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WORKING PAPER

Long-Horizon Mean Reversion for the Brussels Stock Exchange:

Evidence for the 19th Century

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Abstract

In this paper, we introduce a completely new and unique historical dataset of Belgian stock returns during the nineteenth and the beginning of the twentieth century. This high-quality database comprises stock price and company related information on more than 1500 companies. Given the extensive use of CRSP return data and the data mining risks involved it provides an interesting out-of-sample dataset with which to test the robustness of 'prevailing' asset pricing anomalies.
We re-examine mean reversals in long-horizon returns using the framework of Hodrick (1992) and Jegadeesh (1991). Our simulation experiments demonstrate that it has considerably better small sample properties than the traditional regression framework of Fama and French (1988a). In the short run, returns exhibit strong persistence, which is partially induced by infrequent trading. Contrary to Fama and French (1988a) and Poterba and Summers (1988), our results suggest that, in the long run, there is little to no evidence of stock prices containing autoregressive stationary components but instead resemble a random walk. Capital appreciation returns exhibit stronger time-varying behavior than total returns. Belgian stock returns demonstrate significant seasonality in January notwithstanding the absence of taxes. In addition, in contrast to other months, January months do show some evidence of mean reversion.

Keywords: Brussels Stock Exchange, Financial Market History, Market Efficiency, Univariate Stock Return Predictability

JEL Classification: G10, G14, N23

1. Introduction

In his 1970 survey of early empirical studies on the statistical properties of financial asset returns, Fama could still conclude that “the evidence in support of the efficient markets model is extensive, and (…) contradictory evidence is sparse.” (Fama (1970), p. 416). Shiller (1981), Shiller and Perron (1985) and Summers (1986) challenge this assertion, claiming that if stock prices exhibit slowly mean reverting behavior, earlier tests lack statistical power in rejecting the market efficiency hypothesis. In their ‘fads’ model prices can deviate considerably from fundamental values but gradually revert towards their ‘full-information’ values as time passes because investors become aware of overly optimistic or pessimistic market reaction to past information and slowly revise valuation. A first-order autoregressive price process is therefore a reasonable representation of this sort of mean reverting behavior. However, when the implied autocorrelation is high, prices resemble a random walk and successive short-horizon price changes will demonstrate little correlation since it may take several years before the stock price completely adjusts to account for erroneous ‘fad’ shocks. Using this insight, Fama and French (1988a) and Poterba and Summers (1988) report highly significant negative serial dependence in long-horizon U.S. stock returns claiming that predictable variation due to mean reversion or slowly decaying price components accounts for 30% to 40% of total return variances.[1] In addition, a whole plethora of variables that are linked to the business cycle have been found to have predictive power for stock returns.[2] This gives credence to the claim that long-horizon mean

[1] Similar patterns describe stock returns for other countries (Cutler, Poterba and Summers (1990, 1991)), a long time series of U.K. and U.S. stock returns dating back to the eighteenth century (Goetzmann (1993)) and returns to different risky assets like exchange rates, real estate and precious metals (Cutler, Poterba and Summers (1991) and Huizinga (1987)).

[2] Many variables have been used: bond spreads (Keim and Stambaugh (1986), Campbell (1987) and Fama and French (1989)); the dividend-to-price ratio (Ang and Bekaert (2005), Campbell and Shiller (1988a), Campbell and Yogo (2003), Fama and French (1988b, 1989), Goetzmann and Jorion (1993,

reversion is not so much due to irrational behaviour, but to time-varying expected returns. Assuming that expected dividends are not affected (Campbell (1991)), shocks to expected stock returns produce a contemporaneous opposite adjustment to the current stock price. Consistent with the long up and down movements of business conditions, expected risk premiums may be highly persistent but mean reverting. Regardless of whether mean reversion is due to irrational behaviour or rationally varying expected returns, the empirical evidence seems to be taken for granted based on the recent interest in dynamic asset allocation strategies based on the predictability of asset returns (e.g. Campbell and Viceira (2001); Cochrane (1999)).

Nevertheless, testing return predictability raises important methodological issues with regard to the estimation procedure and the data mining problem. Examining the highly volatile return generating process of stocks requires the availability of long time series of high quality to produce tests with reasonable power. The CRSP files provide one such database. Its ready availability has encouraged researchers to devote considerable effort to understanding the return generating process behind its data. Unfortunately, this violates the implicit assumption of classical statistical inference that every hypothesis should be tested with one particular dataset and an a priori choice of the explanatory variables. Instead, the low-cost availability of the CRSP data and the lack of other reliable and independent data sources have led to an explosion of empirical research with thousands of researchers examining the same return data. In a persevering attempt to test hypotheses, however, there is a high probability of detecting spurious relationships without theoretical justification and

1995), Hodrick (1992), Nelson and Kim (1993) and Torous, Valkanov and Yan (2001)); the earnings-to-price ratio (Campbell and Shiller (1988b) and Campbell and Yogo (2003)); changes in the short-term interest rate (Ang and Bekaert (2005), Campbell (1987, 1991), Campbell and Yogo (2003), Hodrick (1992) and Torous et al. (2001)); the aggregate consumption-to-wealth ratio (Lettau and Ludvigson (2001)); other macroeconomic indicators (Balvers, Cosimano and McDonald (1990), Fama (1990), Nelson and Kim (1993)). The literature is vast and we offer only some representative references. We apologize to the authors of the papers that have not been listed.

erroneously identifying instruments with predictive power. The substantial danger of data mining and its implications for the reliability of statistical analysis this practice induces are problems well recognised but hardly considered in empirical research (Denton (1985), Ferson, Sarkissian and Simin (2003), Foster, Smith and Whaley (1997), Lo and MacKinlay (1990) and Merton (1987)). The consequence of data mining is that inferences based on conventional significance levels are inappropriate, leading to over-rejection of the null hypothesis of no predictability. Stylised facts found to describe the dynamic behavior of stock returns can be artefacts of the sample being used (Ferson et al. (2003)). To circumvent these difficulties, researchers can either adjust the critical values of the test statistics or employ a new and independent dataset to test the stylised facts of asset pricing theory.

In this study, we follow the latter approach by studying mean reversion of stock returns using a completely new and unique dataset of historical stock returns from the Brussels Stock Exchange (BSE). To the best of our knowledge, this is probably the most comprehensive and accurately constructed historical index representing more 1500 different common stocks during the period 1832-1914. Moreover, the BSE ranked among the most developed markets during this period. We believe that this independent return database provides a useful and valuable out-of-sample test for different asset pricing anomalies identified in the literature, and, importantly, is not subject to the data mining critique. In addition to the data mining issue, the recent empirical literature questions the reliability of evidence in favor of predictable long-horizon variation in returns. It is argued that the test statistics used have low power and rely unduly on asymptotic results. Kim, Nelson and Startz (1991) and McQueen (1992) apply different estimation and simulation techniques and evaluate the robustness over different subperiods. They find only weak evidence of negative serial correlation in U.S. stock returns and even mean *aversion* in their post-war period. More recently, Ang and Bekaert (2005) question the robustness of the long-horizon return predictability when due account is given to the small sample properties of the estimators. This conflicting evidence about the predictability of stock returns calls for additional research, preferably on fresh data. This paper reconsiders this issue by analyzing the long-horizon serial return properties of BSE stocks during the 19th and the beginning of the 20th century.

The remainder of this paper is organized as follows. In section 2, we briefly describe company specific information contained in the database of the BSE. We document the dataset of historical individual stock returns during the 19th century as well as the construction of the stock return indices and size portfolios used to analyze the mean reverting behavior of stock returns. Section 3 introduces the tests considered to investigate the random walk hypothesis. More specifically, we discuss two related regression techniques and their small sample properties through a simulation experiment. Our results show that, in the short run, returns exhibit strong persistence partially owing to the effect of infrequent trading. In the long run, we find little to no evidence of stock prices containing slowly decreasing temporary components. Rather than strongly mean reverting behavior, BSE stock returns exhibit some form of mean aversion that is eventually 'adjusted'. Section 4 tests the robustness of the previous results. First, we analyse the behavior of BSE stock prices when returns are sampled at lower frequencies. The results corroborate our earlier conclusions of absence of mean reversion. Second, we do find strong seasonal patterns in BSE stock returns. It appears that January returns provide stronger evidence for mean reversion than returns in the other months. This is consistent with the post 1926 U.S. results and the post 1955 U.K. presented by Jegadeesh (1991).

2. Data

We introduce a completely new historical dataset of stock returns for the Brussels Stock Exchange (BSE) starting in 1832.[3] The dataset has been constructed at the University of Antwerp (Belgium). Although at present BSE's importance is rather limited, during the 19^{th} century and the first half of the 20^{th} century it ranked among the largest stock markets in the world according to the International Statistical Institute (Neymarck (1911)). Belgium was one of the first nations on the European continent to industrialize. Measured by industrial output per head, Belgium stood second only after Britain in 1860 and third in 1913 after the U.K. and the U.S.. In addition, a highly developed banking system constituted a vital part of this industrial revolution in Belgium. Thanks to its liberal stock market regulation, the BSE attracted a great deal of domestic and foreign capital. Measured by stock and bond ownership per capita it was 7^{th} in the world as of 1902 (Neymarck (1911) and Maddison (1995)). For the period 1832-1914,[4] covered in this study, official records for stock prices, dividends and other cash distributions as well as market capitalizations are well documented in the archives of the BSE. Using these records, price, dividend and market capitalization data for 1507 different common stocks were hand-collected and entered into the computer enabling the reconstruction of the quantitative history of the BSE according to the modern quality criteria required for doing research in finance (Annaert et al. (2004)).

[3] For a detailed description of the construction of the stock return database of the BSE, see Annaert, Buelens and De Ceuster (2004).

[4] The end of our dataset coincides with the outbreak of the First World War. During this period, the BSE was closed and can be regarded as a natural breaking point in this long time series of stock returns. The dataset is being updated to include stock returns for the remaining period starting in 1915. However, at the timing of writing not all necessary data were entered into the database and checked for accurateness and completeness.

Similar efforts have been made to collect historical stock return data for other countries with special interest to the U.S. (Goetzmann, Ibbotson and Peng (2001, GIP henceforth) and Schwert (1990)). Despite all the efforts, the construction of reliable historical return data and indices is frequently hampered by different kinds of data flaws such as survivorship bias and incomprehensive and inconsistent datasets. These may influence the short and long run statistical properties of returns. The BSE return dataset is not subject to most of these pitfalls because of the availability of highly reliable first-hand data sources (the original Official Quotation lists of the BSE) complemented by secondary sources that allow cross-checking the data enhancing the internal consistency of the database. It comprises individual stock prices and related company specific information for companies officially quoted on the BSE between 1832 and 1914. From 1868 on, more than 100 common stocks were listed on the BSE, gradually increasing to around 600 at the end of our data period. Contrary to historical U.S. datasets where some industries dominate the stock exchange for decades, companies listed on the BSE show a broad diversification across industries such as transportation, financials, industrials, and utilities.

Stock price data as well as the number of stocks admitted to the stock exchange were gathered on a monthly basis. Compared to information on stock prices, accurate reconstruction of precise dividend data on individual stocks is one of the greatest problems experienced in nearly every country where the historical reconstruction of data has made serious progress. However, the Official Quotation lists of the BSE and the secondary sources contain accurate and detailed information on dividends[5] and stock repayments as well as other capital operations allowing us to reconstruct precise dividend data for individual stocks. As further analysis will show, dividends made up

[5] E.g. dividend amount, type of dividend, day of payment, ex-dividend day and currency of denomination.

a large part of the realized returns to Belgian stocks in the 19th century. On average, price appreciation as such did not contribute significantly to total returns. Moreover, as dividends usually show a seasonal pattern, studying price index returns or assuming that all dividends are paid out in one particular month may introduce spurious return seasonalities.

These data enable us to construct highly reliable and accurate equal- and value-weighted stock return indices as well as different size portfolios for the period 1832-1914. As GIP employs this as a proxy for the value-weighted index, we also compute a price-weighted index for comparative purposes. Comparing our results for the value-weighted index to those of our price-weighted index may shed light on the appropriateness of the GIP approach.

We start with an extensive discussion on the univariate properties of these return series. To compare, we also include the GIP price-weighted return index (starting in 1815 and ending in 1925).[6] Table 1 presents summary statistics for the BSE and U.S. stock return data. It contains average nominal monthly continuously compounded total returns, standard deviations, minimum and maximum returns (all in %), as well as skewness, kurtosis and autocorrelations for all indices and size portfolios.[7] For the capital appreciation indices, only average returns are included, as the other statistics are very similar to those of the total return indices. In addition, we provide insight on the size of the BSE. Figure 1 graphs the evolution of the BSE equal-, price- and value-weighted total return indices. We have return data over a period of 83 years or 996 monthly stock price observations. During those years, the number of (purely) Belgian

[6] We are most grateful to William Goetzmann (and the International Center of Finance) for providing these data.

[7] We construct five size portfolios by classifying companies according to their equity market capitalization as recorded at the end of December of the previous year. The stocks composing each size portfolio are equal-weighted to obtain a total and capital appreciation return for every size portfolio. ‘Size I’ to ‘Size V’ comprise the smallest to largest market cap firms respectively.

companies listed on the BSE averaged 145 and reached a maximum of 396 near the end.[8] The average total market capitalization of the BSE amounted to more than 1.1 billion BEF (28 million euros). Total market capitalization was 27% of GNP in 1846, steadily growing to 80% in 1913 (Annaert et al. (2004)). Noticeable is the large difference in market capitalizations between the different size portfolios. The smallest firms ('Size I') have a market cap that is only one fiftieth of the largest ones ('Size V') and represent, on average, less than 2% of the total market capitalization of all firms compared to more than 67% for the largest companies.[9]

The historical return properties across indices and size portfolios for the BSE are generally similar to the patterns we see nowadays. The total return index has an average monthly return of 0.35% (4% yearly) when value-weighted and 0.44% (more than 5% yearly) when equal-weighted. These numbers are substantially lower than the average return for U.S. stocks during the twentieth century, but somewhat higher than the average returns in the GIP dataset. The higher return for the equal-weighted index arises from the high return of the smallest size portfolio 'Size I' (0.68% monthly or more than 8% yearly) that is almost double that of the largest size portfolio 'Size V' (0.35% monthly or more than 4% yearly). As expected, standard deviations exhibit a similar tendency. Smaller firms are considerably more volatile than large caps (4.95% for 'Size I' versus 2.49% for 'Size V' on a monthly basis). Returns on most indices and all size portfolios are marginally to very positively skewed and highly leptokurtic implying a 'fat tailed' distribution.

[8] Annaert et al. (2004) classified all companies listed on the BSE based on geographical location of the major production facilities and country of residence of the company. For this study, we restrict ourselves to the analysis of purely Belgian companies with the most important production facilities located in Belgium. Three other categories were constructed, but correlation coefficients with the purely Belgian index are close to one.

[9] Notice that this distribution is quite similar to that in the U.S. CRSP series; see e.g Fama and French (1993), their Table 1.

Although we do not condition upon the continuity of price records (and as such clearly avoid the selection bias to which many historical studies are subject), a problem often encountered with the construction of historical indices is the lack of continuous stock price data. Certainly, during the nineteenth century, many stocks on the BSE and the NYSE (Annaert et al. (2004), GIP and Schwert (1990)) did not trade very frequently and obviously, this affects the time series properties of the indices and size portfolios. Of course, small stocks are more likely to trade infrequently. However, a lack of trading might even bear on the larger stocks as they were often issued at prices considerably higher than the average daily wage during most of the century. This made stock trading an activity that was only available to the wealthiest individuals and institutions (Annaert et al. (2004)). Infrequent trading of stocks induces serial correlation in the indices and portfolio returns of the BSE. The first-order autocorrelations for the value- and equal-weighted index are close to 0.30 and highly significant. The indices inherit the high autocorrelation mainly from the smallest and to a lesser degree from the largest stocks. The smallest size portfolios show significantly positive serial correlation that extends beyond the first order. The largest size portfolio still has a high first-order correlation of 0.24.[10] However, first-order 'persistence' is partially reversed in the subsequent months.

Table 1 clearly demonstrates the importance of accurate information on dividend data to obtain an adequate view of the performance and univariate properties of historical indices. Comparing average total returns with capital appreciation returns unequivocally shows that during the nineteenth century dividend income constitutes a major part of the return earned by investors. The indices exhibit no or even negative (for the price-weighted index) capital appreciation. The dividend yield is about 0.31%

[10] Given the magnitude of the first-order serial correlation in returns of the value-weighted index and the largest size portfolios, it is questionable that non-synchronicity of returns accounts for all of the short-term persistence in stock returns (see later).

monthly or more than 3.5% yearly. As expected, only the smallest companies have large price appreciation returns with dividends comprising a minor part of the total return. Standard deviations and the other statistics for capital appreciation returns are similar to those of the total returns and are therefore not shown. This implies that dividend income represents a high proportion of total returns but contributes only marginally to total return variances. More importantly, incorporating dividends does not change the higher moments or the short-term dependence of stock returns.

As GIP notice, the return and risk characteristics before and after 1925 are quite different for U.S. indices. During the nineteenth and the first half of the twentieth century, the average monthly return equals 0.10% for the GIP price-weighted index or 1.2% yearly. This low return may be a consequence of deficiencies in constructing the index. Lack of information on dividend income (inclusive of stock repayments) and stock splits as well as delistings (from mergers or bankruptcy) and other capital operations could lead to substantial underestimation of the average return earned by investors. The weighing scheme is another potential factor in affecting performance. The BSE indices show that for Belgian stocks price is not a good proxy for the relative market capitalization of stocks. Table 1 also shows that U.S. returns are considerably more volatile than Belgian returns (4.06% compared to 2.37% for the value-weighted index). Part of it may be due to the smaller number of stocks in the U.S. index that are moreover less spread across industries. In addition, as lack of information on particular corporate capital operations like stock splits and large dividend payouts erroneously lead to highly negative returns for stocks (manifested in the very low minimum returns for the historical U.S. indices), these data flaws possibly influence risk measurement. The first-order autocorrelation is substantially lower and even negative. Apparently, the construction of the U.S. indices is less subject to the problem of infrequent trading than the BSE indices and portfolios. Indeed, GIP only compute returns when they have two adjacent price observations, which eliminates the effect of stale prices.

3. Testing Long-Horizon Mean Reversion

3.1. Preliminary results and caveats

The null hypothesis of stock prices following a random walk imposes a simple restriction on the covariance structure of returns, that is

$$\operatorname{cov}\left(r_t , r_{t-k}\right)=0 \qquad \forall k \neq 0 , \tag{1}$$

where r_t is the continuously compounded return. It is a set of orthogonality conditions on the population autocovariances of stock returns, which determines any test statistics used for testing the mean reversion of the underlying return generating process. Recent studies have applied an assortment of alternative but strongly related test statistics to investigate the high and low frequency univariate properties of returns. The common feature is that they all concentrate on the aggregation of single period returns for better capturing the alleged mean reverting pattern induced by the slowly decaying transitory price component. The basic intuition is unambiguous. When the persistence factor of prices is close to one, single period price changes appear to correspond to a pure random walk. However, compounding returns implies that price movements due to the stationary component add up while random fluctuations average out. Therefore, serial correlations measured over a short time span may be negative causing prices to mean revert in the long run, but are individually too small to reveal significance while analyzing long-horizon autocorrelations through return aggregation might prove economically and statistically significant.

This paper estimates serial correlations of stock returns directly using regression-based techniques.[11] Fama and French (1988a) and McQueen (1992) examine multiperiod autocorrelations by regressing *k*-period returns on lagged *k*-period returns:

$$\sum_{i=1}^{k} r_{t+i-1} = \alpha_k + \beta_k \sum_{i=1}^{k} r_{t-i} + \varepsilon_{t,k}\,, \tag{2}$$

where the slope coefficient β_k is the first-order autocorrelation of the *k*-period stock return. Since there is ex ante little theoretical justification for the exact number '*k*' of single period returns to compound, a series of regressions for increasing holding periods of 1 to 10 years is often run.

In Panel A of Table 2 we present similar regression results for the value-weighted return index of the BSE over the period 1832-1914. Monthly logarithmic returns are summed to obtain overlapping monthly observations on long-horizon returns for ten different *k*-period measurement intervals (k = 12, 24, …, 120). We first correct the slope coefficients for the well-known negative small sample bias in autocorrelation estimates owing to errors made in estimating the unknown true mean from the sample (Kendall (1954) and Marriott and Pope (1954)). Assuming that the true value of the i^{th}-order sample autocorrelation is zero, its expected value in small samples of length T equals $-1/(T-i)$. This is relevant for regression (2), as Richardson and Smith (1994) show that the slope coefficients β_k are approximated by a linear combination of the sample autocorrelation coefficients $\widehat{\rho}_i$. More specifically,

$$\beta_k \approx \sum_{i=1}^{2k-1} \min(i, 2k-i)\,\widehat{\rho}_i \big/ k\,. \tag{3}$$

[11] As an alternative, variance ratio tests that analyze the comparative behavior of volatilities across different holding periods, could be used to investigate the extent of stock return mean reversion. However, both methodologies are related, see Richardson and Smith (1994) and Daniel (2001).

Using this expression for the bias of the sample autocorrelation coefficients, we compute the bias on β_k and subtract it from the regression estimates.

Table 2, Panel A, reports the t-statistic for each bias-adjusted slope coefficient using the autocorrelation and heteroskedasticity consistent covariance matrix of Hansen and Hodrick (1980), where we impose the Newey and West (1987) weights to guarantee a positive definite matrix. At first sight there is quite some evidence for mean reversion as slope coefficients with *k* between 36 and 60 months are statistically significantly negative. Yet, at least three caveats are in order. First, even though the samples we employ to gauge mean reversion in stock returns are considerably larger than earlier studies,[12] for large *k*-period intervals the number of non-overlapping observations remains small, limiting the number of truly independent long-horizon returns. The test statistics, however, rely on asymptotic distribution theory. Therefore, given the relatively small sample sizes for large *k*, it remains doubtful whether we can rely upon the derived asymptotic standard errors. Second, by lack of theoretical arguments for choosing an appropriate lag length *k*, researchers estimate coefficients over different time horizons and then tend to focus on the extreme estimates. Of course, estimates at different lags are highly correlated because autocorrelations at different frequencies are affected by similar (real or spurious) variation (Richardson and Stock (1989) and Richardson (1993)). Moreover, even under the random walk null hypothesis, one should expect some of the individual slope estimates over the vector of multiperiod autocorrelations to be different from zero. Many researchers therefore overstate the significance in favor of mean reversion in stock returns by focusing on the most significant individual point estimates. Instead, one should account for the joint

[12] The BSE dataset consists of 995 monthly return observations, the GIP return series comprises 1331. Previous studies (Fama and French (1988a), Jegadeesh (1991), McQueen (1992), Kim et al. (1991), Poterba and Summers (1988) and Richardson and Stock (1989) all use the CRSP return database starting in 1926 with less than 750 return observations available.

dependence by considering simultaneously the estimated coefficients for all *k*-period measurement intervals. Third, evaluating the time-varying behavior of stock returns following the long-horizon regression approach of (2) has some econometric drawbacks. Although the standard errors of the coefficients take into account the serial correlation of the residuals, induced by using overlapping observations, it is not clear to what extent these corrections are adequate in the samples that we consider. In addition, the *k*-period long-horizon return is a rolling sum of the original series r_t. Valkanov (2003) demonstrates that in a rolling summation of series that are integrated of order zero, the long-horizon variable resembles asymptotically a series integrated of order one. Such persistent stochastic behavior in both the dependent and independent variable might produce the well-known spurious correlation problem (Ferson et al. (2003)) and potentially erroneous identification of return predictability.

All three caveats affect our results. First, to show the impact of the slow convergence to the asymptotic distribution of the test statistics, we simulate the small sample distributions in a Monte Carlo simulation with 25,000 runs. In each run, we first generate T normally distributed return observations, where T is the number of observations for the respective stock return series and where we assure that the simulated series have the same standard deviation as the original ones.[13] For each random series we perform the same regressions as for the original series to obtain the small sample distributions for the t-statistics at each horizon.[14] Of course, we apply the appropriate small sample bias-correction on the slope coefficients. Significance is determined based on the simulated empirical p-values.

[13] In addition, to account for heteroskedasticity, we run a second set of simulations where we introduce GARCH effects. However, the results are generally similar so we restrict ourselves to reporting the results for the case of constant conditional return variances.

[14] Although we could rely on the simulated distribution of the estimated slope coefficient, we prefer to evaluate significance using the simulated distribution of the t-test because the latter is asymptotically a pivotal statistic. That is, its asymptotic distribution does not depend on any unknown population parameters.

From the lower part of Table 2, Panel A it is clear that the small sample distribution of the t-statistic is far from normal rendering the conventional significance levels inappropriate. The simulated distribution is highly negatively skewed for all horizons, especially for the higher aggregation intervals. Notice also the large standard errors for the simulated slope coefficients at higher lags. This suggests that if stock prices contain temporary components they must produce large negative slope coefficients and account for a large fraction of return variances to be identifiable. Yet, at the conventional significance levels the inference only changes for *k*=60 where the coefficient is no longer significantly negative. Mean reversion still appears to stand out.

However, neighbouring regression estimates share many autocovariances, certainly for larger *k*-periods. In our simulations, we find high correlations between surrounding slopes (around 0.90). Not surprisingly, they decline steadily when the return periods overlap lessens.[15] Hence, to account for the second caveat, i.e. the multivariate nature of the test procedure, we compute two joint tests. Richardson and Stock (1989) and Richardson (1993) suggest a Wald statistic to test the hypothesis that the different *k*-lag return coefficients simultaneously equal zero. Let $\hat{\boldsymbol{\beta}}$ be the vector of K different *k*-period return autocorrelation coefficients with asymptotic covariance matrix $\mathbf{V}$, then the Wald test for joint significance is given by

$$W_T\left(\hat{\boldsymbol{\beta}}\right) = \sqrt{T}\hat{\boldsymbol{\beta}}'\mathbf{V}^{-1}\sqrt{T}\hat{\boldsymbol{\beta}} \overset{asy}{\sim} \chi^2_K. \tag{4}$$

As the Wald test does not take into account the sign of the coefficients, we follow Jegadeesh's (1991) and Richardson and Stock's (1989) suggestion and also test whether the *average* autocorrelation coefficient in (2) is significantly different from

[15] The simulated correlation matrix of betas for all *k*-periods closely approximates its analytical counterpart.

zero. To account for small samples, we again rely on the empirical p-values to test the null hypothesis. For the value-weighted total return index Table 2, Panel A shows a Wald statistic of 114.26, which has a p-value virtually zero if it were distributed according to the asymptotic chi-squared distribution with ten degrees of freedom. In contrast, the simulated distribution is much more skewed, resulting in an empirical p-value higher than 10%. The joint test therefore provides much less evidence for mean reversion. The test on the average slope coefficient across all horizons corroborates this conclusion, as it is insignificant at conventional significance levels.

Panel B of Table 2 reports the regression results for the other stock indices and size portfolios. Evidence against the random walk null hypothesis is stronger for the equal-weighted index due to the strongly mean reverting patterns in the returns of the smallest size portfolios. Many of the individual estimates are well below -0.30 and significant at the 1%- or 5%-level. The Wald-statistics confirm their joint significance, certainly for the equal-weighted index. Although irrational expectations can produce similar effects, these slope estimates suggest that time-varying expected returns explain at least 30% of the total variance of 3- to 5-year returns of the equal-weighted index and the smallest size portfolios. These results are consistent with the findings of Fama and French (1988a). However, as expected, stock prices of larger companies do not contain any slowly decaying stationary components. Some of the regression slopes are even positive. All individual estimates as well as the Wald statistics and the average coefficients are insignificant indicating that firms with larger market capitalizations do not demonstrate mean reverting behavior. In general, there is less evidence for mean reversion in total return series than for capital appreciation series. This is most obvious for the value-weighted series, where the Wald statistic for the capital appreciation index is significant with a p-value less than 5%, but insignificant for the total return index. This points to the importance accurate dividend information may have, especially in periods where dividend income is an important component of total return.

To deal with the third caveat, Hodrick (1992) demonstrates that the potential problem of getting spurious significant results due to summing both regressand and regressor can be circumvented by eliminating the overlapping nature of the dependent variable. Moreover, Daniel (2001) and Jegadeesh (1991) demonstrate that, in terms of power, the most optimal test for analysing the mean reverting behavior of stock returns is a regression of the single period return r_t on the lagged *k*-period return:

$$r_t = \alpha_k^M + \beta_k^M \sum_{i=1}^{k} r_{t-i} + \varepsilon_t \,. \tag{5}$$

We will refer to this regression as the 'modified' long-horizon regression. It may thus be the case that the failure to reject the random walk hypothesis for many series in Table 2 is due to a lack of power. In the remainder of the paper, we will focus the discussion on the results for the modified regression given its superior statistical properties.

Before we turn to the results regarding the modified regression, we should draw the attention to a feature of our data that is not consistent with most published results. It is remarkable that we find large significant *positive* serial correlation for the 12-month returns.[16] Its 0.19 is significant at the 5% level. The EW and PW indices in Panel B of Table 2 exhibit the highest point estimates of over 0.25, which are highly significant. This is related to the higher order serial correlations in monthly returns that remain positive after one lag, in particular for the smaller firms (Table 1). Positive autocorrelation in one-year returns seems to imply that the AR(1) return specification

[16] However, note that also Kim et al. (1991) and McQueen (1992) find results for the U.S. consistent with mean aversion in the post World War II period.

postulated by Summers (1986) is inappropriate for shorter horizons. Of course, stale information on stock prices inducing the infrequent trading effect of positive serial correlation could account for the short-horizon persistence in Table 2. Two facts are consistent with this interpretation. First, the degree of positive serial correlation at a 12-month measurement interval is lower for the VW index and the larger size portfolios. Second, the slope coefficient for the GIP data, where stale prices are less of a concern, is very close to zero.[17] To attenuate the impact of stale prices, we will present results based on quarterly and annual data as a robustness check in section 4.

3.2. Modified Long-Horizon Regressions

Table 3 presents the estimation results for the modified long-horizon regressions. Again, Panel A presents summary results about the simulation approach, whereas Panel B reports the bias-adjusted slope coefficients. We compute the bias based on the following relation between the modified regression slope and the autocorrelation coefficients (Richardson and Smith (1994)):

$$\beta_k^M \approx \sum_{i=1}^{k} \widehat{\rho}_i \big/ k \,. \tag{6}$$

As expected from the analytical specifications (3) and (6), the downward bias in the slope coefficients of the modified long-horizon regressions is considerably smaller and equal to –0.001 for all horizons. The Monte Carlo simulations for specification (5) unequivocally establish the better small sample properties of the modified long-horizon regressions. Standard errors for the slopes are much lower than in Table 2 and even decrease for larger measurement intervals. Moreover, although not really converging, the simulated t-distributions of (5) have a considerably smaller left tail than those of (2) and are less negatively skewed at long-horizons. At the short end of

[17] For any given month, GIP only includes stocks in the index that trade during that month and the previous one.

the return horizon intervals, the distribution is nearly symmetric and approximates the conventional (normal) significance levels.

From (6), the slopes of the modified regressions can be interpreted as the average serial correlation coefficient over the return horizon *k*. It is therefore not surprising that the short-horizon estimates of (5) affirm the results of the previous analysis. The bias-adjusted slope coefficients for the 12-month lagging return are positive and highly significant. Given that we forecast one-month instead of *k*-period future returns, the coefficients are substantially smaller than those of the long-horizon regressions, but the pattern remains the same. Positive serial correlation is more pronounced for the EW (0.042) and PW (0.037) than for the VW (0.031) index. The smaller size portfolios also have highly significant positive serial correlation coefficients of over 0.030 reaching a maximum of 0.044 for portfolio 'Size II' (p-value < 0.001%). Although smaller in magnitude, the 12-month coefficient remains significant for the largest portfolios at the 5%-level. Again, non-trading effects of securities can account for the apparent momentum behavior of returns in the short run. However, the magnitude of persistence in stock returns, especially for the larger companies, argues for other possible explanations. First, both positive and negative feedback trading impulses in the stock market are potential sources of short-term positive autocorrelations in returns (Cutler et al. (1990)). Second, in our earlier discussion on time variation in equilibrium expected returns generating mean reversion in ex-post stock returns, we hypothesized that shocks to the discount factor or required returns and expected future dividends should be mutually independent. However, innovations to prospective dividends and expected returns may also exhibit positive correlation. Therefore, an (unexpected) rise in expected dividends would raise stock prices and (ex ante) future returns leading to positive serial correlation in the short run. Given their importance for BSE stock returns, it would be interesting to examine whether dividend innovations relate to the stochastic properties of expected returns. Further research is required to conclude upon this relationship. Finally, positive autocorrelation may arise from persistence in expected returns as such.

It is remarkable that the average positive serial correlation extends beyond 12 months and remains significant for 24-month lagged returns of all indices and size portfolios. Although suggesting considerable market inefficiency, it is questionable that these market microstructure effects affect returns over horizons larger than one year. Closer inspection of the difference in magnitude between the slope coefficients of the 12- and the 24-month return reveals that, on average, positive serial correlation is restricted to the first twelve months. Both for the market indices and the size portfolios the regression slopes decrease substantially, with most 24-month total return coefficients fluctuating between 0.014 and 0.020, which indicates that the serial correlation coefficients beyond the 12^{th} lag are negative, reversing the strong positive serial correlations of the first 12 months. The effect is weaker for the largest stocks and the VW index. Similarly, slightly decreasing slopes can generally be seen up to horizons of 84 to 96 months. This suggests that there is a weak tendency for stock returns to mean revert at durations of more than one year. Particularly the EW index and smaller stocks are subject to that pattern indicating that, although the latter trade infrequently possibly inducing positive correlation with adjacent months, prices adjust in subsequent months as new information about these stocks hits the market.

Though the modified long-horizon regressions have greater power against interesting alternative hypotheses, the evidence of mean reverting patterns in equity returns identified in the previous section, especially for the EW index and small stocks, largely vanishes. The estimated coefficients for both total and capital appreciation returns of all indices (except for the PW index) and size portfolios are negative for horizons between 5 and 8 years; however, they are negligibly small and, more importantly, not significant. The differences between total return and price appreciation returns are less pronounced, but present as in the previous section there is slightly more evidence for mean reversion in the latter series.

Evaluating the joint time series properties of the different horizon estimates for the modified long-horizon specification of (5), we find a highly significant Wald statistic for all indices and size portfolios. Of course, this is arguably to a large extent due to the positive 12-month slope. The fact that the average test is positive (although mostly insignificant) is consistent with this explanation.

In general, we conclude that there is at best some weak evidence for slowly decaying transitory components in stock prices of the BSE during the nineteenth and the beginning of the twentieth century. The slope coefficients for all series do exhibit a U-shaped pattern, but the point estimates are statistically indistinguishable from zero. Given the positive coefficients at the shorter horizons and the often negative, but small and insignificant coefficients at the longer horizons, the results are more consistent with some form of mean aversion that is eventually 'corrected'. Alternatively, market microstructure effects may be responsible for the observed patterns, an issue we will further investigate in section 4. Neither is there strong evidence in favour of mean reversion in U.S. stock returns based on the GIP data. If a slope coefficient is significant it is at the not very restrictive (one-sided) 10% level. The joint Wald test is also significant at this level, but the average slope coefficient is virtually zero.

4. Robustness Analysis

4.1. Quarterly and annual results

Results in section 2 and 3 show that BSE stock returns exhibit large (first-order) serial correlations. Infrequent trading effects may induce this short-term momentum and if so, does not reveal any fundamental economic story about expected returns or investor behavior. Infrequent trading is arguably less of a concern when returns are sampled at lower frequencies. To verify the robustness of our results we therefore rerun our modified long-horizon regressions and simulations across different horizons with quarterly and annual return data.

Table 4 reports the bias-adjusted slope coefficients of the modified regressions estimated using non-overlapping quarterly returns (Panel A) and annual returns (Panel B). We use the same forecasting horizons as in the monthly analysis. In general, the quarterly and annual results are very consistent with the monthly results of section 3. Significantly positive slope coefficients are still found for the shorter horizons. However, estimates grow less than proportional with the frequency. Looking at the quarterly (annual) results of a one-year forecasting horizon (i.e. k = 4 resp. k = 1), Table 3 and 4 show that the quarterly (annual) estimates are somewhat higher than double (six fold) the monthly estimate. Hence, persistence weakens beyond the first month. Nevertheless, these results support our earlier assertion that, apart from market microstructure effects, other more fundamental or behavioural factors may have induced short-term momentum in BSE stock returns.

Conversely, for longer horizons, most quarterly and annual slope coefficients are negative. However, they remain small and generally insignificant. Quarterly estimates for the VW index and the largest size portfolios are all close to zero. The total return series of the former has a minimum value of -0.023, which is only marginally significant. Although annual slope estimates are higher, for the most part, they stay insignificant. The smaller size portfolios and the EW index have larger coefficient estimates, especially for the annual return series. At horizons of 5 and 6 years, we find significantly negative slopes in the order of -0.17. Other forecasting horizons do not exhibit any significant estimates.

Compared to the analysis with monthly data, Table 4 shows that the estimated Wald statistics are substantially lower for slope coefficients estimated with quarterly or annual returns. Estimates are still jointly significant for the EW index and the smaller size portfolios at a quarterly frequency, which is still likely to be driven by the short-horizon persistence. The largely insignificant average slope test corroborates this assertion. More importantly, the Wald and AVG statistics of the largest size portfolios and the VW index are only marginally significant at a quarterly frequency and not significant at an annual frequency. In sum, there does not seem to be much evidence for mean reversion even when the returns are sampled at lower frequencies.

4.2. Seasonality in mean reversion

Prior research on stock return predictability has identified several puzzling asset pricing anomalies. Probably one of the most documented seasonal regularities is the "January or turn-of-the-year effect." Many time series and cross-sectional studies (e.g. Fama and French (1993), Keim (1983), Lakonishok and Smidt (1988) and Schwert (2002)) have found significantly higher returns in January compared to other months. Keim (1983) and Schwert (2002) demonstrate that the January seasonality can be attributed to a size premium, i.e. small firms earn significant abnormal returns during the first month of the year relative to larger firms. Tax-loss selling, window-dressing by institutional investors and market microstructure effects are the most commonly proposed explanations for this return anomaly. The institutional framework during the nineteenth and the beginning of the twentieth century contained none of these factors other than the microstructure effects. This creates an interesting testing ground for the various hypotheses regarding the January effect. If present in the BSE data, it was certainly not generated by any of the above listed factors.

Previous analysis of total versus capital appreciation returns clearly confirms the importance of dividends for evaluating the overall performance of BSE stock indices and size portfolios during the nineteenth and the beginning of the twentieth century. Table 1 showed that capital appreciation only marginally contributes to total returns. In addition, dividends paid out by BSE listed companies during the nineteenth and the beginning of the twentieth century exhibit clear seasonal patterns. This may affect the properties of monthly as well as long-horizon returns if not appropriately accounted for.

The average dividend yield amounts to 0.3% monthly or 3.5% yearly (see Table 1). However, Table 5 presents monthly return statistics for all months of the year and shows that it conceals large cross-sectional differences in dividend yields across months of the year. Two months are noticeable in particular, that is January and July. During those months, the VW index realizes a total return of 1.12% respectively 0.86% on a monthly basis. The EW index slightly underperforms the VW index with an average monthly total return of 0.97% respectively 0.69%.[18] All these monthly averages are significantly different from zero at the 0.01%-level. These high return months reflect the dividend payout policies of BSE quoted companies. Throughout January and July, 21% respectively 16% of all listed companies paid out a dividend whereas in the other months this percentage is only 5% (Annaert et al., 2004). These

[18] In addition to January and July, there are two other months standing out in terms of a high average monthly return, which are February and August. However, since the difference in total versus capital appreciation returns amount to or are lower than the average monthly dividend yield, the latter is certainly not a decisive factor in those months.

seasonal patterns in dividend payments characterize the marked differences in stock returns across months. The monthly dividend income in January and July approximates 0.7% and 0.5% respectively for the EW and VW indices as well as the largest size portfolios. The F-test shows that returns in these months are significantly different from returns in the other months of the year, especially for the VW index and the largest size portfolios. The F-statistic is significant at the 1% (January) and 5% (July) level for the VW index. As expected from previous research (Keim (1983) and Reinganum (1983)), the smallest size portfolio is the best performing one with the highest average return of more than 1.3% during January, but this return is not especially high compared to the other months. In contrast to the large caps (Size V), we therefore do not find any significant January effect for the small caps (Size I) (this result is confirmed for the other small cap portfolios, Size II and III). This evidence seems to contest the size premium hypothesis for the January anomaly.

Many researchers have suggested the January effect is a tax effect. They argue that stock prices experience concentrated tax-loss selling at the end of the year and rebound in January providing investors a higher market return at the beginning of the year. Especially smaller firms are supposed to be liable to such investor behavior given their highly volatile nature and the potential of substantial capital losses. Though the tax hypothesis could be a plausible explanation nowadays, it is questionable that it accounts for the January-effect identified in BSE stock returns during the nineteenth and the beginning of the twentieth century. First, we did not find any official sources or records making reference to the Belgian government levying taxes on capital gains or dividends during that period. Second, our results show that larger rather than smaller companies achieve abnormal returns throughout the month of January disputing the tax-motivated size premium. Last, abnormal returns earned during January appear to be related to more fundamental factors like dividends rather than taxes as the month of July, another high-dividend-yield month, is subject to the same effect. Further research on dividends and how asset prices respond to dividend information is required to examine these effects in more detail.

Obviously, these results imply that BSE stock returns contain a January (and July) component. So, in compliance with Jegadeesh (1991) we examine whether the alleged time-varying behavior in stock returns is also characterized by a seasonal pattern. More specifically, we test whether BSE stock prices have larger slowly decaying stationary components in January compared to other months of the year. We perform the same analysis for the month of July.

The modified long-horizon regression (5) allows testing whether the slowly decaying stationary price components are primarily concentrated in January. To that end, we run the regressions separately within and outside January. Specifically, to test the January seasonal we only consider the *monthly* returns in January as the dependent variable, while the independent variable is, as usual, obtained by aggregating the lagged returns in all months of the chosen aggregation period. Table 6 shows the results for the indices and the size portfolios.[19]

Strikingly different results emerge from the regression with the January returns versus the non-January returns as the dependent variable. The regression slopes for the January months are mostly negative for the EW and VW indices and all size portfolios. Apparently, stationary components of BSE stock prices decay strongly in the month of January, certainly for aggregation intervals between 3 and 6 years. Although the U-shaped pattern in stock returns is more marked for the VW index, only the January slopes for the EW index are highly significant. Bias-adjusted

[19] We limit ourselves to the total return series, as results for the capital appreciation return series are very comparable.

coefficient estimates for 3-, 4-, 5- and 6-year lagged returns of the latter are all below –0.028 and individually significant at the 5%-level. The VW index appears to revert earlier and stronger than the EW index. The regression slopes for aggregation intervals of 24-, 36- and 48-months are well below –0.04, though only marginally significant. The mean of the slope coefficients for the VW index is –0.027 and significant. However, there is hardly evidence for joint dependence as the Wald test is insignificant (p-value > 0.05). Consistent with our earlier results on the relationship between the January-effect and the "reversed" size premium, it is generally not the smallest but the largest size portfolios that are characterised by strong long-term January reversals. At horizons of 2 to 4 years, estimates for the 'Size IV' vary between -0.038 and -0.054 and are highly significant. Moreover, the decay in the stationary component of portfolio 'Size IV' remains strong after 4 years. Returns of portfolio 'Size V' are also mean reverting in January, however, estimated coefficients are insignificant. The corresponding regression slopes for the smaller portfolios, in particular 'Size II and III', are smaller but exhibit the same pattern. Despite all this, we fail to find significant Wald and 'AVG' statistics suggesting that the evidence of slowly decaying price component inducing mean reversion, remains weak.

In contrast, the results for the non-January months do not correspond to stock prices with transitory components and show that if mean reversion is present, it is entirely concentrated in January. Estimates of slope coefficients for the non-January months are negative, yet close to zero and insignificant for horizons beyond 3 years. The strong persistence for the 12- and 24-month returns documented earlier when all months were included in the regressions, can be attributed to the non-January months. Especially the EW index and the smallest size portfolios ('Size I and II') display high persistence during months outside January with slope estimates near or above 0.04

and significant at the 0.01%-level for the aggregation interval of 12 months. Coefficient estimates for 24 months remain significant, but are considerably smaller in magnitude. In the previous section, we already emphasized that these strongly decreasing coefficients suggest short-term mean reversion. Strong positive serial correlation in the short run is not confined to smaller companies. The joint tests strongly reject the random walk null hypothesis for all size portfolios. It appears that the lack of mean reversion found in the previous section when we considered all months jointly, is due to strongly significant persistent behavior of returns in the non-January months.

Remarkably, for the U.S. the GIP data show the same pattern, although less obvious and not significant. Slope estimates are generally lower in the January months, again suggesting that if some mean reversion is present, it is concentrated in January, confirming the results that Jegadeesh (1991) found for the 20th century.

Since Table 5 indicates a similar return effect in the month of July, we perform the same analysis for the July returns. However, the results (not shown) do not correspond to those for January. Regression estimates are close to zero and individually insignificant. As expected, results for the non-July months are very similar to those for the non-January months indicating strong persistent behavior outside of July.

5. Conclusions

This study examines the time-varying behavior of stock prices using a completely new and unique historical database of Belgian stock returns from the Brussels Stock Exchange. The dataset covers the period 1832-1914 or 83 years of highly reliable monthly stock price observations and other company related information representing more than 1500 different common stocks. Given the excessive use of the CRSP return data in asset pricing theory and the data mining risks involved this database provides a useful out-of-sample dataset with which to test the robustness of several asset pricing anomalies.

In order to identify whether stock prices contain slowly decaying stationary price components, we use the procedure developed by Hodrick (1992) and Jegadeesh (1991). As shown in our simulation experiments, this framework has considerably better small sample properties than the regression framework of Fama and French (1988a). In the short run, stock returns demonstrate high persistence partially reflecting infrequent trading effects that induce strong positive serial correlation. Contrary to Fama and French (1988a) and Poterba and Summers (1988), our results indicate that, in the long run, stock prices do not contain large autoregressive temporary components, as stock returns show little to no evidence of mean reverting patterns. Joint analysis of the estimated coefficients shows that long-horizon stock returns resemble random walk behavior. However, BSE stock returns exhibit some form of short-term mean aversion that is eventually 'adjusted' after a few years. We also find that excluding dividend income from returns exaggerates the evidence for mean reversion. This indicates that with the 19th century data, when dividend income constituted a large part of total returns, care must be taken to include accurate dividend information when constructing data sets. Most interestingly, we find a strong January seasonality in BSE returns although we are unaware of the Belgian government levying taxes on capital appreciation or dividends. The long-horizon mean reversion patterns are completely concentrated in January, a pattern that is consistent with results for the U.S. and the U.K. as presented in Jegadeesh (1991). We leave it to further research to investigate whether this remarkable pattern is related to dividend payout policy as we find that in our dataset a large part of dividend income is earned in January.

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Table 1: Summary statistics for the BSE indices and size portfolios and the U.S. indices

The table presents summary statistics of the monthly continuously compounded rates of return. Mean, standard deviation, minimum and maximum are in percentages per month. The size portfolios are quintile portfolios. Each firm is assigned to a portfolio based on its market capitalization in December of the previous year. Portfolios are equally weighted and rebalanced annually. LB(12) stands for the Ljung-Box statistic with 12 lags. 'n.a.' denotes not available.

	Mean	Mean	Standard	Minimum	Maximum	Skewness	Kurtosis	Autocorrelation at lag			LB(12)	Number of Firms		Market Value (mio €)		
	Total	Cap. Appr.	Deviation					1	2	3		Avg	Max	Avg	Min	Max
								Brussels Stock Exchange (1832-1914)								
Value-Weighted	0.347	0.008	2.374	-22.26	14.43	-0.615	22.59	0.296	0.047	-0.043	114.8	145	396	28.20	0.98	92.17
Equal-Weighted	0.436	0.131	2.659	-18.63	21.26	1.429	16.68	0.298	0.135	0.035	149.0	145	396	28.20	0.98	92.17
Price-Weighted	0.113	-0.242	2.524	-23.13	18.09	0.146	16.83	0.239	0.104	0.017	98.4	145	396	28.20	0.98	92.17
Size I (small)	0.679	0.498	4.947	-19.28	49.77	3.234	25.89	0.174	0.181	0.039	86.1	29	77	0.40	0.10	1.14
Size II	0.280	-0.003	3.091	-16.77	25.18	1.771	18.08	0.180	0.163	0.110	127.2	29	77	1.18	0.16	3.36
Size III	0.438	0.085	3.566	-16.70	46.55	3.558	42.08	0.156	-0.009	0.065	53.1	29	77	2.42	0.21	7.36
Size IV	0.250	-0.094	2.954	-21.49	23.27	0.530	16.34	0.220	0.073	0.011	81.8	30	78	5.06	0.45	16.29
Size V (large)	0.347	-0.014	2.491	-22.21	14.93	-0.661	16.00	0.239	-0.009	-0.062	72.5	30	78	19.61	1.86	63.16
								GIP (1815-1925)								
Price-Weighted	0.103	0.021	4.063	-37.58	40.04	-0.232	18.87	-0.012	-0.027	-0.033	14.1	64	120	n.a.	n.a.	n.a.

Table 2: Long-horizon regression

This table presents results for regression (2): $\sum_{i=1}^{k} r_{t+i-1} = \alpha_k + \beta_k \sum_{i=1}^{k} r_{t-i} + \varepsilon_{t,k}$, where r_t are continuously compounded monthly rates of return. In Panel A we present the estimated slope coefficient and its bias-adjusted value for the value-weighted return index. We use the analytical bias correction. This panel also reports the results of a simulation experiment in which we generate normally distributed returns and re-estimate the regression on the simulated series. All results are based on 25000 simulation runs. The t-statistics are corrected for serial correlation and heteroskedasticity in the residuals. In Panel B, we only report the bias-adjusted slope coefficients and indicate the significance level based on the simulated distribution of the t-statistics. Three asterisks denote significance at the (one-sided) 1% level, two at the 5% level and one at the 10% level. VW stands for value-weighted, EW for equal-weighted, and PW for price-weighted. The size portfolios are equally weighted quintile portfolios for which all stocks were ranked on their market capitalization at the end of the previous year. Portfolios are rebalanced annually. The WALD column contains the test result for joint significance of all slopes, whereas the AVG column reports the average slope coefficient. Significance is also based on the respective simulated distributions.

Panel A. Simulation results

	12	24	36	48	60	72	84	96	108	120	WALD	AVG
Beta	0.182	-0.149	-0.404	-0.474	-0.368	-0.154	-0.048	-0.235	-0.276	-0.292		
Adj Beta	0.194	-0.124	-0.367	-0.423	-0.304	-0.076	0.044	-0.128	-0.154	-0.154	114.26	-0.149
t-statistic	(1.87)	(-1.03)	(-2.75)	(-3.17)	(-2.03)	(-0.45)	(0.26)	(-0.92)	(-1.07)	(-1.04)		
					Simulated Distribution							
Mean Adj Beta	-0.004	-0.009	-0.014	-0.019	-0.025	-0.031	-0.037	-0.043	-0.049	-0.056	57.00	-0.029
St. Error	0.076	0.104	0.123	0.138	0.149	0.159	0.167	0.174	0.179	0.184	106.00	0.155
Mean t-statistic	-0.077	-0.128	-0.163	-0.203	-0.242	-0.281	-0.321	-0.365	-0.410	-0.451		
St. Error	1.212	1.288	1.362	1.431	1.496	1.569	1.654	1.731	1.813	1.893		
Fractiles (t)												
1%	-3.022	-3.382	-3.635	-3.821	-4.070	-4.246	-4.543	-4.828	-5.035	-5.321	3.49	-0.331
5%	-2.092	-2.288	-2.421	-2.602	-2.696	-2.865	-3.030	-3.182	-3.319	-3.456	6.11	-0.266
10%	-1.629	-1.753	-1.872	-1.994	-2.105	-2.217	-2.327	-2.442	-2.539	-2.633	8.23	-0.224
20%	-1.062	-1.165	-1.239	-1.306	-1.382	-1.466	-1.543	-1.633	-1.708	-1.788	11.87	-0.166
50%	-0.061	-0.082	-0.120	-0.151	-0.185	-0.222	-0.262	-0.305	-0.345	-0.374	26.28	-0.039
80%	0.931	0.926	0.939	0.935	0.922	0.938	0.947	0.933	0.909	0.912	68.76	0.103
90%	1.445	1.465	1.498	1.511	1.522	1.561	1.582	1.607	1.605	1.596	122.94	0.179
95%	1.873	1.902	1.940	2.017	2.067	2.095	2.157	2.200	2.215	2.235	206.21	0.242
99%	2.644	2.771	2.870	3.043	3.181	3.315	3.462	3.619	3.737	3.904	503.72	0.357

Panel B: Bias-Adjusted Slope Coefficients

	12	24	36	48	60	72	84	96	108	120	WALD	AVG
	Brussels Stock Exchange, General market indices											
VW-total return	0.194**	-0.124	-0.367**	-0.423**	-0.304	-0.076	0.044	-0.128	-0.154	-0.154	114.26	-0.149
VW-capital appr.	0.186*	-0.142	-0.420**	-0.514**	-0.421**	-0.213	-0.124	-0.348*	-0.339	-0.269	262.87**	-0.260*
EW-total return	0.256***	-0.176	-0.456***	-0.568***	-0.452**	-0.221*	-0.138	-0.320**	-0.315**	-0.273*	274.92**	-0.266**
EW-capital appr.	0.265***	-0.177	-0.470***	-0.591***	-0.475***	-0.238*	-0.171	-0.381**	-0.359*	-0.291	310.47**	-0.289**
PW-total return	0.268***	0.129	0.057	0.074	0.182	0.310	0.349	0.263	0.207	0.136	17.73	0.197*
PW-capital appr.	0.254**	0.095	-0.002	0.012	0.144	0.313	0.380	0.304	0.272	0.221	25.05	0.199*
	Brussels Stock Exchange, Size portfolios, total return											
Size I (small)	0.269***	-0.079	-0.298**	-0.364**	-0.293*	-0.180	-0.256	-0.266	-0.134	-0.081	187.99*	-0.168
Size II	0.237***	-0.108	-0.383**	-0.519***	-0.444***	-0.206	-0.142	-0.234	-0.217	-0.180	158.62*	-0.219
Size III	0.245**	-0.161	-0.438***	-0.555***	-0.419**	-0.192	-0.165	-0.412*	-0.379**	-0.347***	198.88*	-0.282**
Size IV	0.153*	-0.102	-0.193*	-0.213	-0.141	0.003	-0.063	-0.176	-0.160	-0.133	51.50	-0.102
Size V (large)	0.163*	-0.023	-0.204	-0.214	-0.090	0.157	0.207	0.103	0.121	0.094	25.92	0.031
	U.S., total return											
GIP data	0.000	-0.074	-0.057	-0.168	-0.256*	-0.295**	-0.357**	-0.413**	-0.389**	-0.324	53.74*	-0.233**

Table 3: Modified long-horizon regression

This table presents results for regression (5): $r_t = \alpha_k^M + \beta_k^M \sum_{i=1}^{k} r_{t-i} + \varepsilon_t$, where r_t are continuously compounded monthly rates of return. In Panel A we present the estimated slope coefficient and its bias-adjusted value for the value-weighted return index. We use the analytical bias correction. This panel also reports the results of a simulation experiment in which we generate normally distributed returns and re-estimate the regression on the simulated series. All results are based on 25000 simulation runs. The t-statistics are corrected for serial correlation and heteroskedasticity in the residuals. In Panel B, we only report the bias-adjusted slope coefficients and indicate the significance level based on the simulated distribution of the t-statistics. Three asterisks denote significance at the (one-sided) 1% level, two at the 5% level and one at the 10% level. VW stands for value-weighted, EW for equal-weighted, and PW for price-weighted. The size portfolios are equally weighted quintile portfolios for which all stocks were ranked on their market capitalization at the end of the previous year. Portfolios are rebalanced annually. The WALD column contains the test result for joint significance of all slopes, whereas the AVG column reports the average slope coefficient. Significance is also based on the respective simulated distributions.

Panel A. Simulation results

	12	24	36	48	60	72	84	96	108	120	WALD	AVG
Beta	0.030	0.014	0.004	-0.001	-0.007	-0.006	-0.004	-0.003	-0.002	0.002		
Adj Beta	0.031	0.015	0.005	0.000	-0.006	-0.005	-0.003	-0.001	-0.001	0.003	78.76	0.004
t-statistic	(2.22)	(2.46)	(1.08)	(0.02)	(-1.52)	(-1.12)	(-0.87)	(-0.51)	(-0.15)	(1.09)		
					Simulated Distribution							
Mean Adj Beta	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002	32.36	-0.001
St. Error	0.009	0.006	0.005	0.005	0.004	0.004	0.003	0.003	0.003	0.003	20.79	0.004
Mean t-statistic	-0.051	-0.083	-0.115	-0.137	-0.162	-0.191	-0.221	-0.250	-0.273	-0.299		
St. Error	1.038	1.064	1.099	1.131	1.167	1.190	1.213	1.237	1.270	1.299		
Fractiles (t)												
1%	-2.482	-2.653	-2.780	-2.932	-3.071	-3.180	-3.286	-3.395	-3.517	-3.645	5.78	-0.014
5%	-1.763	-1.853	-1.950	-2.033	-2.122	-2.216	-2.302	-2.339	-2.444	-2.511	9.19	-0.009
10%	-1.374	-1.440	-1.539	-1.597	-1.663	-1.727	-1.806	-1.866	-1.930	-2.008	11.76	-0.007
20%	-0.919	-0.968	-1.032	-1.081	-1.146	-1.190	-1.230	-1.295	-1.345	-1.401	16.02	-0.005
50%	-0.047	-0.086	-0.100	-0.140	-0.160	-0.187	-0.217	-0.245	-0.278	-0.297	27.47	-0.001
80%	0.815	0.809	0.807	0.811	0.815	0.810	0.802	0.796	0.810	0.818	45.78	0.002
90%	1.285	1.281	1.303	1.326	1.353	1.363	1.358	1.358	1.396	1.417	58.71	0.004
95%	1.676	1.695	1.703	1.755	1.800	1.809	1.846	1.841	1.906	1.927	72.10	0.005
99%	2.402	2.438	2.507	2.628	2.689	2.713	2.736	2.854	2.912	2.941	103.81	0.007

Panel B: Bias-Adjusted Slope Coefficients

	12	24	36	48	60	72	84	96	108	120	WALD	AVG
						Brussels Stock Exchange, General market indices						
VW-total return	0.031**	0.015***	0.005	0.000	-0.006	-0.005	-0.003	-0.001	-0.001	0.003	78.76**	0.004
VW-capital appr.	0.031**	0.015**	0.004	-0.001	-0.008**	-0.008	-0.006	-0.004	-0.003	0.003	86.95**	0.002
EW-total return	0.042***	0.017***	0.005	-0.002	-0.007	-0.009	-0.008	-0.003	0.000	0.003	161.54***	0.004
EW-capital appr.	0.042***	0.017***	0.005	-0.002	-0.007*	-0.010*	-0.009	-0.004	0.000	0.004	180.17***	0.004
PW-total return	0.037***	0.020***	0.011***	0.008**	0.005*	0.005*	0.006*	0.006**	0.006**	0.006***	125.74***	0.011***
PW-capital appr.	0.037***	0.019***	0.011**	0.007**	0.004	0.004	0.005*	0.006**	0.006**	0.007***	135.58***	0.011***
						Brussels Stock Exchange, Size portfolios, total return						
Size I (small)	0.035***	0.017***	0.008**	0.001	-0.002	-0.004	-0.004	-0.002	0.000	0.001	173.49***	0.005*
Size II	0.044***	0.018***	0.007	0.001	-0.005	-0.009*	-0.011**	-0.007	-0.005	0.005*	283.19***	0.004
Size III	0.030**	0.014***	0.003	-0.004	-0.010*	-0.014**	-0.014	-0.007	-0.001	0.003	103.75***	0.000
Size IV	0.037***	0.014**	0.005	0.002	0.000	-0.001	0.000	0.000	0.000	0.004	132.68***	0.006**
Size V (large)	0.023**	0.015**	0.006	0.004	-0.004	-0.002	-0.001	0.001	0.000	0.005**	83.97**	0.005*
						U.S., total return						
GIP data	0.012	-0.001	-0.002	0.005	-0.001	-0.002	-0.002	-0.003	-0.004*	-0.003*	43.17*	0.000

Table 4: Modified long-horizon regression

This table presents results for regression (5): $r_t = \alpha_k^M + \beta_k^M \sum_{i=1}^{k} r_{t-i} + \varepsilon_t$, where r_t are continuously compounded rates of return sampled over a quarterly (Panel A) or an annual (Panel B) frequency. We report the bias-adjusted slope coefficients for the different indices and size portfolios. We use the analytical bias correction. VW stands for value-weighted, EW for equal-weighted, and PW for price-weighted. The size portfolios are equally weighted quintile portfolios for which all stocks were ranked on their market capitalization at the end of the previous year. Portfolios are rebalanced annually.
We evaluate significance using a simulation experiment in which we generate normally distributed returns and re-estimate the regression on the simulated series. All results are based on 25000 simulation runs. The t-statistics are corrected for serial correlation and heteroskedasticity in the residuals. Three asterisks denote significance at the (one-sided) 1% level, two at the 5% level and one at the 10% level. The WALD column contains the test results for joint significance of all slopes, whereas the AVG column reports the average slope coefficient. Significance is also based on the respective simulated distributions.

Panel A. Quarterly results

	4	8	12	16	20	24	28	32	36	40	WALD	AVG
	Brussels Stock Exchange, General market indices											
VW-total return	0.073**	0.029*	0.004	-0.008	-0.023*	-0.021	-0.013	-0.010	-0.005	0.003	59.183*	0.003
VW-capital appr.	0.071**	0.027*	0.002	-0.011	-0.030**	-0.031*	-0.024	-0.020*	-0.014	-0.001	77.298**	-0.003
EW-total return	0.100***	0.036**	0.006	-0.012	-0.027*	-0.035*	-0.029	-0.019	-0.009	0.002	89.860**	0.001
EW-capital appr.	0.103***	0.037**	0.006	-0.012	-0.028**	-0.038**	-0.032	-0.021	-0.008	0.004	105.733***	0.001
PW-total return	0.087***	0.047***	0.028**	0.021**	0.012	0.012	0.015*	0.016**	0.016**	0.016**	69.672**	0.027***
PW-capital appr.	0.085***	0.045***	0.026**	0.017*	0.008	0.009	0.013	0.016*	0.016**	0.017**	74.748**	0.025***
	Brussels Stock Exchange, Size portfolios, total return											
Size I (small)	0.094***	0.036***	0.015	-0.004	-0.012	-0.018*	-0.016	-0.009	-0.006	-0.002	118.161***	0.008
Size II	0.107***	0.043***	0.011	-0.004	-0.021	-0.033**	-0.040**	-0.028	-0.023	0.012	139.307***	0.002
Size III	0.066**	0.029*	0.004	-0.018	-0.036**	-0.048**	-0.048*	-0.030	-0.008	0.006	38.120	-0.008
Size IV	0.082***	0.026*	0.006	-0.003	-0.008	-0.006	-0.004	-0.006	-0.003	0.007	74.656**	0.009
Size V (large)	0.054*	0.032*	0.010	0.005	-0.017	-0.012	-0.006	-0.002	-0.002	0.012	67.076*	0.007

Panel B. Annual results

	1	2	3	4	5	6	7	8	9	10	WALD	AVG
	Brussels Stock Exchange, General market indices											
VW-total return	0.205*	0.028	-0.042	-0.103*	-0.138*	-0.122*	-0.090	-0.077	-0.036	-0.032	38.089	-0.041
VW-capital appr.	0.191*	0.019	-0.052	-0.120*	-0.169**	-0.163*	-0.137*	-0.124*	-0.071	-0.059	48.207	-0.069
EW-total return	0.282***	0.022	-0.067	-0.116*	-0.165**	-0.180**	-0.149*	-0.122*	-0.067	-0.056	69.159**	-0.062
EW-capital appr.	0.286***	0.027	-0.068	-0.118**	-0.172***	-0.191**	-0.163*	-0.130*	-0.066	-0.051	79.342**	-0.065
PW-total return	0.295**	0.140**	0.074	0.045	0.024	0.032	0.045	0.049	0.058*	0.044**	38.211	0.081**
PW-capital appr.	0.278**	0.128*	0.059	0.030	0.007	0.019	0.037	0.046	0.060*	0.048**	44.795	0.071**
	Brussels Stock Exchange, Size portfolios, total return											
Size I (small)	0.294***	0.054	-0.035	-0.063	-0.093*	-0.096**	-0.069*	-0.064	-0.050	-0.049	58.705	-0.017
Size II	0.210**	0.030	-0.039	-0.075	-0.136**	-0.179**	-0.154*	-0.133	-0.118	-0.012	97.156	-0.061
Size III	0.324***	0.047	-0.061	-0.115**	-0.164***	-0.195**	-0.160*	-0.118*	-0.039	-0.013	56.719	-0.049
Size IV	0.101	-0.042	-0.045	-0.073	-0.084*	-0.052	-0.055	-0.055	-0.031	-0.019	40.541	-0.035
Size V (large)	0.182*	0.059	0.013	-0.039	-0.081	-0.062	-0.025	-0.017	0.004	0.027*	29.299	0.006

Table 5: Summary statistics for month-of-the-year total and capital appreciation returns.

This table presents average continuously compounded monthly rates of return in percentages, both for total return and capital appreciation return indices. VW stands for value-weighted, EW for equal-weighted, and PW for price weighted. The size portfolios are equally weighted quintile portfolios for which all stocks were ranked on their market capitalization at the end of the previous year. Portfolios are rebalanced annually. Size I (Size V) contains the 20% smallest (largest) stocks. The significance of the F-test testing whether the average returns of the month indicated differs from the return in the other months is indicated with asterisks. Three asterisks denote significance at the 1% level, two at the 5% level and one at the 10% level.

	Total Return				Capital Appreciation			
	VW	EW	Size I	Size V	VW	EW	Size I	Size V
January	1.123 ***	0.971 **	1.370	0.992 **	0.415 *	0.259	1.206	0.329
February	0.747	0.756	1.370	0.702	0.458 *	0.590 *	1.277	0.431 *
March	0.177	0.574	0.816	0.200	-0.291	0.292	0.775	-0.309
April	0.127	0.375	0.409	-0.039	-0.200	-0.041	0.098	-0.377
May	0.117	0.273	0.217	0.219	-0.368	-0.095	0.011	-0.315
June	-0.079 *	-0.084 *	-0.143	-0.044	-0.227	-0.342 *	-0.631 **	-0.245
July	0.858 **	0.688	0.516	0.979 **	0.307	0.207	0.340	0.465 *
August	0.784 *	1.117 ***	1.748 **	0.914 **	0.664 ***	0.987 ***	1.610 **	0.782 ***
September	0.282	0.482	0.784	0.332	0.030	0.373	0.725	0.152
October	-0.204 **	-0.125 **	-0.003	-0.294 **	-0.495 **	-0.416 *	-0.173	-0.674 **
November	0.311	0.421	1.384	0.200	0.008	0.165	1.272	-0.258
December	-0.075 *	-0.215 **	-0.324 *	0.003	-0.198	-0.412 *	-0.536 *	-0.150

Table 6: Seasonality in modified long-horizon regression

This table presents results for regression (5): $r_t = \alpha_k^M + \beta_k^M \sum_{i=1}^{k} r_{t-i} + \varepsilon_t$ where r_t are continuously compounded monthly rates of return. In Panel A (B) presents the bias-adjusted slope coefficient for January (non-January) months and indicate the significance level based on the simulated distribution of the t-statistics. Three asterisks denote significance at the (one-sided) 1% level, two at the 5% level and one at the 10% level. VW stands for value-weighted, and EW for equal-weighted. The size portfolios are equally weighted quintile portfolios for which all stocks were ranked on their market capitalization at the end of the previous year. Portfolios are rebalanced annually. All BSE series are total return series. All results are based on 25000 simulation runs. The t-statistics are corrected for serial correlation and heteroskedasticity in the residuals. The WALD column contains the test result for joint significance of all slopes, whereas the AVG column reports the average slope coefficient. Significance is also based on the respective simulated distributions.

	12	24	36	48	60	72	84	96	108	120	WALD	AVG
	January months											
	Brussels Stock Exchange, General market indices											
VW-total return	-0.003	-0.051*	-0.043*	-0.040*	-0.036*	-0.018	-0.010	-0.017	-0.024	-0.024	108.62	-0.027**
EW-total return	0.017	-0.020	-0.029**	-0.032**	-0.035***	-0.028**	-0.019*	-0.015	-0.016	-0.017	520.62*	-0.019
	Brussels Stock Exchange, Size portfolios, total return											
Size I (small)	0.010	-0.008	-0.012	-0.011***	-0.013*	-0.014*	-0.009	-0.003	0.002	0.005	431.45	-0.005
Size II	-0.006	-0.011	-0.017*	-0.019***	-0.024**	-0.022*	-0.017	-0.021	-0.018	-0.004	337.70	-0.016
Size III	0.060*	0.011	-0.012	-0.019**	-0.025**	-0.026**	-0.019	-0.006	-0.003	0.001	368.80	-0.004
Size IV	-0.017	-0.054*	-0.043**	-0.038***	-0.035**	-0.027**	-0.021**	-0.019	-0.018	-0.013	309.44	-0.028**
Size V (large)	0.010	-0.034	-0.026*	-0.025	-0.019	-0.002	0.010	0.000	-0.009	-0.003	126.64	-0.010
	U.S., total return											
GIP data	0.003	-0.009	0.005	-0.005	-0.008	-0.001	-0.008	-0.016	-0.017	-0.018	169.78	-0.007
	Non-January months											
	Brussels Stock Exchange, General market indices											
VW-total return	0.034***	0.022***	0.009***	0.004	-0.003	-0.003	-0.002	0.000	0.002	0.006*	108.56**	0.007**
EW-total return	0.044***	0.020***	0.008*	0.001	-0.004	-0.007	-0.007	-0.002	0.001	0.005	155.52***	0.006**
	Brussels Stock Exchange, Size portfolios, total return											
Size I (small)	0.038***	0.019***	0.010***	0.002	-0.001	-0.003	-0.003	-0.002	0.000	0.001	258.60***	0.006**
Size II	0.049***	0.021***	0.009	0.003	-0.003	-0.008*	-0.011**	-0.005	-0.003	0.006**	231.93***	0.006**
Size III	0.028**	0.015**	0.004	-0.003	-0.008*	-0.013*	-0.013	-0.007	-0.001	0.004	85.37**	0.001
Size IV	0.043***	0.020***	0.010**	0.005*	0.003	0.002	0.002	0.002	0.002	0.005	153.99***	0.009***
Size V (large)	0.024**	0.019***	0.009**	0.006*	-0.002	-0.002	-0.002	0.001	0.001	0.006**	105.68**	0.006**
	U.S., total return											
GIP data	0.013	0.000	-0.002	0.006*	0.000	-0.002	-0.002	-0.002	-0.003	-0.002	41.96	0.001

Figure 1: Total return evolution for an investment of 100 in the BSE equal-weighted (RETEW), price-weighted (RETPRW) and value-weighted (RETVW) portfolio (Logarithmic scale).