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## An Empirical Analysis of the 20th Century

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# Mean Reversion in International Stock Markets: An Empirical Analysis of the 20th Century

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**Abstract**

This paper analyzes mean reversion in international stock markets during the years 1900 – 2009, using annual data. Our panel of stock indices in 18 OECD countries allows us to analyze in detail the dynamics of the mean-reversion process. In the period 1900 – 2009 it takes stock prices about 18.5 years, on average, to absorb half of a shock. However, using a rolling-window approach we establish large fluctuations in the speed of mean reversion over time. The highest mean reversion speed is found for the period including the Great Depression and the start of World War II. Furthermore, the early years of the Cold War and the period containing the Oil Crisis of 1973, the Energy Crisis of 1979 and Black Monday in 1987 are also characterized by relatively fast mean reversion. We document half-lives ranging from a minimum of 2.0 years to a maximum of 22.6 years, which underlines the fact that the choice of data sample contributes substantially to the evidence in favor of mean reversion. Our results suggest that the speed at which stocks revert to their fundamental value is higher in periods of high economic uncertainty, caused by major economic and political events.

**Keywords:** mean reversion, market efficiency, cointegration

**JEL classification:** C23, G14, G15

# 1 Introduction

In early March 2009, many stock markets across the world dropped to their lowest value since the dot-com crisis. In less than two years, U.S. equity market indices lost more than 50% of their value. At the time, a discussion was going on about future stock price movements. Some argued that when stocks are down over 50%, an increase must surely follow. And the increase followed indeed. At the end of 2009, stock markets were up more than 30% relative to March 2009. Looking back, it is tempting to think that the increase following the deep drop might have been expected.

The presence or absence of mean reversion has important economic implications. Various studies show that excess returns can be earned by exploiting the mean reversion of stock prices (De Bondt & Thaler 1985, 1987, Jegadeesh & Titman 1993, Balvers et al. 2000, Campbell & Shiller 2001, Gropp 2004). Furthermore, mean reversion implies that stocks become less risky in the long run, making them more attractive for long-term investors. In a study about pension fund regulation, Vlaar (2005) argues that mean reversion in stock prices would strongly increase the attractiveness of equity investments for pension funds. If stock prices are mean-reverting in the long run, low returns are followed by higher expected future returns, which could stimulate pension funds to invest in equity after a downfall of the stock market.

Do stock prices really exhibit mean-reverting behavior in the long run? For more than two decades the economic literature has attempted to answer this question. Although early studies document significant mean reversion, the general thought on the subject is that convincing evidence has yet to emerge.

The economic literature distinguishes between so-called absolute and relative mean reversion. With absolute mean reversion, stock prices are mean-reverting relative to an unspecified mean value. This is equivalent to negative autocorrelation in stock returns. Specifications based on relative mean reversion generally posit a direct relation between stock prices and fundamental indicators, such as dividends and earnings. Fama & French (1988*b*) and Poterba & Summers (1988) were the first to provide empirical evidence in favor of absolute mean reversion. Fama & French (1988*b*) document that $25-40\%$ of the variation in $3-5$ year stock returns can be attributed to negative serial correlation.

A major problem in analyzing mean reversion over long horizons is the limited amount of available data. Fama & French (1988*b*) and Poterba & Summers (1988) analyze the time period from 1926 to 1985, using yearly overlapping returns (based on monthly data) to increase the number of observations. Both studies base their results on long-term returns, with investment horizons between one and ten years. To deal with the issue of dependency, which is inherent in the use of overlapping observations, they apply the method of Hansen & Hodrick (1980). However, this approach suffers from substantial small-sample bias. Richardson & Smith (1991) show that the evidence for long-term mean reversion disappears if the small-sample bias is removed. Moreover, Fama & French (1988*b*) ignore the seasonal effects in stock price movements. Jegadeesh (1991) shows that mean reversion in stock prices is entirely concentrated in January.

Balvers et al. (2000) take a different approach and focus on relative instead of absolute mean reversion. According to Balvers et al. (2000), the stationary relation between the fundamental value of a stock and a benchmark index permits direct assessment of the speed of mean reversion. Moreover, they use annual instead of monthly data to avoid the problem of seasonality. To estimate the mean-reversion process more accurately, Balvers et al. (2000) adopt a panel data approach. Comparing the stock indices of eighteen countries to a world index benchmark during the period 1970 − 1996, they establish significant mean reversion, with a half-life of approximately 3.5 years. The half-life measures the period it takes for stock prices to absorb half of a shock. Balvers et al. (2000) find a 90% confidence interval for the half-life equal to $[2.4, 5.9]$ years.

Several arguments plead against the assumption of a constant speed of mean reversion. For example, Kim et al. (1991) conclude that mean reversion is a pre World War II phenomenon only. Poterba & Summers (1988) find that the Great Depression had a significant influence on the speed of mean reversion. Moreover, we may expect the speed of mean reversion to depend on the economic and political environment; see e.g. Kim et al. (1991). Consequently, the speed of mean reversion is expected to fluctuate over time. Additionally, during long sample period structural breaks in the behavior of stock returns are likely to occur, resulting in model coefficients that change over time (Rapach & Wohar 2006). To our knowledge all previous studies in the field examine mean reversion in a static framework, thereby ignoring fluctuations in the speed of mean reversion over time. In our study we apply the panel data approach of Balvers et al. (2000) to a long data sample of international stock indices. Our large sample of stock indices in 19 countries, spanning a period of more than a century, allows us to analyze in detail the dynamics of the mean-reversion process. In the 1900 – 2009 period, it takes stock prices on average 18.5 years to absorb half of a shock. However, using a rolling-window approach we establish large fluctuations in the speed of mean reversion over time. The highest speed of mean reversion is found for the period including the Great Depression and the start of World War II. Similarly, the early years of the Cold War and the period containing the Oil Crisis of 1973, the Energy Crisis of 1979 and Black Monday in 1987 also show relatively fast mean reversion. We document half-lives ranging from a minimum of 2.0 years to a maximum of 22.6 years, which underlines the fact that the choice of the data sample contributes substantially to the evidence in favor of mean reversion. Our results suggest that stocks revert more rapidly to their fundamental value in periods of high economic uncertainty, caused by major economic and political events.

The remainder of this paper is organized as follows. Section 2 provides an overview of twenty years of research on the mean-reverting behavior of stock prices. The approach used in this paper to test for mean reversion is explained in Section 3. Next, Section 4 describes the data used for the empirical analysis of Section 5. The issue of time-varying mean reversion is addressed in Section 6. Finally, Section 7 concludes.

## 2 Long-term mean reversion: 20 years of research

Some studies have found evidence in favor of mean reversion, whereas others have established strong evidence against it. Several theories have been presented to explain mean reversion in stock prices. These explanations are strongly related to the issue of market efficiency. The efficient market hypothesis states that all available information is reflected in the value of a stock (Fama 1991). Mean reversion in stock prices may reflect market inefficiency. According to Poterba & Summers (1988), mean reversion may be caused by the irrational behavior of noise traders, resulting in stock prices that take wide swings away from their fundamental value. Irrational pricing behavior, in turn, can be caused by fads (McQueen 1992, Summers 1986), overreaction to financial news (De Bondt & Thaler 1985, 1987) or investor's opportunism (Poterba & Summers 1988). Mean reversion in stock prices may also occur in efficient markets. Assuming that all available information is incorporated into stock prices, the value of a stock is determined by the expected returns per share. Consequently, mean reversion is observed when expected returns are mean-reverting (Summers 1986).[1] Fluctuations in expected returns may be explained from uncertainty about the survival of the economy, caused by e.g. a world war or a depression (Kim et al. 1991). Alternatively, they can be caused by rational speculative bubbles and uncertain company prospects can cause fluctuations in expected returns (McQueen 1992). Therefore, mean reversion in stock prices does not contradict market efficiency (Fama & French 1988*b*).

## 2.1 Absolute mean reversion

Fama & French (1988*b*) were the first to document significant evidence in favor of absolute mean reversion at long horizons. They examine several investment horizons between one and ten years and document significant mean reversion, which explains $25 - 40\%$ of the variation in $3 - 5$ year stock returns. Poterba & Summers (1988) use a specific property of the random walk to obtain significant evidence in favor of mean reversion. They establish long-run mean reversion in the United States and several other developed countries. The lack of significance in their results is attributed to the absence of more powerful statistical tests to reject the null hypothesis.

Both Fama & French (1988*b*) and Poterba & Summers (1988) analyze the time period from 1926 to 1985 and work with yearly overlapping stock returns to increase the number of observations. The issue of dependency, which is inherent to the use of overlapping observations, is solved applying the method of Hansen & Hodrick (1980). Richardson & Smith (1991) criticize this approach and address the problem of small-sample bias. They show that the evidence supporting long-term mean reversion disappears if they remove the small-sample bias. Moreover, Richardson & Stock (1990) argue that the use of a larger overlapping interval at longer investment horizons increases the power of the statistical tests used to test the random walk hypothesis. Their more powerful statistical test does not result in a rejection of the random walk hypothesis. Jegadeesh (1991) raises the issue of seasonality caused by the use use of monthly overlapping stock returns.

Apart from the issues related to the use of monthly overlapping stock returns, the results of

Fama & French (1988*b*) are also subject to other types of criticism. McQueen (1992) addresses the issue of heteroskedasticity in the sample period. The highly volatile years tend to have a larger influence on the results because of their relatively heavy weights. McQueen (1992) finds that the highly volatile periods exhibit stronger mean-reverting tendencies and that the overall evidence of mean reversion is therefore overstated. Kim & Nelson (1998) and Kim et al. (1998) criticize Fama & French (1988*b*) and Poterba & Summers (1988) on similar grounds. The issue of heteroskedasticity is directly linked to another point of criticism. Periods of high volatility may not be representative for current stock price behavior. Poterba & Summers (1988) note that the Great Depression has substantial influence on the estimates of the mean-reversion parameters. Excluding this period considerably weakens the evidence of mean reversion. Kim et al. (1991) divide the total sample period into a period before and a period after World War II and conclude that mean reversion is a pre World War II phenomenon only. Furthermore, the post-war period reveals mean aversion, indicating a structural break in stock price behavior.[2]

## 2.2 Relative mean reversion

The lack of evidence for mean reversion is often attributed to small sample size in combination with statistical tests for mean reversion that lack power. A substantial improvement in estimation accuracy maybe achieved by explicitly specifying the fundamental value process (called the benchmark) around which stock prices are mean-reverting. An important question is how to proxy the fundamental value process, which is inherently unobserved. According to the Gorden growth model, the value of a stock equals the discounted future cash flows generated by the stock (Gorden 1959). In practice, these cash flow are the dividends that will be paid out to the owners. As an alternative to estimating future dividends, earnings could be used as a proxy of future cash flows towards investors. Other possible proxies are valuation ratios, such as dividend yield or price-earnings ratios. Campbell & Shiller (2001) examine the mean-reverting behavior of the dividend yield and price-earnings ratio over time. Theoretically, these ratios are expected to be mean-reverting, since fundamentals are determinants of stock prices. If stock prices are high in comparison to company fundamentals, it is expected that an adjustment to either stock prices or fundamentals will follow. Campbell & Shiller (2001) find that stock prices rather than company fundamentals contribute most to adjusting the ratios towards an equilibrium level. Coakley & Fuertes (2006) consider the mean-reverting behavior of valuation ratios and attribute it to differences in investor sentiment. The authors conclude that in the long run financial ratios revert to their mean. In earlier work, Fama & French (1988*a*) link the dividend yield to the expected returns of a stock and find that the latter have a mean-reverting tendency. A second specification of fundamental value is based on asset pricing models. Ho & Sears (2004) link the mean-reverting behavior of stocks to the Fama-French three factor model and conclude that such models cannot capture the mean-reverting behavior of stock prices. Similar conclusions emerge from Gangopadhyay & Reinganum (1996). However, they argue that mean reversion can be explained by the CAPM if the market risk premium is allowed to vary over time. Note that this fluctuation is in accordance with the theoretical explanation of mean reversion in efficient markets; expected returns fluctuate in a mean-reverting manner (Summers 1986). 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 fundamental value, which cannot be captured by the current dividend yield or price-earnings ratio. Moreover, the loss of information due to the use of proxies may contribute to the failure to recognize mean-reverting behavior.

## 3 Mean reversion model

We consider the stock market indices of $N$ countries, observed over $T$ years. Each stock index is expected to revert to its intrinsic value in the long run. In line with Balvers et al. (2000), we assume the following mean-reverting process for each country $i$:

$$r^i_{t+1} \quad = \quad a^i + \lambda^i (p^{*i}_{t+1} - p^i_t) + \varepsilon^i_{t+1}, \tag{1}$$

where $r^i_{t+1}$ equals the continuously compounded return on the stock index of country $i$ between time $t$ and $t+1$, $p^{*i}_{t+1}$ is the natural logarithm of the intrinsic value of the stock index of country $i$ at time $t+1$ and $p^i_t$ is the natural logarithmic stock index of country $i$ at time $t$. The error term $\varepsilon^i_t$ is assumed to be a country-specific stationary process with unconditional mean zero. Parameter $a^i$ is a country-specific constant and $\lambda^i$ indicates the speed of reversion of the index price process of country $i$. The relation between the index return and the deviation from its fundamental value depends entirely on parameter $\lambda^i$. The process in Equation (1) is a mean-reverting process if $0 < \lambda^i < 1$. Mean aversion occurs for $\lambda^i < 0$.

To estimate the parameters $a^i$ and $\lambda^i$ directly, we have to know the fundamental value $p_t^{*i}$. Unfortunately, due to the difficulty of determining firms' intrinsic value, it can generally not be measured. Like Balvers et al. (2000), we assume that the difference in intrinsic value between the natural logarithm of the stock index ($p_t^{*b}$) and the natural logarithm of a benchmark index ($p_t^{*b}$) is a stationary process. The benchmark index can be a global or country-specific stock index and will be specified later. The stationarity assumption cannot be tested empirically, since the intrinsic value processes are unobservable. However, similar to Balvers et al. (2000) we justify the assumption using an economic explanation based on the convergence of per capita GDP. Real per capita GDP across 20 OECD countries displays absolute convergence, which means that the real per capita GDPs converge to the same steady state (Barro & Sala-i Martin 1995). Absolute convergence results from the fact that countries catch up in capital and technology. Developed countries are expected to catch up in capital, as lower per capita GDP implies a larger marginal efficiency of investment (Barro 1991). Catching up in technology occurs because adapting an existing technology is cheaper than inventing a new one. A country's stock index represents the general state of the stock market. At the same time there is a direct relation between the intrinsic value of the stock market and companies generating a country's gross domestic product. Since the GDP across countries converges, so should the fundamental stock price indices. Consequently, the differences in fundamental stock prices across countries that show absolute convergence should be stationary.

We assume the benchmark index $b$ to be defined in such a way that for all countries $i$ the following holds:

$$p_t^{*i} - p_t^{*b} \quad = \quad c^i + \xi_t^i, \tag{2}$$

where $c^i$ is a country-specific constant and $\xi_t^i$ is a zero-mean stationary process. The stationary process $\xi_t^i$ of Equation (2) may be serially correlated over time, as well as correlated across countries. Consider the differences between the returns of country $i$ and the benchmark index $b$ at time

$t+1$:

$$r^i_{t+1} - r^b_{t+1} = \alpha^i - \lambda^i (p^i_t - p^b_t) + \psi^i_{t+1}, \tag{3}$$

where $r^b_{t+1}$ equals the continuously compounded return on the benchmark index between time $t$ and $t+1$, $\alpha^i = a^i - a^b + \lambda^i c^i$ is a country-specific constant, and $\psi^i_{t+1} = \varepsilon^i_{t+1} - \varepsilon^b_{t+1} + \lambda \xi^i_{t+1}$ is the error term. Process $\psi^i_t$ consists of two zero-mean stationary processes, whose statistical properties it inherits. In particular, $\psi^i_t$ is allowed to be correlated over time and across countries. All variables in Equation (3) are observable from historical data, and therefore the country-specific constants and the speed of reversion $\lambda^i$ can be estimated. To deal with serial correlation, $k$ lagged return differentials are added to the equation. Choosing the right value of $k$ (using e.g. Bayesian information criterion) results in a significant purge of autocorrelation in the returns. Thus, the adjusted model becomes

$$r^i_{t+1} - r^b_{t+1} \quad = \quad \alpha^i - \lambda^i (p^i_t - p^b_t) + \sum_{j=1}^{k} \phi^i_j (r^i_{t-j+1} - r^b_{t-j+1}) + \omega^i_{t+1}. \tag{4}$$

Equation (4) boils down to a panel cointegration model (in augmented Dickey Fuller form), according to which the stock market index in country $i$ is cointegrated with the benchmark index for $\lambda^i \neq 0$.

There are several ways to estimate Equation (4). Ordinary least squares (OLS) per country is the most simple approach. Alternatively, we can view Equation (4) as a seemingly unrelated regression (SUR) model and apply feasible generalized least squares (FGLS) to estimate it; see e.g. Johnston & DiNardo (1997). FGLS assumes that the model errors are serially uncorrelated, but may have cross-country contemporaneous correlation. It generally yields more efficient estimates than OLS. Alternatively, we can adopt a panel data approach and assume that the mean reversion speed parameter $\lambda^i$ is constant across all countries (i.e. $\lambda^i = \lambda$). The latter assumption does not imply that the mean-reversion process is synchronized across countries. Only the speed at which stock prices revert to their fundamental values is the same (Balvers et al. 2000). An important advantage of a panel approach is the large increase in sample size and the substantial increase in the power to test the null hypothesis $\lambda = 0$ (corresponding to no mean reversion). Also with panel data we can use FGLS to estimate the cointegration model. With both OLS and FGLS $\hat{\lambda}^i$ and $\hat{\lambda}$ are known to have an upward bias and this bias may be severe (Andrews & Chen 1994). We proceed as in Andrews & Chen (1994) and Balvers et al. (2000) and use simulation to obtain (approximately) mean-unbiased estimates of $\lambda^i$ and $\lambda$, as well as the corresponding (approximately) 95% confidence intervals for the purpose of statistical inference. The advantage of median unbiased estimators is their impartiality; the probability of overestimation equals the probability of underestimation. In situations where the magnitude of the parameters is an important issue, such as in the current context of estimating the speed of mean reversion, the impartiality property is very useful. In contrast to Andrews & Chen (1994) and Balvers et al. (2000), we do not impose normality on the model residuals. As stock returns are generally found to be fat-tailed, we follow a non-parametric approach and employ a wild bootstrap (Mammen 1993) from the empirical distribution of the model innovations. For more details about our bootstrap approach we refer to Appendix A.

## 4 Data

Shortly after the second millennium, Dimson et al. (2002) published a book on the financial history of 17 countries with historically well-developed economies and financial markets. The countries included are Australia, Belgium, Canada, Denmark, France, Germany, Ireland, Italy, Japan, the Netherlands, Norway, South Africa, Spain, Sweden, Switzerland, United Kingdom and the United States. The authors collected annual equity, bond and treasury bill investment data from all over the world over a long horizon. With the aid of many local specialists, they determined the most exact index value possible for each of the 101 years from 1900 to 2000, adjusted for inconsistencies. In addition, they constructed a World Index from the values of the country indices.[3] Every year the authors present an extension of the data, accumulating in an uninterrupted series of 110 yearly stock market returns up to the year 2009. Moreover, by now the set of countries has been extended with Finland and New Zealand. We focus on the 18 OECD countries in the Dimson et al. (2002) data set, which means that we exclude South Africa. Table 1 provides the mean, standard deviation, skewness and kurtosis of the annualized continuously compounded real returns on the stock values between 1900 and 2009 in US dollars. Also shown is the beta coefficient with the world index. Throughout, we use real stock returns and prices to make them comparable across countries and over time.

The largest average real return over the full period is found for New Zealand and equals 8.4%. The lowest average return is found for Italy, where an average real return of 2.3% was realized. The most volatile markets are Germany and Japan. In the first two years after World War I (1919 and 1920) and in the first year after World War II (1946), Germany suffered extreme declines in its stock market prices, resulting in returns of −69%, −110% and −130%, respectively. In each case, the stock market regained the losses a number of years later; during 1924 and 1950 the German stock market skyrocketed with returns of 119% and 180%, respectively. The fluctuations during these historically critical years cause the standard deviations to rise substantially. Similar outliers are found for the Japanese equity market index in the years after World War II. The lowest volatility is observed in Canada, followed by Switzerland and the United States.

The skewness of most countries is negative, which indicates higher volatility in negative returns. Especially Japan and France show relatively high volatility when stock markets decline. If the excess kurtosis is zero, the tails of the return distribution are comparable to those of a normal distribution. In case the excess kurtosis is much greater than zero, the return distribution exhibits fat tails. The market index of the United States has the lowest excess kurtosis; its value of 0.13 indicates that the tails of the return distribution are comparable to a normal distribution. The obvious outlier in excess kurtosis is Japan with an excess kurtosis of 17.8. Germany follows with an excess kurtosis of 6.2.

The last column of Table 1 displays the beta coefficient with respect to the world index. The beta describes the relation between the returns on the country index and the returns on the world index. The lowest beta value is obtained for the United States (0.58) and the highest for Germany (1.54).

## 5 Empirical results

Before estimating the panel data model as introduced in Section 3, we compare each country's index returns individually to a benchmark index. This approach allows us to estimate country-specific values of the mean-reversion parameter $\lambda^i$. Throughout, we apply our models to the annualized continuously compounded real returns on the stock values between 1900 and 2009 in US dollars.

### 5.1 Individual countries

We start with the World Index as the benchmark index in the model of Equation (4). The first column of Table 2 provides the country-specific estimates $\hat{\lambda}_0^i$ based on OLS estimation. The bootstrap approach has been used to obtain median unbiased estimates of $\hat{\lambda}^i$, which are reported in the third column of Table 2. The corresponding 95% confidence intervals are reported in the last column of Table 2. The confidence intervals are relatively wide, emphasizing the high degree of uncertainty involved with the estimates of the speed of mean reversion. The biased estimates are substantially larger than the median unbiased estimates based on the bootstrap method, confirming the positive bias in the OLS estimates and emphasizing the importance of calculating median unbiased estimators. We reject the null hypothesis of no mean reversion ($\lambda^i = 0$) if the value zero is not contained in the 95% confidence interval for $\hat{\lambda}^i$. The estimates in the first column of Table 2 are all positive, but significantly different from zero (at the 5% significance level) for only 8 out of 18 countries.

Table 2 provides country-specific estimates of the speed of mean reversion based on four different benchmark indices, being the stock indices corresponding to the United States, Japan, France and Germany. We cannot not estimate the model of Equation (4) for the benchmark country itself. Although the magnitude of the median unbiased estimates of the mean reversion speed is the same across different benchmarks, there are some differences. For example, with Japan as benchmark, none of the country-specific estimates of the mean reversion speed is significantly different from zero.

## 5.2 Panel data approach

Despite our sample period of more than a century, we find little evidence for mean reversion at the country level. A serious problem with hypothesis testing in cointegration models is the low power of these tests, particularly in relatively small samples. In our particular case we may fail to reject the null hypothesis of no mean reversion ($\hat{\lambda}^i = 0$) simply because our tests lack statistical power. To improve the significance of our estimation results, we apply the panel data model described in Section 3 to the data of Dimson et al. (2002). The panel approach allows us to test for differences in the speed of mean reversion across countries. To test if two or more countries have the same speed of mean reversion, we follow the approach outlined in Appendix A. Regardless of the benchmark index, we cannot reject the null hypothesis that the countries under consideration have the same speed of mean reversion. Subsequently, we estimate the panel data model under the assumption that the speed of mean reversion is the same in all countries under consideration. The lack of significant differences in the speed of mean reversion across countries justifies this assumption. Again the bootstrap method is applied to obtain a mean unbiased estimate of the speed of mean reversion.

For five different benchmark indices Table 4 presents the estimates $\hat{\lambda}_0$ based on FGLS estimation. Also the median unbiased estimates $\hat{\lambda}$ are included in the table, along with 95% confidence intervals. In addition to the speed of mean reversion, the half-life of the mean-reversion process is determined and reported (also in combination with 95% confidence intervals). This half-life is calculated as $\log 0.5/\log(1-\lambda)$, where $\lambda$ is taken to be the median unbiased estimate.[4]

Again we examine the sensitivity of the results to the choice of benchmark. First consider the World Index as the benchmark. The biased speed of mean reversion $\hat{\lambda}_0$ over the full period equals 0.057. The median unbiased estimate of the speed of reversion $\hat{\lambda}$ is 0.037. To interpret this number, consider the initial model of Equation (1), where stock returns are assumed to be a function of the deviation from the intrinsic value. The positive value of $\hat{\lambda}$ implies that a positive deviation between stock price and intrinsic value in this period will result in a negative expected return in the next period. Moreover, the value of lambda reflects the speed at which the price reverts to its fundamental value. Each year a price correction takes place of 3.7% of the logarithmic price deviation from the fundamental value. In order to measure the speed of mean reversion in years, the half-life of a gap between stock price and intrinsic value is considered. Notice that a higher speed of reversion implies a shorter half-life. With the World Index as benchmark, the half-life of a price deviation is 18.5 years. In other words, 50% of a shock to the stock price will be offset in 18.5 years after occurrence. The 95% confidence interval has a lower bound equal to 13.2 years and an upper bound of 23.4 years. The estimation results corresponding to the four other benchmark indices are very similar, leading to the important conclusion that the estimated speed of mean reversion and the associated half life are robust to the choice of benchmark.

Balvers et al. (2000) establish significant mean reversion during the $1970-1996$ period. Their value of the unbiased estimate $\hat{\lambda}$ equals 0.182 (90% confidence interval $[0.110, 0.250]$), which implies a half-life of 3.5 years (90% confidence interval $[2.4, 5.9]$ years). Their results with the United States benchmark index are of a similar magnitude; the unbiased estimate of $\lambda$ equals 0.202, implying a half-life of 3.1 years. Our unbiased estimates of the speed of mean reversion, based on a sample period of more than a century, differ substantially from the results established in Balvers et al. (2000), based on less than three decades only. We observe a much lower speed of mean reversion and a much longer half-life. Balvers et al. (2000) estimate the speed of reversion for the period $1970-1996$ in a similar fashion as we do. However, they use a Monte Carlo simulation to obtain median unbiased estimators, assuming multivariate normality of the residuals of the time series model in Equation (4). Moreover, their empirical analysis is based on Morgan Stanley Capital International (MSCI) stock indices for 18 countries. These countries are Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, the Netherlands, Norway, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States. Our data set contains Finland, Ireland and New Zealand instead of Austria, Hong Kong and Singapore, due to different choices made by the data collectors. For the period $1970-1996$ as considered by Balvers et al. (2000), we establish a mean reversion speed equal to 0.155 (see Section 6.1). This number is very close to their speed of 0.182, confirming that the difference in countries does not substantially affect the results.

### 5.3 Robustness checks

To assess the robustness of our estimation results, we have carried out several robustness checks. Instead of using stock prices in real dollars, we have estimated our models using real stock prices in local currency. Exchange rates have been found to be mean-reverting (Taylor et al. 2001), due to which we may overstate the degree of mean reversion in stock prices quoted in real dollars. The use of real stock prices in local currency does not substantially affect our estimation results. For example, for the full sample period and taking the World Index as our benchmark the median-unbiased estimate of the speed of mean reversion equals 0.037, with 95% confidence interval equal to $[0.026, 0.050]$. These figures are very close to the outcomes in Table 4 based on real stock prices in dollars. Furthermore, we have assessed the influence of outliers in stock returns on our estimation results by leaving out the observations for a couple of years just after World War I, during the Interbellum, and during and just after World War II (see Section 4).[5] Outliers turned out to have little impact on our analysis. With the outliers removed the median unbiased estimate for the mean reversion speed equals 0.042 (based on the World Index benchmark), with 95% confidence interval equal to $[0.029, 0.059]$.

## 6 Time-varying mean reversion

With our panel data model we establish a half-life of 18.5 years for the full sample period, spanning the years 1900 – 2009. Several arguments plead against the assumption of a constant speed of mean-reversion. For example, Kim et al. (1991) conclude that mean reversion is a pre World War II phenomenon only. Furthermore, Poterba & Summers (1988) conclude that the Great Depression had a significant influence on the speed of mean reversion. Also the difference in the speed of mean reversion between our long sample period and the short interval considered by Balvers et al. (2000) suggests changes in the speed of mean-reversion over time. Additionally, during long sample period structural breaks in the behavior of stock returns are likely to occur, resulting in model coefficients that change over time (Rapach & Wohar 2006).

## 6.1 Rolling window approach

Our large panel data set allows us to analyze the speed of mean reversion during shorter time periods. We apply a rolling window estimation approach to (overlapping) time intervals of 27 years. Throughout, we only report results for the World Index benchmark; for the other benchmark indices we establish very similar results.

The choice of the rolling window width is crucial. Too small a window will result in very erratic results, but too large a window will yield too smooth results. Eyeballing makes clear that a window width around 30 years works well. Eventually, we opt for a window width of 27 years. The length of this interval is in accordance with Balvers et al. (2000), who consider the years $1970 - 1996$, facilitating comparison.

Table 5 displays the biased and unbiased estimates of the mean reversion speed, based on 84 rolling windows of 27 yearly returns. The corresponding 95% confidence intervals are provided as well, based on the aforementioned bootstrap method. Clearly, the mean-reversion coefficient $\lambda$ is not constant over time. Its largest value is 0.296, observed during the period 1918 – 1944. The lowest value is obtained for the interval 1901 – 1927 and equals 0.030, which is almost 10 times smaller. The two intervals have a half-life of 2.0 and 22.6 years, respectively. An important issue is the significance of mean reversion. Only during the periods 1900 – 1926 and 1922 – 1948 there is no statistically significant mean reversion.

To visualize the speed of mean reversion over time, Figure 1 displays the median unbiased rolling-window estimates of the speed of mean reversion, in combination with associated 95% confidence intervals. Figure 2 shows the corresponding half-life for the period 1900 – 2009. Throughout, the rolling-window estimates are plotted against the mid-year of the 27-year rolling-window period. In Figure 1, a horizontal line is drawn at the critical value zero.

It is difficult to attribute differences in the speed of mean reversion between two time intervals to one specific year. Consider for example the last two intervals, 1982 – 2008 and 1983 – 2009. The corresponding half-lives are, respectively, 11.2 and 20.2 years. The decrease in half-life by 9.0 years reflects the overall effect of adding one additional year to the rolling-window interval and leaving one year out.

A more appealing interpretation can be found by studying Figure 1, which shows three peaks in the speed of mean reversion. In the first peak there are seven values remarkably larger than others. These points correspond to the seven rolling-window periods between 1914 − 1940 and 1920−1946, with an average speed of mean reversion equal to 0.213 (half-life 2.9 years). All seven intervals include the period 1920−1940, during which the Great Depression and the start of World War II took place. The second peak in Figure 1 is observed for the periods between 1942 − 1968 and 1951 − 1977, which is characterized by an average speed of mean reversion equal to 0.132 (half-life 4.9 years). The years 1951 − 1968 are used for all rolling-window estimates during this period and correspond to an era with a lot of tension related to the Cold War (such as the Berlin Crisis of 1961 and the Cuba Crisis of 1962), as well as the wars in Korea (1950 − 1953) and Vietnam (1959 − 1975). The third peak in Figure 1 is less pronounced than the other two, but still clearly visible. It is observed for the periods between 1967 − 1993 and 1970 − 1996, during which the average speed of mean reversion equals 0.154 (half-life 4.2 years). The years 1970 − 1993 are used for all rolling-window estimates during this period. The Oil Crisis of 1973 and the Energy Crisis of 1979 occurred during this period, as well as Black Monday in 1987.

We may expect to see the effects of the current economic and financial crisis in Figure 1. The interval 1982 – 2008 takes into account the first year (2008) of this crisis. The period 1983 – 2009 additionally contains 2009, the second year of the crisis. Inclusion of the two crisis years does not result in an increase in the speed of mean reversion and a corresponding drop in the half-life, as can be seen from Figures 1 and Figure 2. Although the mean-reversion speed is somewhat higher for the 1982 – 2008 period (0.060) than for 1981 – 2007 (0.040), the mean-reversion speed goes down again during the 1983 – 2009 period (0.034). Since the periods 1982 – 2008 and 1983 – 2009 contain mostly years before the crisis, the years related to the current crisis may not yet get enough weight to influence the speed of mean reversion.

Finally, we compare our results to existing studies analyzing the speed of mean reversion over time. Table 5 makes clear that mean reversion is not only a pre World War II phenomenon (Kim et al. 1991). By contrast, the speed of mean reversion is relatively low during the pre-war periods 1900 – 1926 until 1912 – 1938. During the post-war periods 1946 – 1972 and further the speed of mean reversion is generally much higher. The pre-war average speed of mean reversion equals 0.068, whereas the post-war average is 0.107. Hence, our findings contradict the result established in Kim et al. (1991), who conclude that mean reversion is a pre World War II phenomenon only. In line with Poterba & Summers (1988), our results suggest the Great Depression has substantial influence on the speed of mean reversion. The first peak in Figure 1 is based on the years containing the Great Depression and the start of World War II.

### 6.2 Economic explanation for time-varying mean reversion

Our results suggest that the speed at which stock prices revert to their fundamental value is higher in periods of high economic uncertainty, caused by major events such as the Great Depression, World War II, and the Cold War. We provide two explanations.

In Section 2 we already mentioned that mean reversion in stock prices may occur in efficient markets. Assuming market efficiency, the value of a stock is determined by the expected returns per share. Consequently, mean reversion is observed when expected returns are mean reverting (Summers 1986). Deviations in expected returns from their long-term value may be explained from uncertainty about the survival of the economy, caused by e.g. a world war or a depression (Kim et al. 1991). Our findings 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; much faster than in more tranquil periods. 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. Measures and interventions by financial and government institutions to restore financial stability may also speed up the adjustment process.

Outside the framework of efficient markets, mean reversion may be caused by the irrational behavior of noise traders, resulting in stock prices that take wide swings away from their fundamental value (Poterba & Summers 1988). Irrational pricing behavior, in turn, can be caused by overreaction to financial news (De Bondt & Thaler 1985, 1987). Our results could imply that noise traders overreact heavily to (financial) news in periods of high economic uncertainty. This may work in two directions. At the start of the uncertainty, the overreaction to bad news may take stock prices far below their fundamental value. During recovery, noise traders tend to overreact to the good news, resulting in stock prices far above their fundamental value. In both cases, large price swings in relatively short time result in rapid mean reversion.

The nature of our analysis only permits us to hypothesize that the mean reversion speed is higher in periods of high economic uncertainty. Our explanations are a first attempt to explain the observed phenomenon. We leave further analysis of this issue as an important topic for future research.

# 7 Conclusions

This study analyzes mean reversion in international stock markets during the years 1900 – 2009, using annual data. Our panel of stock indices in 18 OECD countries allows us to analyze in detail the dynamics of the mean-reversion process. In the period 1900 – 2009 it takes stock prices about 18.5 years, on average, to absorb half of a shock. However, using a rolling-window approach we find large fluctuations in the speed of mean reversion over time. The highest speed of mean reversion is found for the period including World War I, the Great Depression and the start of World War II. Also the early years of the Cold War and the period containing the Oil Crisis of 1973, the Energy Crisis of 1979 and Black Monday in 1987 are characterized by relatively rapid mean reversion. We document half-lives ranging from 2.0 years to 22.6 years, which underlines the fact that the choice of data sample contributes substantially to the evidence in favor of mean reversion.

How can we explain time-varying mean-reversion in stock prices? Our results suggest that the speed at which stocks revert to their fundamental value is higher in periods of high economic uncertainty caused by major events such as the Great Depression, World War II and the Cold War. In both efficient and inefficient markets, large price movements in relatively short time may account for the high mean reversion speed.

A time-varying speed of mean reversion has important economic implications. For example, several studies show that excess returns can be earned by exploiting mean reversion of stock prices (De Bondt & Thaler 1985, 1987, Jegadeesh & Titman 1993, Campbell & Shiller 2001, Gropp 2004, Balvers et al. 2000) using contrarian trading strategies. However, to implement such strategies a mean-reversion parameter has to be chosen. Our results show that the estimated speed of mean-reversion depends crucially on the sample period. The generally low value of the mean reversion speed, as well as its huge uncertainty, severely limits the possibilities to exploit mean reversion in a trading strategy.

# Notes

[1]Conrad & Kaul (1988) find that the time-varying process of the expected return indeed reverts to its mean over time.

[2]Mean aversion is movement of stock prices away from their mean value over time.

[3]The world index is a size-weighted portfolio of all country's indices. The weights before 1968 are based on GDP due to a lack of reliable data on capitalization prior to that date. The weights from 1968 onwards are based on market capitalizations published by Morgan Stanley Capital International (MSCI). The sizes are annually adjusted to the GDP or market capitalization at the beginning of the year. (Dimson et al. 2002, page 311)

[4]Since the half-life is a monotonic transformation of the mean reversion parameter $\lambda$, a median unbiased estimator for the half-life is simply obtained as $\log 0.5/\log(1-\hat{\lambda})$ where $\hat{\lambda}$ is the median unbiased estimator for $\lambda$. Similarly, the 97.5% quantile for the half-life is obtained by taking the half-life transformation of the 2.5% quantile for the speed of mean reversion. Notice that the the half-life is only defined for $\lambda > 0$; the half-life converges to infinity for $\lambda \downarrow 0$.

[5]We left out the years 1919 – 1924, 1927, 1935, 1940, 1946, 1948, and 1950.

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Table 1: **Summary statistics for real index returns (in %) during the period 1900 – 2009.**

| | Mean | Standard Deviation | Skewness | Excess Kurtosis | Beta with World Index |
|---|---|---|---|---|---|
| World | 0.049 | 0.196 | -0.427 | 0.861 | 1.000 |
| Australia | 0.072 | 0.226 | -0.627 | 1.374 | 0.808 |
| Belgium | 0.033 | 0.250 | -0.321 | 1.914 | 0.957 |
| Canada | 0.056 | 0.190 | -0.529 | 0.904 | 0.642 |
| Denmark | 0.054 | 0.213 | -0.398 | 2.533 | 0.743 |
| Finland | 0.052 | 0.317 | -0.896 | 3.600 | 1.032 |
| France | 0.030 | 0.296 | -1.252 | 5.291 | 1.149 |
| Germany | 0.033 | 0.441 | 0.377 | 6.226 | 1.536 |
| Ireland | 0.041 | 0.247 | -0.751 | 3.529 | 0.877 |
| Italy | 0.023 | 0.306 | -0.198 | 1.464 | 1.017 |
| Japan | 0.042 | 0.378 | -2.985 | 17.839 | 1.127 |
| Netherlands | 0.052 | 0.242 | -1.126 | 6.090 | 0.875 |
| New Zealand | 0.084 | 0.220 | 0.139 | 2.716 | 0.604 |
| Norway | 0.044 | 0.278 | 2.105 | 5.038 | 0.777 |
| Spain | 0.039 | 0.261 | -0.194 | 1.088 | 0.693 |
| Sweden | 0.060 | 0.244 | -0.592 | 1.013 | 0.857 |
| Switzerland | 0.050 | 0.193 | -0.036 | 0.978 | 0.688 |
| United Kingdom | 0.051 | 0.222 | -0.536 | 2.335 | 0.824 |
| United States | 0.060 | 0.200 | -0.674 | 0.128 | 0.581 |

Table 2: **Speed of mean reversion for individual countries (benchmark: World Index)**

This table reports the country-specific estimates of the speed of mean reversion, based on the World Index benchmark. The sample period covers the years 1900 – 2009. The biased OLS estimate of the speed of mean reversion is reported (‘$\lambda_0^i$’), as well as the median unbiased estimate (‘$\lambda^i$’). For the median unbiased estimator a 95% confidence interval based on the bootstrap approach is also reported (‘95% C.I.’).

| | $\hat{\lambda}_0^i$ | $\hat{\lambda}^i$ | **95% C.I.** |
|---|---|---|---|
| Australia | 0.057 | 0.038 | [0.012, 0.096] |
| Belgium | 0.031 | 0.009 | [-0.022, 0.056] |
| Canada | 0.072 | 0.050 | [0.000, 0.116] |
| Denmark | 0.094 | 0.062 | [-0.018, 0.165] |
| Finland | 0.091 | 0.053 | [-0.029, 0.173] |
| France | 0.026 | 0.002 | [-0.039, 0.038] |
| Germany | 0.074 | 0.046 | [0.006, 0.127] |
| Ireland | 0.084 | 0.062 | [0.009, 0.132] |
| Italy | 0.025 | 0.003 | [-0.035, 0.042] |
| Japan | 0.044 | 0.005 | [-0.045, 0.093] |
| Netherlands | 0.080 | 0.031 | [-0.043, 0.150] |
| New Zealand | 0.034 | 0.020 | [0.002, 0.062] |
| Norway | 0.045 | 0.009 | [-0.051, 0.092] |
| Spain | 0.030 | 0.005 | [-0.039, 0.052] |
| Sweden | 0.105 | 0.077 | [0.009, 0.163] |
| Switzerland | 0.145 | 0.116 | [0.021, 0.226] |
| United Kingdom | 0.130 | 0.092 | [-0.012, 0.229] |
| United States | 0.091 | 0.065 | [0.016, 0.145] |

Table 3: **Speed of mean reversion for individual countries (different benchmarks)**

This table reports country-specific estimates of the speed of mean reversion, based on different benchmark indices (US, Japan, France, and Germany). The sample period covers the years 1900 – 2009. The biased OLS estimate of the speed of mean reversion is given (‘$\lambda_0^i$’), as well as the median unbiased estimate based on the bootstrap approach (‘$\lambda^i$’). Also a corresponding 95% confidence interval for $\hat{\lambda}^i$ is provided (‘95% C.I.’).

| | $\hat{\lambda}_0^i$ | $\hat{\lambda}^i$ | **95% C.I.** | $\hat{\lambda}_0^i$ | $\hat{\lambda}^i$ | **95% C.I.** |
|---|---|---|---|---|---|---|
| **Benchmark:** | **US** | | | **Japan** | | |
| Australia | 0.025 | -0.011 | [-0.048, 0.044] | 0.039 | 0.012 | [-0.027, 0.069] |
| Belgium | 0.059 | 0.033 | [-0.003, 0.106] | 0.080 | 0.046 | [-0.004, 0.142] |
| Canada | 0.006 | -0.010 | [-0.038, 0.041] | 0.045 | 0.015 | [-0.034, 0.076] |
| Denmark | 0.090 | 0.056 | [-0.026, 0.143] | 0.057 | 0.019 | [-0.039, 0.117] |
| Finland | -0.040 | -0.039 | [-0.049, -0.032] | 0.052 | 0.007 | [-0.044, 0.093] |
| France | 0.063 | 0.035 | [0.000, 0.113] | 0.073 | 0.031 | [-0.023, 0.169] |
| Germany | 0.034 | 0.001 | [-0.034, 0.060] | 0.079 | 0.045 | [-0.004, 0.154] |
| Ireland | 0.023 | -0.004 | [-0.040, 0.048] | 0.085 | 0.055 | [-0.009, 0.152] |
| Italy | 0.024 | 0.002 | [-0.034, 0.043] | 0.064 | 0.042 | [-0.001, 0.103] |
| Japan | 0.039 | 0.007 | [-0.033, 0.068] | | | |
| Netherlands | 0.051 | 0.006 | [-0.041, 0.107] | 0.048 | 0.003 | [-0.054, 0.109] |
| New Zealand | -0.021 | -0.028 | [-0.054, -0.016] | 0.030 | 0.008 | [-0.028, 0.049] |
| Norway | 0.103 | 0.072 | [-0.006, 0.182] | 0.066 | 0.031 | [-0.036, 0.122] |
| Spain | 0.043 | 0.016 | [-0.029, 0.074] | 0.075 | 0.048 | [-0.008, 0.133] |
| Sweden | 0.026 | -0.007 | [-0.035, 0.051] | 0.053 | 0.019 | [-0.032, 0.098] |
| Switzerland | -0.008 | -0.018 | [-0.043, -0.008] | 0.062 | 0.031 | [-0.028, 0.110] |
| United Kingdom | -0.006 | -0.020 | [-0.053, -0.004] | 0.063 | 0.027 | [-0.031, 0.110] |
| United States | | | | 0.044 | 0.012 | [-0.032, 0.079] |
| **Benchmark:** | **France** | | | **Germany** | | |
| Australia | 0.037 | 0.024 | [0.004, 0.061] | 0.058 | 0.036 | [0.008, 0.103] |
| Belgium | 0.207 | 0.154 | [0.016, 0.371] | 0.074 | 0.033 | [-0.031, 0.141] |
| Canada | 0.037 | 0.016 | [-0.010, 0.063] | 0.068 | 0.041 | [0.003, 0.120] |
| Denmark | 0.050 | 0.027 | [-0.006, 0.086] | 0.077 | 0.047 | [0.006, 0.143] |
| Finland | 0.059 | 0.025 | [-0.021, 0.109] | 0.080 | 0.045 | [-0.003, 0.148] |
| France | | | | 0.060 | 0.015 | [-0.037, 0.115] |
| Germany | 0.060 | 0.014 | [-0.042, 0.115] | | | |
| Ireland | 0.055 | 0.020 | [-0.033, 0.111] | 0.091 | 0.058 | [0.000, 0.179] |
| Italy | 0.107 | 0.060 | [-0.035, 0.224] | 0.059 | 0.018 | [-0.033, 0.109] |
| Japan | 0.073 | 0.030 | [-0.027, 0.171] | 0.079 | 0.044 | [-0.005, 0.153] |
| Netherlands | 0.030 | 0.001 | [-0.043, 0.044] | 0.082 | 0.046 | [0.009, 0.154] |
| New Zealand | 0.024 | 0.013 | [-0.003, 0.044] | 0.055 | 0.034 | [0.009, 0.100] |
| Norway | 0.147 | 0.111 | [0.029, 0.252] | 0.067 | 0.032 | [-0.032, 0.122] |
| Spain | 0.177 | 0.140 | [0.036, 0.305] | 0.071 | 0.034 | [-0.022, 0.130] |
| Sweden | 0.039 | 0.017 | [-0.014, 0.070] | 0.096 | 0.071 | [0.021, 0.173] |
| Switzerland | 0.039 | 0.013 | [-0.031, 0.067] | 0.082 | 0.052 | [0.007, 0.157] |
| United Kingdom | 0.036 | 0.008 | [-0.036, 0.064] | 0.087 | 0.056 | [0.005, 0.155] |
| United States | 0.035 | 0.014 | [-0.011, 0.058] | 0.072 | 0.045 | [0.011, 0.124] |

Table 4: **Speed of mean reversion based on the panel data model**

This table reports the estimated speed of mean reversion based on the panel data model for different benchmark indices. In the panel data model the speed of mean reversion is assumed to be the same in all 18 countries under consideration. The sample period spans the years 1900 – 2009. The biased FGLS estimate of the speed of mean reversion is given ('$\lambda_0$'), as well as the median unbiased estimate based on the bootstrap approach ('$\lambda$'). Also a corresponding 95% confidence interval for $\hat{\lambda}$ is provided ('95% C.I.'). Finally, the corresponding half-life is reported, with associated 95% confidence interval.

| **Benchmark** | $\hat{\lambda}_0$ | $\hat{\lambda}$ | **95% C.I.** | **Half-life in years (C.I.)** |
|---|---|---|---|---|
| **World** | 0.057 | 0.037 | [0.029, 0.051] | 18.5 [13.2, 23.4] |
| **US** | 0.067 | 0.041 | [0.027, 0.057] | 16.7 [11.8, 25.5] |
| **Japan** | 0.061 | 0.038 | [0.025, 0.055] | 17.9 [12.2, 27.0] |
| **France** | 0.059 | 0.038 | [0.027, 0.054] | 18.1 [12.6, 25.5] |
| **Germany** | 0.065 | 0.042 | [0.029, 0.061] | 16.3 [11.0, 23.4] |

Table 5: **Rolling-window estimates of the speed of mean reversion (benchmark: World Index)**

This table reports rolling-window estimates of the speed of mean reversion, based on the panel data model. The rolling-window interval is reported ('Period'), as well as the biased FGLS estimate of the speed of mean reversion during that period ('$\lambda_0$'). Also the median unbiased estimate is displayed ('$\lambda$') together with a corresponding 95% confidence interval, both based on the bootstrap approach ('95% C.I.').

| **Period** | $\hat{\lambda}_0$ | $\hat{\lambda}$ | **95% C.I.** | **Period** | $\hat{\lambda}_0$ | $\hat{\lambda}$ | **95% C.I.** |
|---|---|---|---|---|---|---|---|
| 1900 to 1926 | 0.082 | 0.030 | [-0.007, 0.100] | 1942 to 1968 | 0.143 | 0.077 | [0.038, 0.128] |
| 1901 to 1927 | 0.100 | 0.042 | [0.003, 0.111] | 1943 to 1969 | 0.164 | 0.100 | [0.056, 0.161] |
| 1902 to 1928 | 0.116 | 0.056 | [0.015, 0.117] | 1944 to 1970 | 0.191 | 0.129 | [0.083, 0.191] |
| 1903 to 1929 | 0.114 | 0.054 | [0.014, 0.113] | 1945 to 1971 | 0.171 | 0.113 | [0.070, 0.199] |
| 1904 to 1930 | 0.133 | 0.060 | [0.018, 0.128] | 1946 to 1972 | 0.152 | 0.105 | [0.052, 0.192] |
| 1905 to 1931 | 0.141 | 0.067 | [0.025, 0.133] | 1947 to 1973 | 0.203 | 0.157 | [0.095, 0.273] |
| 1906 to 1932 | 0.138 | 0.063 | [0.022, 0.122] | 1948 to 1974 | 0.251 | 0.207 | [0.130, 0.340] |
| 1907 to 1933 | 0.135 | 0.059 | [0.020, 0.113] | 1949 to 1975 | 0.185 | 0.125 | [0.082, 0.212] |
| 1908 to 1934 | 0.140 | 0.070 | [0.030, 0.128] | 1950 to 1976 | 0.209 | 0.161 | [0.114, 0.235] |
| 1909 to 1935 | 0.150 | 0.078 | [0.038, 0.135] | 1951 to 1977 | 0.198 | 0.146 | [0.096, 0.229] |
| 1910 to 1936 | 0.151 | 0.089 | [0.046, 0.144] | 1952 to 1978 | 0.148 | 0.084 | [0.049, 0.155] |
| 1911 to 1937 | 0.170 | 0.101 | [0.062, 0.170] | 1953 to 1979 | 0.199 | 0.126 | [0.075, 0.214] |
| 1912 to 1938 | 0.180 | 0.117 | [0.074, 0.179] | 1954 to 1980 | 0.173 | 0.099 | [0.048, 0.184] |
| 1913 to 1939 | 0.207 | 0.135 | [0.088, 0.218] | 1955 to 1981 | 0.188 | 0.118 | [0.071, 0.194] |
| 1914 to 1940 | 0.247 | 0.173 | [0.109, 0.261] | 1956 to 1982 | 0.179 | 0.114 | [0.071, 0.180] |
| 1915 to 1941 | 0.273 | 0.190 | [0.107, 0.306] | 1957 to 1983 | 0.166 | 0.099 | [0.057, 0.160] |
| 1916 to 1942 | 0.270 | 0.197 | [0.124, 0.320] | 1958 to 1984 | 0.177 | 0.100 | [0.057, 0.161] |
| 1917 to 1943 | 0.312 | 0.263 | [0.199, 0.342] | 1959 to 1985 | 0.195 | 0.120 | [0.074, 0.189] |
| 1918 to 1944 | 0.353 | 0.296 | [0.233, 0.371] | 1960 to 1986 | 0.177 | 0.097 | [0.055, 0.156] |
| 1919 to 1945 | 0.310 | 0.234 | [0.171, 0.326] | 1961 to 1987 | 0.173 | 0.099 | [0.056, 0.160] |
| 1920 to 1946 | 0.229 | 0.136 | [0.079, 0.233] | 1962 to 1988 | 0.181 | 0.109 | [0.066, 0.166] |
| 1921 to 1947 | 0.145 | 0.054 | [0.003, 0.155] | 1963 to 1989 | 0.179 | 0.103 | [0.058, 0.166] |
| 1922 to 1948 | 0.133 | 0.036 | [-0.005, 0.123] | 1964 to 1990 | 0.186 | 0.102 | [0.055, 0.174] |
| 1923 to 1949 | 0.199 | 0.114 | [0.053, 0.215] | 1965 to 1991 | 0.192 | 0.116 | [0.068, 0.181] |
| 1924 to 1950 | 0.171 | 0.080 | [0.027, 0.170] | 1966 to 1992 | 0.201 | 0.121 | [0.068, 0.181] |
| 1925 to 1951 | 0.172 | 0.078 | [0.024, 0.164] | 1967 to 1993 | 0.213 | 0.140 | [0.092, 0.201] |
| 1926 to 1952 | 0.190 | 0.096 | [0.038, 0.200] | 1968 to 1994 | 0.227 | 0.155 | [0.108, 0.216] |
| 1927 to 1953 | 0.190 | 0.093 | [0.040, 0.174] | 1969 to 1995 | 0.236 | 0.164 | [0.122, 0.222] |
| 1928 to 1954 | 0.184 | 0.083 | [0.033, 0.165] | 1970 to 1996 | 0.233 | 0.155 | [0.111, 0.221] |
| 1929 to 1955 | 0.187 | 0.088 | [0.038, 0.161] | 1971 to 1997 | 0.203 | 0.112 | [0.071, 0.173] |
| 1930 to 1956 | 0.166 | 0.075 | [0.028, 0.135] | 1972 to 1998 | 0.191 | 0.102 | [0.059, 0.160] |
| 1931 to 1957 | 0.176 | 0.085 | [0.040, 0.150] | 1973 to 1999 | 0.229 | 0.150 | [0.105, 0.219] |
| 1932 to 1958 | 0.166 | 0.082 | [0.039, 0.141] | 1974 to 2000 | 0.199 | 0.123 | [0.078, 0.191] |
| 1933 to 1959 | 0.163 | 0.078 | [0.033, 0.131] | 1975 to 2001 | 0.183 | 0.095 | [0.055, 0.162] |
| 1934 to 1960 | 0.170 | 0.078 | [0.037, 0.136] | 1976 to 2002 | 0.164 | 0.074 | [0.030, 0.137] |
| 1935 to 1961 | 0.176 | 0.079 | [0.037, 0.134] | 1977 to 2003 | 0.137 | 0.041 | [0.004, 0.101] |
| 1936 to 1962 | 0.168 | 0.052 | [0.012, 0.109] | 1978 to 2004 | 0.131 | 0.039 | [0.003, 0.091] |
| 1937 to 1963 | 0.164 | 0.054 | [0.010, 0.110] | 1979 to 2005 | 0.125 | 0.035 | [0.003, 0.091] |
| 1938 to 1964 | 0.162 | 0.046 | [0.010, 0.102] | 1980 to 2006 | 0.120 | 0.044 | [0.010, 0.098] |
| 1939 to 1965 | 0.168 | 0.061 | [0.020, 0.123] | 1981 to 2007 | 0.119 | 0.040 | [0.012, 0.085] |
| 1940 to 1966 | 0.141 | 0.053 | [0.021, 0.108] | 1982 to 2008 | 0.133 | 0.060 | [0.018, 0.121] |
| 1941 to 1967 | 0.141 | 0.064 | [0.030, 0.116] | 1983 to 2009 | 0.109 | 0.034 | [0.002, 0.085] |

Figure 1: **Rolling-window estimates of speed of mean reversion (benchmark: World Index)**

This figure displays the median unbiased rolling-window estimates of the speed of mean reversion, as a function of the mid-year of the rolling-window time interval. The speed of mean reversion is estimated using the panel data model in combination with the bootstrap approach. The solid line represents the median unbiased estimate of the speed of mean reversion and the two dashed lines constitute the corresponding 95% confidence interval.

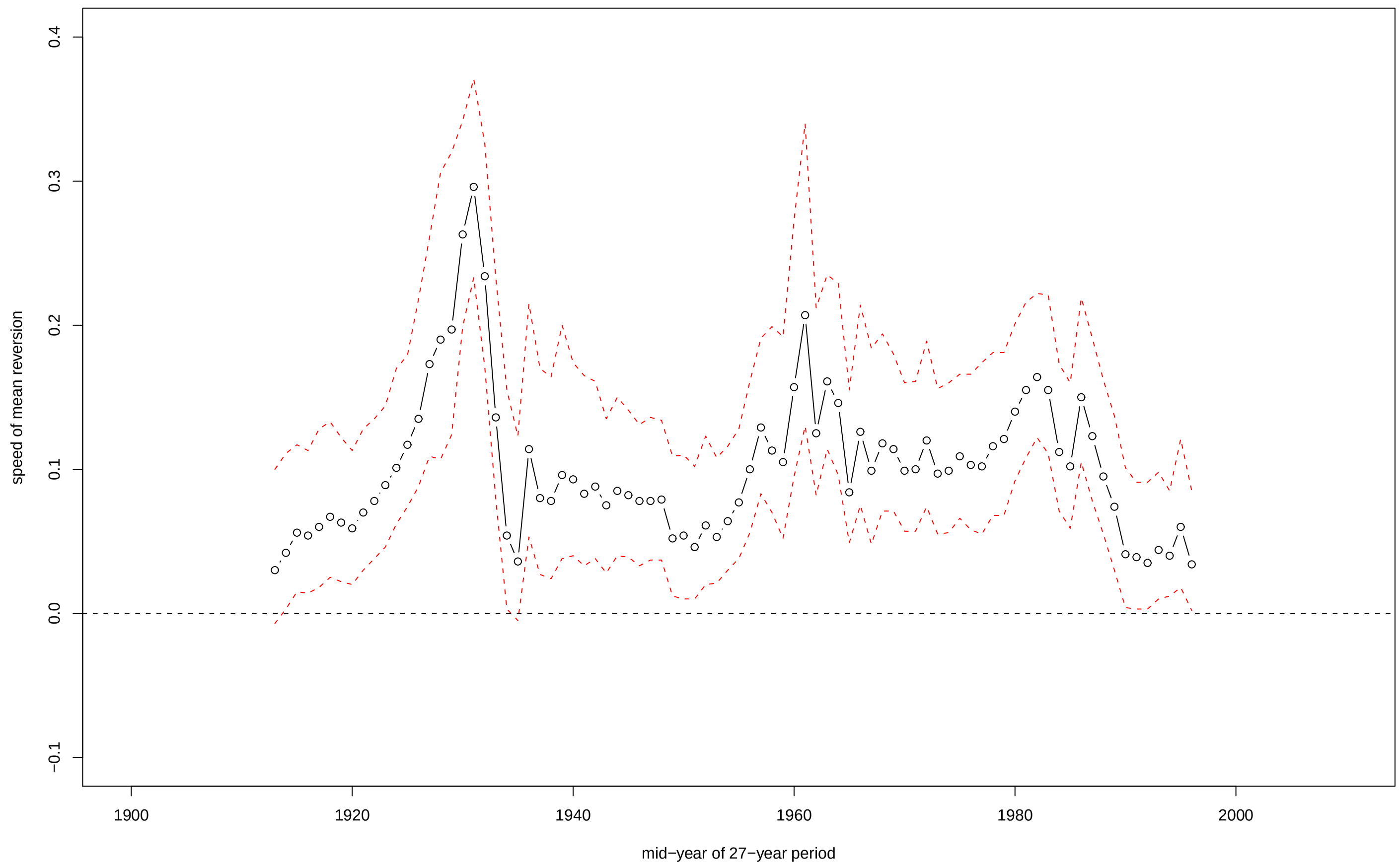
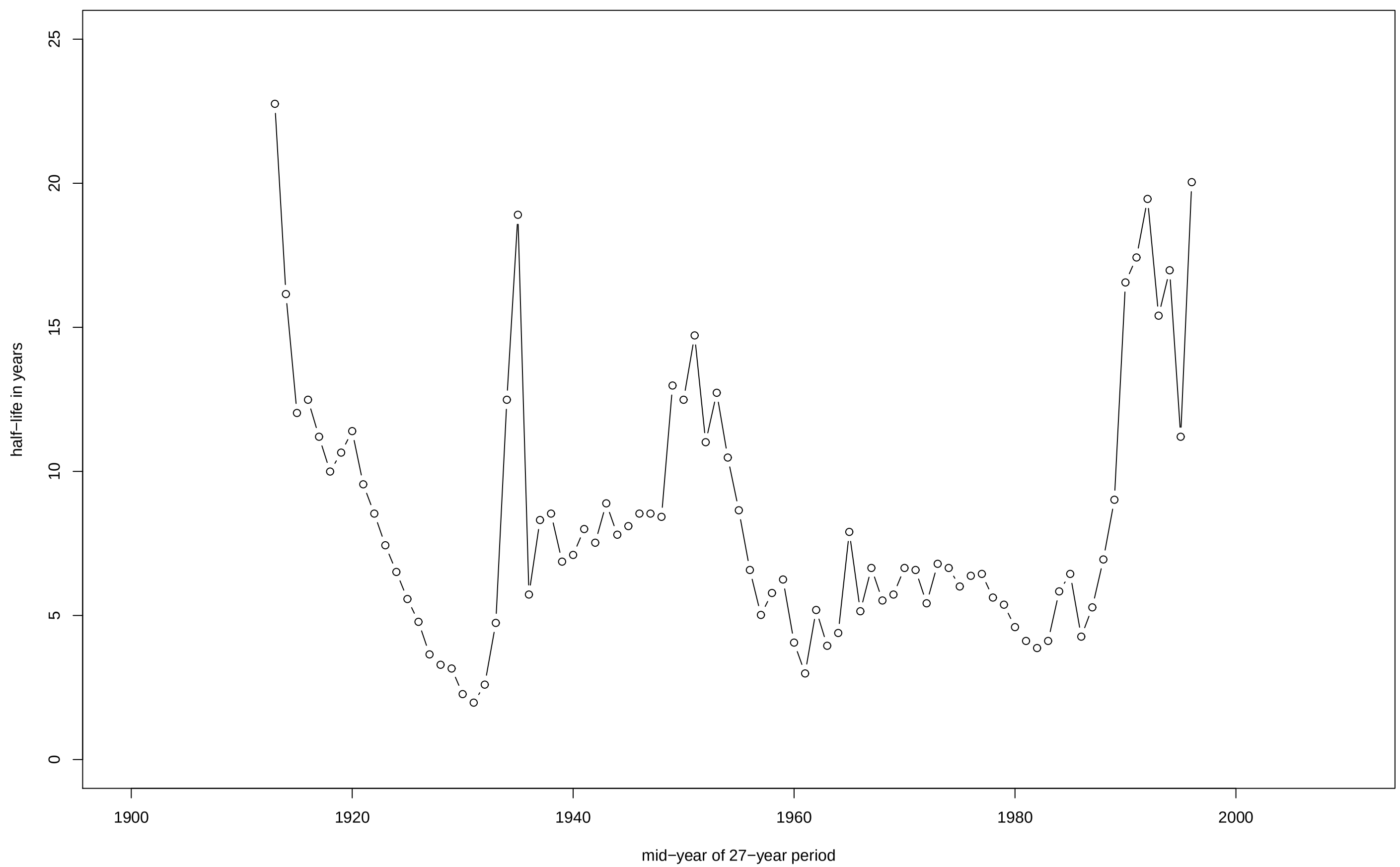


Figure 2: **Rolling-window estimates of half-life (1900-2009)**

This figure displays the median unbiased rolling-window estimates of the half-life, as a function of the mid-year of the rolling-window time interval. The half-life has been estimated using the panel data model in combination with the bootstrap approach.



# Appendix A Bootstrap Method

## A.1 Median-unbiased estimator and confidence interval

The simulation approach to obtain a median unbiased estimator of $\lambda$ in Equation (4) is based on Andrews & Chen (1994), whereas the wild bootstrap is based on Mammen (1993).

Take a grid of values $\lambda_{0,1}, \ldots, \lambda_{0,n}$. Then for each $\lambda_{0,j}$ follow the following steps.

1. **Step 1:** Estimate Equation (4) using FGLS applied to the original data (yielding $\hat{\alpha}$, $\hat{\lambda}$, and $\hat{\phi}_1, \ldots, \hat{\phi}_k$) and store the residuals.

2. **Step 2:** Employ a wild bootstrap to the residuals stored in Step 1, in such a way that any cross-sectional correlation is maintained.

3. **Step 3:** Using $\hat{\alpha}$ and $\hat{\phi}_1, \ldots, \hat{\phi}_k$ (obtained in Step 1) and the bootstrapped residuals (from Step 2), recursively calculate values of the return deviations in the model of Equation (4), imposing $\lambda = \lambda_{0,j}$. This yields a set of bootstrapped return deviations: $(r_t^i - r_t^b)^*$, for $t = 1, \ldots, T - k$ and $i = 1, \ldots, N$.

4. **Step 4:** Apply FGLS estimation to the bootstrapped return deviations and estimate the panel model of Equation (4). This yields an estimate $\hat{\lambda}^*$.

5. **Step 5:** Repeat Steps 2 to 4 a large number of times, say $B = 5000$, yielding $\hat{\lambda}_1^*, \ldots, \hat{\lambda}_B^*$.

For each value $\lambda_{0,j}$ $(j = 1, \ldots, n)$, calculate $m_j(\lambda^*)$, the median of $\hat{\lambda}_1^*, \ldots, \hat{\lambda}_B^*$. By means of interpolation on $m_1(\lambda^*), \ldots, m_n(\lambda^*)$, determine the value $\lambda_0$ for which the bootstrapped return distribution has median $\hat{\lambda}$, with $\hat{\lambda}$ estimated from the original data using FGLS. Subsequently, repeat Steps 1 to 5, but omit the first step and replace it by Step 1a below:

**Step 1a:** Estimate estimate $\alpha$ and $\phi_1, \ldots, \phi_k$ under the restriction that $\lambda = \lambda_0$, yielding $\tilde{\alpha}$ and $\tilde{\phi}_1, \ldots, \tilde{\phi}_k$. Store the corresponding residuals.

Furthermore, use the residuals from Step 1a in Step 2 and the estimated parameters from Step 1a in Step 3. After Step 4, turn back to Step 1a. Stop as soon as the estimates $\hat{\lambda}^*$, $\tilde{\alpha}$ and $\tilde{\phi}_1, \ldots, \tilde{\phi}_k$ do not substantially change anymore. Convergence is usually reached after two or three iterations.

To estimate confidence bounds, we apply the same procedure to the 2.5 and 97.5 percentiles instead of the median. Also for the country-specific estimates of $\lambda$ (based on cross-sectional data only) we can proceed as above to obtain median unbiased estimates and associated confidence intervals, using OLS instead of FGLS. Throughout, we have taken the grid (-0.10,0.40) with steps of 0.01.

### A.2 Hypothesis testing

To test whether two countries $i$ and $j$ have the same speed of mean reversion (given the same benchmark index), we treat the median unbiased estimates $\hat{\lambda}^i$ and $\hat{\lambda}^j$ (and the other estimated model coefficients) as though they were the true parameter values. Subsequently, we bootstrap return differences for both countries on the basis of these parameter values as outlined in Steps 2 and 3 above. Next, we estimate the cointegration model using FGLS. However, instead of restricting the speed of mean reversion to be the same across countries, we allow it to vary. This yields the biased estimates of $\lambda^i$ and $\lambda^j$. Subsequently, we obtain the median unbiased estimates of $\lambda^i$ and $\lambda^j$ by following Steps 1 until 5 above (again allowing the speed of mean reversion to vary over time). We repeat this a large number of times, say $M = 5,000$ times. Finally, we calculate $\hat{\lambda}^{i,m} - \hat{\lambda}^{j,m}$ for $m = 1, \ldots, M$, as well as the corresponding 2.5% and 97.5% quantiles of $\hat{\lambda}^{i,m} - \hat{\lambda}^{j,m}$. If zero is not contained in the resulting 95% confidence interval, we reject the null hypothesis $\lambda^i = \lambda^j$. In a similar way we can test for differences in the speed of mean reversion across more than two countries.