The Long Memory of Equity Volatility and the Macroeconomy: International Evidence

Lena Dräger* Duc Binh Benno Nguyen† Marcel Prokopczuk‡
Philipp Sibbertsen§

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Abstract

This paper examines long memory volatility in international stock markets. We show that long memory volatility is widespread in a panel dataset of eighty-two countries and that the degree of memory in the panel can be related to macroeconomic variables such as short- and long-run interest rates and unemployment. Moreover, we find that developed economies possess longer memory in volatility than emerging and frontier countries and that stock market jumps are negatively correlated with long memory of volatility. Overall, our results provide some evidence of a link between stock market uncertainty and macroeconomic conditions, which is prevalent across a large range of countries.

JEL classification: G15, C22, F30, F40

Keywords: International; Long Memory; Volatility; Stock Market Uncertainty

*School of Economics and Management, Leibniz University Hannover, Koenigsworther Platz 1, 30167 Hannover, Germany. Email: draeger@gif.uni-hannover.de.

†School of Economics and Management, Leibniz University Hannover, Koenigsworther Platz 1, 30167 Hannover, Germany.

‡School of Economics and Management, Leibniz University Hannover, Koenigsworther Platz 1, 30167 Hannover, Germany and ICMA Centre, Henley Business School, University of Reading, Reading, RG6 6BA, U.K. Email: prokopczuk@fmt.uni-hannover.de

§School of Economics and Management, Leibniz University Hannover, Koenigsworther Platz 1, 30167 Hannover, Germany. Email: sibbertsen@statistik.uni-hannover.de.

I Introduction

Ever since the global financial crisis in 2008/9, analyzing and reducing uncertainty on financial markets has become one of the most relevant research tasks for economists and financial analysts alike. While uncertainty can stem from developments in financial markets, it is also possible that uncertainty arises from unpredictable changes in economic policy or in macroeconomic conditions in general. While the literature mostly focuses on the negative effects of economic policy uncertainty on macroeconomic variables such as investment, output growth and employment (Baker et al., 2016; Husted et al., 2019), there is also evidence that higher economic policy uncertainty correlates with higher stock market volatility and lower stock returns (Antonanakis et al., 2013).

However, while the previous literature focuses mainly on testing the effect of policy or macroeconomic uncertainty on stock markets, there is yet little evidence on a potential relationship between stock market uncertainty and the macroeconomic environment. Hence, in this paper we derive a measure of uncertainty in stock markets based on the degree of long memory in stock market volatility for a large country panel dataset. First, we show that long memory in equity volatility is prevalent in almost every international equity index: 94% of the countries in our sample possess long memory in stock market volatility with an average memory parameter of 0.27, which implies a half-life of shocks to the volatility process of 18 months. We then exploit the cross-sectional and time-series variation of the memory parameter to determine the correlation of long memory in equity volatility with macroeconomic indicators. While we do not aim at identifying causality, we thus link the literature on long memory stock market volatility to the literature on the effect of economic policy uncertainty on both macroeconomic and financial market developments.

The degree of long memory (Bollerslev & Mikkelsen, 1996; Ding & Granger, 1996) is frequently used in the literature as a measure to assess the stability of stock markets. Long memory or long-range dependence allows for improved long-term forecasts due to the higher persistence in volatility. Interpreting volatility as a measure of risk, the degree of long memory in stock market volatility may be interpreted as a measure of uncertainty in stock markets, since pronounced long-range dependence in volatility allows for a long-term risk prediction. High degrees of long memory hence imply a low degree of uncertainty.

Our results suggest that long memory in stock market volatility can be related to macroeconomic variables in both the time-series and the cross-sectional dimension. First, we find that the degree of long memory is higher, and thus stock market uncertainty is lower, in more developed and more stable economies. Second, countries with a higher degree of long memory in stock markets over time tend to have lower short-run interest rates. This suggests that the link between uncertainty in stock markets and macroeconomic variables works mainly through an interest rate channel, which may also be affected by changes in monetary policy or policy uncertainty (Husted et al., 2019). When evaluating this relationship for the U.S., we find that the interest rate channel works more robustly via long-run interest rates, and there is an additional relation between high unemployment and low uncertainty. The latter effect is in contrast to the findings by Baker et al. (2016), but may be driven by the specific time span of our analysis.

We shed new light on long memory in volatility by exploiting and combining the methodologies of three strands of literature. First, we extend the current research, which only focuses on major economies and large firms by investigating an international panel dataset of 82 countries including both developed and emerging countries. Second, we allow for a time-varying degree of long memory. Third, long memory so far has only been analyzed in the time-series dimension, and not in the cross-sectional dimension.

Long memory properties have been investigated in the dynamics of both stock returns and volatility. Typically, the **A**uto**R**egressive **F**ractionally **I**ntegrated **M**oving **A**verage (ARFIMA) model by Granger & Joyeux (1980), Granger (1981) and Hosking (1981) and the **F**ractionally **I**ntegrated **G**eneralized **A**utoregressive **C**onditional **H**eteroskedasticity (FIGARCH) model introduced by Baillie et al. (1996) are used. These models are the natural generalizations of the well-known **A**uto**R**egressive **M**oving **A**verage (ARMA) model and the **G**eneralized **A**utoregressive **C**onditional **H**eteroskedasticity (GARCH) model that allow for fractional integration, i.e. the degree of integration can take any real value, not just zero or one.

Several studies investigate the long memory of returns and volatility both in the U.S. stock market and in international stock markets. Bollerslev & Mikkelsen (1996) and Ding & Granger (1996) show that the conditional variance and absolute returns of the S&P 500 index possess long memory, respectively. Both papers rely on the FIGARCH model. Breidt et al. (1998) also find long memory in the variance of equally weighted and value-weighted CRSP stock market index returns by fitting a long memory stochastic volatility model and relying on the ARFIMA model. Lobato & Savin (1998) investigate long memory properties of the U.S. stock market index and thirty individual stock returns in the U.S. They apply a semiparametric test to returns, squared and absolute returns and find that squared returns exhibit long memory properties while the levels of returns do not. Sadique & Silvapulle (2001) and Henry (2002) consider the long memory property of various international stock indices including Germany, Japan, Korea, Malaysia, New Zealand, Singapore, Taiwan and the U.S. Sadique & Silvapulle (2001) rely on both the modified rescaled range tests and the Geweke & Porter-Hudak (1983) (GPH) estimator while Henry (2002) relies on both parametric and semiparametric estimation methods including the GPH estimator, the estimator of Robinson (1994) and the ARFIMA model. Kasman et al. (2009) show evidence of long memory dynamics in both the conditional mean and variance for eight Central and Eastern European countries' stock markets and also rely on the both semiparametric and parametric estimation procedures. While long memory has been investigated extensively both in the U.S. and international stock markets, the works so far have mainly focus on the detection of long memory. We contribute to the existing literature by largely extending the sample of countries to eighty-two and examining the cross-sectional variation of long memory across countries and its link to macroeconomic variables. Nguyen et al. (2019) investigate the cross-sectional variation of long memory in volatility at the firm level. They provide evidence of long memory in volatility for the cross-section of U.S. stocks and find a negative price for long memory volatility.

The rest of the paper is organized as follows. Section II describes our data set and estimation procedure for long memory. Section III investigates long memory in the cross-section of countries. Section IV presents robustness tests. Section V concludes.

II Data and Methodology

A Data

The data used for our analyses come from various sources. For our international stock index data we follow Pukthuanthong & Roll (2015) and include eighty-two countries for which we obtain the data from Datastream.[1] If available, we rely on daily observations of the total return indices which include the dividends, and use the price index otherwise.[2] The sample covers the period from December 1964 until December 2015.[3]

For each country we obtain country-specific macroeconomic variables from the Global Financial Database. We include the real gross domestic product (GDP), the consumer price index (CPI), unemployment, short maturity and long maturity interest rates.[4] Most of the short maturity yields are 3-month treasury bills and most of the long maturity yields are 10-year government bonds. Hence from now on we refer to them as treasury bills (Tbill) and government bonds (Gov.Bonds). Both are given in percentage form per annum. The Real GDP data is obtained in U.S. dollar currency converted using exchange rates from the Global Financial Database.[5]

B Semiparametric Estimation of Long Memory

We present details on the estimation procedure of long memory in the Technical Appendix. In the following empirical analyses, we employ the Geweke & Porter-Hudak (1983) estimator and the bandwidth $m = N^{0.5}$ following the existing literature (Geweke & Porter-Hudak, 1983; Diebold & Rudebusch, 1989; Hurvich & Deo, 1999; Henry, 2002).[6] Results with alternative bandwidth choices and the Local Whittle estimator are reported in the Section IV.

We refer to d as the memory parameter and differentiate between three cases: A time series has short memory if $d = 0$. A time series has negative memory or is anti-persistent if $d < 0$. A time series has long memory if $0 < d < 1$ where it is non-stationary if $0.5 < d < 1$. In this range the autocorrelations of the time series decay hyperbolically and are therefore significantly positive even for large lags. The higher the memory parameter

[1] Table 8 in the Online Appendix presents an overview of the countries, the selected indices and the sample period.

[2] Prices are cleaned of outliers by removing observations which deviate by more than 10 standard deviations from the median using a rolling window of 50 observations (Barndorff-Nielsen et al., 2009).

[3] For Bangladesh, Slovenia and Zimbabwe, the last available observations are from April 2013, October 2010 and October 2006, respectively.

[4] The data for the U.S. is supplemented by data provided by Amit Goyal (website: http://www.hec.unil.ch/agoyal/) and FRED.

[5] Unfortunately, the Global Financial Database does not cover our complete sample of countries with macroeconomic variables. GDP data is available for seventy-two countries, inflation data is available for eighty countries, unemployment data is available for sixty-nine countries, treasury bill rates are available for seventy-eight countries and government bond rates are available for seventy-three countries.

[6] Typically, empirical researches rely on this bandwidth choice since it is robust against short-range dependencies in the data.

d the more pronounced is the autocorrelation structure of the series. This pronounced long-term autocorrelation structure allows for improved long-term forecasts compared to the situation of $d \leq 0$ where long-term forecasts become imprecise due to the fast exponential decay of the autocorrelations.

III Long Memory Volatility in International Equity Markets

In this section we provide evidence of long memory volatility in the cross-section of eighty-two countries. First, we show that long memory volatility is prevalent in most countries but that the memory parameter varies across countries in Section III.A. Section III.B refers long memory to predictability and Section III.C relates the memory parameter to macroeconomic variables in the time-series dimension. Section III.?? relates the memory parameter to macroeconomic variables in the cross-section of countries and separately investigates the memory in developed and emerging countries.

A Descriptive Statistics

We apply the GPH estimator to the time series of squared returns for the selected eighty-two countries. Table 1 provides summary statistics for the memory parameter d. The mean memory parameter over the eighty-two countries is 0.27 and the mean standard deviation is 0.13. If the time series exhibit short memory, the mean should be approximately zero. The estimated parameter lies between 0 and 0.5 and in combination with the average t-statistic of 3.95 imply the presence of long memory in volatility for the eighty-two countries on average, which is mean-reverting. The value of 0.27 suggests a half-life of roughly 18 months compared to a value of 0.20 for a half-life of 12 months for the mean-reversion. In fact, 87% of the parameters are positive and statistically significant at the 5% level or lower. Further, the 5% to 95% quantiles suggest that most parameters lie in the interval $(0, 0.5)$. We find that 94% of the countries exhibit long memory in volatility, where $0 < d < 0.5$, while 4% show anti-persistence and 2% show non-stationary long memory in volatility. We hence conclude that most international stock markets exhibit long memory in volatility. These results extend the current literature which focuses on the U.S. and some major countries like Japan or the U.K. (Cheung & Lai, 1995; Sadique & Silvapulle, 2001; Henry, 2002).

The countries with the highest memory parameter are Taiwan, Finland and Kuwait, while countries with the lowest memory parameter are Bahrain and Egypt. Figure 1 displays the estimates for the eighty-two countries. The G-7 countries, representing the major advanced economies and those making the largest percentage of global wealth, do not possess the longest or shortest memory. But six of the seven major economies have a memory parameter higher than 0.3 while the ten countries with the shortest memory are all "frontier" countries.[7] In the following we closely investigate potential drivers of the memory parameter.

B Long Memory and Predictability

Typically, long memory time series are described as highly persistent time series, for which the autocorrelation function is decaying at a hyperbolic rate rather than an exponential rate as for short memory processes. Intuitively, the higher persistence of the time series can be linked to higher predictability or lower uncertainty. In this section, we empirically show the link between long memory and predictability for the volatility of the stock indices.

At the same time, this exercise presents a validity check for our long memory estimates. A higher memory parameter should be associated with higher forecasting performance, if our memory estimates are correct and not biased by the quality of the data or spurious long memory.

We run monthly predictability regressions of the realized volatility for each country separately both in-sample and out-of-sample. We obtain monthly realized volatility observations by summing squared daily returns within each month (Bollerslev et al., 2014). We rely on the state of the art (Heterogeneous) Autoregressive models of Realized Volatility (HAR-RV) following Corsi (2009).[8] The independent variables are lagged observations of the realized volatility and we consider five different specifications by including the

[7]Even though the beginning of the sample period varies across the countries, the memory parameters are comparable. In our empirical analysis we also consider the same sample size for all countries, which delivers qualitatively similar results.

[8]We also considered simple Autoregressive models including the lags 1, 6, 12, 24 and 60, leading to qualitatively similar results.

volatility from the previous month (HAR(1)), six months (HAR(2)), one year (HAR(3)), two years (HAR(4)) and 5 years (HAR(5)):

$$HAR(1) : RV_{t+1}^{M} = \alpha + \beta RV_t^{M} + \epsilon_{t+1} \quad (1)$$

$$HAR(2) : RV_{t+1}^{M} = \alpha + \beta RV_t^{M} + \beta RV_t^{6M} + \epsilon_{t+1} \quad (2)$$

$$HAR(3) : RV_{t+1}^{M} = \alpha + \beta RV_t^{M} + \beta RV_t^{6M} + \beta RV_t^{1Y} + \epsilon_{t+1} \quad (3)$$

$$HAR(4) : RV_{t+1}^{M} = \alpha + \beta RV_t^{M} + \beta RV_t^{6M} + \beta RV_t^{1Y} + \beta RV_t^{2Y} + \epsilon_{t+1} \quad (4)$$

$$HAR(5) : RV_{t+1}^{M} = \alpha + \beta RV_t^{M} + \beta RV_t^{6M} + \beta RV_t^{1Y} + \beta RV_t^{2Y} + \beta RV_t^{5Y} + \epsilon_{t+1} \quad (5)$$

The multiperiod volatilities are normalized sums of the one-month realized volatilities. The six-months' realized volatility is exemplarily given by:

$$RV_t^{6M} = \frac{1}{6}(RV_t^{M} + RV_{t-1}^{M} + ... + RV_{t-5}^{M}) \quad (6)$$

The models are able to mimic the behavior of long memory processes and exhibit strong forecasting performance, despite the simplicity of both the model and the estimation. We form tertile portfolios by sorting the cross-section of country stock market indices by the memory parameter. We then compute the average adjusted R^2, t-statistic, F-statistic and out-of-sample R^2_{OOS} for each tertile portfolio.[9]

The results are reported in Table 2. Panel A shows the adjusted R^2 of the in-sample predictability regressions. There is a strictly monotonic pattern of explanatory power, which is increasing in the memory parameter. This is further supported by the increasing t-statistics and F-statistics in Panel B. Countries with higher memory parameters have stronger explanatory power and the predictor variables are more statistically significant than countries with shorter memory in volatility. Lastly, in Panel C, the R^2_{OOS} also show that the out-of-sample forecasting performance of long memory countries is stronger than short memory countries. There is a strictly monotonic pattern for the short horizon model, HAR(1), which diminishes when including more lags. A graphical illustration of the results is reported in Figure 2.

We thus show that the degree of memory in volatility is a proxy for predictability. At the same time this exercise validates our estimation approach of memory. Our results are

[9]We report t-statistics of the slope coefficient for HAR(1) and F-statistics for the joint significance of the slope coefficients for the remaining models.

true for both in-sample and out-of-sample, while we allow for various model specifications including short memory processes and long memory mimicking processes.

C Time Variation of Long Memory and Macroeconomic Factors

We first investigate the temporal variation of the memory parameter for the individual countries and their relationships with macroeconomic variables. This allows us to to conclude on what macro environments cause high or low memory parameters over time. For this purpose, we allow for a time-varying memory parameter. We estimate the memory parameter by applying the GPH estimator at a monthly frequency to a rolling window of five years of daily return data. We start with a separate analysis of the U.S. and consider the complete cross-section in a second step.

1 Evidence for the U.S.

First, we regress the monthly memory parameter of the U.S. on the following macroeconomic variables: inflation proxied by changes in the Consumer Price Index (Inflation), the log unemployment rate (Unemployment), the 3-months Treasury bill rate (Tbill), the 10-year government bond rate (Gov.Bonds), real gross domestic product (GDP) and an indicator function (Recession) that represents periods of recession as defined by the National Bureau of Economic Research (NBER):

$$d_{U.S.,t} = \alpha_{U.S.} + \beta_{U.S.} X_{U.S.,t} + \epsilon_t \tag{7}$$

where d_t stands for the memory parameter at time t, X_t contains one or more of the macroeconomic variables and ϵ_t is the error term.[10] All time series are at monthly frequency except for GDP, which is quarterly. We follow Bloom (2009) and de-trend the time series for unemployment and for real GDP using the Hodrick–Prescott filter. Table 3 reports the results. Our interpretations refer to the terms predictability, uncertainty and low memory parameters interchangeably.

[10]Since our memory estimates d_t rely on rolling window estimates, one might argue that there is barely temporal variation in our estimates. If this is true, this should work against our empirical analysis and we should not find any significant drivers of the memory parameter, but we do. In addition, we repeat the analysis relying on smaller rolling windows using 12 months of daily return data. The results are qualitatively similar.

Over the full sample period from 1964 to 2015, we find that inflation has a negative relationship with the degree of long memory, which is statistically significant at the 10% level (Model 1). However, the explanatory power of the model with inflation as only regressor is rather low with an adjusted R^2 of 0.8% and the variable becomes insignificant in the full model including all regressors. Economically, the negative sign of the coefficient implies that in times of lower inflation, the memory of U.S. market volatility is rather longer. Ball (1992) presents a model which gives an interpretation to the well-known empirical observation that high levels of inflation often coincide with high uncertainty regarding future inflation. In the model, the monetary authority is expected to keep inflation low when it is already low. However, when inflation is high, central bankers face a trade-off between disinflating the economy and the resulting recession, which causes in higher uncertainty on the future path of inflation. Our result suggests that some of this effect might also translate to uncertainty in the U.S. stock market.

The unemployment rate affects the memory parameter positively and is statistically significant at the 5% level (Model 2). The adjusted R^2 is of similar magnitude when including the inflation as a regressor with a value of only 1.17%. However, unlike inflation the unemployment rate has a robust effect in all models. Overall, this implies that an increase in the unemployment rate tends to coincide with a period of lower stock market uncertainty. However, this effect may vary depending on the business cycle stance of the economy. As argued in Veronesi (1999), good news in bad times (and bad news in good times) are generally related to increased stock market uncertainty. Regarding the effect of unemployment news on stock markets, Boyd et al. (2005) argue that unemployment news contain information on future interest rates, the equity risk premium, and corporate earnings and dividends. As shown by the authors, when the economy is in an expansionary phase, bad news of rising unemployment seem to trigger lower interest rate expectations, and hence higher stock prices. During contractions, by contrast, bad news of rising unemployment leads firms to revise their growth expectations downwards, leading to lower stock prices. Overall, the authors find a positive effect of bad unemployment news on stock prices, since expansionary phases happen more regularly than recessions. Our results in Models 7 and 8, where we also control for a recession effect, suggest that the overall positive effect of higher unemployment is not just relevant for the level of stock prices, but also for their degree of long memory.

Moreover, we find in Models 3 and 4 that both the short- and long-term interest rates given by Tbill and Gov.Bonds have a negative impact on the memory parameter which is statistically significant at the 1% level. The adjusted R^2 are the highest with values of 24.53% and 36.30%, respectively. Note, however, that the effect of short-run interest rates switches sign when we control for the other macroeconomic variables in Models 7 and 8. Overall, it thus seems that higher short-run interest rates may be associated with lower uncertainty once we control for other macroeconomic factors, while higher long-run interest rates coincide with higher uncertainty. The opposing effects of short vs. long-run interest rates may be interpreted together with the effect of inflation: In order to mitigate risks from high inflation, central banks typically raise short-run interest rates. Hence, higher short-run interest rates should help to reduce any uncertainty from high inflation. At the same time, increasing short-run interest rates usually coincide with falling asset prices. In the sense that lower stock market prices are also more stable, both effects may work to reduce stock market uncertainty. By contrast, an increase in long-run interest rates points to a more long-term change in the dynamics of both interest rates and asset prices. Our results suggest that this would increase, rather than reduce, stock market preditability. Overall, the fact that inflation becomes insignificant in Models 7 and 8 suggests that the effect of inflation changes on stock market uncertainty in the U.S. works indirectly via changes in short- and long-run interest rates. The importance of short- and long-run interest rates for explaining dynamics in stock market uncertainty is reiterated by the large values of adjusted R^2 of 24.53% and 36.3% in Models 3 and 4, respectively.

Finally, both real GDP and the recession dummy do not significantly affect the long memory parameter of stocks in the U.S..

2 Evidence for the Full Cross-Section

We repeat the analysis from above and estimate the same regression as Equation (7) for each of the countries in our sample individually. An overview of the results is shown in Table 4, where we report median estimates for the cross-section, the percentage of countries for which we find a negative (positive) and statistically significant coefficient and the average t-statistic and adjusted R^2 across all countries.

Overall, the median values deliver the similar results for the entire cross-section as for the U.S.: Only short- and long-run interest rates have a significant effect on stock market uncertainty in the majority of countries in our sample. However, in the full sample of countries we find negative effects of both short- and long-run interest rates in 63% and 55% of the regressions, whereas positive effects are less common with 24% and 22%, respectively. The average adjusted $R2$ across the individual regressions also suggests that interest rates are the main driver of stock market uncertainty. As argued above, this is not surprising given that the transmission of macroeconomic shocks to asset markets works precisely via changes in interest rates.

Instead of investigating the relationship between the long memory parameter and the macroeconomic variables for each country separately, we next examine the complete cross-section over the sample period. We employ two different approaches relying on either portfolio sorts or cross-sectional regressions. Since there is no common recession definition for all countries in our sample, we instead account for stock market jumps directly. Intuitively, a stable country should exhibit fewer stock market jumps. To identify the jumps, we apply the common jump test proposed by Barndorff-Nielsen & Shephard (2006).[11] The test relies on the bipower variation, which decomposes the quadratic variation into its part due to continuous movements and a jump part. We rely on two measures of jumps. First, we compute the BNS jump statistic for each month and country using a pool of daily returns following Pukthuanthong & Roll (2015). The first measure is given by the jump statistic for each month. Our second measure presents an indicator function which shows whether the current month exhibits a statistically significant jump at a 5% significance level.

Each month, we sort the countries by their memory parameter and form tertile portfolios where the countries with the lowest memory parameter are in the first tertile and countries with the highest memory parameter are in the third tercile. We then compare averages of macroeconomic variables for the tercile portfolios. Table 5 reports average inflation, unemployment, treasury bill rates, government bond rates, GDP and jump

[11] Pukthuanthong & Roll (2015) show, with the help of simulations using different jump size and frequency, that this test is preferable compared to the ones proposed by Jiang & Oomen (2008), Lee & Mykland (2008) and Jacod & Todorov (2009).

measures for the tertile portfolios.[12] There is a monotonic pattern in all of the tercile portfolios (except for GDP): We find that unemployment rates as well as short- and long-run interest rates are lower for countries with long memory. Not surprisingly, the BNS statistic also suggests that countries with high memory parameters exhibit fewer jumps. Overall, stability in stock markets in our country sample correlates with macroeconomic stability. However, there is little variation with respect to inflation and real GDP, as countries with memory in the highest tercile show only similar inflation rates and only somewhat higher real GDP.

Testing for the significance of the average spread of the high minus low (LMS) portfolio reveals that the difference in spreads is significant when testing for an effect of unemployment, government bonds, and the BNS jumps. While the difference for real GDP is only marginally significant, there is no significant effect of short-run interest rates.

We also conduct cross-sectional regressions of the memory parameter by estimating the following regression:

$$d_{i,t} = \alpha_{i,t} + \beta_{i,t} X_{i,t} + \epsilon_{i,t} \tag{8}$$

where d_i is the memory parameter of country i, X_i contains one or more macroeconomic variables and ϵ_i is the error term. Table 6 reports the average coefficient estimates. The slope coefficients of the unemployment rate as well as short- and long-run interest rates are all negative and statistically significant at the 1% level, while the BNS coefficient is positive and significant. For inflation and GDP, we do not find any significant relationship.[13]

Our results suggest that countries with stable economies possess longer memory volatility compared to less stable countries. Intuitively, a stable country should hence exhibit fewer jumps as well. The remaining effect remain only robust for short-run interest rates in the model with all control variables. By contrast, the effect of unemployment becomes insignificant and the effect of the long-run interest rate turns positive. Overall

[12]Looking at the cross-section of countries, one might argue that GDP per capita is a more appropriate measure of comparison than GDP. Our main results rely on real GDP, but we also repeated the analysis using GDP per capita, which leads to qualitatively similar results.

[13]We also conduct panel regressions and find qualitatively similar results. The slope coefficients of Unemployment, Tbill and Gov.Bonds are negative and statistically significant at the 1% level, while the BNS coefficient is positive and statistically significant as well. We account for both fixed effects and heteroskedasticity in the regression. Detailed results are reported in Table 9 of the Online Appendix.

and in line with our results for the U.S., it seems that the degree of long memory in stocks in our large cross-section is primarily affected by interest rates. Here, however, it seems that higher short-run rates induce higher uncertainty, while higher long-run rates are related with lower uncertainty.

Since our country cross-sections contains both industrial and emerging economies, we test additionally whether developed countries possess longer memory, and thus more stability, in stock markets than emerging countries. We differentiate between Organisation for Economic Co-operation and Development (OECD) countries and emerging countries as defined by Thomson Reuters Tickhistory (TRTH). We also differentiate between developed, emerging and frontier countries, as defined by the classification of Morgan Stanley Capital International (MSCI). This yields the following cross-sectional regression:

$$d_i = \alpha_i + \beta_i D_i + \epsilon_i \tag{9}$$

where d_i is the memory parameter of country i, D_i is a dummy variable indicating whether a country is part of group of countries and ϵ_i is the error term. If emerging countries have a shorter memory than developed countries, the coefficient is expected to be negative and statistically significant.

We run three sets of regressions. First, we regress the memory parameter on country-type dummies over the complete sample period from 1964 until 2015, resulting in a cross-sectional regression with eighty-two observations. Since the classification of MSCI and the inclusion in the OECD group has changed within our sample period, one could argue that the first analysis leads to biased results. We hence repeat the same analysis, but estimate the regression only for the most recent eight years for the period from 2008 until 2015. Lastly, we use the time series of memory parameters from the previous sections estimated from rolling windows and estimate the cross-sectional regression in each month. The regression equation is then modified as:

$$d_{i,t} = \alpha_{i,t} + \beta_{i,t} D_{i,t} + \epsilon_{i,t} \tag{10}$$

We are interested in the temporal variation of the slope coefficient $\beta_{i,t}$ and report time-series averages for these.

The results are presented in Table 7 in Panel A, B and C, respectively. We can confirm the presumption that economically stronger countries have higher memory parameters than weaker countries for the period from 1964 until 2015 in Panel A. This holds true for both definitions of either TRTH or MSCI. OECD and developed countries exhibit a significantly higher memory parameter, while emerging (TRTH) and frontier countries possess a significantly shorter memory in volatility. The adjusted R^2 vary from 1.43% to 16.36%. The results remain qualitatively similar when considering the subsample from 2008 until 2015 in Panel B. Finally, the time series averages of the slope coefficients deliver the same message.

IV Robustness

In this section, we run various robustness tests including alternative long memory estimates and predictive regressions. All results are reported in the Online Appendix.

A Estimation of the Memory Parameter

For our main analysis we follow the existing literature and choose the ad hoc bandwidth parameter of $m = N^{0.5}$. We repeat the exercises using a bandwidth parameter of $m = N^{0.6}$ and $m = N^{0.7}$. Further, we apply the GPH estimator to absolute returns rather than squared returns as in our main analysis (Bollerslev & Wright, 2000). Lastly, we follow another commonly used approach to estimate long memory, the Local Whittle estimator. The Local Whittle estimator is obtained by minimizing the following objective function:

$$\hat{d}_{LW} = \arg\min_{d \in \theta} \left[log \left(\frac{1}{m} \sum_{j=1}^{m} \frac{I(\lambda_j)}{\lambda_j^{2d}} \right) - \frac{2d}{m} \sum_{j=1}^{m} log \lambda_j \right], \quad \theta \subseteq (-0.5, 0.5) \tag{11}$$

where m is restricted to $m < \frac{N}{2}$. The originally proposed estimator by Whittle (1951) presents an approximate maximum likelihood approach, which is extended by the Local Whittle estimator. Under mild assumptions similar to those for the GPH estimator, Robinson (1995a) derives the asymptotic distribution:

$$\sqrt{m}(\hat{d}_{LW} - d_0) \xrightarrow[d]{} N\left(0, \frac{1}{4}\right) \tag{12}$$

Table 10 reports the time-series regression of the memory parameter on macroeconomic variables for the U.S. The table presents results based on the four alternative memory estimators in Panel A, B, C and D, respectively. Even though the magnitudes of the slope coefficients slightly differ, the relationship between the variables and the memory parameter remains qualitatively similar. Generally, inflation, short and long interest rates have a negative impact on the memory parameter while unemployment has a positive relationship with the memory parameter.[14] The adjusted R^2 vary from 0%–41%, 0%–63%, 0%–34% and 0%–52% in the univariate regressions for the four alternative estimators, respectively. For comparison, the adjusted R^2 varies from 0%-36% in our main analysis using the GPH estimator and $m = N^{0.5}$.

Table 11 compares the memory parameter in developed and emerging countries for the alternative memory estimators. OECD countries and developed (MSCI) countries have statistically significantly higher memory parameters while emerging countries (TRTH) and frontier countries have statistically significantly shorter memory in volatility for all four estimators. The adjusted R^2 vary from 1%–16%, 1%–23%, 2%–16% and 0%–8% in the univariate regressions for the four estimators, respectively. For comparison, the adjusted R^2 varies from 1%–16% in our main analysis using the GPH estimator and $m = N^{0.5}$.

Table 12 investigates the average macroeconomic variables of tertile portfolios sorted by the memory parameter. Countries with higher memory parameters exhibit fewer jumps (higher BNS and lower BNS-I) and show lower government bond rates. This result is true and statistically significant for all four estimators. Additionally, countries with a higher memory parameter have lower unemployment rates, which is statistically significant for three of the four estimators.

B Predictive Regresssions

In Section III, we investigate the contemporaneous relationship between the memory parameter and macroeconomic variables' cross-section of countries. It is argued in the literature that changes in macroeconomic variables affect stock markets only with a lag. Paye (2012) investigates the predictability of stock return volatility by multiple macroeconomic

[14]There is one exception. Unemployment has a negative and statistically significant impact on the memory parameter when using the bandwidth of $m = N^{0.7}$.

variables including up to two lags, while Engle et al. (2013) show that macroeconomic fundamentals are important for forecasting of stock market volatility at both both short and long horizons.

We hence repeat our time-series analysis, but investigate a lagged relationship rather than a contemporaneous one for the U.S. Equation (7) is modified as follows:

$$d_{U.S.,t} = \alpha_{U.S.} + \beta_{U.S.} X_{U.S.,t-h} + \epsilon_t \tag{13}$$

considering lags from one quarter, half a year and one year ($h = 1, 2, 4$).[15] Table 13 presents the results for the three horizons in the three panels. Consistent with our main results, we find that inflation, short- and long-run interest rates and GDP have a negative impact on the memory parameter while unemployment has a positive relationship with the memory parameter. The relationship between GDP and the memory parameter diminishes for longer horizons and the slope coefficient is no longer statistically significant. The adjusted R^2 varies between 0% and 39% for the univariate regressions. Hence, the relationship between memory and macroeconomic variables found in our main contemporaneous analysis persists into the future for up to one year.

V Conclusion

In this paper we shed new light on long memory in the volatility of international equity markets. With the help of portfolio sorts and cross-sectional regressions, we demonstrate how the memory parameter of a country stock index volatility can be explained by country-specific macroeconomic variables such as inflation, unemployment rates, interest rates and jumps. We show that macroeconomic variables help explain the memory parameter, both in the time-series and the cross-sectional dimension. Following the existing literature, we provide economically reasonable explanations for the sign of the relationships. In addition, classifications such as OECD, developed, emerging or frontier countries also matter for the memory parameter. More developed countries possess a higher memory parameter while frontier and emerging countries possess a shorter memory in volatility. Therefore, the memory of the volatility can be seen as a proxy for the

[15] We conduct this analysis in quarterly frequency because GDP data is only available at this frequency.

stability of the country. Our results are robust against various variations of the examined models.

VI Technical Appendix

Geweke & Porter-Hudak (1983) introduce an estimator which is based on the log-periodogram. A linear regression is employed to the spectral density relying on the first m periodogram ordinates. Empirically, the spectral density of a stationary process X_t is estimated by the periodogram:

$$I_X(\lambda_j) = \frac{1}{2\pi N} \left| \sum_{t=1}^{N} X_t e^{-it\lambda} \right|^2, \quad t = 1, ..., N \tag{14}$$

where the periodogram is not affected by centering of the time series for Fourier frequencies $\lambda_j = 2\pi j/N$ $(j = 1, ..., [(N-1)/2])$. The negative slope coefficient β_1 in the regression presents the estimator:

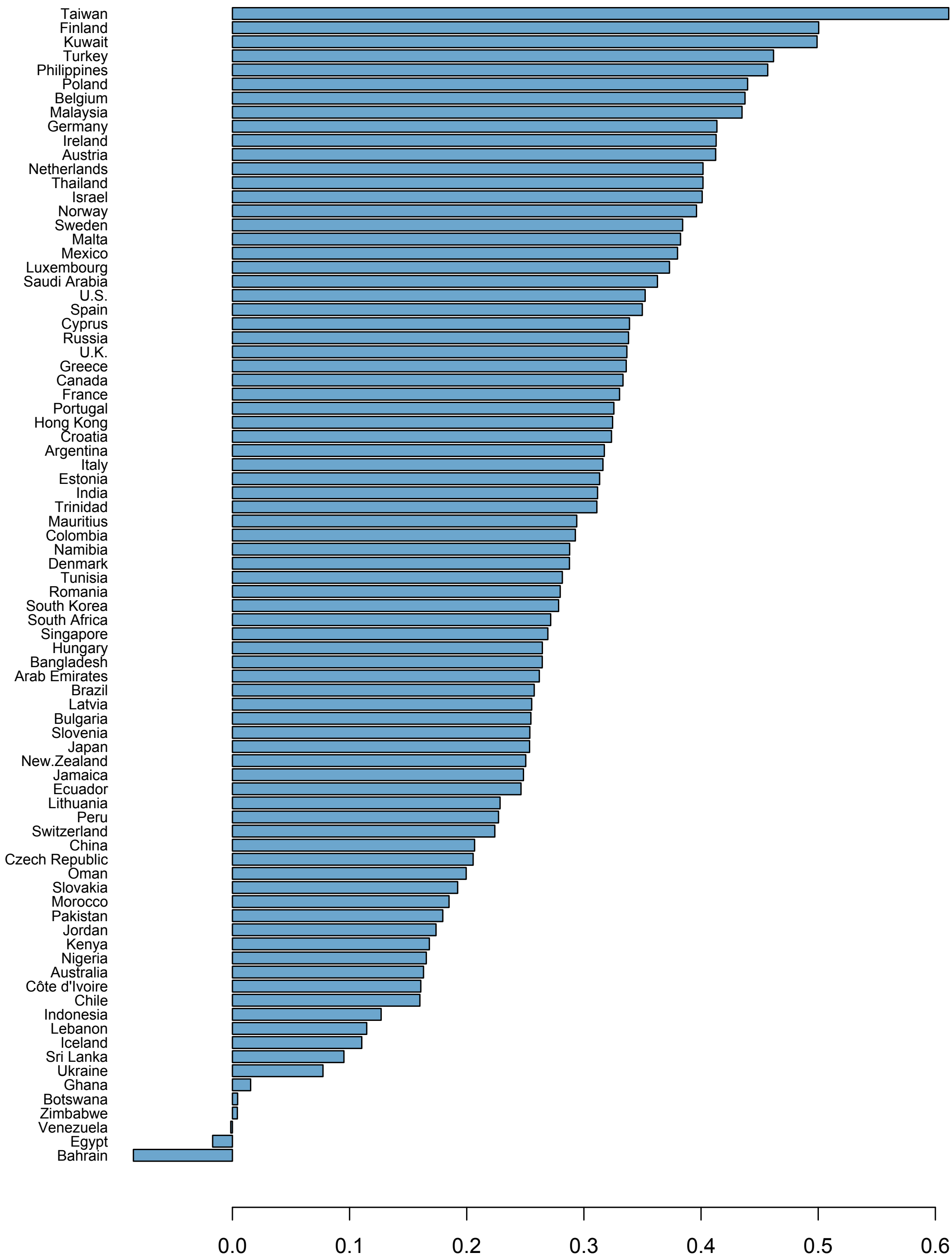
$$log(I(\lambda_j)) = \beta_0 + \beta_1 log[4sin^2(\lambda_j/2)] + \epsilon_j, \quad j = 1, ..., m \tag{15}$$

The asymptotic standard errors for the long memory parameter can be obtained from the asymptotic distribution, which is derived by Robinson (1995b) under mild conditions $(m \to \infty, N \to \infty, \frac{m}{N} \to 0)$:

$$\sqrt{m}(\hat{d} - d) \underset{d}{\longrightarrow} N\left(0, \frac{\pi^2}{24}\right) \tag{16}$$

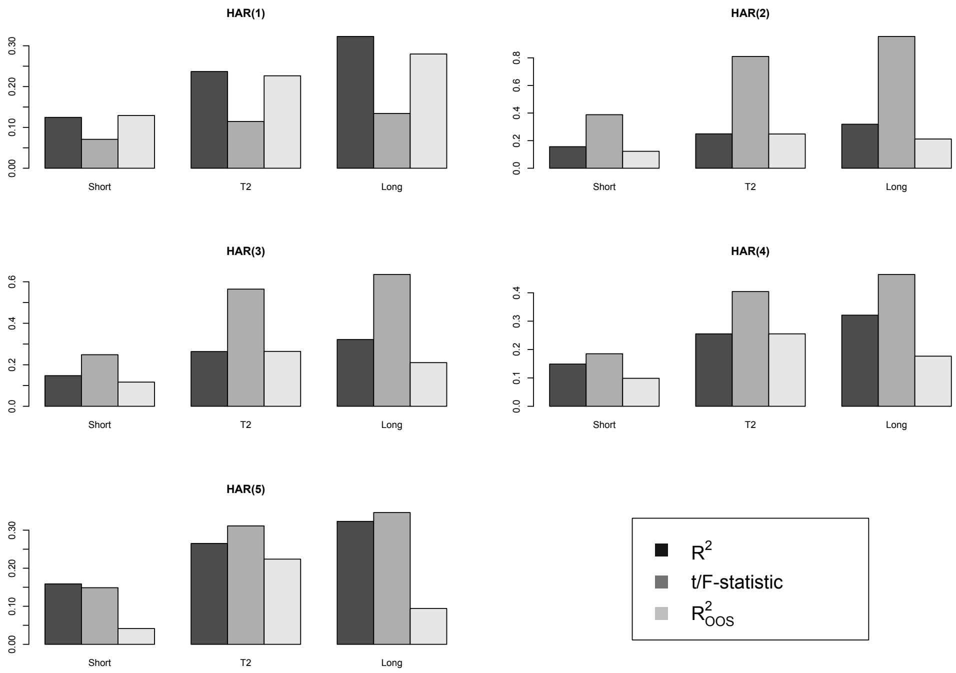
The choice of the bandwidth parameter m results into a bias–variance trade-off. If the m is chosen too low and hence too close to the origin, an increased variance is the result, while a m chosen too high and hence too far from the origin leads to bias.

Figure 1: Memory Estimates of International Countries



This figure shows the memory parameter estimates applying the GPH estimator and a bandwidth parameter of $m = N^{0.5}$ to the eighty-two countries for the period from January 1964 until December 2015.

Figure 2: Predictability of Tertile Portfolios



This figure reports adjusted R^2, t-statistics, F-statistics and R^2_{OOS} for tertile portfolios of the cross-section of countries. For a better presentation, the test statistics are all divided by 100.

Table 1: Summary Statistics

This table presents the summary statistics for the long memory volatility of international countries. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. Obs. in column (1) stands for the number of observations, SD stands for the standard deviation, column (2) reports selected quantiles; t-statistic in column (3) reports the mean t-statistic, Sign. at 5% reports the proportion of significant long memory estimates, while the remainder of column (3) reports the proportion of the memory parameter being in a certain interval.

Descriptive		Quantiles		Memory	
Obs.	82	5%	0.01	t-statistic	3.95
Mean	0.27	25%	0.20	Sign. at 5%	0.87
SD	0.13	Median	0.28	-0.5<d<0.0	0.04
Skewness	-0.41	75%	0.35	0.0<d<0.5	0.94
Kurtosis	0.28	95%	0.46	0.5<d<1.0	0.02

Table 2: Long Memory and Predictability – Cross-Section of Countries

This table reports the results predictive regressions. We estimate the proposed HAR models by simple linear regressions including the previous 1, 6, 12, 24 and 60 observations. We form tertile portfolios where countries with the lowest memory parameter are in the first tertile and countries with the highest memory parameter are in the third tertile. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. We report average adjusted R^2 in Panel A, average t-statistics and F-statistics in Panel B and out-of-sample R^2 in Panel C.

	T1	T2	T3
Panel A: Adjusted R^2			
HAR(1)	0.1246	0.2370	0.3229
HAR(2)	0.1560	0.2491	0.3190
HAR(3)	0.1476	0.2638	0.3217
HAR(4)	0.1488	0.2552	0.3212
HAR(5)	0.1588	0.2651	0.3230
Panel B: T-statistic/F-statistic			
HAR(1)	7.0841	11.4621	13.4188
HAR(2)	38.7906	81.0082	95.4979
HAR(3)	24.8456	56.4617	63.5065
HAR(4)	18.5080	40.4269	46.4415
HAR(5)	14.8762	31.1230	34.6305
Panel C: R^2_{OOS}			
HAR(1)	0.1292	0.2265	0.2798
HAR(2)	0.1227	0.2482	0.2118
HAR(3)	0.1165	0.2645	0.2104
HAR(4)	0.0986	0.2552	0.1766
HAR(5)	0.0415	0.2239	0.0943

Table 3: Long Memory of the U.S.

This table presents the coefficients from the regressions of the memory parameter on macroeconomic variables for the U.S. for the period from 1964 until 2015. The regressors are the inflation, the log unemployment, the treasury bill and the government bond rates and the GDP growth. Recession is the indicator function that represents periods of expansion and recession defined by the NBER. All the macroeconomic variables are monthly except for GDP, hence Model 5 and Model 8 are on a quarterly basis. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$ applied to squared returns. Stars indicate significance of the mean differences: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
(Intercept)	0.4244***	0.4070***	0.5356***	0.7847***	0.4352***	0.4125***	0.9302***	1.0393***
	(0.0142)	(0.0114)	(0.0161)	(0.0299)	(0.0275)	(0.0121)	(0.0434)	(0.0566)
Inflation	−7.9649*						3.9341	2.1536
	(4.2795)						(3.3853)	(4.9511)
Unemployment		0.2143**					0.7310***	0.7641***
		(0.0998)					(0.1290)	(0.0925)
Tbill			−0.0452***				0.0501***	0.0930***
			(0.0045)				(0.0115)	(0.0150)
Gov.Bonds				−0.0711***			−0.1283***	−0.1719***
				(0.0054)			(0.0137)	(0.0178)
GDP					−5.0221			1.4630
					(3.1868)			(2.7594)
Recession						−0.0344	0.0270	−0.0084
						(0.0363)	(0.0286)	(0.0533)
adj. R^2	0.0080	0.0117	0.2453	0.3630	0.0145	−0.0003	0.4181	0.6271

Table 4: Long Memory of the Cross-Section of Countries

This table presents the statistics from the regressions of the memory parameter on the macroeconomic variables for eighty-two countries for the period from 1964 until 2015. The regressors are the inflation, the log unemployment, treasury bill and the government bond rates, and the GDP growth. Recession is the indicator function that represents periods of expansion and recession defined by the NBER. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. The first row reports the median of the coefficients over the cross-section. The second (third) row reports the percentage of countries for which the slope is negative (positive) and statistically significant at a 5% level. The fourth row reports the average absolute t-statistic across all countries and the fifth row reports the average adjusted R^2 over all countries.

	Inflation	Unemployment	Tbill	Gov.Bonds	GDP	Recession	KS ex. GDP	KS
Median	-0.15	0.07	-0.01	-0.02	-0.05	-0.01		
$\beta < 0$ (significant)	6.49%	18.97%	62.69%	55.00%	2.50%	18.99%		
$\beta > 0$ (significant)	3.90%	24.14%	23.88%	21.67%	0.00%	13.92%		
t-statistic	0.97	2.16	8.04	8.02	0.81	1.61		
Adj. R^2	0.01	0.04	0.20	0.19	0.01	0.02	0.37	0.37

Table 5: International Portfolio Sorts

This table presents the average macroeconomic variables of the tertile portfolios sorted by the memory parameter. The investigated countries are the eighty-two following Pukthuanthong & Roll (2015) over the period from 1964 until 2015. Long memory is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. The column *LMS* reports the difference of the third and first portfolio with t-statistics in squared brackets.

	T1	T2	T3	T3-T1 (LMS)	
Inflation	0.0039	0.0034	0.0034	-0.0005	$[-1.2397]$
Unemployment	7.7295	7.3664	6.9280	-0.8015	$[-3.0940]$
Tbill	12.0172	10.5784	9.5123	-2.5048	$[-1.0116]$
Gov.Bonds	9.8846	8.5284	7.7230	-2.1616	$[-3.2466]$
GDP	0.0034	0.0033	0.0067	0.0034	[1.8528]
BNS	-3.9505	-0.3542	-0.2565	3.6940	[2.0753]
BNS-I	0.0843	0.0299	0.0180	-0.0662	$[-4.5159]$

Table 6: Cross-Sectional Regressions

This table presents results from the cross-sectional regressions. The dependent variable is the memory parameter for each country and the regressors are the inflation, the log unemployment, treasury bill and government bond rates, GDP growth and jumps measured by BNS. The investigated countries are the eighty-two following Pukthuanthong & Roll (2015) over the period from 1964 until 2015. Long memory is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. We report time-series averages and standard errors in parentheses below. Stars indicate significance of the mean differences: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	0.0036***	8.3460***	11.9472***	10.6636***	0.0015	−4.3354***	0.2287***
	(0.0009)	(0.0663)	(0.4604)	(0.1186)	(0.0042)	(0.8375)	(0.0197)
Inflation	−0.0003						−0.1006
	(0.0017)						(0.4048)
Unemployment		−3.7159***					−0.0008
		(0.1661)					(0.0011)
Tbill			−4.3856***				−0.0047**
			(1.3340)				(0.0021)
Gov.Bonds				−5.4660***			0.0068**
				(0.3698)			(0.0030)
GDP					−0.0086		
					(0.0088)		
BNS						10.1832***	0.0308***
						(2.0815)	(0.0055)

Table 7: Long Memory in Developed and Emerging Countries

This table presents the cross-sectional regressions of the memory estimates on the dummy variables. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. The investigated countries are the eighty-two following Pukthuanthong & Roll (2015) over the period from 1964 until 2015 in Panel A. Panel B investigates the subperiod from 2008 until 2015. OECD, Emerging, Developed and Frontier indicate whether a country is part of the OECD group, an emerging, developed or a frontier country according to the definition of Thomson Reuters Tickhistory (TRTH) or Morgan Stanley Capital International (MSCI). We repeat the estimation of the memory parameter at a monthly frequency relying on rolling windows of five years of daily observations. Each month we run the same cross-sectional regression as in Panel A and B and report the time-series averages of the coefficients in Panel C with the standard errors in parentheses below. We also report the average of the adjusted R^2 over the sample period. Stars indicate significance of the mean differences: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: 1964-2015						
(Intercept)	0.2444***	0.3250***	0.2472***	0.2609***	0.3115***	0.2428***
	(0.0170)	(0.0246)	(0.0160)	(0.0167)	(0.0160)	(0.0388)
OECD (TRTH)	0.0836**					
	(0.0286)					
Emerging (TRTH)		−0.0748**				
		(0.0298)				
Developed (MSCI)			0.0953**			0.0997**
			(0.0302)			(0.0457)
Emerging (MSCI)				0.0466		0.0646
				(0.0316)		(0.0457)
Frontier (MSCI)					−0.1142***	−0.0455
					(0.0278)	(0.0448)
adj. R^2	0.0853	0.0616	0.0996	0.0143	0.1636	0.1919
Panel B: 2008-2015						
(Intercept)	0.3608***	0.5255***	0.3548***	0.4279***	0.4496***	0.2177***
	(0.0268)	(0.0386)	(0.0237)	(0.0275)	(0.0277)	(0.0584)
OECD (TRTH)	0.1675***					
	(0.0448)					
Emerging (TRTH)		−0.1542**				
		(0.0468)				
Developed (MSCI)			0.2324***			0.3694***
			(0.0446)			(0.0689)
Emerging (MSCI)				−0.0252		0.1850**
				(0.0516)		(0.0689)
Frontier (MSCI)					−0.0898*	0.1420**
					(0.0489)	(0.0677)
adj. R^2	0.1396	0.1098	0.2466	−0.0096	0.0288	0.2936
Panel C: Time-Series Averages						
Coefficient	0.0455***	−0.0120**	0.0402***	0.0363***	−0.0552***	
	(0.0048)	(0.0054)	(0.0067)	(0.0038)	(0.0065)	
adj. R^2	0.0518	0.0551	0.0947	0.0125	0.0463	

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Online Appendix

Table 8: Overview of Country Sample

This table presents the eighty-two countries and their availability from Datastream. We rely on a common currency, the U.S. dollar, for all values. We work with either the total return index (“RI”) or the pure price index (“PI”).

Country	Datastream Availability		Index Identification	Datastream Mnemonic		Country	Datastream Availability		Index Identification	Datastream Mnemonic
Argentina	2-Aug-93	31-Dec-15	ARGENTINA MERVAL	ARGMERV(PI)~U$		Lithuania	31-Dec-99	31-Dec-15	OMX VILNIUS (OMXV)	LNVILSE(RI)~U$
Australia	1-Jan-73	31-Dec-15	AUSTRALIA-DS MarKET	TOTMAU$(RI)		Luxembourg	2-Jan-92	31-Dec-15	LUXEMBURG-DS MarKET	TOTMKLX(RI)
Austria	1-Jan-73	31-Dec-15	AUSTRIA-DS Market	TOTMKOE(RI)~U$		Malaysia	2-Jan-80	31-Dec-15	KLCI COMPOSITE	KLPCOMP(PI)~U$
Bahrain	31-Dec-99	31-Dec-15	DOW JONES BAHRAIN	DJBAHR$(PI)		Malta	27-Dec-95	31-Dec-15	MALTA SE MSE -	MALTAIX(PI)~U$
Bangladesh	1-Jan-90	1-Apr-13	BANGLADESH SE ALL SHARE	BDTALSH(PI)~U$		Mauritius	29-Dec-95	31-Dec-15	S&P/IFCF M MAURITIUS	IFFMMAL(PI)~U$
Belgium	1-Jan-73	31-Dec-15	BELGIUM-DS Market	TOTMKBG(RI)~U$		Mexico	4-Jan-88	31-Dec-15	MEXICO IPC (BOLSA)	MXIPC35(PI)~U$
Botswana	29-Dec-95	31-Dec-15	S&P/IFCF M BOTSWA0.	IFFMBOL(PI)~U$		Morocco	31-Dec-87	31-Dec-15	MOROCCO SE CFG25	MDCFG25(PI)~U$
Brazil	7-Apr-83	31-Dec-15	BRAZIL BOVESPA	BRBOVES(RI)~U$		Namibia	31-Jan-00	31-Dec-15	S&P/IFCF M NAMBIA	IFFMNAL(PI)~U$
Bulgaria	20-Oct-00	31-Dec-15	BSE SOFIX	BSSOFIX(PI)~U$		Netherlands	1-Jan-73	31-Dec-15	NETHERLAND-DS Market	TOTMKNL(RI)~U$
Canada	31-Dec-64	31-Dec-15	S&P/TSX COMPOSITE INDEX	TTOCOMP(RI)~U$		New Zealand	4-Jan-88	31-Dec-15	NEW ZEALAND-DS MarKET	TOTMNZ$(RI)
Chile	2-Jan-87	31-Dec-15	CHILE GENERAL (IGPA)	IGPAGEN(PI)~U$		Nigeria	30-Jun-95	31-Dec-15	S&P/IFCG D NIGERIA	IFGDNGL(PI)~U$
China	3-Apr-91	31-Dec-15	SHENZHEN SE COMPOSITE	CHZCOMP(PI)~U$		Norway	2-Jan-80	31-Dec-15	NORWAY-DS MarKET	TOTMNW$(RI)
Colombia	10-Mar-92	31-Dec-15	COLOMBIA-DS Market	TOTMKCB(RI)~U$		Oman	22-Oct-96	31-Dec-15	OMAN MUSCAT SECURITIES MKT.	OMANMSM(PI)~U$
Côte d’Ivoire	29-Dec-95	31-Dec-15	S&P/IFCF M CÔTE D’IVOIRE	IFFMCIL(RI)~U$		Pakistan	30-Dec-88	31-Dec-15	KARACHI SE 100	PKSE100(PI)~U$
Croatia	2-Jan-97	31-Dec-15	CROATIA CROBEX	CTCROBE(PI)~U$		Peru	2-Jan-91	31-Dec-15	LIMA SE GENERAL(IGBL)	PEGENRL(PI)~U$
Cyprus	3-Sep-04	31-Dec-15	CYPRUS GENERAL	CYPMAPM(PI)~U$		Philippines	2-Jan-86	31-Dec-15	PHILIPPINE SE I(PSEi)	PSECOMP(PI)~U$
Czech Republic	9-Nov-93	31-Dec-15	CZECH REP.-DS NON-FINCIAL	TOTLICZ(RI)~U$		Poland	16-Apr-91	31-Dec-15	WARSAW GENERALINDEX	POLWIGI(RI)~U$
Denmark	31-Dec-69	31-Dec-15	MSCI DENMARK	MSDNMKL(RI)~U$		Portugal	5-Jan-88	31-Dec-15	PORTUGAL PSI GENERAL	POPSIGN(PI)~U$
Ecuador	2-Aug-93	31-Dec-15	ECUADOR ECU (U$)	ECUECUI(PI)		Romania	19-Sep-97	31-Dec-15	ROMANIA BET (L)	RMBETRL(PI)~U$
Egypt	2-Jan-95	31-Dec-15	EGYPT HERMES FINANCIAL	EGHFINC(PI)~U$		Russia	1-Sep-95	31-Dec-15	RUSSIA RTS INDEX	RSRTSIN(PI)~U$
Estonia	3-Jun-96	31-Dec-15	OMX TALLINN (OMXT)	ESTALSE(PI)~U$		Saudi Arabia	31-Dec-97	31-Dec-15	S&P/IFCG D SAUDI ARABIA	IFGDSB$(RI)
Finland	2-Jan-91	31-Dec-15	OMX HELSINKI (OMXH)	HEXINDX(RI)~U$		Singapore	1-Jan-73	31-Dec-15	SINGAPORE-DS MarKET EX TMT	TOTXTSG(RI)~U$
France	1-Jan-73	31-Dec-15	FRANCE-DS Market	TOTMKFR(RI)~U$		Slovakia	14-Sep-93	31-Dec-15	SLOVAKIA SAX 16	SXSAX16(PI)~U$
Germany	31-Dec-64	31-Dec-15	DAX 30 PERFORMANCE	DAXINDX(RI)~U$		Slovenia	31-Dec-93	14-Oct-10	SLOVENIAN EXCH. STOCK (SBI)	SLOESBI(PI)~U$
Ghana	29-Dec-95	31-Dec-15	S&P/IFCF M GHA0.	IFFMGHL(PI)~U$		South Africa	1-Jan-73	31-Dec-15	SOUTH AFRICA-DS MarKET	TOTMSA$(RI)
Greece	26-Jan-06	31-Dec-15	ATHEX COMPOSITE	GRAGENL(RI)~U$		South Korea	31-Dec-74	31-Dec-15	KOREA SE COMPOSITE (KOSPI)	KORCOMP(PI)~U$
Hong Kong	2-Jan-90	31-Dec-15	HANG SENG	HNGKNGI(RI)~U$		Spain	2-Jan-74	31-Dec-15	MADRID SE GENERAL	MADRIDI(PI)~U$
Hungary	2-Jan-91	31-Dec-15	BUDAPEST (BUX)	BUXINDX(PI)~U$		Sri Lanka	2-Jan-85	31-Dec-15	COLOMBO SE ALLSHARE	SRALLSH(PI)~U$
Iceland	31-Dec-92	31-Dec-15	OMX ICELAND ALLSHARE	ICEXALL(PI)~U$		Sweden	28-Dec-79	31-Dec-15	OMX STOCKHOLM (OMXS)	SWSEALI(PI)~U$
India	2-Jan-87	31-Dec-15	INDIA BSE (100) NATIONAL	IBOMBSE(PI)~U$		Switzerland	1-Jan-73	31-Dec-15	SWITZ-DS Market	TOTMKSW(RI)~U$
Indonesia	2-Apr-90	31-Dec-15	INDONESIA-DS Market	TOTMKID(RI)~U$		Taiwan	31-Dec-84	31-Dec-15	TAIWAN SE WEIGHTED	TAIWGHT(PI)~U$
Ireland	1-Jan-73	31-Dec-15	IRELAND-DS MarKET	TOTMIR$(RI)		Thailand	2-Jan-87	31-Dec-15	THAILAND-DS MarKET	TOTMTH$(RI)
Israel	23-Apr-87	31-Dec-15	ISRAEL TA 100	ISTA100(PI)~U$		Trinidad	29-Dec-95	31-Dec-15	S&P/IFCF M TRINIDAD & TOBAGO	IFFMTTL(PI)~U$
Italy	1-Jan-73	31-Dec-15	ITALY-DS MarKET	TOTMIT$(RI)		Tunisia	31-Dec-97	31-Dec-15	TUNISIA TUNINDEX	TUTUNIN(PI)~U$
Jamaica	29-Dec-95	31-Dec-15	S&P/IFCF M JAMAICA	IFFMJAL(PI)~U$		Turkey	4-Jan-88	31-Dec-15	ISE TIOL 100	TRKISTB(PI)~U$
Japan	1-Jan-73	31-Dec-15	TOPIX	TOKYOSE(RI)~U$		Ukraine	30-Jan-98	31-Dec-15	S&P/IFCF M UKRAINE	IFFMURL(PI)~U$
Jordan	21-Nov-88	31-Dec-15	AMMAN SE FINANCIAL MarKET	AMMANFM(PI)~U$		Utd. Arab	1-June-05	31-Dec-15	MSCI UAE	MSUAE$
Kenya	11-Jan-90	31-Dec-15	KENYA NAIROBI SE	NSEINDX(PI)~U$		United Kingdom	1-Jan-65	31-Dec-15	UK-DS MarKET	TOTMUK$(RI)
Kuwait	28-Dec-94	31-Dec-15	KUWAIT KIC GENERAL	KWKICGN(PI)~U$		United States	4-Jan-68	31-Dec-15	S&P 500 COMPOSITE	S&PCOMP(RI)~U$
Latvia	3-Jan-00	31-Dec-15	OMX RIGA (OMXR)	RIGSEIN(RI)~U$		Venezuela	2-Jan-90	31-Dec-15	VENEZUELA-DS MarKET	TOTMVE$(RI)
Lebanon	31-Jan-00	31-Dec-15	S&P/IFCF M LEBANON	IFFMLEL(PI)~U$		Zimbabwe	6-Apr-88	6-Oct-06	ZIMBABWE INDUSTRIALS	ZIMINDS(PI)

Table 9: Long Memory for the Cross-Section of Countries – Panel Regression

This table presents the statistics from the panel regressions of the memory parameter on macroeconomic variables for eighty-two countries for the period from 1964 until 2015. The regressors are the inflation, the log unemployment, treasury bill and the government bond rates, and the GDP growth. Recession is the indicator function that represents periods of expansion and recession defined by the NBER and BNS presents the Barndorff-Nielsen et al. (2009) jump test statistic. The memory parameter is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. Stars indicate significance of the mean differences: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Inflation	-0.0027						-0.0425	-0.0680
	(0.0227)						(0.0927)	(0.1472)
Unemployment		-0.0057^{***}					-0.0014^{***}	-0.0267
		(0.0002)					(0.0003)	(0.0530)
Tbill			-0.0003^{***}				-0.0008	-0.0024
			(0.0001)				(0.0007)	(0.0015)
Gov				-0.0046^{***}			-0.0078^{***}	-0.0070^{***}
				(0.0003)			(0.0008)	(0.0014)
GDP					-0.0138			-0.1210^{*}
					(0.0304)			(0.0706)
BNS						0.0001^{**}	0.0009^{***}	0.0034^{***}
						(0.0000)	(0.0004)	(0.0010)

Table 10: Long Memory of the U.S. – Alternative Long Memory Estimates

This table presents the coefficients from the regressions of the memory parameter on the macroeconomic variables for the U.S. for the period from 1964 until 2015. The regressors are the inflation, the log unemployment, treasury bills and government bond rates and GDP growth. Recession is the indicator function that represents periods of expansion and recession defined by the NBER. All macroeconomic variables are monthly except for GDP, hence Model 5 and Model 8 are on a quarterly basis. Long memory is estimated with the GPH estimator and a bandwidth choice of $m = N^{0.6}$ and $m = N^{0.7}$ in Panel A and B, respectively. The GPH estimator is applied to absolute returns and a bandwidth of $m = N^{0.5}$ in Panel C and Panel D shows results relying on the LW estimator and $m = N^{0.5}$. Stars indicate significance of the mean differences: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Panel A: GPH estimator ($m = N^{0.6}$)								
(Intercept)	0.4373***	0.4148***	0.5999***	0.9142***	0.4136***	0.4117***	0.9819***	1.1624***
	(0.0176)	(0.0142)	(0.0189)	(0.0358)	(0.0244)	(0.0151)	(0.0527)	(0.0604)
Inflation	−10.3997*						5.3654	2.0343
	(5.3207)						(4.1047)	(5.2583)
Unemployment		0.2539**					0.5740***	1.1672***
		(0.1242)					(0.1564)	(0.1170)
Tbill			−0.0652***				0.0240*	0.0975***
			(0.0053)				(0.0139)	(0.0158)
Gov.Bonds				−0.0940***			−0.1246***	−0.1951***
				(0.0064)			(0.0166)	(0.0184)
GDP					−1.3916			2.9567***
					(1.0635)			(0.8567)
Recession						0.0454	0.1032**	0.0575
						(0.0451)	(0.0346)	(0.0425)
adj. R^2	0.0092	0.0104	0.3308	0.4108	0.0070	0.0000	0.4472	0.7193
Panel B: GPH estimator ($m = N^{0.7}$)								
(Intercept)	0.2889***	0.2790***	0.3745***	0.5912***	0.2772***	0.2793***	0.5961***	0.6656***
	(0.0089)	(0.0072)	(0.0094)	(0.0143)	(0.0127)	(0.0077)	(0.0215)	(0.0323)
Inflation	−5.6173**						2.5356	1.9762
	(2.6987)						(1.6747)	(2.8152)
Unemployment		−0.1573**					−0.0811	0.2652***
		(0.0628)					(0.0638)	(0.0626)
Tbill			−0.0345***				0.0024	0.0264**
			(0.0026)				(0.0057)	(0.0085)
Gov.Bonds				−0.0592***			−0.0624***	−0.0881***
				(0.0026)			(0.0068)	(0.0098)
GDP					0.4833			1.2870**
					(0.5524)			(0.4587)
Recession						−0.0132	0.0083	−0.0060
						(0.0229)	(0.0141)	(0.0228)
adj. R^2	0.0108	0.0170	0.3587	0.6349	−0.0023	−0.0022	0.6429	0.6990

Long Memory of the U.S. – Alternative Long Memory Estimates Continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Panel C: GPH estimator (absolute returns; $m = N^{0.5}$)								
(Intercept)	0.5223***	0.5059***	0.6125***	0.8071***	0.5037***	0.5100***	0.9182***	1.0064***
	(0.0116)	(0.0093)	(0.0131)	(0.0248)	(0.0157)	(0.0099)	(0.0361)	(0.0455)
Inflation	−7.4465**						2.1738	0.2664
	(3.4964)						(2.8094)	(3.9656)
Unemployment		0.2155**					0.6103***	0.6458***
		(0.0813)					(0.1070)	(0.0882)
Tbill			−0.0374***				0.0381***	0.0737***
			(0.0037)				(0.0095)	(0.0119)
Gov.Bonds				−0.0566***			−0.1001***	−0.1342***
				(0.0045)			(0.0114)	(0.0139)
GDP					−1.8885**			−0.0508
					(0.6830)			(0.6461)
Recession						−0.0211	0.0273	−0.0044
						(0.0297)	(0.0237)	(0.0321)
adj. R^2	0.0115	0.0194	0.2501	0.3435	0.0617	−0.0016	0.4017	0.6342
Panel D: LW estimator ($m = N^{0.5}$)								
(Intercept)	0.3837***	0.3567***	0.4945***	0.7241***	0.3528***	0.3526***	0.7975***	0.8827***
	(0.0120)	(0.0094)	(0.0123)	(0.0203)	(0.0164)	(0.0100)	(0.0299)	(0.0404)
Inflation	−12.9398***						2.3408	1.0516
	(3.5222)						(2.5542)	(3.7541)
Unemployment		0.2536**					0.3982***	0.6321***
		(0.0821)					(0.0925)	(0.0825)
Tbill			−0.0428***				0.0303***	0.0610***
			(0.0030)				(0.0082)	(0.0107)
Gov.Bonds				−0.0655***			−0.0976***	−0.1289***
				(0.0034)			(0.0094)	(0.0123)
GDP					−1.5143**			1.3986**
					(0.7193)			(0.6124)
Recession						0.0321	0.0494**	−0.0035
						(0.0315)	(0.0217)	(0.0305)
adj. R^2	0.0360	0.0248	0.3775	0.5215	0.0300	0.0001	0.5449	0.7117

Table 11: Long Memory in Developed and Emerging Countries – Alternative Estimates

This table presents the cross-sectional regressions of the memory estimates on the dummy variables. The investigated countries are the eighty-two following Pukthuanthong & Roll (2015) over the period from 1964 until 2015. Long memory is estimated with the GPH estimator and a bandwidth choice of $m = N^{0.6}$ and $m = N^{0.7}$ in Panel A and B, respectively. The GPH estimator is applied to absolute returns and a bandwidth of $m = N^{0.5}$ in Panel C and Panel D shows results relying on the LW estimator and $m = N^{0.5}$. Stars indicate significance of the mean differences: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: GPH estimator ($m = N^{0.6}$)						
(Intercept)	0.2515***	0.3573***	0.2616***	0.2814***	0.3345***	0.2209***
	(0.0183)	(0.0275)	(0.0177)	(0.0188)	(0.0182)	(0.0428)
OECD (TRTH)	0.1242***					
	(0.0308)					
Emerging (TRTH)		−0.0907**				
		(0.0332)				
Developed (MSCI)			0.1206***			0.1612**
			(0.0334)			(0.0505)
Emerging (MSCI)				0.0500		0.1104**
				(0.0355)		(0.0505)
Frontier (MSCI)					−0.1189***	−0.0053
					(0.0317)	(0.0495)
adj. R^2	0.1583	0.0738	0.1297	0.0119	0.1388	0.2189
Panel B: GPH estimator ($m = N^{0.7}$)						
(Intercept)	0.2083***	0.3166***	0.2225***	0.2462***	0.3022***	0.2112***
	(0.0167)	(0.0262)	(0.0165)	(0.0180)	(0.0168)	(0.0397)
OECD (TRTH)	0.1415***					
	(0.0281)					
Emerging (TRTH)		−0.0853**				
		(0.0317)				
Developed (MSCI)			0.1278***			0.1391**
			(0.0312)			(0.0468)
Emerging (MSCI)				0.0434		0.0785*
				(0.0339)		(0.0468)
Frontier (MSCI)					−0.1330***	−0.0420
					(0.0292)	(0.0458)
adj. R^2	0.2318	0.0715	0.1632	0.0078	0.1959	0.2630

Long Memory in Developed and Emerging Countries – Alternative Estimates Continued

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel C: LW estimator ($m = N^{0.5}$)						
(Intercept)	0.2546***	0.3028***	0.2551***	0.2587***	0.3054***	0.2449***
	(0.0147)	(0.0212)	(0.0137)	(0.0139)	(0.0135)	(0.0329)
OECD (TRTH)	0.0544**					
	(0.0246)					
Emerging (TRTH)		−0.0423				
		(0.0256)				
Developed (MSCI)			0.0667**			0.0769*
			(0.0260)			(0.0388)
Emerging (MSCI)				0.0540**		0.0678*
				(0.0263)		(0.0388)
Frontier (MSCI)					−0.0958***	−0.0353
					(0.0235)	(0.0380)
adj. R^2	0.0456	0.0209	0.0646	0.0380	0.1618	0.1838
Panel D: GPH estimator (absolute returns; $m = N^{0.5}$)						
(Intercept)	0.3938***	0.4584***	0.3932***	0.4154***	0.4228***	0.3842***
	(0.0140)	(0.0195)	(0.0131)	(0.0136)	(0.0139)	(0.0338)
OECD (TRTH)	0.0502**					
	(0.0235)					
Emerging (TRTH)		−0.0685**				
		(0.0236)				
Developed (MSCI)			0.0657**			0.0747*
			(0.0247)			(0.0399)
Emerging (MSCI)				−0.0136		0.0177
				(0.0257)		(0.0399)
Frontier (MSCI)					−0.0340	0.0046
					(0.0243)	(0.0390)
adj. R^2	0.0422	0.0839	0.0701	−0.0090	0.0117	0.0498

Table 12: International Portfolio Sorts – Alternative Long Memory Estimates

This table presents the average macroeconomic variables of the tertile portfolios sorted by the memory parameter. The investigated countries are the eighty-two following Pukthuanthong & Roll (2015) over the period from 1964 until 2015. Long memory is estimated with the GPH estimator and a bandwidth choice of $m = N^{0.6}$ and $m = N^{0.7}$ in Panel A and B, respectively. The GPH estimator is applied to absolute returns and a bandwidth of $m = N^{0.5}$ in Panel C and Panel D shows results relying on the LW estimator and $m = N^{0.5}$. The column *LMS* reports the difference of the third and first portfolio with t-statistics in squared brackets.

	T1	T2	T3	T3- T1 (LMS)	
Panel A: GPH estimator ($m = N^{0.6}$)					
Inflation	0.0038	0.0035	0.0033	-0.0005	$[-0.6361]$
Unemployment	7.7592	7.5606	6.8455	-0.9137	$[-2.4542]$
Tbill	11.9322	8.4317	11.3281	-0.6040	$[-0.2547]$
Gov.Bonds	10.2931	8.0374	8.0045	-2.2886	$[-3.4877]$
GDP	0.0018	0.0059	0.0038	0.0020	[1.7396]
BNS	-3.7743	-0.2091	-0.1562	3.6182	[2.0425]
BNS-I	0.0955	0.0148	0.0095	-0.0860	$[-3.9556]$
Panel B: GPH estimator ($m = N^{0.7}$)					
Inflation	0.0037	0.0031	0.0034	-0.0003	$[-0.4056]$
Unemployment	7.5144	7.4730	6.8688	-0.6456	$[-1.3959]$
Tbill	13.4881	9.9356	8.6620	-4.8262	$[-1.4858]$
Gov.Bonds	10.1239	8.4567	7.3953	-2.7287	$[-6.3381]$
GDP	0.0037	0.0033	0.0083	0.0046	[4.0613]
BNS	-3.6394	-0.2806	-0.1811	3.4583	[2.0498]
BNS-I	0.0904	0.0197	0.0113	-0.0791	$[-3.5078]$
Panel C: GPH estimator (absolute returns; $m = N^{0.5}$)					
Inflation	0.0037	0.0031	0.0033	-0.0004	$[-0.5899]$
Unemployment	7.7897	7.5074	6.7241	-1.0656	$[-3.0034]$
Tbill	13.6766	9.4347	8.6176	-5.0591	$[-1.4161]$
Gov.Bonds	9.5664	8.9168	7.8552	-1.7113	$[-3.1334]$
GDP	0.0044	0.0041	0.0066	0.0022	[1.7534]
BNS	-2.5185	-1.5721	-0.4765	2.0419	[2.8122]
BNS-I	0.0698	0.0382	0.0242	-0.0456	$[-4.2736]$
Panel D: LW estimator ($m = N^{0.5}$)					
Inflation	0.0042	0.0041	0.0047	0.0005	[0.8343]
Unemployment	7.3763	7.1598	6.6214	-0.7549	$[-3.2149]$
Tbill	13.0206	10.3177	9.8895	-3.1312	$[-1.2597]$
Gov.Bonds	9.9875	8.6120	7.9389	-2.0485	$[-3.7036]$
GDP	-0.0011	0.0056	0.0069	0.0079	[2.5104]
BNS	-4.0822	-0.9068	-0.4097	3.6724	[2.3223]
BNS-I	0.1148	0.0323	0.0203	-0.0945	$[-4.4816]$

Table 13: Long Memory of the U.S. – Predictive Regressions

This table presents the coefficients from the regressions of the memory parameter on the macroeconomic variables for the U.S. for the period from 1964 until 2015. The regressors are the log consumer price index, the log unemployment, treasury bill and the government bond rates and GDP growth lagged by h quarters. Recession is the indicator function that represents periods of expansion and recession defined by the NBER. All macroeconomic variables are monthly except for GDP, hence Model 5 and Model 8 are on a quarterly basis. Long memory is estimated with the GPH estimator and a bandwidth parameter of $m = N^{0.5}$. Stars indicate significance of the mean differences: * significant at $p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Panel A: $h = 1$								
(Intercept)	0.4141***	−0.2506***	0.5431***	0.7936***	0.4041***	0.4106***	−0.0709	−0.5865**
	(0.0110)	(0.0748)	(0.0159)	(0.0298)	(0.0197)	(0.0121)	(0.0817)	(0.2577)
Inflation	−7.0080***						−5.9748***	−2.9321**
	(1.3868)						(1.0603)	(1.3907)
Unemployment		0.3704***					0.5207***	0.8053***
		(0.0416)					(0.0471)	(0.1399)
Tbill			−4.6635***				7.1164***	8.0271***
			(0.4380)				(0.8769)	(1.7104)
Gov.Bonds				−7.1906***			−12.2448***	−12.7036***
				(0.5306)			(0.9129)	(1.7059)
GDP					−1.5167*			2.4658**
					(0.8577)			(1.0392)
Recession						−0.0174	0.0706**	0.0094
						(0.0363)	(0.0261)	(0.0477)
adj. R^2	0.0747	0.2044	0.2699	0.3754	0.0206	−0.0025	0.5744	0.5654
Panel B: $h = 2$								
(Intercept)	0.4130***	−0.2238**	0.5758***	0.8045***	0.4051***	0.3989***	0.3890***	0.0728
	(0.0113)	(0.0756)	(0.0149)	(0.0309)	(0.0198)	(0.0120)	(0.0924)	(0.2718)
Inflation	−4.7089**						−4.3664***	0.5189
	(1.4380)						(1.1830)	(1.5008)
Unemployment		0.3554***					0.1884***	0.3474**
		(0.0421)					(0.0522)	(0.1456)
Tbill			−5.3730***				−0.2507	−1.1136
			(0.3853)				(0.9404)	(1.7749)
Gov.Bonds				−7.1496***			−5.7493***	−4.6440**
				(0.5328)			(1.0173)	(1.8860)
GDP					−1.2340			2.2171*
					(0.8512)			(1.1180)
Recession						0.0876**	0.1299***	0.0509
						(0.0360)	(0.0291)	(0.0527)
adj. R^2	0.0310	0.1878	0.3889	0.3707	0.0108	0.0160	0.4704	0.4701
Panel C: $h = 4$								
(Intercept)	0.4134***	−0.2527***	0.5527***	0.7942***	0.4045***	0.4070***	0.0494	−0.4678*
	(0.0112)	(0.0749)	(0.0157)	(0.0300)	(0.0198)	(0.0121)	(0.0887)	(0.2687)
Inflation	−5.6349***						−4.4262***	−1.8303
	(1.4095)						(1.1396)	(1.4541)
Unemployment		0.3715***					0.4305***	0.7147***
		(0.0417)					(0.0508)	(0.1455)
Tbill			−4.8666***				4.9223***	5.7397**
			(0.4214)				(0.9381)	(1.7702)
Gov.Bonds				−7.1153***			−10.2998***	−10.6401***
				(0.5280)			(0.9809)	(1.7865)
GDP					−1.3775			2.6813**
					(0.8563)			(1.0822)
Recession						0.0153	0.0795**	0.0347
						(0.0363)	(0.0280)	(0.0499)
adj. R^2	0.0470	0.2053	0.3033	0.3727	0.0155	−0.0027	0.5086	0.5244