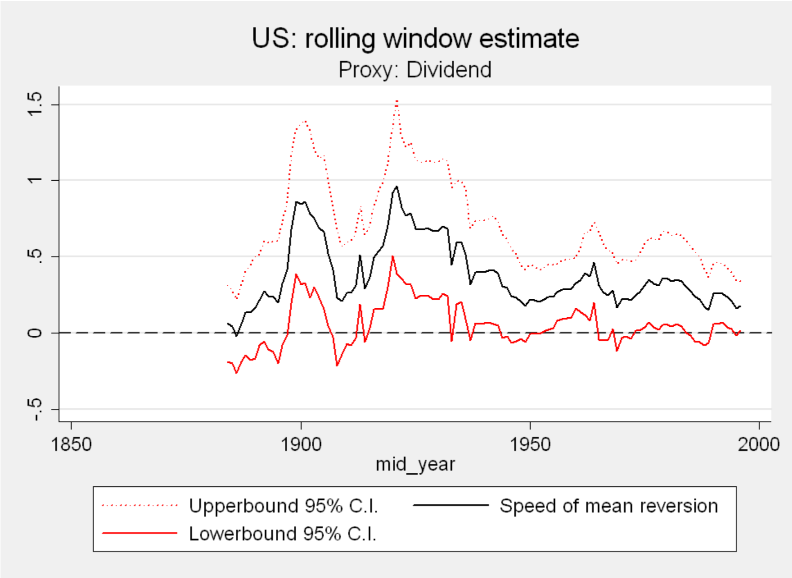
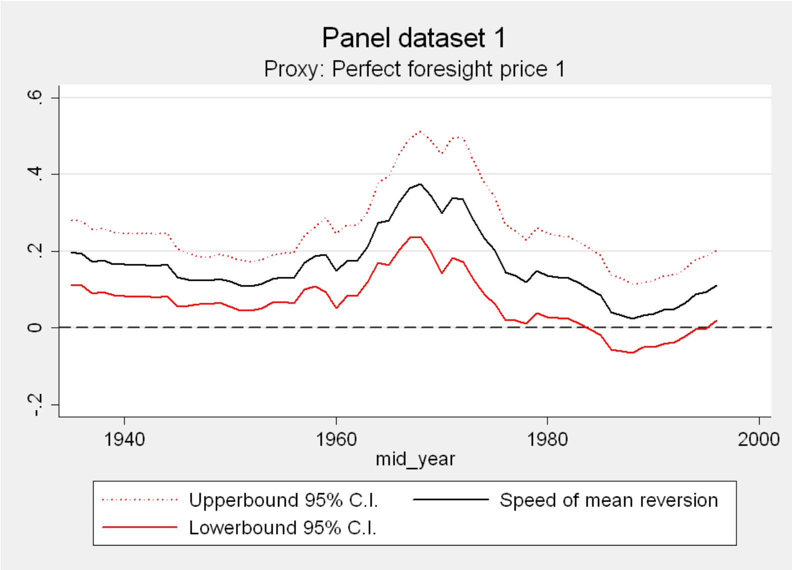




**Figure 3 Rolling window estimates for panel dataset 1**



## Conclusion

This thesis analyses the long term dynamic adjustment of stock prices to the fundamental value process. Building on previous findings on the long term relation between company fundamentals and stock prices we develop several proxies of the fundamental value process, whereby we explicitly take into account *expected* future cash flows instead of realised cash flows. We argue that the single equation Error Correction Model provides a better approximation of the dynamic process of relative mean reversion than the commonly used simple mean reversion model, based on the following findings:

- Not all relevant variables included in our datasets contain a unit root. Since the single equation ECM is appropriate for both co-integrated and long-memoried data, these stationary variables do not pose any problems to our estimation results;
- The short term effect is often significantly different from zero. Therefore, the simple mean reversion model, which assumes that there is no short term effect, is likely to lead to biased estimates;
- The co-integrating relation between the proxy for the fundamental value and the stock price is often different from one, and probably varies over time. The assumption of a constant co-integrating relation, which underlies the simple mean reversion model, is likely to influence the estimates of the speed of mean reversion.

Unlike previous studies on relative mean reversion, we already find significant evidence of mean reversion at the country level for all proxies except for the hindsight price. The significance of our findings is improved even further when the three long datasets of the United States, Sweden and Denmark are combined to a cross-section dataset. For our shorter panel dataset, including 13 countries, we do not find significant evidence of mean reversion, which stresses the importance of obtaining sufficiently long time series and correcting for small sample bias. Using rolling window estimation, we find large fluctuations in the speed of mean reversion over time. However, we can not confirm the conclusion of Spierdijk et al (2010) that the speed at which stocks revert to the fundamental value is higher in periods of high economic uncertainty. Our findings do suggest that the estimated speed of mean reversion depends crucially on the sample period. In addition, the mean reversion parameter is very small, and even turns out insignificant during some periods. This indicates that it would be unwise to base an investment strategy on mean reversion, given the large amount of risk in assuming an incorrect speed of mean reversion.

Long term investors like pension funds may be tempted to base the forecasts of their financial position on a mean reversion parameter. When this parameter is based on absolute mean reversion, stock returns are assumed to be negatively autocorrelated. This assumption decreases the long term risk. In addition, expected returns could be modelled as a function of returns in the past; a period of negative returns would lead to an upward adjustment of the forecast of expected returns in the coming years.
If the parameter is based on relative mean reversion, expected returns on individual assets are expected to revert to a proxy for the fundamental value process. When the proxy is based on stock indices, such as is the case in the studies of Balvers et al. (2000) and Spierdijk et al (2010), the proxy itself may be included in the investment portfolio. If this is the case, a reversion relation between different indices included in the portfolio may exist, leading to negative correlation between assets. When the proxy is based on company fundamentals, or other variables exogenous to the investment portfolio, prices are expected to revert to this exogenous mean over time. When multiple assets depend on the same mean, also correlation between assets may occur. Given the proxies which we have modelled, the mean itself can be expected to fluctuate over time. Given the uncertainty surrounding the correct

modelling of the fundamental value process, as well as the changing speed of mean reversion over time, it does not seem advisable to base forecasts of the financial position of pension funds and other long term investors on a parameter of relative mean reversion. Such a parameter is likely to lead to overly optimistic and unrealistic expectations.

The research on relative mean reversion could be further improved by developing proxies which capture the variation in the degree of risk averseness even more accurately. Even though the perfect foresight price, the hindsight price and the Gordon model include a discount rate, hereby capturing expectations regarding future cash flows, it has proven to be rather complicated to model a stochastic discount factor. When the discount rate is held constant during the sample period, the perfect foresight price and the hindsight price are basically a long moving average of dividends; these proxies will not make sharp movements unless dividends move much sharper. In addition, the Gordon model with constant discount rate and dividend growth rate shows exactly the same variation as the dividend process. The application of a structural break may be a first step in the right direction, but the extensive research on discount rates, of which we have only covered a fraction in this thesis, suggests that discount rates are likely to be more variable over time.

By applying a stochastic discount factor to our proxies, we may be able to approximate the fundamental value process more accurately. Fama (1991) suggests that '(…) if the variation through time in expected returns is rational, driven by shocks to tastes or technology, then the variation in expected returns should be related to variation in consumption, investments and savings.' [91] When the behaviour of expected returns can be related to business conditions, we may be able to model a proxy which accurately captures the variation in risk aversion over time through a stochastic discount factor. Consequently, the remaining deviation of the stock price from this fundamental value process can be interpreted as trading behaviour which further amplifies the stock price movements away from the fundamental value. As Fama (1991) mentions: 'In the end, I think we can hope for a coherent story that (…) related the behaviour of expected returns to the real economy in a rather detailed way. Or we can hope to convince ourselves that no such story is possible.'

[91] Fama (1991): 1610

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## Annex I Data description

Dataset 1

The first dataset consists of the stock indices of 13 countries, from 1973 to 2009, obtained from Thomson Reuters Datastream.[92] Datastream provides indices which are calculated based on a representative list of stocks for each market. The number of stocks for each market is determined by the size of the market. The sample covers a minimum of 75 - 80% of total market capitalisation. The following variables are obtained from DataStream: [93]

- Price index: expresses the theoretical growth in value of a share holding over a specified period, assuming that dividends are not reinvested to purchase additional units of stocks.
- Return index: expresses the theoretical growth in value of a share holding over a specified period, assuming that dividends are reinvested to purchase additional units of stocks.
- Dividend yield: total dividend amount for the index, expressed as a percentage of the total market value for the constituents of that index.
- Market value: the sum of share price multiplied by the number of ordinary shares in issues for each index constituent. The amount in issue is updated whenever new tranches of stock are issued or after a capital change.
- Price/earnings ratio: total market value divided by total earnings.

These variables are all provided in millions of units of local currency.

The exchange rates and inflation rates provided by Dimson et al (2002) are used to obtain the real values in US dollars, which enables comparison of the indices between countries and corrects for periods of high inflation. Dimson et al (2002) describe these variables as follows:

- The inflation rates are derived from the consumer price indices for each country, although for one or two early subperiods in a couple of countries, the wholesale price index is employed.
- The exchange rates are year-end rates, and where there is a choice, market rather than official rates have been used. Exchange Rates are expressed as the number of US dollars equivalent to one unit of the local currency.

The Dimson dataset contains inflation rates and exchange rates from 1900 to 2005. We extend these rates to 2009 with data obtained from Datastream, following the methodology described in Dimson et al (2002).

Dataset 2

Long time-series are obtained for the US, Danish and Swedish market. In order to analyse these time series as panel data the three series are combined, whereby the same time period (1922 – 2009) is used for all three markets.

*United States*
Shiller (2001) provides yearly stock prices, earnings and dividends and the Consumer Price Index for the US market from 1871–2009. The stock price data is based on the January values of the Standard and Poor Composite Stock Price Index, which reflects

[92] The countries included are: Australia, Belgium, Canada, Denmark, France, Germany, Ireland, Japan, Netherlands, South Africa, Switzerland, UK, US.
[93] See Thomson Reuters (2008) for the calculations of each variable and a detailed description of the equity indices.

all sectors of the US equity markets.[94] The data is provided in both nominal and real values in January 2010 US dollars.

*Denmark*

The Danish Institut for Nationaløkonomi has published an overview of annual total stock returns and dividend yields for the period 1922–1999. Nielsen and Risager (2001) indicate that: 'Because there are a large number of both small and large caps in the sample, returns are likely to be representative of the whole market.' The index is value weighted, whereby weights are adjusted at new issuances and withdrawals from the exchange. The variables are defined as follows:

- Annual total stock return: the sum of the dividend yield and the capital gain.
- Dividend yield: dividends paid out during the calendar year divided by the stock price quoted at the end of the previous year (late December). It is assumed that dividends are not reinvested within the year they are paid out.

This data is combined with the Danish total market value obtained from Datastream in order to calculate the total market value as well dividends from 1922 to 2009. The exchange rates and inflation rates provided by Dimson et al (2002) are used to obtain the real values in dollars for this time period.

*Sweden*

The Swedish Central Bank (Sveriges Riksbank) provides a yearly stock price index, a stock return index and a dividend index from 1919 to 2006, as described in Waldenström (2007). The variables are defined as follows:

- Stock price index: composite stock price index (exclusive of dividends) based on end-of-month quotes on the Stockholm Stock Exchange.
- Stock return index: composite stock return index (with dividends reinvested) based on end-of-month quotes on the Stockholm Stock Exchange.
- Long-run yield index: index number for annual dividends paid out on stocks listed on the Stockholm Stock Exchange

The Central Bank data is combined with the Swedish total market value obtained from Datastream in order to calculate the total market value as well dividends from 1919 to 2009. The exchange rates and inflation rates provided by Dimson et al (2002) are used to obtain the real values in dollars for this time period.

[94] Reference is made to Chapter 26 of Shiller (2001) 'Market Volatility', which provides a detailed description of the data.

## Annex II Deriving the Error Correction Model

*Static mean reversion model:*

$$p_t = p_t^* + u_t \tag{1.1}$$

$$u_t = \alpha u_{t-1} + v_t \tag{1.2}$$

*Basic mean reversion model*

$p_t = p_{t-1} + a + \lambda(p_t^* - p_{t-1}) + \in_t$

(2)

As indicated by Spierdijk et al (2010) equation (2) is directly derived from the two component model of equation (1.1) and (1.2), defining $\lambda = (1-\alpha)$ and

$\in_t = (1-\lambda)\delta_t + \eta_t$

and substituting the fundamental value process $p_t^*$ for $p_{t-1}^* + \delta_t$, as follows:

$$p_t = p_t^* + u_t \tag{1.1}$$

$$p_{t-1}^* + \delta_t + a + \alpha u_{t-1} + \eta_t$$

$$p_{t-1}^* + \delta_t + a + (1-\lambda).(p_{t-1} - p_{t-1}^*) + \eta_t$$

$$p_t^* + a + p_{t-1} - (p_t^* - \delta_t) - \lambda(p_{t-1} - (p_t^* - \delta_t)) + \eta_t$$

$$a + p_{t-1} + \lambda(p_t^* - p_{t-1}) + (1-\lambda)\delta_t + \eta_t$$

$$p_{t-1} + a + \lambda(p_t^* - p_{t-1}) + \in_t \tag{2}$$

*Single Equation Error Correction Model (ECM)*

$$\Delta p_t = \alpha_0 + \beta_0 \Delta p_t^* + \beta_1(p_{t-1} - \beta_2 p_{t-1}^*) + u_t \tag{3}$$

Equation (3) is directly derived from the two component model of equation (1.1) and (1.2)

$$p_t = p_t^* + u_t \tag{1.1}$$

When $p_t$ is regressed on $p_t^*$ we obtain the error correction term:

$\xi_t = p_t - \beta p_t^*$

whereby $\beta$ is a co-integrating coefficient.

The static co-integrating model (1.1) can be expressed in ECM form, as follows:

$$p_t - (p_{t-1} - p_{t-1}) = \beta p_t^* + \beta(p_{t-1}^* - p_{t-1}^*) + \psi_t$$

$$p_t - p_{t-1} = -(p_{t-1} - p_{t-1}^*) + \beta(p_t^* - p_{t-1}^*) + \psi_t$$

$$\Delta p_t = -(p_{t-1} - p_{t-1}^*) + \beta \Delta p_t^* + \psi_t$$

When we substitute $(p_{t-1} - p_{t-1}^*)$ by the lagged error correction term $\xi_{t-1}$, the ECM model becomes:

$$\Delta p_t = -\xi_{t-1} + \beta \Delta p_t^* + \psi_t$$

where the error correction coefficient term is -1 by construction, meaning a perfect adjustment made every period, which seems too restrictive. Thus, we allow for variation in the error correction coefficient by rewriting the model as follows:

$\Delta p_t = \alpha_0 + \beta_0 \Delta p_t^* + \beta_1 \xi_{t-1} + \psi_t$ whereby $\xi_t = p_t - \beta_2 p_t^*$

## Annex III Theory on co-integration and error correction

Spurious regression

Suppose that $p_t$ and $p_t^*$ are independent I(1) variables (contain a unit root), generated by:

$$p_t - p_{t-1} = v_t$$

$$p_t^* - p_{t-1}^* = w_t$$

Where $v_t \sim iid(0,\sigma_v^2)$ and $w_t \sim iid(0,\sigma_w^2)$ and $v_t$ and $w_t$ are independent of each other. Clearly there should be no systemic relation between $p_t$ and $p_t^*$, and the OLS estimate of the following regression is expected to be insignificantly different from zero as the sample size increases:

$$p_t = \beta p_t^* + u_t \qquad (1.1)$$

Granger and Newbold (1974) demonstrate that this regression will in fact lead to spurious results, whereby the coefficients are statistically significant even though there is no true relationship.

As $T \to \infty$,

a) the OLS estimate $\hat{\beta}$ obtained from (1.1), does not converge to the true value of zero

b) the t-statistics diverge to infinity

Co-integration

Suppose that $p_t$ and $p_t^*$ are I(1) variables linked by a long-run equilibrium relationship, than part of the stochastic processes of both variables will be shared, and deviations from the equilibrium relationship will be corrected over time:

$$p_t - p_{t-1} = v_t + \beta(p_{t-1} - p_{t-1}^*)$$

$$p_t^* - p_{t-1}^* = v_t + \beta(p_{t-1}^* - p_{t-1})$$

When I(1) variables share such a stationary linear relationship, these variables are termed to be co-integrated. Consequently, the linear combination $\xi_t = p_t - \beta p_t^*$ must be stationary, whereby we assume:

1) $\xi_t \sim iid(0,\sigma_\xi^2)$, which ensures that there is a stationary co-integrating relationship between $p_t$ and $p_t^*$.

2) $v_t$ and $w_t$ are stationary and independently distributed of $\xi_t$, implying that $p_t^*$ is exogenous.

Under these assumptions the OLS-estimate $\hat{\beta}$ is consistent (has an asymptotic normal distribution) and the t-statistics converge to a standard normal random variable. Consequently,

The Error Correction process

Engle and Granger (1987) suggested a model to capture both the short- and the long-run dynamics of co-integrated time series, whereby:

- First an estimate of $\xi_t$ is obtained by regressing $p_t$ on $p_t^*$.
- The lagged residuals of this regression are used as a measure of the error correction term in the following model:

  $$\Delta p_t = \alpha_0 + \beta_0 \Delta p_t^* + \beta_1 \xi_{t-1} + \psi_t$$

This approach assumes endogeneity between the cointegrating time series; it does not clearly distinguish the dependent from the independent variables. In addition, the

Engle and Granger approach is only appropriate when the variables are truly co-integrated. Since the power of unit root tests is low, especially in small samples sizes, and the co-integrating relationship may vary over time, we are likely to draw faulty inferences from the Engle and Granger (1987) procedure.

Since our sample size is small and the assumption of continuous co-integration may not hold over long time periods, the preferred model is a single equation ECM:

$$\Delta p_t = \alpha_0 + \beta_0 \Delta p_t^* + \beta_1 (p_{t-1} - \beta_2 p_{t-1}^*) + u_t \qquad (3)$$

All the variables in the single equation ECM are stationary, and therefore, the ECM has no spurious regression problem. This model is appropriate for both co-integrated and long-memoried, but stationary data.[95] The single equation ECM requires exogeneity, as this model clearly distinguishes between the dependent and the independent variable. Exogeneity is assumed given the finding of Campbell and Shiller (2001) that prices rather than fundamentals (dividends or earnings) do most of the adjustment in bringing the price-earnings (P/E) and price-dividend (P/D) ratios back towards their long-run equilibrium levels.

[95] Pesaran and Shin (1999) demonstrate that Autoregressive Distributed Lag (ARDL) Models, which are appropriate for stationary data, are in fact equivalent to ECMs, which indicates that ECM's can be applied to both stationary and non-stationary data.

## Annex IV Estimating the discount rate

We estimate the expected return by comparing the geometric mean of the realized total return for each country to:

1. The geometric mean of the estimates provided by the Gordon constant dividend growth model. The Gordon return is calculated as follows:

   $RG_{t+1} = \frac{D_{t+1}}{P_t} + G_{t+1}$ = real dividend yield + real dividend growth rate

   whereby $G_{t+1} = \log D^i_{t+k} - \log D^i_t$
2. The estimates of the expected return provided by Jorion et al (1999), which are based on the geometric mean of the capital gain, covering the 1930-1996 period.
3. The estimates of the expected return provided by Dimson et al (2002), which are based on the geometric mean of the total return. Dimson et al (2002) calculate the expected return for various time periods, whereby we use:
   - the 1920 – 2000 period for dataset 1
   - the 1970 – 2000 period for dataset 2

*Dataset 1 Estimates of the expected return (in %)*

| | Total return | Gordon estimate | Dimson estimate | Jorion estimate |
|---|---|---|---|---|
| United States | 6.32 | 8.07% before 1950, 4.74% after 1950 | 6.7 | 6.95 |
| Denmark | 6.18 | 5.04 | 5.1 | 5.19 |
| Sweden | 5.89 | 12.43 | 7.6 | 7 |

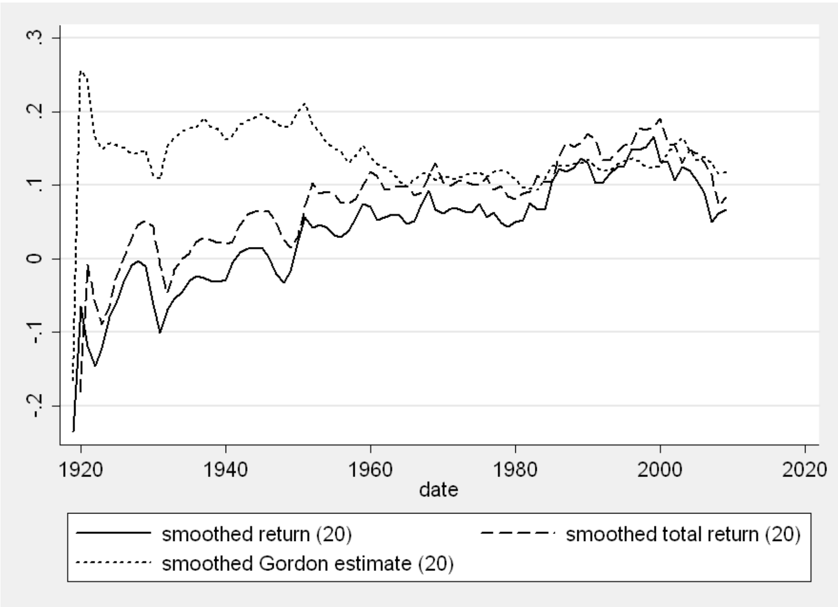
*Dataset 2 Estimates of the expected return (in %)*

| | Geometric mean total return | Geometric mean Gordon estimate | Dimson estimate 1970 – 2000 Based on total return | Jorion estimate 1930 -1996 Based on capital gain |
|---|---|---|---|---|
| Australia | 6.49 | 17.14 | 4 | n.a. |
| Belgium | 5.44 | 14.54 | 7.4 | 3.51 |
| Canada | 7.81 | 16.29 | 5.3 | 5.35 |
| Denmark | 7.43 | 11.00 | 8.1 | 5.19 |
| France | 8.09 | 18.00 | 8.3 | 4.29 |
| Germany | 7.74 | 11.61 | 6.1 | 5.81 |
| Ireland | 10.48 | 17.50 | 8.6 | 5.14 |
| Japan | 5.09 | 9.37 | 3.9 | n.a. |
| Netherlands | 8.93 | 11.86 | 10 | 4.74 |
| South Africa | 7.04 | 11.90 | 6 | n.a. |
| Switzerland | 10.61 | 14.72 | 6 | 6.84 |
| UK | 7.35 | 14.39 | 7.6 | 5.2 |
| USA | 8.56 | 10.94 | 7.2 | 6.95 |

Is there a structural break in the expected return?

In line with the findings of Fama and French (2002) for the US market, we examine whether a structural break should be applied to the Swedish and Danish market as well. We do this by comparing the mean of the Gordon estimate in several time periods to the mean of the realised real total return. In addition, we visually inspect a 20-year moving average of each estimate.

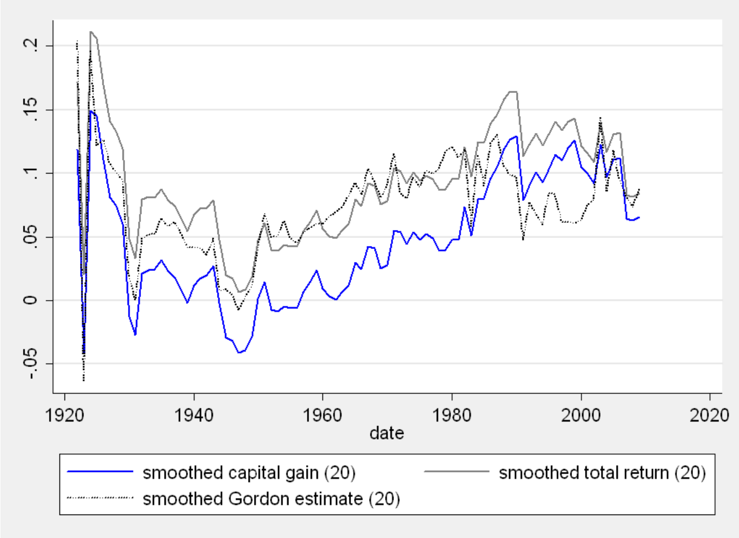
*Sweden*




| Time period | Gordon estimate (geom. mean) | Total return (geom. mean) |
|---|---|---|
| 1919-1929 | 0.132652 | 0.031936 |
| 1930-1939 | 0.133672 | 0.9138125 |
| 1940-1949 | 0.184559 | 0.071423 |
| 1950-1959 | 0.113059 | 0.146129 |
| 1960-1969 | 0.096464 | 0.047531 |
| 1970-1979 | 0.132715 | 0.09284 |
| 1980-1989 | 0.111295 | 0.215378 |
| 1990-1999 | 0.11708 | 0.128121 |
| 2000-2009 | 0.096509 | 0.9095994 |

Contrary to the findings of Fama and French (2002) for the US, in Sweden the Gordon estimate and the capital gain/ total return seem to converge *after* 1950. The mean of the Gordon estimate is indeed much higher than the mean of the total return for the period before 1950. Nevertheless, thereafter total return and the Gordon estimate are not in line; especially for the period from 1980 – 1989 the total return is much higher. Thus, no clear structural break can be identified for the Swedish market.

*Denmark*




| Time period | Gordon estimate (geom.mean) | Total return (geom. mean) |
|---|---|---|
| 1922-1929 | 0.060725 | 0.103323 |
| 1930-1939 | -0.0488492 | -0.0332149 |
| 1940-1949 | 0.015033 | 0.013686 |
| 1950-1959 | 0.084492 | 0.10419 |
| 1960-1969 | 0.060314 | 0.040403 |
| 1970-1979 | 0.112475 | 0.112301 |
| 1980-1989 | 0.072382 | 0.160629 |
| 1990-1999 | 0.075232 | 0.074776 |
| 2000-2009 | 0.033126 | 0.0035833 |

Capital gain, total return and the Gordon estimate all seem to follow the same trend over time, although the Gordon estimate drops below the capital gain after 1980. Even though the means diverge in several time periods, there is no clear ‘structural break’ such as identified by Fama and French (2002) for the US market.

## Annex V Tests for unit root and co-integration

### Dataset 1: Individual countries

Augmented Dickey Fuller (ADF) test
H0: Unit root/ I(1)
H1: Stationary
Reject Ho when the t-value < ADF critical value.

United States and Sweden:
ADF critical value (5% level) excluding time trend: -2.888
ADF critical value (5% level) including time trend: -3.445

Denmark:
ADF critical value (5% level) excluding time trend: -2.900
ADF critical value (5% level) including time trend: -3.463

| Variables (log) | United States t-statistics | # lags/ | Trend | Sweden t-statistics | # lags/ | Trend | Denmark t-statistics | # lags/ | Trend |
|---|---|---|---|---|---|---|---|---|---|
| Price index | -2.395* | 2 | T | -2.568 | 0 | T | -1.625 | 2 | - |
| Return index | -2.789* | 2 | T | - | - | | - | - | |
| Dividend | -3.634** | 0 | T | 1.107 | 2 | - | -2.094 | 1 | T |
| Earnings (30) | 0.983 | 2 | - | n.a. | n.a. | | n.a. | n.a. | |
| Perfect foresight price 1 | -3.691** | 2 | T | 1.340 | 2 | - | -1.855 | 1 | T |
| Perfect foresight price 2 | -4.374*** | 1 | T | 1.362 | 2 | - | -1.855 | 1 | T |
| Hindsight price 1 | -3.738** | 2 | T | 1.964 | 2 | - | -1.350 | 1 | T |
| Hindsight price 2 | -4.633*** | 1 | T | 1.925 | 2 | - | -1.350 | 1 | T |
| Gordon 1 | -3.634** | 0 | T | 1.107 | 2 | - | -2.094 | 1 | T |
| Gordon 2 | -2.899 | 0 | T | 1.107 | 2 | - | -2.094 | 1 | T |

n.a.: the variable is not included in the dataset
* = significant at 10% c.l.
** = significant at 5% c.l.
***= significant at 1% c.l.

In Sweden and Denmark we can not reject the zero hypothesis of a unit root at the 5% c.l. for any of the variables. In the United States, all independent variables with the exception of Earnings (30) and Gordon 2, are found to be stationary.

Engle Granger test for co-integration
H0: Spurious regression
H1: Co-integration
DF critical value (5% level) : -2.888

| Dependent variable: **Log (price index)**<br>Independent variables (log) | **United States**<br>t-statistics | **Sweden**<br>t-statistics | **Denmark**<br>t-statistics |
|---|---|---|---|
| Dividend | -3.95*** | -3.374** | -3.917*** |
| Earnings (30) | -2.735* | n.a. | n.a. |
| Perfect foresight price 1 | -3.634 *** | -3.372** | -2.956** |
| Perfect foresight price 2 | -3.601*** | -3.384** | -2.956** |
| Hindsight price 1 | -3.545*** | -2.151 | -2.725* |
| Hindsight price 2 | -3.553*** | -2.148 | -2.725* |
| Gordon 1 | -3.95*** | -3.374** | -3.917*** |
| Gordon 2 | -3.18** | -3.374** | -3.917*** |

In Sweden and Denmark, all variables (with the exception of the natural logarithm of the hindsight price) are found to be co-integrated with capital gain, which is in line with the findings of the ADF test. In the United States, all variables with the exception of the natural logarithm of Earnings (30) are found to be co-integrated with capital gain. This finding contradicts the outcomes of the ADF test, since stationary variables can not be co-integrated.

When the dependent and the independent variable both contain a unit root, and are co-integrated, an Error Correction Model can be applied. But, as mentioned in chapter 4, single equation ECM's can also be applied to stationary data, given that Autoregressive Distributive Lag (ARDL) models are in fact equivalent to ECM's.[96] Thus, even when we do not have consistent evidence on the existence of a co-integrating relation and/ or stationary variables are included in the regression, as is the case in the US, the single equation ECM can still be applied to estimate the speed of mean reversion. The same applies to the outcomes of the unit root and co the panel datasets reported below.

**Panel data**

Panel unit root test

Im-Pesaran-Shin test

Ho: All panels contain unit roots
H1: Some panels are stationary

| Variable (log) | **Dataset 1** | | **Dataset 2** | |
|---|---|---|---|---|
| | Statistic | P-value | Statistic | P-value |
| Price index | 2.6986 | 0.9965 | -2.8445 | 0.0022*** |
| Return index | - | - | -2.1630 | 0.0153** |
| Dividends | 2.9868 | 0.9986 | -1.1268 | 0.1299 |
| Earnings (10) | n.a. | n.a. | 3.4966 | 0.9998 |
| Perfect foresight price 1 | 4.4768 | 1.0000 | -6.8815 | 0.0000*** |
| Perfect foresight price 2 | 4.2987 | 1.0000 | -5.4074 | 0.0000*** |
| Hindsight price 1 | 4.4837 | 1.0000 | - | - |
| Hindsight price 2 | 4.4515 | 1.0000 | - | - |
| Gordon 1 | 2.9869 | 0.9986 | -1.1268 | 0.1299 |
| Gordon 2 | 3.0776 | 0.9990 | n.a. | n.a. |

n.a.: the variable is not included in the dataset
-    : the test can not be performed

Test for co-integration

Bivariate Engle-Granger methodology in combination with the IPS unit root test

H0: all panels contain spurious regression
H1: some panels are co-integrated

| Dependent variable: **log (price index)** | **Dataset 1** | | **Dataset 2** | |
|---|---|---|---|---|
| Independent variable (log) | Statistic | P-value | Statistic | P-value |
| Dividends | 2.7371 | 0.0031*** | -6.9251 | 0.0000*** |
| Earnings (10) | n.a. | n.a. | -2.6107 | 0.0045*** |
| Perfect foresight price 1 | -2.5613 | 0.0052*** | -5.0956 | 0.0000*** |
| Perfect foresight price 2 | -2.6262 | 0.0043*** | -5.0911 | 0.0000*** |
| Hindsight price 1 | 0.8300 | 0.7967 | - | - |
| Hindsight price 2 | 0.6223 | 0.7331 | - | - |
| Gordon 1 | -2.7371 | 0.0031*** | -6.9251 | 0.0000*** |
| Gordon 2 | -2.7371 | 0.0031*** | n.a. | n.a. |

[96] Pesaran and Shin (1999)

## Annex VI Empirical results based on total return

The research findings reported in chapter 6 are all based on the price index (PI), whereby the dependent variable of equation (4.2) is equal to the continuously compounded capital gain:

$$\Delta p_t^i = \log(PI_{t+1}^i) - \log(PI_t^i)$$

In order to assess the robustness of our findings we re-estimate the single equation Error Correction Model based on the total return index (RI), whereby the dependent variable is equal to the continuously compounded total return:

$$\Delta p_t^i = \log(RI_{t+1}^i) - \log(RI_t^i)$$

At country level, we find that only the perfect foresight price gives a significant finding of the speed of mean reversion for both the US, Sweden and Denmark. In the US, also dividends and Gordon1 give a significant finding of $\hat{\beta}_1^i$, but this is not the case in the other two countries.
When we combine these three countries in panel dataset 1, we find again that only the perfect foresight price gives a significant estimate of $\hat{\beta}_1^i$ when Fixed Effect estimation is applied. When we repeat these regressions with Generalized Least Squares (GLS) we do not find any significant estimates of the speed of mean reversion. In addition, all significant estimates of the speed of mean reversion are much smaller than the estimates reported in chapter 6.

The findings based on panel dataset 2 are very similar to the findings reported in chapter 6, which is not surprising since the summary statistics of the capital gain and the total return for dataset 2 are very similar (see Table 2.1 and 2.2 in chapter 5). When we estimate the single equation ECM with Fixed Effects or Random Effects, we find very high and significant estimated of $\hat{\beta}_1^i$. Following the correction for cross-section correlation and heteroskedasticity by using GLS, all estimates become very small and insignificant. These findings stress once more the importance of obtaining sufficiently long time series to be able to find significant estimates of the speed of mean reversion.

**United States (1871 – 2009): FGLS estimation**

| Proxy (log) | $\hat{\beta}_0^i$ | $\hat{\beta}_1^i$ | $\hat{\beta}_2^i$ |
|---|---|---|---|
| Dividend/ Gordon 1 | -0.023<br>(-0.17) | 0.041<br>(2.36)** | 6.674<br>(165.01)*** |
| Smoothed earnings (30) | 0.820<br>(1.05) | -0.009<br>(-0.40) | 1.015<br>(12.46)*** |
| Perfect foresight price 1 | 1.123<br>(4.11)*** | -0.054<br>(-2.80)*** | 5.696<br>(172.26)*** |
| Perfect foresight price 2 | 1.106<br>(4.13)*** | -0.055<br>(-2.80)*** | 5.196<br>(173.49)*** |
| Hindsight price 1 | -0.447<br>(-1.42) | 0.021<br>(1.13) | 7.871<br>(133.49)*** |
| Hindsight price 2 | -0.396<br>(-1.30) | 0.017<br>(0.87) | 7.588<br>(123.60)*** |
| Gordon 2 | 0.0515<br>(0.39) | 0.024<br>(1.27) | 5.277<br>(151.50)*** |

* = significant at 10% c.l.
** = significant at 5% c.l.
***= significant at 1% c.l.

**Sweden (1919 – 2009): FGLS estimation**

| | $\hat{\beta}_0^i$ | $\hat{\beta}_1^i$ | $\hat{\beta}_2^i$ |
|---|---|---|---|
| Dividend/ Gordon1/ Gordon 2 | -0.261<br>(-1.29) | -0.006<br>(-0.13) | 1.312<br>(54.34)*** |
| Perfect foresight price 1 | 0.248<br>(0.63) | -0.081<br>(-2.22)** | 1.708<br>(81.26)*** |
| Perfect foresight price 2 | 0.402<br>(0.97) | -0.081<br>(-2.13)** | 1.789<br>(84.55)*** |
| Hindsight price 1 | 1.789<br>(-2.65)** | 0.020<br>(0.46) | 0.133<br>(1.84)* |
| Hindsight price 2 | -1.533<br>(-2.30)** | -0.050<br>(-1.01) | 3.286<br>(37.02)*** |

**Denmark (1922 – 2009): FGLS estimation**

| Proxy (log) | $\hat{\beta}_0^i$ | $\hat{\beta}_1^i$ | $\hat{\beta}_2^i$ |
|---|---|---|---|
| Dividend/ Gordon | -0.066<br>(-0.65) | 0.020<br>(0.48) | 3.072<br>(55.12)*** |
| Perfect foresight price | 0.406<br>(1.47) | -0.097<br>(-2.60)** | 2.131<br>(71.64)*** |
| Hindsight price | -0.304<br>(-0.87) | 0.034<br>(0.71) | 2.372<br>(57.74)*** |

**Dataset 1: FE or RE estimation**

Reported statistics FE: t
Reported statistics RE: P>|z|

| | $\hat{\beta}_0^i$ | $\hat{\beta}_1^i$ | $\hat{\beta}_2^i$ | Estimation method |
|---|---|---|---|---|
| Dividend | 0.008<br>(0.918) | -0.007<br>(0.394) | -3.081<br>(0.000)*** | RE |
| Gordon 1 | 0.008 (0.917) | -0.007<br>(0.375) | -0.312<br>(0.000)*** | RE |
| Gordon 2 | 0.010<br>(0.893) | -0.007<br>(0.403) | -0.411<br>(0.000)*** | RE |
| Perfect foresight price 1 | 0.399<br>(1.95)** | -0.041<br>(-2.59)*** | 2.196<br>(133.50)*** | FE |
| Perfect foresight price 2 | 0.427<br>(2.11)** | -0.044<br>(-2.86)*** | 2.161<br>(133.91)*** | FE |
| Hindsight price 1 | -0.457<br>(0.058)* | -0.002<br>(0.775) | 1.473<br>(0.000)*** | RE |
| Hindsight price 2 | -0.417<br>(0.078)* | -0.003<br>(0.745) | 1.067<br>(0.000)*** | RE |

**Dataset 1: GLS estimation**

Reported statistics: P>|z|

| Depvar: price | $\beta_0$ | $\beta_1$ | $\beta_2$ |
|---|---|---|---|
| Perfect foresight price 1 | -0.005 (0.611) | - | - |
| Perfect foresight price 2 | 0.333 (0.041)** | -0.006 (0.507) | 0.100 (0.000)*** |
| Hindsight price 1 | -0.096 (0.587) | -0.009 (0.356) | 0.111 (0.000)*** |
| Hindsight price 2 | -0.075 (0.662) | -0.009 (0.343) | 0.081 (0.000)*** |
| Gordon 1 | -0.080 (0.142) | -0.013 (0.152) | - |
| Gordon 2 | -0.077 (0.159) | -0.013 (0.150) | - |
| Dividend | -0.080 (0.144) | -0.013 (0.151) | -0.084 (0.000)*** |

\- No Stata output

**Dataset 2: FE or RE estimation**

Reported statistics FE: t
Reported statistics RE: P>|z|

| | $\hat{\beta}_0^i$ | $\hat{\beta}_1^i$ | $\hat{\beta}_2^i$ | Estimation method |
|---|---|---|---|---|
| Earnings (10) | 1.5179 (19.49)*** | -0.3797 (-13.57)*** | 0.7009 (130.30)*** | FE |
| Dividend/ Gordon | 0.6159 (10.05)*** | -0.1528 (-4.82)*** | 0.8337 (76.58)*** | FE |
| Perfect foresight price 1 | -0.2585 (-1.89)* | -0.2806 (-10.08)*** | 1.0665 (107.42)*** | FE |
| Perfect foresight price 2 | -0.1018 (-0.72) | -0.3063 (-9.91)*** | 0.3741 (11.48)*** | FE |
| Hindsight price 1 | -0.4946 (-2.90)*** | -0.0888 (-2.60)** | 0.6332 (37.63)*** | FE |
| Hindsight price 2 | -0.4406 (-2.63)*** | -0.0894 (-2.58)** | 0.6295 (37.17)*** | FE |

* = significant at 10% c.l.
** = significant at 5% c.l.
***= significant at 1% c.l.

**Dataset 2: GLS estimation**

Reported statistics: P>|z|

| | $\hat{\beta}_0^i$ | $\hat{\beta}_1^i$ | $\hat{\beta}_2^i$ |
|---|---|---|---|
| Earnings (10) | 0.9338518 (0.000)*** | -0.0060852 (0.111) | -1.261769 (0.000)*** |
| Dividend/ Gordon | 0.568267 (0.000)*** | -0.0051445 (0.319) | 1.723067 (0.000)*** |
| Perfect foresight price 1 | 0.1253811 (0.139) | -0.0012637 (0.791) | -2.294956 (0.000)*** |
| Perfect foresight price 2 | 0.1894732 (0.197) | -0.004646 (0.412) | - |
| Hindsight price 1 | -0.6661139 (0.000)*** | 0.0002847 (0.962) | 10.57905 (0.000)*** |
| Hindsight price 2 | -0.6159857 (0.000)*** | -5.68e-06 (0.999) | 15.6843 (0.000)*** |

\- No Stata output