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Stock Return Predictability before the First World War

Rebecca Stuart

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Rebecca Stuart

University of Neuchâtel
and
Queen's University Belfast

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Abstract

This paper studies the predictability of stock returns using monthly data on eight markets over the period 1876-1913. In contrast to much of the existing literature I find broad predictability across stock markets. Market interest rates and seasonal dummies generally have predictive power, and in almost all of series studied there is a statistically significant autoregressive component. These relationships appear to be stable over the sample period. Testing returns from multiple indices for the same market indicates that the compilation of the index does not systematically affect its predictability. Finally, the results are robust to the exclusion of extreme observations.

Keywords: stock returns, interest rates, Gold Standard.

JEL Numbers: G1, N2.

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Contact information: email: rebecca.j.stuart@gmail.com, website: https://www.rebeccastuart.net/, address: Université de Neuchâtel, Institut de recherches économiques, Rue A.-L. Breguet 2, CH-2000, Neuchâtel.

1. Introduction

This paper studies the predictability of stock returns in a broad cross-section of countries using monthly data over the period 1876-1913. To my knowledge, this is by far the broadest cross-country study of stock market predictability for this period. The Classical Gold Standard has been referred to as the 'first era of globalization'[1], during which the stability and convertibility of the gold standard enabled large sums of capital to flow across borders in search of the highest return. Indeed, it has been argued that the level of capital flows and financial integration during this period were not matched again until the turn of the following century.[2] It is therefore interesting to examine how predictable movements in stock markets were during this period when there were few barriers to prevent capital taking advantage of profitable opportunities.

A number of historical studies of stock market predictability have focussed on the role of cash flows - dividends - for stock returns. Here, the dividends reflect expectations of the business cycle and therefore act as a signal for the future value of the firm. Much of the literature has focussed on the US, with mixed results. For instance, Golez and Koudijs (2018) use annual stock market data for what they consider 'the most important equity markets of the last four centuries', which they take to be the US for the period under review in this study. They find that dividends forecast returns and attribute this in part, at least, to business cycle movements. Goetzmann et al., (2001) study the power of past returns and dividend yields to forecast future long-horizon returns in the US. Although they find some evidence of predictability in sub-periods, there is overall little long-term predictability. Chen (2009a) also uses US data but finds no predictability of returns using the dividend yield over period under review in this study.

There are also some studies for other countries' stock markets. LeBris et al., (2019) study data on price and dividends of a single French company over the period 1372-1946, finding that changes in expectations of future dividends explain a significant fraction of price variations. DeLong and Brecht (1992) study the German stock market and find that

[1] Obstfeld and Taylor (2005, p. 25).

[2] The exact timing varies by study. See for instance, Baldwin and Martin (1999), Bordo and Murshid (2006), Volosovych (2011) and Bekaert and Mehl (2019).

in the period before the First World War stock price had too low volatility to be rational forecasts of future dividends. Jacobsen and Zhang (2013) and Bouman and Jacobsen (2002) find evidence of various calendar effects in UK stock market data over historical periods.[3]

This paper therefore differs from most of the existing historical literature by studying the predictive power of a broader set of variables for stock returns. In contrast to these studies which focus on dividends, studies of more recent data often use broader datasets. Indeed, the relationship between stock returns and macroeconomic factors has also been well documented (see Assefa et al., (2017) and references therein). Naturally, obtaining monthly data across eight countries for the sample period under review is difficult. In this paper, I study the role of nominal interest rates, seasonality and, to a lesser extent, inflation rates and economic activity in predicting stock returns.

The paper also differs from the existing literature, which looks at single markets, by studying a broad cross-section of eight markets. Indeed, this is one of the broadest datasets on stock returns compiled for this time period. For instance, although the sample size increases over time, Goetzmann et al., (2005) use data for the period under review for five exchanges, all of which are included in this study.[4] Similarly, in their studies of stock market integration, for much of their 19th century sample period, Bekaert and Mehl (2019) and Bastidon et al., (2018) have data on four exchanges.[5] A recent study by Anarkulova et al., (2022) of the distribution of long-term equity returns includes data on just three countries before 1890. In their study of stock market volatility and monetary policy, Eichengreen and Tong (2003) use data on four exchanges for much of the sample period used in this study.[6]

[3] Urquhart and McGroarty (2014) study calendar effects in US data from 1900 to 2013. They find that these calendar effects vary over time and/or may only be present during certain market conditions.
[4] See Table 1 in Goetzmann et al. (2005). The exchanges are Australia, Belgium, France, US and UK.
[5] See Figure 2 in Bastidon et al., (2018), and Appendix A in Bekaert and Mehl (2019).
[6] See Table 1 in Eichengreen and Tong (2003). The exchanges are Australia, France, US and UK. In addition, Quinn and Voth (2008) indicate that they use a similar dataset to Eichengreen and Tong (2003), and it may be assumed that it is not substantially larger.

Using a broad geographical sample allows me to draw more general conclusions about stock market predictability during the period. Indeed, the mixed results in the literature for predictability in the US market is not generalized here. I find that the US market is something of an exception and that overall there is broad predictability in stock markets.

Naturally, there are differences in the compilation of the data when looking across eight markets in this way, including sectoral and geographic coverage, and various weighting methodologies. Indeed, Schwert (1990, p. 418-9) argues that some form of predictability in US stock returns may result from the weighting used to construct the index. Therefore, I include all series which are available for each of the markets. In total, the analysis here includes 14 series for the eight markets studied.

There are four main findings. First, in contrast to much of the existing literature focussed on the US, there is broad predictability across stock markets. In particular, interest rates have predictive power across almost all markets in this study. In addition, there is a statistically significant autoregressive component in almost half of the series studied. Second, an extension to the model indicates that there is seasonal predictability in most of series studied. Moreover, the relationship appears to be stable over the sample period. Tests reveal that the 'January' and the 'sell in May' effects which are evident in more recent data, are not present in this sample period. However, recognising that economies were more agricultural at the time, there is some weak evidence of a 'harvest effect'. Third, contrary to Schwert (1990)'s finding, there is no pattern which suggests that the weighting of the index affects substantially whether or not it is predictable. Indeed, sectoral or geographic (domestic and foreign firms) differences also do not appear to determine predictability either in- or out-of-sample. Fourth, these results are robust to the exclusion of extreme observations.

The paper is structured as follows: The next section discusses the data and some descriptive statistics. Section 3 sets out the empirical strategy and the results of the model. Section 4 asks how reliable the predictive relationship is. Specifically, I ask whether crisis conditions drive the result, how predictability evolved over the sample period, and whether the finding that index compilation does not determine predictability also holds out-of-sample. Section 5 concludes.

2. The data

2.1 Stock returns data

In this paper, 14 monthly price series covering 8 markets are used. The markets represent Australia, Belgium, Germany, France, Ireland[7], Russia, the UK and the US. This dataset has the broadest geographical coverage possible for the sample period. All series used here are available for the entire sample period. The log-differences of indices are used to calculate returns. This is the same procedure as used in Jorion and Goetzmann (1999) and Eichengreen and Tong (2003).

The series are for capital gains, that is, they are exclusive of dividends, however, they differ in their compilation in other respects, including sectoral coverage, weighting and the domicile of firms included in the index. For instance, in general the indices have broad sectoral coverage. However, sometimes the only available index is narrower (industrial and commercial listings in Australia, blue chip firms in France). Differences in index compilation are common in both historical and more recent studies.[8] Because of these differences, I include all series that are available in each market.

The data are listed in Table 1. Briefly, one series is used for Australia, Russia and Germany, two for Belgium, France, Ireland and the US, and three for the UK. For the most part multiple series for the same country are obtained from the same source. In these instances, the difference between the series is usually the weighting of the underlying share prices. For instance, for the Belgian and French markets, the two series are market capitalization weighted and unweighted, while the three series for Ireland are market capitalization weighted, price-weighted and unweighted.

One exception is the UK, for which all three series obtained from Campbell et al., (2019) are market capitalization weighted. Here the difference between series is instead the

[7] Ireland was not an independent country during this sample period, however, the exchange in Dublin operated separately from London. For a discussion of the development of the Irish stock exchanges, see Thomas (1986).

[8] For instance, see Bekaert and Mehl (2019) who discuss how their historical and recent data are not uniform in construction.

types of firms listed: the three indices represent a narrow index focusing primarily on domestic firms, a broad index of all firms listed on the London exchange and a blue chip index.

For the US, two series are obtained from different sources. The first series is the Common Stock Price Index compiled by the Cowles Commission obtained through the St Louis Federal Reserve Economic Data (FRED) website. These data are, in general, arithmetic averages of the highest and lowest prices of the month weighted by the number of shares outstanding at the end of the month.[9] The second series is from Goetzmann et al., (2005) and is price-weighted.

As noted previously, Australian data are for the industrial and commercial listings on the Sydney Exchange, while German data are taken from the NBER macrohistory database and are composed of two separate series spliced together. These series are described as: an unweighted index of representative stocks for the period 1871-1889 and a weighted index of a larger number of stocks for the period 1890-1913.

Finally, for Russia, individual data for stocks listed on the St Petersburg Stock Exchange are available for the period under review from the Yale International Centre for Finance's St Petersburg Stock Exchange Project. However, information to compute a market capitalization weighted index is not available. Therefore, an unweighted (or equally weighted) price series is calculated from these data by the author.

2.2 Descriptive statistics

The average returns and variances of the fourteen series are included in the final two columns of Table 1. Over the sample, average monthly returns are highest in the series for Australia, Germany, Russia, the US (both series) and Belgium. Average returns are highest in the German and US series, and lowest in the unweighted Irish series and the narrow and blue-chip UK series. Indeed, returns according to the latter three indices are all marginally negative over the sample period. Turning to the variances, returns in the

[9] For more information, see Moore (1961, p.24). This series is widely used in the literature, see for instance, Shiller (2005).

US (both series) exhibit high variance over the sample, followed by Russian returns. The Australian series and the two Irish series have the lowest variance.

One question that arises is, were these markets likely to be inefficient during the gold standard compared to today? This period has been referred to as the 'first era of globalization'[10] with capital flowing freely across borders. It also covers the first era of modern communications, allowing for news to spread rapidly via the telegram and improvements in rail transport.[11] Michie (1987, p. 46) notes that by 1871 New York brokers were spending $0.8 million per annum on telegrams to London and that transatlantic cable companies deliberately located offices near to stock exchanges in order to provide express services to traders. As a result, investors were able to respond quickly to news in other jurisdictions. For instance, Triner and Wandschneider (2005) argue that the behaviour of markets during the Brazilian financial crisis of 1890/91 is a precedent for the contagious financial crises that emerging markets faced at the end of the twentieth century. Thus, there is no particular reason to expect markets to be less efficient during the period under review, than they are today.

2.3 Interest rate data

Interest rates are also collected from several sources. Australian data are collected from Butlin et al., (1971), and are three-month discount rates of Australian trading banks. For Belgium, the data are sourced from Drappier (1937) who compiled discount rates in the open market. However, these data are at a quarterly frequency, and so they are linearly interpolated to achieve a monthly frequency. As a result, some precision is lost in the exact timing of interest rate changes. For Germany and France, I use open market rates from the NBER microhistory database. For the UK, I use the prime short-term rate from the Bank of England's Millennium of Macroeconomic Data database. This rate is also used for Ireland since it was part of the United Kingdom at this time. For the US, data on call money rates in New York are taken from Macauley (1938).

[10] See Bordo and Meissner (2015).

[11] Hoag (2006) uses an event study analysis on one security with a dual listing on the London and New York exchanges from the time that the cable became operational to show that the information lag decreased from 10 days to being instantaneous.

In the absence of monthly interest rate data for Russia, which the author has not been able to locate, the average of the four European interest rates (UK, Germany, France and Belgium) is used.[12] An alternative would be to use the first principal component of these rates.[13] The correlation between the first principal component and the average of the four European interest rate series is in excess of 0.99, and the main results are unaffected whichever series is chosen. Indeed, using the interest rate of the country closest to Russia – Germany – in the Russian analysis also replicates the main results.

2.4 Discussion of interest rate series

Figure 1 shows the interest rates. Turning first to the interest rates of the European countries, these move quite similarly throughout the sample period. Indeed, the correlation between these series ranges from 0.61 (between the French and German interest rates) and 0.81 (between the French and Belgian interest rates). The US interest rate series also generally moves in line with the European series, although the correlation is much lower (between 0.21 and 0.31). Indeed, there are several periods of marked deviations, for instance around 1880 and between 1900 and 1905. In addition, the US interest rate often appears more volatile than the European rates, even when it is co-moving with them (see for instance around 1890 and 1893). In contrast, the Australian interest rate moves entirely differently from the other rates. It does not show a cyclical pattern, but generally declines over the sample period. Most likely this arises from the relatively small banking system in Australia at the time, and the general lack of competition in local financial markets.

The behaviour of Australian interest rates raises the question of stationarity. Standard tests indicate that the null hypothesis of a unit root can be rejected at the 1% significance

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[12] There is little difference if the mean of these rates is used. Indeed, UK, German and French interest rates all prove significant in the regressions below.

[13] Principal components are calculated by obtaining the eigenvectors and eigenvalues of the variance-covariance matrix of the underlying series. The eigenvectors are sorted by decreasing eigenvalues to obtain the weightings. These weightings are then multiplied by the underlying series – in this case, the returns series – to obtain the principal components. The first principal component is the series obtained by multiplying the eigenvector associated with the largest eigenvalue by the underlying series and is therefore the component that captures the most variance.

level in all cases with the exception of the Australian interest rate.[14] Therefore, in the analysis below, the Australian interest rate is included in differences, while the remaining interest rates are included in levels.[15]

3. Predictability of stock markets during the Gold Standard

3.1 Interest rates and stock returns

The predictability of stock market data is first tested by including the interest rate, along with the lagged dependent variable as regressors, and thus estimate:

(1) $r_{i,t} = \alpha_1 + \alpha_2 r_{i,t-1} + \alpha_3 int_{i,t-1} + e_t$

Where $r_{i,t}$ is the return from period t - 1 to period t on the exchange in country i, that is $r_{i,t}$ = ln (p_t/p_{t-1}) where p_t is the price index for the exchange. In addition, int_i is the interest rate in county i.[16] A separate regression is run for each of the fourteen series. The regressions are estimated using Newey-West standard errors that are robust to heteroscedasticity.

The results are presented in panel (a) of Table 2. Four points are of note. First, the parameter on the interest rate is negative and significant in ten of the fourteen cases. A negative relationship between interest rates and stock prices is consistent with the cash flow hypothesis whereby an increase in interest rates today indicate a slowing of activity, and therefore cash flows, in the future. The exceptions where interest rates are not significant are the regression for Australia, the regressions for the US and the regression for the market-capitalization weighted index in France. In all other cases, the lagged interest rate has predictive power for returns.

[14] Augmented Dickey Fuller test including an intercept, with lags chosen using the Schwarz information criterion. For the Australian interest rate, the p-value is 0.16. If a trend is also included, the p-value is 0.15.

[15] An alternative is to either the market rate or the official Bank rate from UK which, given colonial links, may have had some impact in Australia at the time. However, it is clear from Figure 1 that domestic Australian rates were not strongly influenced by UK rates. Moreover, using UK rates instead of Australian rates does not impact the results below.

[16] Or change in the interest rate in the case of Australia.

Second, the compilation of the index has little impact on the pattern to predictability. In general, the result for a stock market is the same regardless the weighting or sectoral breadth used in the index.

Third, the lagged dependent variable is significant in seven regressions, suggesting that there is predictability in returns from month to month. Interestingly, in several cases where more than one series on returns is available, the lagged dependent variable has predictive power in only one case: it is significant in the regression using unweighted returns for Ireland, in the regression using the narrow index in the UK and the price-weighted index for the US.

Finally, the r-squareds for these regressions indicate that the model generally explains less than five per cent of the variation in returns. Thus, although the parameters are statistically significance, the economic significance is less clear.

3.2 Test for seasonality

Next, I test for another source of predictability in stock returns: seasonality. Miron (1986), Mankiw and Miron (1990) and Barsky et al (1988) have discussed the reduction in seasonality in US and British interest rates in the period after 1914. A question that arises is whether this was a wider financial market phenomenon that can also be observed in stock prices. To test this, I estimate an augmented version of equation (1):

(2) $$r_{i,t} = \alpha_1 + \alpha_2 r_{i,t-1} + \alpha_3 int_{i,t-1} + \sum_{j=1}^{11} \beta_j D_j + e_t$$

where D_j are a set of eleven dummies taking a value of 1 in each month between January and November. The results are presented in panel (b) of Table 2. In the interest of brevity, rather than reporting the results for 11 seasonal dummies, I report the results of Wald tests for the hypothesis that the seasonal dummies are all zero. In 13 of 14 cases, we can reject the hypothesis that all the dummies are zero at the 5% significance level. Thus, the argument of Schwert (1990) that the weighting of an index might determine whether it exhibits seasonal effects appears to be rejected. Interestingly, given that Schwert (1990) was analysing US data, the only case in which the seasonal dummies are not significant is the regression including the price-weighted US series. Finally, the inclusion of seasonal dummies marginally increases the significance of the parameters on the lagged dependent variables and lagged interest rate.[17] This suggests that seasonality in the interest rate is not driving the significant parameter estimates in equation (1) in panel (a) of Table 2.[18]

The r-squareds of the regressions indicate that for the most part between 10 and 20 per cent of the variation in returns is explained by this model. The exception is the price-weighted US series, which has an r-squared of just 3.7 per cent, however, the average r-squared of the remaining regressions is 13 per cent, which is respectable given the volatility of stock prices. Indeed, the adjusted r-squareds indicate that this model explains on average twice as much of the variation in stock returns compared to equation (1). Overall, the inclusion of the seasonal dummies suggests predictability that may be economically as well as statistically significant.

3.3 Other calendar effects

There is a literature on the "January effect" in more recent data.[19] Indeed, Jacobsen and Zhang (2013) find that the January effect emerged in UK stock returns in the 1830s around the time that Christmas became a public holiday. Panel (b) of Table 2 therefore also includes the results of Wald tests of the hypothesis that only the dummy for January is zero. We can only reject the null hypothesis at the 5% significance level in three cases. Interestingly, this failure to reject occurs in the market that Jacobsen and Zhang (2013) studied (UK blue-chip series) and in the Irish market (both series), which was closely related to the UK market at the time (see Stuart (2017) and Stuart (2018)).

[17] It is noticeable that using French market capitalization weighted returns, the interest rate is insignificant in panels (a) and (b) of Table 2. This analysis is based on open market rates, but an alternative is the official Banque de France rate, which is also available for the sample period. The lag of this rate is significant when included in Equation (2) (p-value = 0.01), while the seasonal dummies are also jointly significant (p-value = 0.00).

[18] This is further confirmed by the fact that seasonally adjusting the interest rate series included in equation (1) does not alter the overall result.

[19] See Keane (1983).

Since we know that economies were more dependent on agriculture during this period, and that stringencies in markets often occurred around harvest time[20], the third set of Wald test results in Table 2 examines whether there is an effect in August and September.[21] Here it is possible to reject the null hypothesis in half the cases. Interestingly, the results are, for the most part, geographically dispersed: the failure to reject occurs across five different markets (Belgium, Germany, France, Ireland and the UK). Most notably, all three series included for the UK fail to reject, indicating a particularly strong result.

Finally, we consider the 'Sell in May and go away' effect identified in historical UK data by Bouman and Jacobsen (2002). They find that there is a 'winter' effect, whereby returns are higher between November and April than they are during the rest of the year. To test this, I follow Bouman and Jacobsen (2002), and include a dummy which takes a value of one for the months November to April is included in equation (2) instead of the eleven individual month dummies. The results are never statistically significant and are therefore not included here for brevity.

Overall, while there is clear evidence of broad seasonality in the data as set out in Section 3.2, there is limited evidence for specific calendar effects, with the possible exception of a harvest effect.

3.4 Macroeconomic data – US and UK

Studies of more recent data often test the predictive power of macroeconomic variables for stock market returns. In these cases, economic fundamentals contain information about the business cycle and therefore future cashflows (Chen (2009b).[22] To my knowledge, this relationship has not been studied in historical stock market data. One reason for this is probably that, in the period covered in this sample, monthly data on many macroeconomic variables is not widely available. This section therefore focusses on

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[20] See for instance Hanes and Rhode (2013, p. 201) who note: "A poor cotton harvest depressed export revenues and reduced international demand for American assets, which depressed American stock prices".

[21] In Australia, February and March are tested for the harvest season.

[22] Economic and financial variables that statistically significantly predict stock returns include interest rates, monetary growth rates, changes in industrial production, inflation rates, earnings-price ratios, as well as dividend yields (Pessaran and Timmermann (1995)).

a narrower set of markets for which some monthly data on prices and economic activity are available during the period.

Monthly data on wholesale prices in the UK are available from the Bank of England's Millennium of Macroeconomic Data database, and data on the consumer price index is available from Shiller (2005) for the US. I next add the log change in the price level into the equations for UK and US returns, and estimate the following:

(3) $$r_{i,t} = \alpha_1 + \alpha_2 r_{i,t-1} + \alpha_3 int_{i,t-1} + \sum_{j=1}^{11} \beta_j D_j + \alpha_3 inf_{i,t-1} + e_t$$

Where $inf_{i,t}$ is the log change of the price level in country i from one month to the next. The results are presented in Table 3. In the case of the broad and narrow UK series, inflation is significant, however, it is not significant in for the US series or the UK blue-chip series (p-value = 0.057). This may relate to measurement error in the US CPI series[23], whereas the UK series is generally considered to be very well measured.[24] However, adjusted r-squareds of the UK regressions do not increase much compared to Table 2 even when inflation is significant in the regression. The Wald test for the joint significance of the seasonal dummies in the UK regressions suggests that their predictive power is unchanged.

In addition, as measures of economic activity, I use monthly data on unemployment in the UK and on railway receipts for the UK and US.[25] As such, I replace the inflation rate in equation (3) with each measure of economic activity in turn. None of the economic activity variables are ever significant, with the exception of railway receipts in the broad UK series (p-value = 0.039).

Overall, while there is some evidence that macroeconomic data, in particular inflation, may be a predictor for stock returns, it is insufficient to draw any firm conclusions. Moreover, as is clear from the earlier analysis, such findings for one or two exchanges may not generalize to a broader geographical sample.

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[23] See Kaufmann (2020) for a discussion of measurement error in historical price indices.

[24] See Hauzenberger et al., (2021) for a discussion.

[25] Unemployment and detrended rail receipts for the UK are sourced from the Bank of England's Millennium of Macroeconomic Data database. Railroad freight ton miles revenue for the US is sourced from the NBER Macrohistory database. The US railroad data are included in the regression in log differences.

3.6 Results: some conclusions

Overall, the existing literature generally indicates mixed results for predictability in stock markets historically. One reason for this may be a focus on the US market, which I also find has limited predictability. However, the results presented here, for a much wider set of markets, suggest that in fact predictability in stock markets is quite a general result. Although not all types of calendar effects identified in the literature are present in the series studied here, the finding of broad seasonality and the predictive power of the lagged dependent variable and interest rates holds widely across the markets studied. Moreover, the result is not markedly affected by the index compilation.

4. How reliable are predictions?

In this Section, I address three questions. First, there were several crises during the sample period which would have affected one or several markets, and I therefore ask whether extreme observations are driving the results. Second, I ask whether the predictability of stock returns changed over the sample period. Finally, I test whether geography or index compilation impact the out-of-sample predictability of the returns.

4.1 Removing extreme observations

The sample period is characterized by several financial crises, which would have affected both interest rates and stock returns. Some of these were relatively contained, though serious, crises. For instance, in 1882, following the collapse of l'Union Générale, the French market crashed, causing a serious economic crisis. Almost a quarter of the agents de change came close to collapse, and the exchange itself was only saved by a loan from the Banque de France. Other crises spread across international frontiers. For instance, in 1890 with the Barings crisis led to a panic affecting London, several continental European countries, the United States and some of Latin America. This was followed by a wave of banking panics which began in 1893 in the United States and spread to Europe and Australia (Bordo and Filardo (2005)).

The question therefore arises whether these crises periods – either due to a domestic shock, or from an international spillover – lead to increased correlation in financial market data and drive the results in Section 3. One test for this might be to use a dummy for crises, such as compiled by Funke et al., (2016), however, such databases are generally annual rather than monthly. Moreover, while choosing the exact month for the start of a financial crisis may be straightforward in some cases, in others it would require a strong degree of subjectivity. Therefore, I take a more objective approach and remove extreme observations that are in excess of two standard deviations of the mean of each series, with the aim of removing periods of crisis from the sample. On average, this removes 5% of observations, although across individual series there is some variation.[26] I then re-estimate equation (2) with the remaining observations.

The results are presented in Table 4 and can be compared with those in panel (b) of Table 2. Overall, there is little impact on the main result. The lagged interest rate is no longer significant in the regressions for the unweighted French series and the Cowles US series. However, it is now significant in the market capitalization weighted French series and the price-weighted US series. Moreover, in two cases the lagged dependent variable is now significant compared to panel (b) of Table 2 (the French unweighted series and the US price-weighted series). Overall, dropping these extreme values has resulted in the US price-weighted series becoming more predictable, although it continues to be the only case in which the seasonal dummies are insignificant. Finally, the r-squareds are generally marginally higher in these regressions than those of the baseline specification in Table 2.

4.2 Does predictability change over time?

One question which arises is whether predictability increases or decreases over time. For instance, if we believe that predictability arises from some market inefficiency, then improvements in communication and dissemination of information generally, might result in a reduction of predictability over time. On the other hand, it may be that later in the sample the data are better measured, and if there truly is predictability in the data, then this may increase with reduced measurement error. Moreover, Urquhart and McGoarty (2014) and Jacobsen and Zhang (2013) find that seasonal predictability is often present for only short periods of time.

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[26] Specifically, it removes between 3.1% and 6.2% of observations in each series.

As a result, I test for a structural break in equation (2). With no prior expectation for when a break may occur, a Chow test for a break midway through the sample period fails to reject the null of no breaks in all cases, with the exception of the market capitalization weighted Belgian series (p-value = 0.042). Therefore, it appears that in general there is no change in the predictive relationship over time.

4.3 Out-of-sample predictions

The results in Section 3 indicate that in-sample predictability is not country-specific or dependent on the method of compilation of the index. Here, I examine whether this is also the case out-of-sample. Out-of-sample fit in a historical setting raises an unusual question. Generally, the model is estimated up to a certain date, and the out-of-sample forecast for the remainder of the sample is evaluated against the observed data. However, choosing this cut-off is arbitrary, and particularly so for a historical sample period. As a result, I use the leave-one-out (LOO) cross validation method to test the out-of-sample fit of these models. This is a special case of the leave-k-out cross validation methods (Bruce and Martin (1989)), which uses model estimates from multiple subsets of the sample for validation. In a dataset with n observations, the model is run on a subsample of (n-1) observations, and then a fitted value for the omitted observation is estimated. The difference between the fitted value and the observed value of the variable – the error – is calculated and then squared.

This process is repeated until every observation in the dataset has been excluded once.[27] The squared errors are then averaged across all test cases to obtain a mean square error for the model, and the square root of this is the root mean square error (RMSE). The RMSE can then be compared across regressions.

In each case, the RMSE is reported in panel (c) of Table 2. In general, there is no particular pattern associated with series weighting. The highest RMSEs are for the two US series which is perhaps unsurprising given the low level of significance that was found in the analysis in Section 3. In contrast, some of the lowest average RMSEs are for the Australian series, the market capitalization weighted Irish series and the UK broad and blue-chip

[27] This method creates two 'groups' of observations either side of the one being left out. The model is run so that there are never less than 24 observations in a group, as per Teh et al., (2010).

series. Overall, it does not appear that a particular compilation methodology for an index generally results in a lower RMSE.

5. Conclusions

This paper undertook the a broad cross-country study of stock market the predictability of stock returns the period 1876-1913. Existing literature on historical stock market predictability generally focusses on individual markets, or a narrow set of markets. The data collected here on eight stock markets is, to my knowledge, the broadest geographical sample compiled for the period.

Many historical studies have focussed on the predictive power of dividends. However, studies of more recent data have shown that a much broader set of data, including financial and macroeconomic variables, can predict stock returns, in addition to dividend yields. As a result, this paper studied the role of nominal interest rates, seasonality and, to a lesser extent, inflation rates and economic activity in predicting stock returns.

Moreover, this paper differs from the existing literature in using data on 14 returns series in eight markets. Using such a sample allows me to draw more general conclusions about stock market predictability during the period than has previously been drawn in the literature. Moreover, using multiple series for the same market also enables me to draw conclusions about the role of index compilation for predictability.

There are four main findings:

First, interest rates have broad predictive power across almost all markets in this study. In addition, there is a statistically significant autoregressive component in almost half of the series studied, and some evidence that inflation may also predict stock prices. This is in contrast to the existing literature, which has often focussed on one country, usually the US, and which has provided mixed results for the predictability of stock markets.

Second, an extension to the model indicates that there is seasonal predictability in most of series studied. Overall, the predictive relationship appears to be stable over the sample period. While the 'January effect' and the 'sell in May' effect is not present during the sample period, there is weak evidence of a 'harvest effect'.

Third, contrary to Schwert (1990)'s finding, there is little evidence to suggest that the weighting of the index affects whether or not it is predictable. Indeed, sectoral or geographic (domestic and foreign firms) differences also do not appear to determine predictability either in- or out-of-sample.

Fourth, these results are robust to the exclusion of extreme observations.

References

Annaert, J., F. Buelens and M.J.K. De Ceuster, (2012), 'New Belgian Stock Market Returns: 1832-1914', *Explorations in Economic History*, 49, 189-204.

Annarkulova, A., S. Cederburg and M. S. O'Doherty, (2022), 'tocks for the long run? Evidence from a broad sample of developed markets', *Journal of Financial Economics*, 143, 409-433.

Assefa, Tibebe A., Omar A. Esquedab and André Varella Mollick, (2017), 'Stock returns and interest rates around the World: A paneldata approach', *Journal of Economics and Business*, 89, 20-35.

Baldwin, Richard and Philippe Martin, (1999), 'Two waves of globalisation: superficial similarities, fundamental differences', NBER Working Papers Series, Working Paper 6904, January.

Barsky, Robert B., N. Gregory Mankiw, Jeffrey A. Miron and David N. Weill, (1988), 'The worldwide change in the behavior of interest rates and prices in 1914', *European Economic Review*, 32(5), 1123-1147.

Bastidon, C., M. Bordo, A. Parent and M. Weidenmier, (2018), 'Stock Market Integration Since 1885: A Network Perspective', Paper presented at the 2018 WEHC, mimeo.

Bekaert, G. and A. Mehl, (2019), ' On the global financial market integration 'swoosh' and the trilemma', *Journal of International Money and Finance*, 94, 227-245.

Bordo, Michael D. and Andrew Filardo (2005), "Deflation in a historical perspective," BIS Working Papers No 186, November.

Bordo, Michael D. and Christopher M. Meissner, (2015), 'Financial Globalisation, Financial Development and Financial Crises in the Golden Age, 1870-1914', Paper prepared for the conference "Financial Systems and Economic Growth: Conference in Honor of Richard Sylla" Stern School of Business, New York University March 27-28.

Bordo, M. and A. P. Murshid, (2006), 'Globalization and changing patterns in the international transmission of shocks in financial markets', *Journal of International Money and Finance*, 25(4), 655-674.

Bouman, Sven and Ben Jacobsen, (2002), 'The Halloween Indicator, "Sell in May and Go Away": Another Puzzle', *American Economic Review*, 92(5), 1618-1635.

Campbell, G., R. Grossman and J. Turner, (2019), 'Before the cult of equity: New monthly indices of the British share market, 1829-1929', CEPR Discussion Papers, DP13717.

Chen, Long, (2009a), "On the reversal of return and dividend growth predictability: A tale of two periods", *Journal of Financial Economics*, 92, 128-151.

Chen, Shiu-Sheng, (2009b), "Predicting the bear stock market: Macroeconomic variables as leading indicators", *Journal of Banking and Finance*, 33(2), 211-223.

Cowles, A. the 3rd, and Associates, (1939), Common Stock Indices, Cowles Commission for Research in Economics, Principa Press, Inc, Bloomington Indiana, Second edition.

DeLong, Bradford J. and Marco Brecht, (1992), "'Excess Volatility' and the German Stock Market, 1876-1990", NBER Working Paper No. 4054.

Drappier, Jean-Marie, (1937), "La Conjoncture des cours des valeurs mobilières, de leurs dividendes et des taux d'intérêt en Belgique de 1830 à 1913", Bulletin de l'Institut des Sciences Économiques, 4, 391-449.

Eichengreen, B. and H. Tong, (2003), 'Stock Market Volatility and Monetary Policy: What the Historical Record Shows', in Reserve Bank of Australia 2003 Conference: Asset Prices and Monetary Policy, ed. Anthony Richards and Tim Robinson, 108–42. Sidney, AU: Reserve Bank of Australia.

Funke, Manuel, Moritz Schularick and Christoph Trebesch, (2016), "Going to extremes: Politics after financial crises, 1870–2014", *European Economic Review*, 88(C), 227-260.

Goetzmann, William N., Lingfeng Li and K. Geert Rouwenhorst, (2005), 'Long-Term Global Market Correlations', *The Journal of Business*, 78(1), 1-38.

Goetzmann, William N., Roger G. Ibbotson, Liang Peng, (2001), "A new historical database for the NYSE 1815 to 1925: Performance and predictability", *Journal of Financial Markets*, 4, 1-32.

Golez, Benjamin and Peter Koudijs, (2018), "Four centuries of return predictability", Journal of Financial Economics127, 248-263.

Grossman, Richard S., Ronan C. Lyons, Kevin Hjortshøj O'Rourke and Madeleine A. Ursu, (2014), 'A monthly stock exchange for Ireland, 1864-1930', *European Review of Economic History*, 18(3), 248-276.

Hanes, Christopher and Paul W. Rhode, (2013), "Harvests and Financial Crises in Gold Standard America", Journal of Economic History, 73(1), 201-246.

Hauzenberger, Niko, Florian Huber, Daniel Kaufmann, Rebecca Stuart and Cedric Tille, (2021), "150 years of Swiss interest rates", Technical Report.

Hoag, C., (2006), "The Atlantic telegraph cable and capital market information flows", *The Journal of Economic History*, 66(2), 342-353, June.

Jacobsen, Ben and Cherry Y. Zhang, (2013), 'Are Monthly Seasonals Real? A Three Century Perspective,' *Review of Finance*, 17(5), 1743-1785.

Jorion, P. and W. Goetzmann, (1999), 'Global Stock Markets in the Twentieth Century', *Journal of Finance,* LIV, 953-980.

Kaufmann, Daniel (2020), "Is deflation costly after all? The perils of erroneous historical classifications," *Journal of Applied Econometrics*, 35, 614-628.

Keane, Simon M. (1983), Stock Market Efficiency: Theory, Evidence and Implications, Philip Allan, Oxford.

Lamberton, D. McL., (1958), 'Security Prices and Yields 1875–1955', Pamphlet, Sydney Stock Exchange Research and Statistical Bureau, Sydney.

Le Bris, D. and P. Hautcoeur, (2010), 'A Challenge to Triumphant Optimists? A Blue Chips Index for the Paris Stock-Exchange (1854-2007)', *Financial History Review*, 17(2), 141-183.

Le Bris, David, William N. Goetzmann and Sébastien Pouget, (2019), "The present value relation over six centuries: The case of the Bazacle company", *Journal of Financial Economics*, 132, 248-265.

Macauley, Frederick R. (1938), The movements of interest rates, bond yields and stock prices in the United States since 1856, NBER, New York.

Mankiw, Gregory N. and Jeffrey A. Miron, (1990), "Should the Fed smooth interest rates? The case of seasonal monetary policy", NBER Working Paper No 3388.

Michie, R., (1987), *The London and New York Stock Exchanges 1850-1914*, Unwin Hyman Ltd, London.

Miron, Jeffrey A., (1986), "Financial panics, the seasonality of the nominal interest rate and the founding of the Fed", *American Economic Review*, 76(1), 125-140.#

Obstfeld, Maurice and Alan M. Taylor, (2005), Global Capital Markets: Integration, Crisis, and Growth, Cambridge University Press, Cambridge.

Pesaran, M. Hashem and Allan Timmermann, (1995), "Predictability of Stock Returns: Robustness and Economic Significance", *The Journal of Finance*, 50(4), 1201-1228.

Quinn, D. P. and H-J. Voth, (2008), A Century of Global Market Correlations, *American Economic Review: Papers & Proceedings*, 98(2), 535–540.

Shiller, R. J., (2005), Irrational Exuberance, Princeton University Press, Broadway Books, 2nd edition.

Schwert, William G., (1990), "Indexes of U.S. Stock Prices from 1802 to 1987", *The Journal of Business*, 63(2), 399-426.

Stuart, Rebecca, (2017), 'Co-movements in stock market returns, Ireland and London, 1869-1929', *Financial History Review*, 2017, 24(2), 167-184.

Stuart, Rebecca, (2018), 'The co-movement of the Irish, UK and US stock markets, 1869-1925', *Essays in Economic and Business History*, 36(1), 23-46.

Teh, Sin Yin, Abdul Rahman Othman, and Michael Boon Chong Khoo, (2010), 'Dichotomous Logistic Regression with Leave-One-Out Validation', *International Journal of Mathematical and Computational Sciences*, 4(2), 296-305.

Thomas, W. A., (1986), The Stock Exchanges of Ireland, Francis Cairns Publications, Liverpool.

Triner, G. D. and K. Wandschneider, (2005), "The Baring Crisis and the Brazilian Encilhamento, 1889–1891: An Early Example of Contagion Among Emerging Capital Markets", Financial History Review, 12(2), 199-225.

Urquhart, Andrew and Frank McGroarty, (2014), "Calendar effects, market conditions and the Adaptive Market Hypothesis: Evidence from long-run U.S. data", *International Review of Financial Analysis*, 35, 154-166.

Volosovych, V., (2011), 'Measuring financial market integration over the long run: Is there a U-shape?', *Journal of International Money and Finance*, 30(7), 1535-1561.

Table 1: Data sources, compilation and descriptive statistics, 1876-1913

Country	Code	Source	Type of firms	Index weighting	Mean	Variance
Australia	AUS	Lamberton (1958)	Commercial and Industrial	Chained value ratio formula*	0.177	0.019
Belgium (weighted)	BEL(1)	Annaert et al., (2012)	Belgian firms	Market-capitalisation weighted	0.043	0.034
Belgium (unweighted)	BEL(2)	Annaert et al., (2012)	Belgian firms	Unweighted/equally weighted	0.148	0.064
Germany	GER	NBER Macrohistory Database (Vierteljahrshefte zur Konjunkturforschung, Sonderheit 36)	For 1870-1889: 'representative stocks'. For 1890-1913: data are for a 'larger number of stocks'	For 1870-1889: unweighted index For 1890-1913: 'weighted index'	0.171	0.058
France (weighted)	FRA(1)	LeBris and Hautcoeur (2010)	Blue Chip firms	Market capitalisation weighted	0.064	0.028
France (unweighted)	FRA(2)	LeBris and Hautcoeur (2010)	Blue Chip firms	Unweighted/Equally weighted	0.045	0.029
Ireland (weighted)	IRE(1)	Grossman et al., (2014)	All listed firms	Market capitalisation weighted	0.012	0.010
Ireland (unweighted)	IRE(2)	Grossman et al., (2014)	All listed firms	Unweighted/equally weighted	-0.011	0.015
Russia	RUS	International Center for Finance, St Petersburg Stock Exchange Project	All listed firms	Unweighted/equally weighted	0.135	0.086
UK (broad)	UK(1)	Campbell et al., (2020)	All listed firms	Market capitalisation weighted	0.006	0.020
UK (narrow)	UK(2)	Campbell et al., (2020)	UK Firms	Market capitalisation weighted	-0.007	0.012
UK (Blue chip)	UK(3)	Campbell et al., (2020)	Blue Chip firms	Market capitalisation weighted	-0.011	0.022
US (Cowles)	US(1)	NBER Macrohistory Database (Cowles Commission)	Includes virtually all industrial, public utility, and railroad common stocks actively traded on the NYSE.	Arithmetic averages of the highest and lowest prices of the month weighted by shares outstanding at month-end.	0.130	0.107
US (price weighted)	US(2)	Goetzmann, et al., (2001)	All listed firms	Price weighted	0.186	0.146

Notes: * Calculated as: a portfolio allocated in proportion to the monetary value of all quoted shares, recalculated each month.

Table 2: Regression results, testing predictability, 1876-1913, n=455

	AUS	BEL(1)†	BEL(2)†	GER	FRA(1)†	FRA(2)†	IRE(1)†	IRE(2)†	RUS	UK(1)†	UK(2)†	UK(3)†	US(1)†	US(2)†
	(a) $\boldsymbol{r_{i,t} = \alpha_1 + \alpha_2 r_{i,t-1} + \alpha_3 int_{i,t-1} + e_t}$													
Lagged dependent variable	-0.174	0.262	0.269	0.169	-0.079	0.045	0.016	0.107	0.167	0.077	0.155	0.033	0.289	0.030
	(0.108)	(0.040)**	(0.055)**	(0.076)*	(0.076)	(0.041)	(0.066)	(0.050)*	(0.077)*	(0.052)	(0.044)**	(0.046)	(0.056)**	(0.050)
	[-1.614]	[6.498]**	[4.859]**	[2.222]*	[-1.039]	[1.103]	[0.234]	[2.122]*	[2.170]*	[1.487]	[3.496]**	[0.728]	[5.196]**	[0.594]
Lagged interest rate	0.002	-0.004	-0.005	-0.003	-0.003	-0.005	-0.001	-0.001	-0.003	-0.002	-0.001	-0.001	-0.001	-0.001
	(0.005)	(0.001)**	(0.001)**	(0.001)**	(0.002)	(0.002)**	(0.000)*	(0.001)**	(0.001)*	(0.001)**	(0.000)*	(0.001)*	(0.001)	(0.001)
	[0.381]	[-3.781]**	[-3.595]**	[-2.728]**	[-1.670]	[-2.928]**	[-2.554]*	[-2.784]**	[-2.450]*	[-3.635]**	[-2.581]*	[-2.317]*	[-1.163]	[-1.336]
Constant	0.002	0.011	0.014	0.010	0.009	0.012	0.003	0.004	0.010	0.006	0.003	0.004	0.003	0.006
	(0.001)*	(0.003)**	(0.004)**	(0.004)**	(0.005)	(0.004)**	(0.001)*	(0.002)*	(0.004)**	(0.002)**	(0.001)*	(0.002)*	(0.003)	(0.003)
	[2.443]*	[3.714]**	[3.453]**	[2.991]**	[1.908]	[3.131]**	[2.283]*	[2.330]*	[2.672]**	[3.398]**	[2.388]*	[2.108]*	[1.327]	[1.812]
R^2	0.036	0.106	0.103	0.054	0.021	0.037	0.020	0.037	0.041	0.045	0.051	0.014	0.090	0.007
Adj. R^2	0.030	0.102	0.099	0.050	0.017	0.033	0.015	0.033	0.036	0.040	0.047	0.010	0.086	0.003
	(b) $\boldsymbol{r_{i,t} = \alpha_1 + \alpha_2 r_{i,t-1} + \alpha_3 int_{i,t-1} + \sum_{i=1}^{11} \beta_i D_i + e_t}$													
	Tests for significance of seasonal dummies (Ho: parameter(s) = 0)													
Seasonal effect	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.035*	0.000**	0.000**	0.000**	0.001**	0.170
January effect	0.088	0.389	0.306	0.290	0.706	0.758	0.002*	0.001**	0.245	0.117	0.113	0.833	0.007**	0.082
Harvest effect‡	0.331	0.005*	0.043*	0.181	0.000**	0.001*	0.662	0.416	0.297	0.307	0.013*	0.001**	0.125	0.403
Lagged dependent variable	-0.170	0.266	0.285	0.168	-0.075	0.053	0.033	0.100	0.159	0.072	0.134	-0.011	0.299	0.041
	(0.121)	(0.042)**	(0.055)**	(0.078)*	(0.080)	(0.046)	(0.059)	(0.049)*	(0.079)*	(0.053)	(0.042)**	(0.048)	(0.054)**	(0.049)
	[-1.414]	[6.370]**	[5.202]**	[2.147]*	[-0.942]	[1.135]	[0.560]	[2.052]*	[2.002]*	[1.346]	[3.207]**	[-0.220]	[5.495]**	[0.839]
Lagged interest rate	0.001	-0.003	-0.004	-0.004	-0.003	-0.005	-0.002	-0.002	-0.004	-0.003	-0.002	-0.002	-0.002	-0.003
	(0.004)	(0.001)**	(0.001)**	(0.001)**	(0.002)	(0.002)**	(0.000)**	(0.001)**	(0.001)**	(0.001)**	(0.000)**	(0.001)**	(0.001)*	(0.002)
	[0.212]	[-3.349]**	[-3.012]**	[-3.661]**	[-1.547]	[-2.793]**	[-3.174]**	[-3.901]**	[-2.771]**	[-4.095]**	[-4.535]**	[-3.896]**	[-1.973]*	[-1.824]
Constant	-0.000	0.012	0.011	0.024	0.008	0.015	0.004	0.007	0.015	0.010	0.009	0.013	0.004	0.008
	(0.003)	(0.005)*	(0.007)	(0.006)**	(0.005)	(0.005)**	(0.003)	(0.002)**	(0.007)*	(0.003)**	(0.002)**	(0.003)**	(0.007)	(0.008)
	[-0.101]	[2.486]*	[1.551]	[4.019]**	[1.541]	[3.021]**	[1.335]	[2.780]**	[2.263]*	[3.004]**	[4.912]**	[4.496]**	[0.643]	[1.086]
R^2:	0.092	0.202	0.172	0.111	0.104	0.131	0.123	0.105	0.071	0.101	0.177	0.129	0.132	0.037
Adj. R^2	0.063	0.179	0.148	0.085	0.078	0.105	0.098	0.079	0.043	0.075	0.153	0.103	0.111	0.010
	(c) Leave-one-out analysis													
Mean RMSE	0.012	0.017	0.024	0.023	0.017	0.016	0.010	0.013	0.031	0.014	0.010	0.014	0.032	0.040

Note: † See column (2) of Table 1 for country codes. ‡ For Australia, the harvest effect is tested using February and March. */** indicates significance at the 5%/1% level, respectively. Standard errors in (), t-statistics in []. First difference of interest rate used for Australia instead of lagged interest rates (see section 2.4).

Table 3: Results for UK and US stock returns including inflation, 1876-1913

	(1) UK Broad	(2) UK Narrow	(3) UK Blue-chip	(4) US Cowles	(5) US price-weighted
Lagged dependent variable	0.052	0.108	-0.027	0.295	0.038
	(0.054)	(0.042)*	(0.048)	(0.056)**	(0.050)
	[0.970]	[2.557]*	[-0.552]	[5.270]**	[0.758]
Lagged interest rate	-0.003	-0.002	-0.002	-0.002	-0.003
	(0.001)**	(0.000)**	(0.001)**	(0.001)*	(0.001)
	[-4.180]**	[-4.651]**	[-3.956]**	[-2.022]*	[-1.934]
Lagged inflation rate	0.001	0.001	0.001	0.000	0.001
	(0.001)*	(0.001)*	(0.001)	(0.001)	(0.001)
	[2.003]*	[2.368]*	[1.908]	[0.390]	[0.582]
Constant	0.010	0.009	0.014	0.004	0.009
	(0.003)**	(0.002)**	(0.003)**	(0.007)	(0.008)
	[3.199]**	[5.159]**	[4.646]**	[0.682]	[1.157]
Wald test of joint significance of seasonal dummies (p-values)					
Seasonal dummies	0.001	0.000	0.000	0.002	0.374
R^2	0.110	0.191	0.137	0.137	0.039
Adj R^2	0.082	0.165	0.110	0.110	0.008

Note: */** indicates significance at the 5%/1% level, respectively. Standard errors in (), t-statistics in [].

Table 3: Results for UK and US including inflation, 1876-1913

Note: */** indicates significance at the 5%/1% level, respectively. Standard errors in (), t-statistics in [].

Table 4: Results excluding extreme observations, 1876-1913

	AUS	BEL(1)	BEL(2)	GER	FRA(1)	FRA(2)	IRE(1)	IRE(2)	RUS	UK(1)	UK(2)	UK(3)	US(1)	US(2)
Constant	0.002	0.008	0.007	0.014	0.007	0.006	0.006	0.006	0.019	0.009	0.008	0.010	0.002	0.011
	(0.001)*	(0.003)**	(0.005)	(0.005)**	(0.003)*	(0.003)	(0.002)**	(0.002)**	(0.005)**	(0.003)**	(0.002)**	(0.002)**	(0.005)	(0.006)
	[2.127]*	[2.606]**	[1.555]	[2.997]**	[2.244]*	[1.912]	[3.255]**	[2.803]**	[3.568]**	[3.496]**	[4.964]**	[4.602]**	[0.301]	[1.866]
Lagged	0.015	0.209	0.322	0.184	0.060	0.191	-0.004	0.169	0.223	0.057	0.142	-0.010	0.291	0.097
dependent	(0.055)	(0.053)**	(0.050)**	(0.046)**	(0.043)	(0.049)**	(0.065)	(0.049)**	(0.053)**	(0.051)	(0.044)**	(0.046)	(0.049)**	(0.047)*
variable	[0.266]	[3.921]**	[6.415]**	[4.020]**	[1.388]	[3.886]**	[-0.060]	[3.413]**	[4.219]**	[1.120]	[3.221]**	[-0.211]	[5.957]**	[2.069]*
Lagged	-0.001	-0.002	-0.003	-0.003	-0.003	-0.002	-0.001	-0.001	-0.004	-0.002	-0.001	-0.001	-0.001	-0.003
interest rate	(0.002)	(0.001)**	(0.001)**	(0.001)**	(0.001)*	(0.001)	(0.000)**	(0.000)**	(0.001)**	(0.001)**	(0.000)**	(0.000)**	(0.001)	(0.001)**
	[-0.285]	[-3.126]**	[-2.726]**	[-3.075]**	[-2.556]*	[-1.914]	[-3.519]**	[-3.536]**	[-3.049]**	[-3.597]**	[-3.484]**	[-2.693]**	[-1.455]	[-2.872]**
	Wald test of joint significance of seasonal dummies (p-values)													
Seasonal dummies	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.006**	0.001**	0.000**	0.000**	0.001**	0.170
Obs	422	407	427	413	416	411	409	406	428	400	408	408	412	406
R^2	0.162	0.185	0.206	0.117	0.144	0.176	0.123	0.105	0.071	0.098	0.148	0.115	0.123	0.054
Adj. R^2:	0.121	0.185	0.206	0.117	0.144	0.176	0.109	0.124	0.091	0.067	0.120	0.085	0.094	0.023

Note: See column (2) of Table 1 for country codes. */** indicates significance at the 5%/1% level, respectively. First difference of interest rate used for Australia instead of lagged interest rates (see section 2.4).

Figure 1: Interest rate series, 1876-1913