Global connectedness across bond markets*

Stig V. Møller† Jesper Rangvid‡

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Abstract

We provide first tests of gradual diffusion of information across bond markets. We show that excess returns on bond markets around the world react with a lag to excess returns on a global bond portfolio: high returns on the global bond portfolio signal high expected returns on bond markets in many countries. Results are strong in-sample and out-of-sample, and hold after controlling with variables often used to predict bond returns. Excess returns on a global bond portfolio also predict inflation rates around the world. Investors learn about fundamentals in different countries (inflation rates) that influence expected returns around the world after observing returns on a global portfolio.

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†CREATES, Aarhus University, Fuglesangs Allé 4, 8210 Aarhus, Denmark. Phone: (45) 8716 4825 and e-mail: svm@econ.au.dk.

‡Department of Finance, Copenhagen Business School, Solbjerg Plads 3, 2000 Frederiksberg, Denmark. Phone: (45) 3815 3615 and e-mail: jr.fi@cbs.dk.

1 Introduction

Since the seminal contribution of Hong and Stein (1999), the 'gradual information diffusion hypothesis', i.e. the hypothesis that news travel slowly across markets, has been subject to thorough examination. Past stock returns on related firms, sectors, or countries (or past information about firm characteristics or the macroeconomy, such as past oil prices) have been used to predict stock returns on other firms, sectors, or countries, see, e.g., Hong, Torous and Valkanov (2007), Hou (2007), Cohen and Frazzini (2008), Driesprong, Jacobsen and Maat (2008), Menzly and Ozbas (2010), Rapach, Strauss and Zhou (2013), and Rapach, Strauss, Tu and Zhou (2016). A common feature of this literature is its use of stock market data, mostly from the US.

We provide first tests of the gradual information diffusion hypothesis for government bond markets around the world. Government bonds are fundamentally different from stocks. For instance, they are virtually free of cash-flow and default risk. Support for the gradual information diffusion hypothesis is enhanced if it prevails in other countries than the US and other markets than stock markets.

Our hypothesis is that investors pay attention to lagged signals that aggregate information about factors that influence the future value of the asset they trade. We hypothesize that global bond markets are connected such that returns on a global bond portfolio aggregates information about fundamentals that influence expected returns on local bond markets around the world. We test this by evaluating whether lagged returns on a global bond portfolio predict returns on individual bond markets around the world.

We consider excess returns on government bonds in 14 countries for which we have monthly return data spanning almost five decades, from January 1970 through October 2016. We define the excess bond return in country i as the monthly return on the 10-year government bond of country i in excess of the monthly return on a short T-bill of country i. We calculate the excess return to a global bond portfolio as the equal-weighted excess return from the 14 bond markets.

We first show that lagged excess returns on the global bond portfolio predict excess bond returns in individual countries. Each predictive regression controls for local returns, i.e. we predict the excess bond return in country i using its lagged value as well as the lagged excess return on the global bond portfolio. We find strong evidence that lagged local returns do not predict local returns, but lagged global returns do. The sign of the predictive coefficient is positive, as expected, i.e. positive excess returns on the global portfolio last month signal positive excess returns on government bond markets around the world this month. We test whether we can replace returns on the global bond portfolio with returns on, e.g., the US bond portfolio, inspired by Rapach, Strauss and Zhou (2013), who predict international stock returns with US stock returns. We find that returns on the global portfolio capture a significantly larger fraction of excess return variation around the world than excess returns from US bonds. Ilmanen (1995) predicts excess returns around the world by the lagged real yield of a global bond portfolio as well as its lagged yield spread. We control for these variables in the regressions. We find that lagged returns on the global bond portfolio contain significantly more information about expected bond excess returns around the world than the real yield on the global portfolio or its yield spread.

These in-sample results point toward a special role of the global bond portfolio when it comes to information relevant for determining expected bond returns around the world. We know from literature on stock-return predictability that in-sample predictability does not necessarily imply that a predictor variable is useful for investors in real time, however, see Goyal and Welch (2008). To evaluate whether excess returns on the global bond portfolio contain useful information for investors in real time, we conduct out-of-sample tests. We find that out-of-sample R^2s are positive and significant when predicting local excess returns around the world with lagged excess returns on the global portfolio, whereas they are insignificant or negative when using lagged local excess returns, the yield spread, or the real bond yield. We also evaluate the performance of two net zero-cost trading strategies, inspired by Ilmanen (1995), that go long in bonds when excess returns on the global portfolio indicate positive next-period expected returns and go either short in bonds, or does nothing, when it indicates negative next-period returns. The trading strategies generate large and significant improvements in mean returns and Sharpe ratios compared to buy-and-hold strategies. We conclude that excess returns on the global bond portfolio contain important information for real-time investors about returns on government bonds around the world.

The underlying idea in the gradual information diffusion hypothesis is that news about international returns travel slowly across markets, market participants extract information about fundamentals that influence the future value of the assets they trade by observing signals that aggregate information, the signal contains information relevant for several assets, and cross-market return predictability results in the end. What is then the underlying source of information relevant for bond market investors that returns on the global portfolio contain? Campbell and Ammer (1993) argue that bond returns are driven mainly by news about future inflation. We hypothesize that returns on the global portfolio contain information about future inflation. To test this hypothesis, we use excess returns on the global bond portfolio to predict inflation rates around the world. We report strong predictability results. The sign of the estimated predictive coefficient is negative, i.e. an increase in lagged excess returns on the global portfolio signals a reduction in expected inflation rates around the world. It also signals, as mentioned above, an increase in expected excess returns on bond markets around the world. This is what we would expect based on the Campbell and Ammer (1993) variance decomposition that implies that declines in inflation correlates with increases in excess returns from bonds. The effects also line up with insights in Brandt and Wang (2003) where positive news about inflation lower risk aversion and consequently expected risk premia. Our results point to the following explanation: Investors extract information about underlying economic factors that influence future rates of inflation around the world by observing the return on the global bond portfolio. Investors expect future rates of inflation to be low when returns on the global bond portfolio are high. In the end, lagged returns on the global bond portfolio predict local rates of inflation with a negative sign and local excess returns with a positive sign.

Global capital markets have become increasingly integrated since the 1980s (Lane & Milesi-Ferretti, 2007, Rangvid, Santa-Clara & Schmeling, 2016, and Bekaert & Mehl, 2017). When markets become more integrated, it is natural to expect that they react faster to global information, too. As the final exercise, we thus investigate whether there is time variation in the degree to which international bond markets react to changes in the return on the global bond portfolio. We examine whether there is a tendency that international bond markets increasingly react contemporaneously. Using recursive panel estimations, we find that international bond markets react relatively less to lagged changes in the return on the global bond portfolio when markets become more integrated, i.e. during the last part of our sample period, and relatively more to contemporaneous changes. In line with the gradual information diffusion hypothesis, this means that when market become more integrated, gradual diffusion of information is reduced and contemporaneous diffusion increased.

We note that there are a number of advantages using excess returns on the global portfolio to predict local bond returns in real time. First, compared to other often used predictive variables, such as yield spreads (Campbell and Shiller, 1991), real yields (Ilmanen, 1995), forward spreads (Fama and Bliss, 1987), and linear combinations of forward rates (Cochrane and Piazzesi, 2005; Dahlquist and Hasseltoft, 2013; Zhu, 2015) that are all persistent variables, the excess return on the global portfolio has a low degree of persistence. Bauer and Hamilton (2017) demonstrate why this is important. Bauer and Hamilton examine five widely used bond-return predictors, and show that their high degree of autocorrelation causes a downward bias in standard errors in predictive regressions, making the predictors look more statistically significant than they really are. The predictor we propose has a low degree of persistence. Second, a recent literature uses macroeconomic factors to predict bond returns, see, e.g., Ludvigson and Ng (2009), Cooper and Priestley (2009), Cieslak and Povala (2015), and Zhou and Zhu (2016). Macroeconomic factors are published with a lag and subject to subsequent revisions (and often persistent, too). Returns on the global portfolio are readily available in real time, and not subject to revisions. Finally, as argued in Ilmanen (1995), international government bond markets are useful to study theories of asset price behavior, as government bond markets are not subject to some of the risks influencing stock markets, such as default risk or cash-flow uncertainty.

The rest of the paper is structured as follows. In the next section, we describe the data we use and provide summary statistics. Section 3 contains results from in-sample regressions, and Section 4 shows how excess returns from the global bond portfolio contain useful information for investors in real time, i.e. out-of-sample. Section 5 shows that returns on the global portfolio contains information about expected inflation, too. A final section concludes.

2 Summary statistics of bond returns

We consider 14 developed countries: Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Norway, Spain, Sweden, the United Kingdom, and the United States. The sample period is January 1970 to October 2016. The bond return data are from the Global Financial Database from which we use the series "Total Return Indices - Bonds" and "Total Return Indices - Bills" to compute returns on 10-year government bonds in excess of the T-bill return. Following Solnik (1993), Ang and Bekaert (2007), Hjalmarsson (2010), and Rapach, Strauss and Zhou (2013), among others, we compute returns in national currency. We construct a global portfolio of government bonds as an equal weighted average of all $N = 14$ countries:

$$r_{global,t} = \frac{1}{N}\sum_{i=1}^{N} r_{i,t} \tag{1}$$

where $r_{i,t}$ is the time t excess return on country i's 10-year government bond. Our results remain robust if we instead of equal weights construct the world portfolio using, e.g., GDP weights.

Table 1 shows means, standard deviations, and first-order autocorrelations of bond excess returns for the 14 countries, as well as the return on the global portfolio. The means of the monthly excess returns range from 0.14% (Sweden) to 0.26% (Germany). The lowest standard deviation is 1.45% (Austria), while the highest is 3.43% (United Kingdom). The first-order autocorrelations of returns are mostly positive but close to zero, i.e. these are time series with low persistence.

The returns are all positively correlated, though perhaps less than one would initially expect. The average correlation between the different pairs of returns is 0.36 (correlation matrix available upon request).

We also use benchmark predictive variables proposed in the literature. Inspired by Ilmanen (1995), we consider the yield spread and the real yield of the global bond portfolio. Ilmanen

(1995) was first to analyze these variables in an international setting, but their use dates back at least to Campbell and Shiller (1991). The yield spread is the difference in yields between the 10-year government bond and the T-bill rate. The real yield is the difference between the 10-year government bond yield and the year-on-year inflation rate. We analyze both local and global versions of the yield spread and the real yield. The global versions are computed as equal weighted averages across countries. We obtain inflation rates from the OECD database.

We plot the time series of global excess returns in Figure 1 together with the global yield spread and the global real yield. One difference between global excess returns and the benchmark variables is particularly striking: The benchmark variables (the global yield spread and the global real yield) are considerably more persistent. The first-order autocorrelation of global bond excess return is 0.24 (Table 1), while the global yield spread and the global real yield are highly persistent with first-order autocorrelations of 0.97 and 0.99.

3 Bond return regressions

We regress the one-month ahead excess bond return in country i, $r_{i,t+1}$, on the current month's return in country i, $r_{i,t}$, and the current month's global return, $r_{global,t}$:

$$r_{i,t+1} = \alpha_i + \beta_i r_{i,t} + \gamma_i r_{global,t} + \varepsilon_{i,t+1} \tag{2}$$

We run the regressions country-by-country and as a panel. In the country-by-country regressions, we report for each country i estimates of β_i and γ_i, heteroskedasticiy robust p-values (White, 1980), wild bootstrap p-values, and the R^2. The wild bootstrap is suitable for regressions like Eq. (2) with uncorrelated but possibly heteroskedastic errors (Wu, 1986, Goncalves and Kilian, 2004, and McKinnon, 2006). We implement the wild bootstrap in a similar way as Rapach, Strauss and Zhou (2013) and describe the procedure in the appendix.

There are no overlapping observations in our regressions and $r_{i,t}$ and $r_{global,t}$ are not persistent (Table 1), as mentioned. This means that the usual concerns regarding inference in return-predicting regressions (see Stambaugh, 1999; Ang and Bekaert, 2007; and Bauer and Hamilton, 2017) are not an issue in our setting.

By controlling for country i's own lagged return in Eq. (2), we make sure that any statistical significance of the lagged global return is not simply due to country i's own autocorrelation pattern coupled with contemporaneously correlated bond returns, see, e.g., Boudoukh, Richardson and Whitelaw (1994) and Rapach, Strauss and Zhou (2013).

We also run a panel regression to make a statement about the average predictive relationship across countries. Hjalmarsson (2010) and Rapach, Strauss and Zhou (2013) show that the predictive power is enhanced in predictive panel regressions if imposing the restriction that the coefficients to the predictive variables are equal across the individual relations. That is, we estimate a pooled version of Eq. (2), imposing the restrictions that $\beta_i = \overline{\beta}$ and $\gamma_i = \overline{\gamma}$ for all $i = 1, \ldots, N$. In our hypothesis tests of $\overline{\beta} = 0$ and $\overline{\gamma} = 0$, we follow the procedure in Ang and Bekaert (2007) and Thompson (2011) and make use of standard errors that are robust to heteroskedasticity as well as contemporaneous correlations among country returns.

Table 2 shows the results. There are two overall conclusions. First, the lagged excess return in country i is generally not a significant predictor of this period's excess return on bonds from country i. Second, the lagged excess return on the global portfolio is a significant predictor of this period's excess return on bonds from country i. This means that information contained in returns from country i does not matter when it comes to how investors form expectations about next period's excess bond return of that same country i. On the other hand, observing this period's excess return on the global portfolio, investors take this into account when they form expectations about how returns on bonds from individual countries will change going forward. The coefficient to the lagged global return is positive in all cases. The implication is that a higher (lower) excess return on the global portfolio this month implies higher (lower) expected returns in the individual countries going forward. This is natural if information travels slowly across markets. It implies that when investors have a more favorable view on global bonds in general, they extrapolate this to imply that bonds in any country i are expected to perform well, too. On average, a one percentage point increase (decrease) in excess returns on the global bond portfolio this month implies a 0.3 percentage points increase (decrease) in returns in individual countries, as the coefficient to the global excess return in the pooled regression reveals.

There are only two countries for which the global excess return is not a significant predictor: Germany and the US. Rapach, Strauss and Zhou (2013) study stock markets and show that returns from the US stock market lead returns in stock markets in other countries. This raises the question of whether the global bond factor is de facto representing a US bond factor or, in other words, whether we can generate similar results if we replace returns on the global portfolio with returns on the US portfolio when predicting returns around the world. To investigate this, we run pooled regressions of one-month ahead returns in the individual countries on each country return, one at a time. For instance, we replace excess returns on the global bond portfolio with Austrian excess bond returns in the panel-predictive regression, then with Belgium returns, etc., and thus, as part of this exercise, also replace with US returns. For instance, for Austria, the panel regression thus takes the form:

$$r_{i,t+1} = \alpha_i + \bar{\gamma} r_{Austria,t} + \varepsilon_{i,t+1} \tag{3}$$

and similarly for the other countries. Figure 2 plots R^2 statistics from these panel regressions. The conclusion is that returns on the global bond portfolio contain the larger fraction of information about expected returns around the world. The R^2 from this regression is close to 2%.[1] The individual bond market that contains the most information is the French, but its R^2 is less than 1.5%, i.e. considerably lower than when we use returns on the global portfolio. The R^2 is app. 1.3% when predicting with US returns. This means that it is the general information about how global bond markets move that is relevant for how investors form expectations about returns in different countries, and not information about returns in one country, and thus not only information about the US, either.

We argue that investors around the world learn about future returns in individual countries by observing returns on the global bond portfolio this period. Do other kinds of information about global bond markets matter as much as returns on the global portfolio? We check this

[1] This is different from the $R^2 = 2.2\%$ in Table 2. The reason is that Table 2 shows results from Eq. (2), i.e. from regressions controlling with returns in country i, whereas we naturally do not control with returns in country i in Figure 2.

by comparing how our results change if we incorporate information from other variables that have been used to predict international bond returns in the literature, i.e. what happens if we include the global yield spread and/or the global real yield in our regressions. The results appear from Tables 3a and 3b. In Table 3a, we show results from regressions where we predict excess returns in country i by lagged excess returns in country i itself, lagged yield spread of the global bond portfolio, and its lagged real yield, i.e. in this regression we do not include lagged excess returns of the global bond portfolio. In Table 3b, we include the same variables, but add lagged excess returns of the global bond portfolio. Comparing results from Tables 3a and 3b, the conclusion is that predictive power is significantly increased when including excess returns on the global bond portfolio. First, the excess return on the global bond portfolio retains its significance in Table 3b, i.e. is significant for almost all countries and significant in the pooled regression, even after controlling with the global yield spread and global real yield. The global yield spread and global real yield are significant in some countries, but insignificant in many.[2] Second, the R^2 increases markedly when including global excess returns. In Table 3a, the R^2 for Austria is 3.6%, while it is 6.7% in Table 3b. For Belgium the increase is from 2.1% to 5.4%, for Canada from 2.1% to 3.6%, etc.[3] In the pooled regression, the R^2 increases from 1.0% when excluding (Table 3a) the excess return on the global bond portfolio to 3.0% when including it (Table 3b). The global excess return is the main driver of international bond returns.

4 Out-of-sample evidence

The in-sample results presented so far indicate that returns on the global bond portfolio aggregate information relevant for investors when they form expectations about returns in individual countries going forward. In-sample predictability is not, however, a guarantee that predictability pays off to investors in real time (Goyal and Welch, 2008). To evaluate

[2] We have also analyzed the predictive power of the local yield spread and the local real yield. In general, the global variables tend to perform slightly better than the local variables (results available upon request).

[3] We show R^2s in all tables. We use a higher number of regressors in Table 3b than in Table 3a. Given the high number of observations used in the regression (app. 600 observations), there is, however, no big difference between R^2 and $\overline{R}^2$ for the same type of regression. In other words, the increase in R^2 from Tables 3a to Table 3b is not because more regressors are employed in Table 3b.

whether investors would have benefitted from knowing about information contained by the predictor variable, we need to know whether the predictive variable is useful in an out-of-sample setting. In this section, we show that the global bond excess return predicts international bond excess returns out-of-sample.

We compute out-of-sample forecasts from the following three models:

$$r_{i,t+1} = \alpha_i + \beta_i r_{i,t} + \varepsilon_{i,t+1} \tag{4}$$

$$r_{i,t+1} = \alpha_i + \gamma_i r_{global,t} + \varepsilon_{i,t+1} \tag{5}$$

$$r_{i,t+1} = \alpha_i + \bar{\gamma} r_{global,t} + \varepsilon_{i,t+1} \tag{6}$$

where the parameters are estimated recursively using an expanding window. Model (4) uses the lagged local bond return as regressor, while models (5) and (6) use the lagged global bond return as regressor. The difference between models (5) and (6) is that the latter constrains the individual slope coefficients to be equal across countries, such that $\gamma_i = \bar{\gamma}$, for all $i = 1, ..., N$. This restriction potentially improves forecasting performance as it leads to more stable parameter estimates, see Hjalmarsson (2010) and Rapach, Strauss and Zhou (2013).

We evaluate the performance of the models in (4)-(6) using the Campbell and Thompson (2008) out-of-sample R^2 (R^2_{OoS}). We test the null that $R^2_{OoS} \leq 0$ (no predictability) against the alternative that $R^2_{OoS} > 0$ using the Clark and West (2007) statistic for which the standard normal distribution is a good approximation asymptotically when comparing forecasts from nested models.

A positive R^2_{OoS} measures the percentage-point improvement in the average mean squared prediction error that results from using a predictive variable compared to using the historical average of excess returns. In other words, when the R^2_{OoS} is positive, the predictive variable contains relevant information about time-varying expected returns. If the R^2_{OoS} is negative, the investor would have been better off predicting returns using a simple average of historical returns. We use the 1970-1980 period to generate the initial estimates of the predictive regressions, and then update recursively, and generate predictions, each month. The out-of-sample period is thus 1980:1-2016:10.

Table 4 contains the results. In the first column, we present results where we predict with local excess returns, then results from predictions using excess returns on the global bond portfolio, with unconstrained predictive coefficients, and, next, subject to the restriction that $\gamma_i = \bar{\gamma}$, for all $i = 1, ..., N$. Lastly, results from predictions using the global yield spread and the global real yield, respectively, are shown. We generally find that R^2_{OoS}s are positive, and significantly so, when we predict with excess returns on the global bond portfolio. When we pool the regressions and impose the restriction of equal predictive coefficients, we find even stronger out-of-sample results. In almost all countries, the R^2_{OoS} is significantly positive. The average R^2_{OoS} is 2.17%, i.e. mean squared prediction errors are slightly more than two percentage points lower when using excess returns on the global bond portfolio to predict bond excess returns around the world compared to using the historical average.

It is only excess returns on the global bond portfolio that systematically predict international returns out-of-sample. Local excess returns are generally worse predictors than the historical average, and the same goes for variables often used to predict returns in the literature, i.e. the global yield spread and the global real yield. They generally produce negative R^2_{OoS}s. This implies that the global yield spread and the global real yield do not contain useful information about movements in expected international excess bond returns out-of-sample, and the investors would have been better off using the historical average when it comes to predicting returns.

Campbell and Thompson (2008) show that the R^2_{OoS} has an economic interpretation, too. It can be used to provide a theoretical bound on the increase in average excess returns that a mean-variance investor can obtain if the investor relies on the predictive variable when making portfolio decisions. Take the first country, Austria, as an example. The Sharpe ratio from Table 1 is 0.14 (= 0.2%/1.45%). The R^2_{OoS} is 6.7%. Campbell and Thompson (2008) show that the increase in return that is potentially achievable if conditioning investment decisions on the predictive variable is given by the ratio of the R^2_{OoS} and the squared Sharpe ratio for the asset return that is predicted. In our case, this is $0.067/0.14^2 = 3.5$. This means that a mean-variance investor would theoretically be able to increase average excess returns by a proportional factor of about 3.5 if using the information in $r_{global,t}$ when making portfolio decisions. This is arguably a very large effect, but also by far the largest. Consider as another example the last country in the table, the US. The Sharpe ratio from Table 1 is 0.10 (= 0.25%/2.41%) and the R^2_{OoS} is 0.15%. The proportional increase in returns an investor can achieve by relying on the information content in global excess returns is $0.0015/0.10^2 = 0.14$. Hence, an investor with mean-variance preferences can theoretically improve the average monthly return obtained from investing in US bonds by a proportional factor of 14%.

Instead of using R^2_{OoS} to calculate theoretical bounds on how much performance can be improved, we can directly calculate implications for performance of easily implementable trading strategies. We consider two such strategies, inspired by Ilmanen (1995). The first strategy invests in bonds of country i if the signal is positive (if last month's excess return on the global bond portfolio is positive) and sells the bond if the signal is negative. The trading strategy is a zero-cost strategy, i.e. purchase of the bond is financed by borrowing at the T-bill rate and proceeds from selling are invested at the T-bill rate. The return from this strategy is thus an excess return over and above the rate on T-bills. We call this a $(1, -1)$ strategy as the investor goes either long or short. The second strategy buys the government bond when the signal is positive (the purchase is again assumed financed by borrowing at the T-bill rate), but does nothing when the signal is negative. We call this a $(1, 0)$ strategy.

We illustrate the results from implementing such trading strategies in Table 5 and Figure 3. Table 5 shows the annualized average monthly return from each market as well as the Sharpe ratios and Figure 5 shows time series plots of cumulative returns. We compare the performance of the two trading strategies with that of a buy-and-hold strategy. Consider Table 5 first. If the investor relies on the signal form lagged local government bond excess returns, the trading performance would not be much different from the performance of the buy-and-hold strategy. Both the mean return and the Sharpe ratio are more or less similar to the ones of the buy-and-hold strategy. Things are different if basing the trading strategy on excess returns from the global bond portfolio. The mean return is 0.6 percentage points higher for the $(1, 0)$ strategy and the Sharpe ratio increases by 50%, from 14% to 21%. For the $(1,-1)$ strategy, mean returns are almost 50% higher compared to the buy-and-hold strategy (3.3% versus 4.6%). The standard deviation of returns from the $(1,-1)$ is also higher than for the $(1,0)$ strategy, though, as the Sharpe ratio is on par with the Sharpe ratio from the $(1,0)$ strategy. Thus, like for the $(1,0)$ strategy, the Sharpe ratio of the $(1,-1)$ strategy is app. 50% higher than the Sharpe ratio of the buy-and-hold strategy. An investor would clearly have benefitted from using excess returns on the global bond portfolio when making investment decisions in international bond markets.

Is the out-of-sample predictive power contained by global excess bond returns sample specific or prevalent during the whole sample period? Figure 3 shows the time series evolution of the cumulative value resulting from investing one unit of currency in 1980 and following, respectively, a buy-and-hold strategy, the $(1,-1)$ strategy using local country excess bond returns as signal, and the $(1,-1)$ strategy using excess bond returns on the global bond portfolio as signal. The figure shows that the $(1,-1)$ trading strategy using returns on the global portfolio has significantly paid off. Performance has been stable during the sample period. The cumulative value of the investment has been steadily increasing during the sample period, even when performance perhaps has been less robust over the last couple of years. The $(1,-1)$ strategy using local excess bond returns has in some countries performed better than the buy-and-hold strategy but in others worse. Generally, performance of the strategy using excess returns on the global portfolio is considerably more reliable when making international bond investment decisions in real time.

5 Economic explanation

Returns on a global bond portfolio predict returns on bond markets around the world. When news travel across markets with a delay, as in the gradual information diffusion hypothesis, and when returns on a global portfolio aggregate information relevant for bond markets around the world, investors learn about factors influencing expected bond returns internationally by observing returns on the global portfolio. But what news relevant for bond markets around the world does the global bond portfolio aggregate? We hypothesize that

$r_{global,t}$ contains information about macroeconomic fundamentals relevant for bond markets around the world.

Campbell and Ammer (1993) find that bond returns are driven mainly by news about future inflation. Brandt and Wang (2003) develop a model in which good news about inflation lowers aggregate risk aversion and expected bond returns. Hence, a natural candidate for fundamental macroeconomic risk that influences bond returns in individual countries is inflation risk. If returns on the global bond portfolio contain information about expected inflation in different countries, it is natural that it contains information about bond returns in different countries, too. Given that global, and not local, returns influence expected returns on international bond markets, global returns should contain information about local inflation rates over and above information contained by local bond returns. To test the hypothesis that global returns contain information about expected inflation in different countries, we run regressions where we relate inflation in country i at time $t+1$ to lagged bond returns in country i and lagged returns on the global bond portfolio, i.e.

$$\pi_{i,t+1} = \alpha_i + \beta_i r_{i,t} + \gamma_i r_{global,t} + \varepsilon_{i,t+1} \tag{7}$$

where $\pi_{i,t+1}$ is the time $t+1$ inflation rate in country i. Inflation rates are more persistent than returns. The average AR1 coefficient for the local inflation rates is 0.41. In order to take resulting autocorrelation in the error term into account, we use a block bootstrap procedure (rather than the wild bootstrap, as above) when computing standard errors, i.e. we show p-values based on Newey and West (1987) standard errors and based on block-bootstrapped standard errors.[4]

Table 6 contains the results. We find that $r_{global,t}$ generally contains information about future local inflation rates, whereas $r_{i,t}$ does not. In fact, there is no single country where local returns contain significant information about future local inflation, whereas global returns contain significant information in most cases. Furthermore, in the pooled regression, local returns are clearly insignificant, whereas the global return is clearly significant.

[4] To be clear: The predictors themselves are not persistent. It is the dependent variable that is persistent. The regressions are still not subject to the usual concerns in regressions using persistent predictors.

We find that an increase in returns on the global portfolio implies a reduction in expected future local inflations rates (Table 6) and an increase in expected local bond excess returns (Table 2). This makes sense from the perspective of the Campbell and Ammer (1993) variance decomposition. This decomposition shows that an unexpected decline in inflation implies an unexpected increase in bond excess returns. As mentioned, inflation and bond excess returns are negatively correlated in the model of Brandt and Wang (2003), too.

Figure 2 showed that returns on the global bond portfolio predict bond returns around the world stronger than local bond returns do. We can run similar regressions where we predict local inflation rates. Figure 4 shows R^2s from Figure 2 against R^2s from regressions predicting inflation rates in the different countries. The figure shows that global bond returns predict both inflation rates and returns around the world better than returns in any other country. We conclude that the return on the global portfolio of government bonds predicts both local excess returns and local inflation rates, i.e. aggregates useful information about fundamentals that influences how investors value bonds and thus affects bond returns around the world as well.

$r_{global,t}$ contains more information about expected bond market returns than $r_{i,t}$. Following the theoretical model of Hong, Torous and Valkanov (2007), this leads us to expect $r_{global,t}$ to carry more information about bond market fundamentals than $r_{i,t}$. We find supportive evidence of this prediction by showing that $r_{global,t}$ has more information content about future local inflation rates than $r_{i,t}$. The information global return shocks contain about local inflation rates is only gradually picked up by market participants and lagged global returns therefore contain predictive power for local bond returns around the world.

6 Time-varying evidence

According to the gradual information diffusion hypothesis, market participants extract information about fundamentals that influence the future value of assets by observing lagged signals that aggregate information relevant for several assets. If market participants had unlimited resources, they would follow specific information for each asset. Due to attention constraints (Cohen & Frazzini, 2008), they limit themselves to aggregate information.

Global capital markets have become increasingly integrated, in particular since the 1980s, as documented in, e.g., Lane & Milesi-Ferretti (2007), Rangvid, Santa-Clara & Schmeling (2016), and Bekaert & Mehl (2017). When financial markets become more integrated, a natural hypothesis arises that market participants react faster to global information. In terms of our setting, this implies that markets around the world should be expected to react faster to information contained by the global bond portfolio, and less to its lagged information, when markets become more integrated. In this section, we test whether this holds true for our sample of developed markets, for which we have time series extending back to the 1970s. We estimate two recursive panel regressions:

$$
\begin{aligned}
r_{i,t+1} &= \alpha_i + \bar{\gamma} r_{global,t} + \varepsilon_{i,t+1}, && (8)\\
r_{i,t} &= \alpha_i + \bar{\gamma} r_{global,t} + \varepsilon_{i,t+1}. && (9)
\end{aligned}
$$

The regression in Eq. (8) predicts returns on market i by the lagged return on the global bond portfolio. In Eq. (9), we explain period t return on market i with period t return on the global bond portfolio. In other words, in the first regression, we examine the extent to which markets react gradually to aggregate information, in the next we examine the extent to which markets react contemporaneously.

The initial estimation in the recursive estimation is based on the 1970 to 1980 period. Afterwards, we add one month in each estimation. Figure 5 shows the R^2s from the two recursive panel regressions. The figure reveals that the R^2 from Eq. (9) is increasing throughout the recursive sample period. This means that during the period global capital markets have become more integrated, the contemporaneous reaction of international bond markets to information in the global bond portfolio has been increasing. Similarly, bond markets around the world react to a lesser extent with a lag.[5] These findings are in line with the hypothesis

[5] Section 4 showed that lagged returns on the global bond portfolio contain relevant information for investors who base their trades on this information, i.e. contain significant out-of-sample information. The out-of-sample period we examine in Section 4 is the same as the sample period over which we run our recursive panel estimations in this section. In other words, even when the importance of lagged returns on the global bond portfolio for expected international bond returns is somewhat diminished when markets become more integrated, as one would expect according to the 'gradual information diffusion hypothesis',

that global bond markets have become more integrated, and thus react faster to information affecting many markets. They are also in line with how the gradual information hypothesis should develop when markets become more integrated.

7 Conclusion

We investigate international bond markets. We find that returns on a global portfolio of bonds predict returns on bonds around the world. The effect is strong, significant, prevails in many countries, holds in-sample and out-of-sample, and dominates when controlling for variables that are often used to predict bond returns. The return on a global bond portfolio also has some advantages compared to variables typically used to predict bond returns, such as its low persistence, the fact that it is available in real time and not subject to revisions, and is easily constructed. The return on the global bond portfolio also predicts inflation rates around the world. Thereby, it aggregates information about fundamentals relevant for bond pricing around the world. Investors incorporate this information when they form expectations about future bond returns, and return predictability arises. In the end, an increase in lagged returns on the global portfolio lowers expectations to inflation around the world.

Our paper expands the literature that tests the 'gradual information diffusion hypothesis'. The existing literature looks at stock market data, mostly from the US. We examine bond market data from around the world. We find support for the hypothesis.

lagged returns on the global bond portfolio still matter for out-of-sample trading.

Literature

Ang, A., Bekaert, G. (2007). Stock return predictability: Is it there? *Review of Financial Studies* 20, 651-707.

Bauer, M., Hamilton, J. (2017). Robust bond risk premia. *Working Paper*, University of California at San Diego.

Bekaert, G., Mehl, A. (2017). On the global financial market integration 'Swoosh' and the Trilemma. *Manuscript*, Columbia Business School.

Boudoukh, J., Richardson, M., Whitelaw, R. (1994). A tale of three schools: Insights on autocorrelations of short-horizon stock returns. *Review of Financial Studies* 7, 539-573.

Brandt, M., Wang, K. (2003). Time-varying risk aversion and unexpected inflation. *Journal of Monetary Economics* 50, 1457-1498.

Campbell, J., Ammer, J. (1993). What moves the stock and bond markets? A variance decomposition for long-term asset returns. *Journal of Finance* 48, 3-37.

Campbell, J., Shiller, R. (1991). Yield spreads and interest rate movements: A bird's eye view. *Review of Economic Studies* 58, 495-514.

Campbell, J., Thompson, S. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies* 21, 1509-1531.

Cieslak, A., Povala, P. (2015). Expected returns in Treasury bonds. *Review of Financial Studies* 28, 2859-2901.

Clark, T., West, K. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics* 138, 291-311.

Cochrane, J., Piazzesi, M. (2005). Bond risk premia. *American Economic Review* 94, 138-160.

Cohen, L., Frazzini, A. (2008). Economic links and predictable returns. *Journal of Finance* 63, 1977-2011.

Cooper, I., Priestley, R. (2008). Time-varying risk premiums and the output gap. *Review of Financial Studies* 22, 2801-2833.

Dahlquist, M., Hasseltoft, H. (2013). International bond risk premia. *Journal of International Economics* 90, 17-32.

Driesprong, G, Jacobsen, B., Maat, B. (2008). Striking oil: Another puzzle? *Journal of Financial Economics* 89, 307-327.

Goncalves, S., Kilian, L. (2004). Bootstrapping autoregressions with heteroskedasticity of unknown form. *Journal of Econometrics* 123, 89-120.

Fama, E., Bliss, R. (1987). The information in long-maturity forward rates. *American Economic Review* 77, 680-692.

Goyal, A., Welch, I. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies* 21, 1455-1508.

Hjalmarsson, E. (2010). Predicting global stock returns. *Journal of Financial and Quantitative Analysis* 45, 49-80.

Hong, H., Stein, J. (1999). A unified theory of underreaction, momentum trading and overreaction in asset markets. *Journal of Finance* 54, 2143-2184.

Hong, H., Torous, W., Valkanov, R. (2007). Do industries lead stock markets? *Journal of Financial Economics* 83, 367-396.

Hou, K., (2007). Industry information diffusion and the lead-lag effect in stock returns. *Review of Financial Studies* 20, 1113-1138.

Ilmanen, A. (1995). Time-varying expected returns in international bond markets. *Journal of Finance* 50, 481-506.

Lane, P.R., Milesi-Ferretti, G.M. (2007). The external wealth of nations mark II: revised and extended estimates of foreign assets and liabilities, 1970–2004. *Journal of International Economics* 73, 223–250.

Ludvigson, S., Ng, S. (2009). Macro factors in bond risk premia. *Review of Financial Studies* 22, 5027-5067.

MacKinnon, J. G. (2006). Bootstrap methods in econometrics. *Economic Record* 82, S2-S18.

Menzly, L., Ozbas, O. (2010). Market segmentation and the cross-predictability of returns. *Journal of Finance* 65, 1555-1580.

Newey, W., West, K. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55, 703-708.

Rangvid, Santa-Clara, P., Schmeling, M. (2016). Capital market integration and consumption risk sharing over the long run. *Journal of International Economics* 103, 27-43.

Rapach, D., Strauss, J., Zhou, G. (2013). International stock return predictability: What is the role of the United States? *Journal of Finance* 68, 1633-1662.

Rapach, D., Strauss, J., Tu, J., Zhou, G. (2016). Industry interdependencies and cross-industry return predictability. *Working Paper*, Olin School of Business, Washington University in St. Louis.

Solnik, B. (1993). The performance of international asset allocation strategies using conditioning information. *Journal of Empirical Finance* 1, 33-55.

Stambaugh, R. (1999). Predictive regressions. Journal of Financial Economics 54, 375-421.

Thompson, S. (2011). Simple formulas for standard errors that cluster by both firm and time. *Journal of Financial Economic*s 99, 1-10.

Zhou, G., Zhu, X. (2016). Bond return predictability and nacroeconomy: The international link. *Working Paper*, Washington University in St. Louis, Olin School of Business.

Zhu, X. (2015). Out-of-sample bond risk premium predictions: A global common factor. *Journal of International Money and Finance* 51, 155-173.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* 48, 817-838.

Wu, C. F. J. (1986). Jackknife, bootstrap and other resampling methods in regression analysis. *Annals of Statistics* 14, 1261-1295.

Table 1. Summary statistics of bond excess returns.

Country	AVG	SD	$AR1$
Austria	0.20%	1.45%	0.15
Belgium	0.21%	1.71%	0.06
Canada	0.22%	2.12%	0.08
Denmark	0.21%	2.35%	0.06
Finland	0.19%	2.12%	0.00
France	0.20%	1.82%	0.12
Germany	0.26%	1.69%	0.15
Italy	0.17%	2.16%	0.26
Japan	0.24%	1.87%	0.00
Norway	0.17%	1.69%	0.06
Spain	0.18%	1.81%	0.14
Sweden	0.14%	1.53%	0.14
United Kingdom	0.24%	3.43%	−0.21
United States	0.25%	2.41%	0.10
Global	0.21%	1.21%	0.24

The table reports monthly averages (AVG), standard deviations (SD), and first-order autocorrelations ($AR1$) for 10-year government bond excess returns in national currency. The sample period is 1970:1 to 2016:10.

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Table 2. Forecasting local bond returns using lagged local and global bond returns.

Country	β_i			γ_i			R^2
Austria	−0.02	(0.78)	[0.79]	0.29	(0.00)	[0.00]	5.2%
Belgium	−0.13	(0.10)	[0.12]	0.37	(0.00)	[0.00]	3.5%
Canada	−0.03	(0.66)	[0.67]	0.29	(0.00)	[0.00]	2.0%
Denmark	−0.03	(0.68)	[0.71]	0.31	(0.01)	[0.01]	2.0%
Finland	−0.14	(0.05)	[0.05]	0.42	(0.00)	[0.00]	3.9%
France	−0.02	(0.79)	[0.80]	0.28	(0.01)	[0.01]	3.0%
Germany	0.09	(0.26)	[0.28]	0.11	(0.27)	[0.28]	2.5%
Italy	0.18	(0.01)	[0.02]	0.27	(0.01)	[0.02]	8.3%
Japan	−0.06	(0.40)	[0.44]	0.23	(0.00)	[0.00]	1.9%
Norway	0.00	(0.95)	[0.96]	0.16	(0.03)	[0.04]	1.4%
Spain	0.08	(0.25)	[0.28]	0.21	(0.00)	[0.00]	3.7%
Sweden	0.06	(0.49)	[0.54]	0.17	(0.03)	[0.04]	3.2%
United Kingdom	−0.31	(0.00)	[0.00]	0.56	(0.00)	[0.00]	7.1%
United States	0.09	(0.16)	[0.17]	0.05	(0.67)	[0.69]	1.1%
Pooled	−0.06	(0.31)	[0.49]	0.30	(0.00)	[0.03]	2.2%

The table reports estimation results from forecasting regressions:

$$r_{i,t+1} = \alpha_i + \beta_i r_{i,t} + \gamma_i r_{global,t} + \varepsilon_{i,t+1}$$

where $r_{i,t+1}$ is the time $t+1$ excess return on country i's 10-year government bond and $r_{global,t}$ is the time t excess return on an equal-weighted portfolio of government bonds. For each regression, the table reports slope estimates, heteroskedasticity-robust p-values in parentheses, wild bootstrap p-values in brackets, and the R^2. The last row of the table reports pooled estimates where we impose the restrictions that $\beta_i = \bar{\beta}$ and $\gamma_i = \bar{\gamma}$ for all i. The sample period is 1970:1 to 2016:10.

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Table 3a. Forecasting local bond returns using lagged local bond returns, lagged global yield spreads, and lagged global real yields.

Country	β_i			ϕ_{1i}			ϕ_{2i}			R^2
Austria	0.14	(0.68)	[0.71]	2.35	(0.00)	[0.03]	0.34	(0.25)	[0.45]	3.6%
Belgium	0.06	(0.08)	[0.09]	2.70	(0.01)	[0.01]	0.85	(0.02)	[0.05]	2.1%
Canada	0.07	(0.64)	[0.66]	2.97	(0.01)	[0.02]	1.04	(0.03)	[0.09]	2.1%
Denmark	0.07	(0.69)	[0.73]	2.80	(0.02)	[0.07]	0.60	(0.30)	[0.45]	1.2%
Finland	0.00	(0.04)	[0.04]	2.38	(0.05)	[0.10]	0.87	(0.09)	[0.23]	1.0%
France	0.12	(0.81)	[0.82]	2.41	(0.02)	[0.04]	0.89	(0.02)	[0.09]	2.9%
Germany	0.15	(0.27)	[0.30]	1.95	(0.05)	[0.08]	0.01	(0.98)	[0.99]	3.0%
Italy	0.24	(0.02)	[0.04]	3.13	(0.01)	[0.02]	1.35	(0.01)	[0.02]	8.6%
Japan	0.00	(0.40)	[0.45]	1.43	(0.20)	[0.28]	0.50	(0.29)	[0.54]	0.5%
Norway	0.06	(0.96)	[0.96]	0.62	(0.56)	[0.63]	0.49	(0.22)	[0.46]	0.7%
Spain	0.14	(0.30)	[0.34]	2.43	(0.01)	[0.02]	0.68	(0.09)	[0.19]	3.3%
Sweden	0.14	(0.49)	[0.51]	1.48	(0.09)	[0.14]	0.53	(0.14)	[0.34]	2.6%
United Kingdom	−0.21	(0.00)	[0.00]	2.10	(0.20)	[0.25]	0.02	(0.99)	[1.00]	4.5%
United States	0.11	(0.15)	[0.17]	2.20	(0.10)	[0.14]	1.18	(0.02)	[0.06]	2.2%
Pooled	0.04	(0.45)	[0.66]	2.26	(0.00)	[0.01]	0.69	(0.00)	[0.00]	1.0%

The table reports estimation results from forecasting regressions:

$$r_{i,t+1} = \alpha_i + \beta_i r_{i,t} + \phi_{1i} ys_{global,t} + \phi_{2i} ry_{global,t} + \varepsilon_{i,t+1}$$

where $r_{i,t+1}$ is the time $t+1$ excess return on country i's 10-year government bond, $ys_{global,t}$ is the time t global yield spread, and $ry_{global,t}$ is the time t global real yield. Otherwise see the notes to Table 2.

Table 3b: Forecasting local bond returns using lagged local bond returns, lagged global bond returns, lagged global yield spreads, and lagged global real yields.

Country	β_i			γ_i			ϕ_{1i}			ϕ_{2i}			R^2
Austria	−0.03	(0.68)	[0.71]	0.29	(0.00)	[0.00]	2.48	(0.00)	[0.00]	0.28	(0.33)	[0.41]	6.7%
Belgium	−0.14	(0.08)	[0.09]	0.38	(0.00)	[0.00]	2.80	(0.00)	[0.00]	0.87	(0.01)	[0.02]	5.4%
Canada	−0.03	(0.64)	[0.66]	0.28	(0.00)	[0.00]	2.97	(0.01)	[0.01]	1.05	(0.02)	[0.06]	3.6%
Denmark	−0.03	(0.69)	[0.73]	0.31	(0.01)	[0.02]	2.81	(0.02)	[0.03]	0.56	(0.33)	[0.41]	2.8%
Finland	−0.14	(0.04)	[0.04]	0.42	(0.00)	[0.00]	2.48	(0.04)	[0.06]	0.87	(0.08)	[0.14]	5.0%
France	−0.02	(0.81)	[0.82]	0.28	(0.01)	[0.01]	2.34	(0.02)	[0.05]	0.89	(0.02)	[0.06]	4.4%
Germany	0.09	(0.27)	[0.30]	0.11	(0.26)	[0.31]	1.90	(0.06)	[0.16]	−0.05	(0.90)	[0.94]	3.2%
Italy	0.16	(0.02)	[0.04]	0.29	(0.01)	[0.01]	3.29	(0.01)	[0.01]	1.42	(0.00)	[0.01]	10.5%
Japan	−0.06	(0.40)	[0.45]	0.23	(0.00)	[0.00]	1.42	(0.19)	[0.26]	0.48	(0.29)	[0.44]	2.3%
Norway	0.00	(0.96)	[0.96]	0.16	(0.04)	[0.04]	0.62	(0.56)	[0.63]	0.48	(0.22)	[0.38]	1.7%
Spain	0.07	(0.30)	[0.34]	0.22	(0.00)	[0.00]	2.54	(0.00)	[0.01]	0.69	(0.08)	[0.15]	5.0%
Sweden	0.06	(0.49)	[0.51]	0.17	(0.03)	[0.04]	1.48	(0.08)	[0.11]	0.52	(0.15)	[0.25]	3.9%
United Kingdom	−0.31	(0.00)	[0.00]	0.56	(0.00)	[0.00]	1.96	(0.23)	[0.44]	−0.11	(0.92)	[0.96]	7.3%
United States	0.09	(0.15)	[0.17]	0.04	(0.72)	[0.74]	2.17	(0.10)	[0.15]	1.18	(0.02)	[0.05]	2.2%
Pooled	−0.06	(0.30)	[0.49]	0.30	(0.00)	[0.03]	2.26	(0.00)	[0.00]	0.68	(0.00)	[0.01]	3.0%

The table reports estimation results from forecasting regressions:

$$r_{i,t+1} = \alpha_i + \beta_i r_{i,t} + \gamma_i r_{global,t} + \phi_{1i} ys_{global,t} + \phi_{2i} ry_{global,t} + \varepsilon_{i,t+1}$$

where $r_{i,t+1}$ is the time $t+1$ excess return on country i's 10-year government bond, $r_{global,t}$ is the time t excess return on an equal-weighted portfolio of government bonds, $ys_{global,t}$ is the time t global yield spread, and $ry_{global,t}$ is the time t global real yield. Otherwise see the notes to Table 2.

Table 4. Out-of-sample evidence.

Country	Local return R^2_{OoS}		Global return R^2_{OoS}		Global return R^2_{OoS}, pooled		Global yield spread R^2_{OoS}		Global real yield R^2_{OoS}	
Austria	−0.46%	(0.00)	4.99%	(0.00)	6.70%	(0.00)	0.86%	(0.02)	−0.27%	(0.63)
Belgium	−0.97%	(0.26)	1.47%	(0.00)	2.09%	(0.00)	0.00%	(0.25)	0.11%	(0.16)
Canada	−1.77%	(0.32)	0.84%	(0.01)	1.77%	(0.00)	−0.25%	(0.22)	−0.22%	(0.21)
Denmark	−0.84%	(0.63)	0.84%	(0.00)	1.83%	(0.00)	−0.44%	(0.23)	−0.63%	(0.62)
Finland	−4.03%	(0.92)	2.72%	(0.00)	3.78%	(0.00)	0.02%	(0.21)	−0.08%	(0.28)
France	−0.96%	(0.09)	1.20%	(0.00)	2.14%	(0.00)	−0.98%	(0.57)	−0.07%	(0.19)
Germany	0.07%	(0.06)	1.44%	(0.00)	1.48%	(0.00)	0.10%	(0.17)	−1.84%	(0.82)
Italy	1.29%	(0.00)	5.10%	(0.00)	5.68%	(0.00)	−0.70%	(0.38)	0.21%	(0.02)
Japan	−2.11%	(0.74)	0.04%	(0.01)	0.16%	(0.01)	−1.10%	(0.66)	−0.55%	(0.81)
Norway	−0.21%	(0.34)	0.63%	(0.03)	−0.80%	(0.01)	−0.91%	(0.85)	−0.01%	(0.21)
Spain	1.59%	(0.02)	2.69%	(0.00)	2.81%	(0.00)	−3.70%	(0.63)	−0.23%	(0.22)
Sweden	0.69%	(0.07)	2.30%	(0.00)	3.61%	(0.00)	−0.49%	(0.75)	−0.68%	(0.47)
United Kingdom	−9.74%	(0.82)	−0.68%	(0.58)	−1.05%	(0.08)	−1.85%	(0.40)	−1.16%	(0.95)
United States	0.51%	(0.07)	−0.02%	(0.15)	0.15%	(0.03)	−0.71%	(0.60)	0.14%	(0.10)
Average	−1.21%		1.68%		2.17%		−0.73%		−0.38%	

We test the null hypothesis that the out-of-sample R^2 (R^2_{OoS}) is equal to zero or negative against the alternative that it is positive using the Clark-West (2007) test. P-values from the test are in parentheses. The out-of-sample period is from 1980:1 to 2016:10.

Table 5. Performance of trading strategies.

Country	Buy and hold		Local				Global			
			1,0		1,-1		1,0		1,-1	
	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe	Mean	Sharpe
Austria	2.9%	0.15	3.0%	0.20	3.2%	0.17	4.1%	0.28	5.3%	0.29
Belgium	3.6%	0.17	3.4%	0.20	3.1%	0.14	4.0%	0.24	4.4%	0.20
Canada	3.5%	0.13	3.8%	0.18	4.1%	0.15	4.4%	0.21	5.4%	0.20
Denmark	3.4%	0.13	3.3%	0.15	3.2%	0.12	4.1%	0.21	4.9%	0.19
Finland	3.1%	0.13	1.9%	0.10	0.6%	0.03	4.8%	0.27	6.4%	0.27
France	3.7%	0.16	3.1%	0.18	2.5%	0.11	4.0%	0.23	4.3%	0.19
Germany	3.2%	0.16	3.7%	0.22	4.2%	0.20	3.8%	0.23	4.5%	0.22
Italy	3.8%	0.14	4.9%	0.23	6.0%	0.22	4.8%	0.22	5.8%	0.22
Japan	3.3%	0.14	2.9%	0.13	2.6%	0.11	3.1%	0.14	2.8%	0.12
Norway	2.7%	0.13	2.2%	0.12	1.6%	0.08	3.0%	0.18	3.4%	0.16
Spain	3.5%	0.17	3.0%	0.20	2.5%	0.12	3.9%	0.25	4.3%	0.21
Sweden	2.2%	0.11	2.7%	0.20	3.3%	0.17	2.9%	0.19	3.6%	0.18
United Kingdom	3.4%	0.13	1.9%	0.09	0.5%	0.02	3.7%	0.17	4.0%	0.15
United States	3.9%	0.13	4.1%	0.16	4.4%	0.15	4.5%	0.18	5.1%	0.17
Average	3.3%	0.14	3.1%	0.17	3.0%	0.13	3.9%	0.21	4.6%	0.20

Mean is the annualized sample mean of monthly excess returns. We compute the Sharpe ratio as the sample mean over the sample standard deviation (not annualized).

Table 6. Forecasting local inflation using lagged local and global bond returns.

Country	β_i			γ_i			R^2
Austria	−0.02	(0.20)	[0.14]	−0.04	(0.05)	[0.03]	0.8%
Belgium	−0.01	(0.31)	[0.33]	−0.03	(0.14)	[0.15]	2.5%
Canada	−0.00	(0.74)	[0.71]	−0.07	(0.00)	[0.01]	3.8%
Denmark	0.01	(0.69)	[0.58]	−0.06	(0.04)	[0.05]	1.5%
Finland	−0.02	(0.26)	[0.19]	−0.06	(0.01)	[0.03]	3.6%
France	−0.00	(0.86)	[0.86]	−0.05	(0.02)	[0.02]	2.5%
Germany	0.00	(1.00)	[1.00]	−0.02	(0.33)	[0.35]	0.4%
Italy	−0.03	(0.06)	[0.14]	−0.05	(0.09)	[0.12]	3.7%
Japan	−0.01	(0.69)	[0.75]	−0.05	(0.03)	[0.06]	1.2%
Norway	−0.02	(0.23)	[0.24]	−0.03	(0.20)	[0.22]	1.6%
Spain	−0.02	(0.41)	[0.38]	−0.05	(0.07)	[0.06]	1.2%
Sweden	−0.00	(1.00)	[1.00]	−0.06	(0.06)	[0.09]	1.4%
United Kingdom	0.03	(0.02)	[0.00]	−0.12	(0.00)	[0.00]	3.5%
United States	−0.00	(0.89)	[0.87]	−0.09	(0.00)	[0.00]	8.9%
Pooled	−0.00	(0.72)	[0.62]	−0.06	(0.00)	[0.00]	1.8%

The table reports estimation results from forecasting regressions:

$$\pi_{i,t+1} = \alpha_i + \beta_i r_{i,t} + \gamma_i r_{global,t} + \varepsilon_{i,t+1}$$

where $\pi_{i,t+1}$ is the time $t+1$ inflation rate in country i, $r_{i,t}$ is the time t excess return on a 10-year government bond in country i, and $r_{global,t}$ is the time t excess return on an equal-weighted portfolio of government bonds. For each regression, the table reports slope estimates, heteroskedasticity and autocorrelation robust p-values in parentheses, block bootstrap p-values in brackets, and the R^2. The last row of the table reports pooled estimates where we impose the restrictions that $\beta_i = \bar{\beta}$ and $\gamma_i = \bar{\gamma}$ for all i. The sample period is 1970:1 to 2016:10.

Table 7. Evidence from emerging countries.

Country	β_i			γ_i			R^2
Bulgaria	−0.17	(0.02)	[0.02]	0.45	(0.00)	[0.00]	7.7%
China	0.12	(0.28)	[0.35]	0.20	(0.02)	[0.02]	6.9%
Croatia	−0.01	(0.82)	[0.84]	0.27	(0.03)	[0.03]	1.9%
Czech Republic	−0.10	(0.38)	[0.43]	0.42	(0.01)	[0.01]	4.8%
Hungary	−0.09	(0.37)	[0.41]	0.31	(0.14)	[0.16]	1.7%
India	0.01	(0.94)	[0.96]	0.35	(0.07)	[0.07]	3.8%
Korea	−0.02	(0.89)	[0.91]	0.34	(0.08)	[0.10]	5.4%
Malaysia	−0.02	(0.87)	[0.90]	0.37	(0.00)	[0.00]	6.5%
Poland	0.07	(0.44)	[0.48]	0.50	(0.00)	[0.00]	8.2%
South Africa	−0.10	(0.25)	[0.27]	0.25	(0.04)	[0.05]	2.5%
Taiwan	0.14	(0.20)	[0.22]	0.21	(0.01)	[0.01]	7.3%
Thailand	−0.23	(0.01)	[0.01]	0.60	(0.01)	[0.01]	5.9%
Pooled	−0.07	(0.07)	[0.15]	0.36	(0.00)	[0.00]	3.8%

The table reports estimation results from forecasting regressions:

$$r_{i,t+1} = \alpha_i + \beta_i r_{i,t} + \gamma_i r_{global,t} + \varepsilon_{i,t+1}$$

where $r_{i,t+1}$ is the time $t+1$ excess return on country i's 10-year government bond and $r_{global,t}$ is the time t excess return on an equal-weighted portfolio of government bonds. For each regression, the table reports slope estimates, heteroskedasticity-robust p-values in parentheses, wild bootstrap p-values in brackets, and the R^2. The last row of the table reports pooled estimates where we impose the restrictions that $\beta_i = \bar{\beta}$ and $\gamma_i = \bar{\gamma}$ for all i. The sample period is 2000:1 to 2016:10.

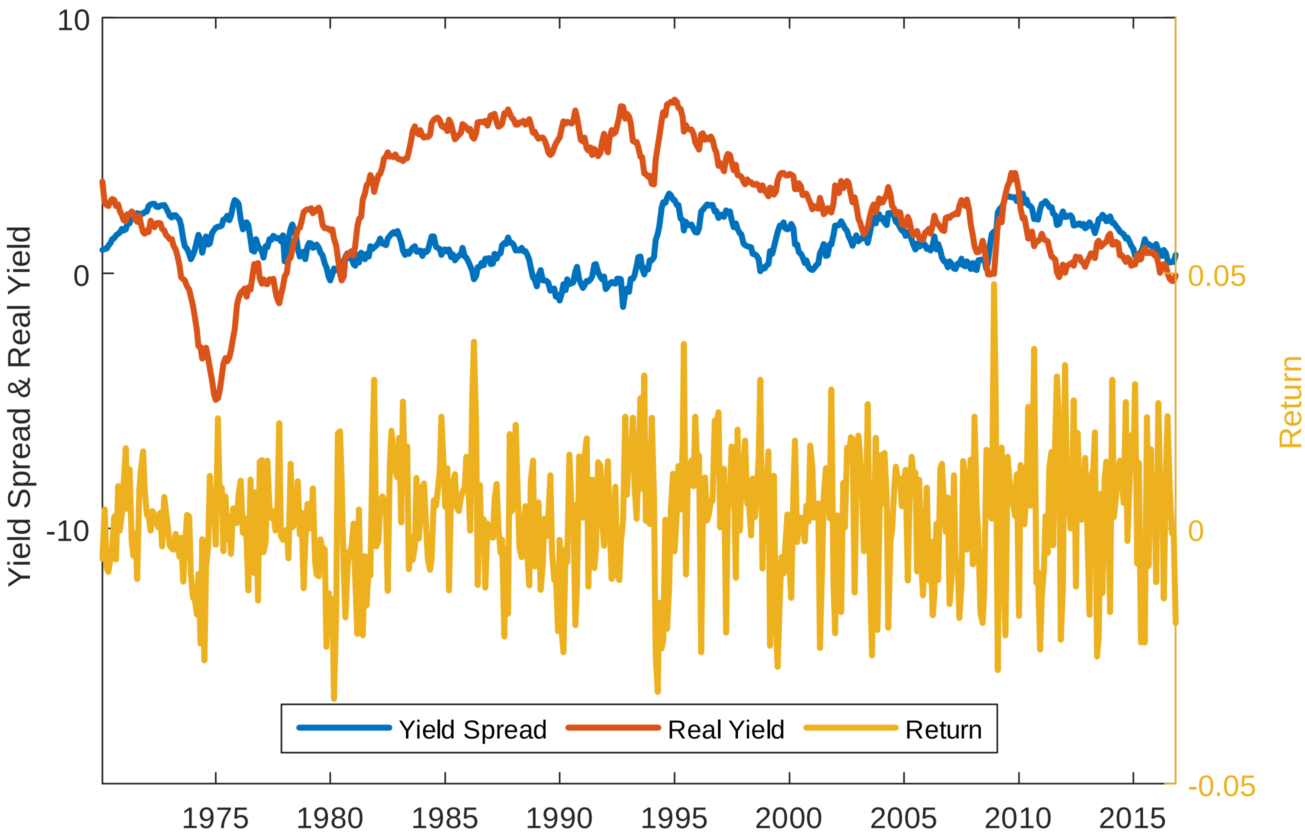

Figure 1. Global yield spread, global real yield, and global return.

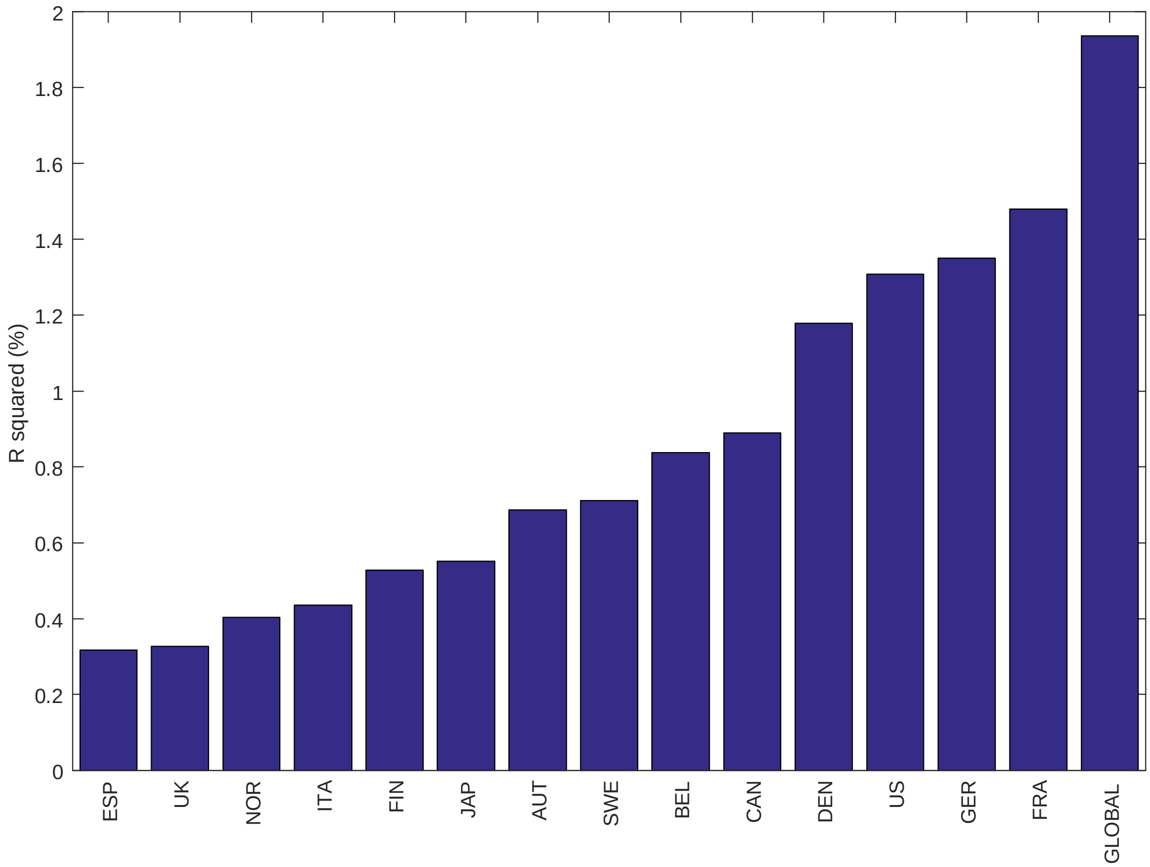

Figure 2. R^2 from return panel regressions.

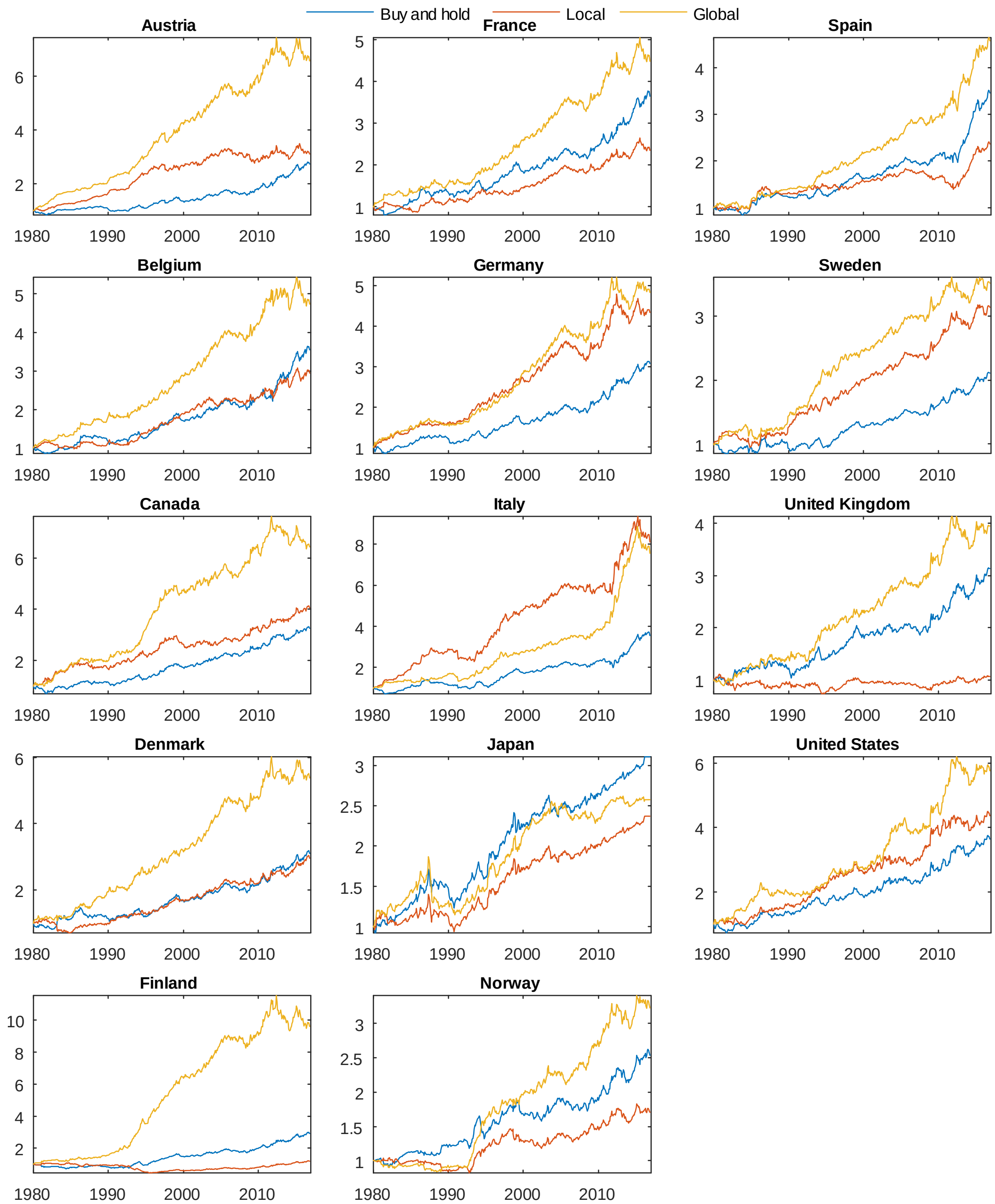

Figure 3. Government bond excess return indexes. We plot return indexes for three investment strategies, which start at one unit of currency on Dec. 31, 1979. The first strategy is a buy and hold strategy that in each period earns the excess return on the ten-year government bond in country i. The second and third strategy take long (short) positions in country i's ten-year government bond if the forecast is positive (negative), using either the lagged local or global excess bond return as signal. All three strategies are zero-investment strategies, assuming that a long position in long-term bonds is financed by a short position in short-term bonds.

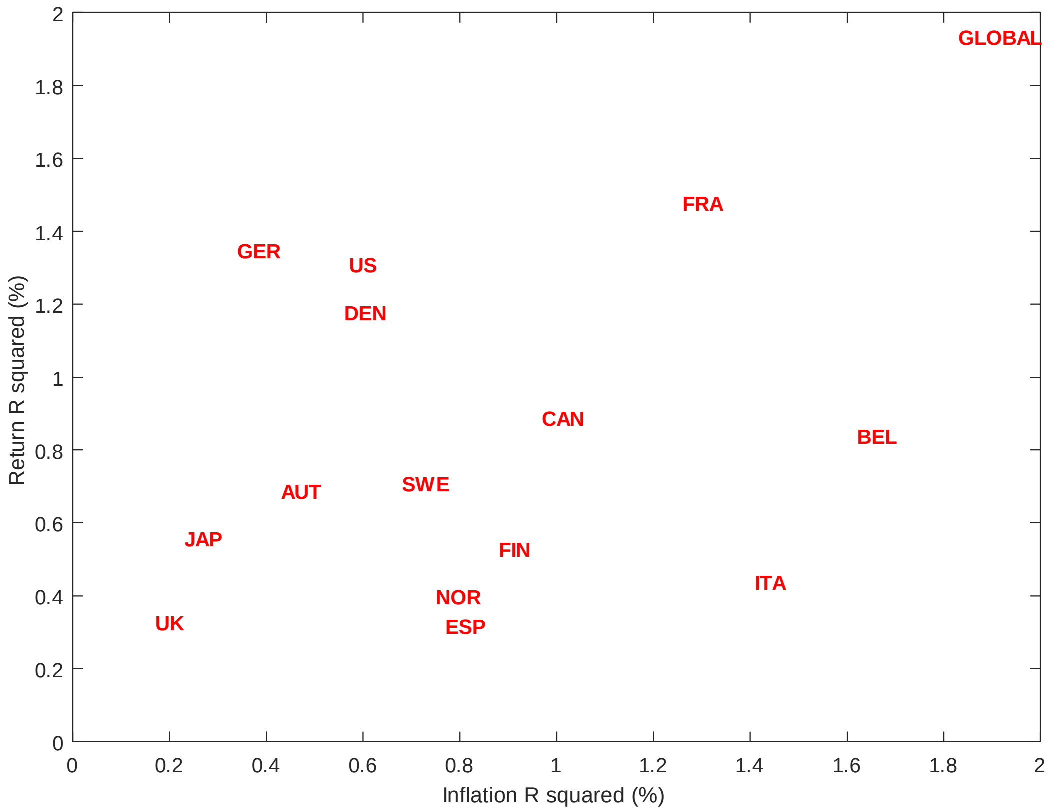

Figure 4. The relation between return and inflation predictablity.

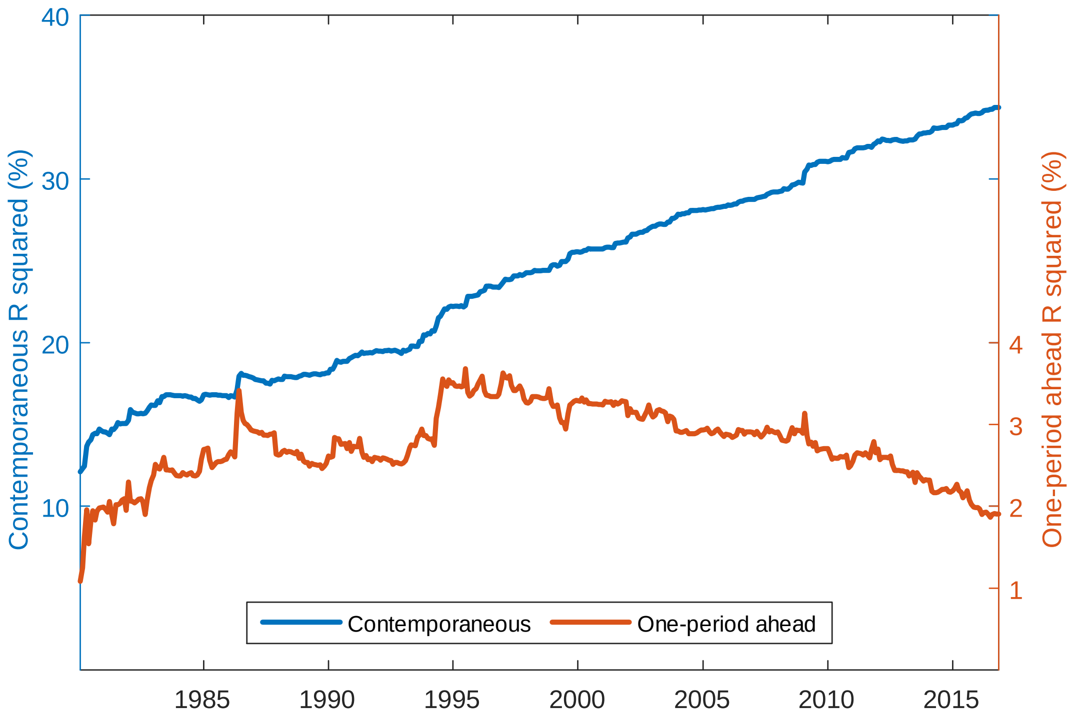

Figure 5. R^2s from recursive regressions.

Appendix

This Appendix briefly describes the wild bootstrap procedure and the block bootstrap procedure that we use in our analysis when testing for return predictablity and inflation predictability, respectively.

Wild bootstrap procedure. We follow Rapach, Strauss and Zhou (2013) closely in our specification of the wild bootstrap procedure. Hence, we bootstrap under the null of no return predictablity, allow for conditional heteroskedasticity in returns, and make sure to preserve the contemporaneous correlations between the variables used in the regressions. The main difference is that we use two-sided empirical p-values rather than one-sided empirical p-values. The empirical p-values are based on 10,000 bootstrap replications.

Block bootstrap. In contrast to the return predictability regressions, the inflation predictability regressions have autocorreleted error terms. We use Newey-West standard errors as well as a block bootstrap procedure to address the issue of dependence in the error term. The regression model is given by:

$$\pi_{i,t+1} = \alpha_i + \beta_i r_{i,t} + \gamma_i r_{global,t} + \varepsilon_{i,t+1} \tag{10}$$

where $\pi_{i,t+1}$ is the inflation rate in country i, $r_{i,t}$ is the excess return in country i, and $r_{global,t}$ is the global excess return. The bootstrap procedure first collects the data for country i in $Z_{i,t} = [\pi_{i,t+1}, r_{i,t}, r_{global,t}]$ for $t = 1,...,T-1$. One country at a time, we then resample with replacement from overlapping blocks of the data in the matrix Z_i. We set the average block size to 12 observations but our results are robust toward other reasonable choices of the block size. We estimate the regression model in each bootstrap sample and save the slope coefficients. We set the number of bootstrap replications to 10,000 and compute the bootstrap standard error on the coefficients as the standard deviation of the 10,000 simulated slope coefficients.