BI Norwegian Business School - campus Oslo

GRA 19703

Master Thesis

Thesis Master of Science

International Bond Return Predictability

Navn: André Lerberg Elnan, Alexander Willis Folker

Start: 15.01.2021 09.00

Finish: 01.07.2021 12.00

International Bond Return Predictability

Master Thesis

by
André L. Elnan and Alexander W. Folker
Master of Science in Business, Major in Finance

Campus:
BI Oslo

Supervisor:
Alessandro Graniero

Oslo, June 29, 2021

ABSTRACT

We study time-varying risk premia across international bond- and equity markets by running predictive regressions of excess returns. We find that the single factor of Cochrane and Piazzesi (2005) and global factor of Dahlquist and Hasseltoft (2013) have lost some of their predictive power in later years, but they both individually and jointly predict excess bond returns across countries. The deterioration of yield-based predictors suggests that there are other important factors that drive risk premia. Finally, our results indicate that investors' required risk compensation is related to international business cycles.

Acknowledgements

We extend our gratitude to our supervisor Alessandro Graniero for his contributions, encouragement, and outstanding guidance towards our thesis.

We would also like to thank the library staff for providing help with data collection, and BI Norwegian Business School for making the necessary resources available to us.

Lastly, we thank our families for their support throughout this journey.

Contents

List of Figures II

List of Tables III

1 Introduction and Motivation 1

2 Related Literature 3

3 Data 6

3.1 Government Bond Data 6

3.2 GDP Data 7

3.3 Stock Data 8

3.4 Descriptive Statistics 9

4 Predictive Regressions 10

4.1 Bond Returns 10

4.2 Single-factor model 13

4.3 Introducing Lags 18

4.4 FB regressions & CP factors for non-US countries 20

4.5 Summary - CP factors and FB regressions 23

4.6 The Global CP factor 24

4.7 Summary - Global factor model 31

4.8 Predicting Stock Returns 32

5 Conclusion 35

A Appendix 41

List of Figures

1 Country-specific GDP weights 1960.01 - 2020.12 7
2 Single factor regression coefficients - US 14
3 Local CP factors (in %) 1999.01 - 2020.12 22
4 Rolling correlations 1975 - 2020 25
5 CP and global CP factor 1975 - 2020 26
6 Single factor regression coefficients - All Countries 1999 - 2020 . 41
7 Slope coefficients - Dai, Singleton and Yang (2004) 42
8 Bond excess returns 1988.01 - 2020.12 43
9 Local CP factors (in %) 1975.01 - 2009.12 44

List of Tables

1 Government Bond Data 6
2 Stock Return Data 8
3 International Bond Yield Statistics 9
4 Fama-Bliss Excess Return Regression 11
5 Estimates Of The Single-Factor Model 16
6 Lagged Regression Estimates 19
7 Fama-Bliss Regression For Additional Countries 20
8 Estimates Of The Single-Factor For Additional Countries 21
9 Local and Global CP Factors Correlation - US, UK, GER 26
10 Local and Global CP Factors Correlation - All Countries 26
11 CP- and GCP Regression Estimates 27
12 Estimates of The Local and Global Factor Model 28
13 Bond Joint Regression 1975.01 - 2020.12 30
14 Joint Regression Estimates - Local and Global CP Factor 31
15 Excess Stock Return Regression - Global Factor 1988 - 2020 . . 33
16 CP, GCP and Joint Regression Estimates 1975.01 - 2020.12 . . . 45
17 CP, GCP and Joint Regression Estimates 1988.01 - 2020.12 . . . 46
18 Excess Stock Return Regressions For Additional Countries . . . 47
19 Lagged Bond Return Regressions For Additional Countries . . . 49

1 Introduction and Motivation

For decades, the Expectation Hypothesis (EH) of the term structure of interest rates has been a core hypothesis within portfolio theory, asset pricing theory, and hedging theory. By definition, the Expectation Hypothesis states that long-term rates are entirely determined by current- and expected future short-rates, which restricts risk premium to be zero or at least constant over time. Thus, the theory rejects the existence of time-varying risk premia. In this thesis, we will focus on predictability of bond risk premia by running regressions of excess returns on term structure-related variables such as yields, spot rates, and forward rates. Excess return predictability and time-varying risk premia are two sides of the same coin, both violating the Expectations Hypothesis (Veronesi, 2016), hence, obtaining significant slope coefficients in such regressions are essentially evidence of time-varying risk premia.

It is beyond us to derive new and improved models on this topic. However, we seek to test predictability of bond risk premia for a chosen set of economies and study drivers of yield dynamics from an international perspective by running regressions containing combinations of well-known factors that evidently describe bond return variations. First, we will consider running classic Fama and Bliss (1987, (FB)) regressions and Cochrane and Piazzesi (2005, (CP)) regressions on the US economy to test whether their methodologies still hold in modern financial data. Then, we will extend their research to account for additional countries and test whether risk premia is predictable outside the US. Further, our empirical analysis on international bond risk premia will be built on Dahlquist and Hasseltoft (2013) who provided evidence for time-varying risk premia across four international markets. Finally, we study whether factors from bond risk premia incorporates any predictive information about local stock markets.

From an academic perspective, studying bond risk premia is interesting as it is closely linked to why required risk compensation varies over time. The topic has gained increased interest over the last decade with an ever-growing body of literature approaching the topic from different angles. Seminal publications such as Fama and Bliss (1987), Cochrane and Piazzesi (2005) and Dahlquist and Hasseltoft (2013), suggests that an investor, on average, can expect profits through long-term investments in bonds and funding the strategy through short-term borrowings. Further, institutional investors such as asset managers or fixed income portfolio managers can use bond risk premia to know whether they should have shorter or longer duration in their portfolio. A high-risk premium tells us that we should invest in longer-term bonds, and vice versa.

Other uses of studying bond risk premia extend to monetary policy and security comparison. Central banks shape the future expectations of interest rates through short-term rates which ultimately affect bond premia, and investors use it to get a better perspective on where they could expect better risk-adjusted returns, and what asset classes to outweigh respectively to others. Both institutional and non-institutional investors can benefit from this.

In summary, we wish to test:

(1) Excess return predictability on US government bonds for updated data motivated by Cochrane and Piazzesi (2005).

(2) Test predictability of international risk premia by applying the methodology of Dahlquist and Hasseltoft (2013).

(3) Test whether term structure factors for bond return predictability also contain predictive power for stock returns.

2 Related Literature

The Expectations Hypothesis is a classic term structure theory that was first introduced by Frederick R. Macaulay in 1938 (Sangvinatsos, 2010). The hypothesis states that the current forward rates reflect the future expected short-term rates, and thus restrict the liquidity premium to be either zero or constant over time. However, literature that documents the failure of the Expectation Hypothesis goes back to the 1980s. Fama and Bliss (1987) and Campbell and Shiller (1991) found that forward rates did not predict future short rates on a one-year horizon, but rather forecasts excess returns as well as changes in interest rates at longer horizons.

The approach of regressing excess returns on forward rates as predictive variables was later adopted by Cochrane and Piazzesi (2005) who strengthened the evidence against the Expectation Hypothesis by defining a single factor of multiple US bond yields rather than single yields with specific maturities. Interestingly, this single factor (CP factor) is almost uncaptured by the three classical principal components (level, slope and curvature) which seems to explain almost all variation in yields (e.g. Litterman and Scheinkman (1991)). This conclusion raised the question on how factors based on interest rates can explain so much of the variation in risk premia while having such a small effect on the cross-section of yields. Duffee (2011) challenged this common belief that term structure dynamics are driven by factors represented as functions of yields. He found a hidden factor that goes unrecognized in standard term structure models that offsets the effects of risk premia and thereby the expectation of future interest rates, which leaves the three principal components largely unaffected. This implies that there are certain elements within future bond returns that seem to be unrelated interest rates. This was further documented by Ludvigson and Ng (2009) who found that macroeconomic fundamentals in the US, in addition to yield-based factors, contain important forecasting power for bond returns.

While the majority of literature shows highly significant and robust results for the US, the international evidence is mixed. For instance, Hardouvelis (1994) and Bekaert and Hodrick (2001) found little evidence against the Expectation Hypothesis internationally, whereas Dahlquist and Hasseltoft (2013) found that country-specific factors and a common global factor both individually and jointly predict international risk premia. Wright (2011) found indications of a declining global risk premia since the 1990s through decomposing cross-sections of international yields and portrays this result as a consequence of uncertainty in monetary policy and inflation.

Although the term structure of interest rates embodies the foundation of financial markets, the literature that links equity market returns to bond returns has been limited, but increasing over the last decades. Fama and French (1989) found that three factors (Fama & French Three-Factor Model) can predict returns on stocks and bonds, implying that variations in returns are common across securities. Cooper and Priestley (2009) found that the output gap, a macroeconomic factor for the US, also contains predictable information on both equity and bond risk premia. Koijen et al. (2017) studies the relationship between macroeconomic risk and investors' required risk compensation and found that the both the single factor of Cochrane and Piazzesi (2005) and the slope of the yield curve are leading indicators of business cycle turning points. Additionally, they found that these factors are highly positively correlated with value stock returns but uncorrelated with returns on growth stocks.

Since the majority of literature concerning the term structure of interest rates has been centered on the US economy, less is known about other economies. Our thesis contributes to the literature by reviewing and extending influential papers to account for multiple countries, provide updated estimates and link these results to relevant financial theories.

3 Data

In this section we describe the data that we use, sources used for data collection, and some descriptive statistics that are relevant for our further investigation throughout this paper.

3.1 Government Bond Data

We have gathered data sets of monthly (end of month) zero-coupon yields or prices for the US, Germany, Japan, Switzerland, and the UK. Our analysis requires data on one- to five-year maturity bonds for the respective countries. US zero-coupon bond data is from The Center of Research in Security Prices (CRSP). For the remaining countries, most of the data is from Wright (2011), up until mid-2009, and has thus been supplemented with data from Global Financial Data (2021) from 2009 up until the end of 2020.

Country	Source	Data Range	# obs.	Methodology
USA	CRSP	1952.06-2020.12	823	Fama-Bliss
Japan	Wright (2011)	1985.01-2009.05	293	Svensson
Germany	Wright (2011)	1973.01-2009.05	437	Svensson
UK	Wright (2011)	1979.01-2009.05	365	Spline
Switzerland	Wright (2011)	1988.01-2009.05	257	Svensson
Japan[2]	Global Financial Data (2021)	2009.06-2020.12	139	Bootstrap
Germany[2]	Global Financial Data (2021)	2009.06-2020.12	139	Svensson
UK[2]	Global Financial Data (2021)	2009.06-2020.12	139	Spline
Switzerland[2]	Global Financial Data (2021)	2009.06-2020.12	139	Svensson

Table 1. *Government bond yields, data sources, range and estimation method.*

Table 1 shows country-specific data sources of zero-coupon yields. Since data is gathered from different sources depending on what period the yields are from, the top half of the table shows data ranges that are used for replicating, while the bottom half shows data sets that are used to extend the data and conduct further analysis. In addition to showing resources used, the table also gives us an overview of the data range for each data set, number of observations, and the estimation method used for each set of zero-coupon yields.

3.2 GDP Data

Data on country-specific GDP comes from *OECD Quarterly National Accounts Database*. The data set includes PPP-adjusted quarterly GDP data for all of our countries. Monthly GDP data is obtained by holding the GDP constant in each quarter. This is needed when we construct a global return-forecasting factor as in Dahlquist and Hasseltoft (2013).

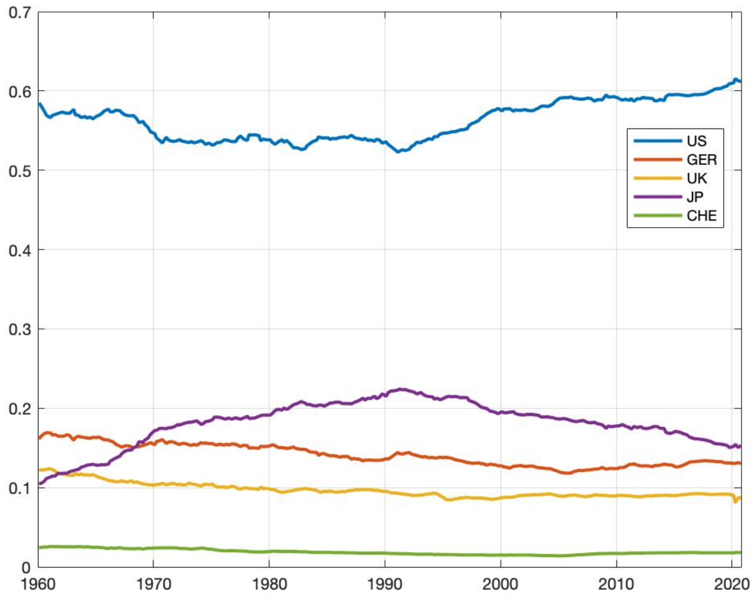


Figure 1. *Relative GDP weights 1960.01 - 2020.12 for United States, Germany, UK, Japan and Switzerland*

Figure 1 shows the relative PPP-adjusted GDP weights for each country for the entire GDP sample collected. The size of the US gross domestic product dominates the other economies, while Japan, Germany, and the UK are somewhat similar in size (10-20%), with Japan bearing the most weight over time. Switzerland is the smallest economy in this sample, hovering steadily around 2 percent for the entire period.

3.3 Stock Data

We collect value-weighted stock returns for each country that we use in our analysis of stock return predictability. For the US, end-of-month stock returns are for firms listed on NYSE, AMEX and NASDAQ, and are gathered from CRSP (2021b). Data for the other countries is from French (2021)'s Data Library. French estimate these with raw data from Morgan Stanley Capital International for 1975 to 2006 and from Bloomberg for 2007 to the present.

Country	Source	Data Range	# obs.	Description
USA	CRSP	1960.01-2020.12	723	Value-weighted
Japan	French (2021)	1975.01-2020.12	552	Value-weighted
Germany	French (2021)	1975.01-2020.12	552	Value-weighted
UK	French (2021)	1975.01-2020.12	552	Value-weighted
Switzerland	French (2021)	1975.01-2020.12	552	Value-weighted

Table 2. *International returns data sources, range, number of observations and methodology. All data from French library is formed by book-to-market (B/M); earnings-price (E/P); cash earnings to price (CE/P); and dividend yield (D/P).*

3.4 Descriptive Statistics

International bond yield summary statistics for our selected countries are summarized in Table 3. The yield curve is upward sloping across maturities, and short-term bonds tend to be less volatile than long term bonds. We also see that yields are highly correlated across maturities and perfectly correlated for longer term bonds in all of the countries.

	Maturity	Mean	Std.dev.	I.	II.	III.	IV.	V.	VI.	VII.	VIII.	IX.	X.
US	1	2.94	2.31	1.00					1.00	0.89	0.78	0.58	0.74
	2	3.19	3.32	0.99	1.00				1.00	0.92	0.83	0.65	0.81
	3	3.43	2.28	0.98	1.00	1.00			1.00	0.93	0.87	0.72	0.85
	4	3.65	2.24	0.96	0.99	1.00	1.00		1.00	0.94	0.90	0.77	0.88
	5	3.82	2.18	0.95	0.98	0.99	1.00	1.00	1.00	0.95	0.92	0.80	0.90
UK	1	3.89	3.30	1.00					0.89	1.00	0.94	0.78	0.90
	2	3.99	3.23	1.00	1.00				0.92	1.00	0.96	0.80	0.93
	3	4.13	3.17	0.99	1.00	1.00			0.93	1.00	0.97	0.83	0.95
	4	4.26	3.10	0.98	0.99	1.00	1.00		0.94	1.00	0.98	0.86	0.96
	5	4.36	3.04	0.97	0.99	1.00	1.00	1.00	0.95	1.00	0.98	0.89	0.97
GER	1	2.73	2.83	1.00					0.78	0.94	1.00	0.82	0.97
	2	2.86	2.82	1.00	1.00				0.83	0.96	1.00	0.84	0.98
	3	3.02	2.81	0.99	1.00	1.00			0.87	0.97	1.00	0.85	0.99
	4	3.19	2.79	0.98	0.99	1.00	1.00		0.90	0.98	1.00	0.86	0.99
	5	3.34	2.77	0.97	0.99	1.00	1.00	1.00	0.92	0.98	1.00	0.88	0.99
JP	1	0.91	1.83	1.00					0.58	0.78	0.82	1.00	0.90
	2	1.00	1.80	1.00	1.00				0.65	0.80	0.84	1.00	0.88
	3	1.13	1.81	0.99	1.00	1.00			0.72	0.83	0.85	1.00	0.88
	4	1.27	1.82	0.98	0.99	1.00	1.00		0.77	0.86	0.86	1.00	0.88
	5	1.39	1.84	0.96	0.98	0.99	1.00	1.00	0.80	0.89	0.88	1.00	0.89
CHE	1	1.75	2.38	1.00					0.74	0.90	0.97	0.90	1.00
	2	1.74	2.23	0.99	1.00				0.81	0.93	0.98	0.88	1.00
	3	1.82	2.16	0.98	1.00	1.00			0.85	0.95	0.99	0.88	1.00
	4	1.93	2.12	0.97	0.99	1.00	1.00		0.88	0.96	0.99	0.88	1.00
	5	2.06	2.09	0.96	0.98	0.99	1.00	1.00	0.90	0.97	0.99	0.89	1.00

Table 3. *International Bond Yield Statistics 1990.01 - 2020.12. Column I-X presents correlations, I-V on yields between different maturities and VI-X on yields with same maturities but across countries.(VI. US; VII. UK; VIII. Germany; IX. Japan; X. Switzerland)*

In general, we find highly positive correlations across countries suggesting that country-specific yields follow each other closely. While correlations of yields are higher among European countries, we find the lowest correlation between Japan and the US.

4 Predictive Regressions

To test for time-varying risk premia, we will use insights from previous research on the literature of bond return predictability, in particular Fama and Bliss (1987), Cochrane and Piazzesi (2005), and Dahlquist and Hasseltoft (2013). Their methodologies involve running predictability regressions of future realized bond returns in excess of risk-free rates which are regressed on variables related to the term structure of interest rates. By replicating their methodologies and extend the literature with updated datasets, we study whether their models still can be applied for bond risk premia predictability. By doing so, we can conclude on our research question on whether the results of these articles are still valid, and simultaneously, whether the market expectations contain important information about long-term bond yields.

4.1 Bond Returns

Fama and Bliss (1987) provided several contributions to the literature by studying whether forward rates could contain important information about excess return predictability. They use the spread between forward rates and the corresponding spot rates as their explanatory variables. As this publication mark the foundation of this methodology, we consider it a natural starting point when exploring time-varying risk premia.

Fama and Bliss (1987) define the log yield, $y_{c,t}^{(n)}$, and the log forward rate, $f_{c,t}^{(n)}$ for country c as:

$$y_{c,t}^{(n)} = -\frac{1}{n} p_{c,t}^{(n)} \qquad \textit{and} \qquad f_{c,t}^{(n)} = p_{c,t}^{(n-1)} - p_{c,t}^{(n)} \tag{1}$$

where $p_{c,t}^{(n)}$ is the log price of the n-year zero coupon bond at time t.

The log holding return is defined as the difference in log price

$$r_{c,t+1}^{(n)} = p_{c,t+1}^{(n-1)} - p_{c,t}^{(n)}. \tag{2}$$

and they use this to define the one-year excess log return as:

$$rx^{(n)}_{c,t+1} = r^{(n)}_{c,t+1} - y^{(1)}_{c,t} \iff rx^{(n)}_{c,t+1} = p^{(n-1)}_{c,t+1} - p^{(n)}_{c,t} - y^{(1)}_{c,t} \quad (3)$$

which corresponds to the difference between the holding period return from holding a security for one year and the yield for that corresponding year.

By regressing the one-year excess return of bonds with different maturities on the spread between one-year forward rates and the one-year spot rate (forward-spot spread), they aim to determine whether the forward rate incorporates information about risk premia required by investors.

$$rx^{n}_{c,t+1} = a^n + \beta^n_c(f^n_{c,t} - y^1_{c,t}) + \varepsilon^n_{c,t+1} \quad (4)$$

If β^n_c is different from 1.0, then the forward-spot spread observed at period t contains information about the one-year spot rate, making it predictable.

	(1964.01-2003.12)		(1964.01-2020.12)		(1999.01-2020.12)	
Maturity	$\beta^{(n)}_c$	R^2	$\beta^{(n)}_c$	R^2	$\beta^{(n)}_c$	R^2
2	0.99	0.16	0.80	0.11	-0.09	0.00
	(0.26)		*(0.26)*		*(0.56)*	
3	1.35	0.17	1.07	0.12	0.20	0.01
	(0.35)		*(0.34)*		*(0.62)*	
4	1.61	0.18	1.28	0.14	0.31	0.01
	(0.45)		*(0.40)*		*(0.57)*	
5	1.27	0.09	1.03	0.07	0.44	0.03
	(0.58)		*(0.43)*		*(0.54)*	

Table 4. *Fama-Bliss Regression. We use Newey-West standard errors accounting for conditional heteroskedasticity and serial correlation up to 12 lags in parantheses.*

Fama and Bliss (1987) found evidence that the forward-spot spread significantly forecasts the one-year excess return for n-year bonds, and thereby establishing evidence against the EH. The same methodology was later applied by Cochrane and Piazzesi (2005) with a data set spanning from 1964 to 2003 who drew the same conclusion, with R^2 up to 18 percent. Through replication, we manage to obtain the same results as Cochrane and Piazzesi (2005) and extend this to include data up to December 2020 (mid column) and test whether the results hold for more recent years (right side column). Table 4 summarizes the results.

Starting the sample from 1964, we find that the Fama-Bliss results still hold even when we extend the sample size to include more recent data, but these results are slightly weakened compared to what Cochrane and Piazzesi (2005) found. Why is it the case for the extended sample? The last column in Table 4 suggests that the significance has disappeared for the last two decades, implying that the forward-spot spread no longer can predict risk premia and thereby fails to reject the EH. Thus, as we extend the data sample, we also capture the periods where the model performs poorly which explains why we observe weaker significance for our full sample (1964-2020). There are two potential explanations for these weak estimates: either the sample is too short to permit the model from detecting predictability, or the model just does not fit well with modern financial data. Although the latter sounds more likely, we will test this by comparing it to the single factor model derived by Cochrane and Piazzesi (2005). Their model became the new benchmark for predictive regression models, as it managed to double the explanatory power of traditional predictability regressions.

4.2 Single-factor model

Cochrane and Piazzesi (2005) propose a new predictor of bond risk premia. They define a single factor as a single linear combination of forward rates that is able to predict the one-year excess return on one- to five-year maturity bonds. The single factor (CP factor) is constructed by estimating linear combinations of yields and forward rates for each country c:

$$CP_{c,t}^{(n)} = \boldsymbol{\gamma_{c,t}^{T}} \boldsymbol{f}_{c,t} \tag{5}$$

where $\boldsymbol{\gamma_c}$ and $\boldsymbol{f}_{c,t}$ represents the below vectors:

$$\boldsymbol{\gamma}_c = [\gamma_{c,0} \quad \gamma_{c,1} \quad \gamma_{c,2} \quad \gamma_{c,3} \quad \gamma_{c,4} \quad \gamma_{c,5}\ ]^T \tag{6}$$

$$\boldsymbol{f}_{c,t} = \begin{bmatrix} 1 & y_{c,t}^{(1)} & f_{c,t}^{(2)} & f_{c,t}^{(3)} & f_{c,t}^{(4)} & f_{c,t}^{(5)} \end{bmatrix}^T \tag{7}$$

Gammas are slope coefficients that are estimated by regressing average excess returns across all maturities on the one-year yield and the four one-year forward rates. This regression is as below:

$$\bar{rx}_{c,t+1}^{(n)} = \gamma_{c,0} + \gamma_{c,1} y_{c,t}^{(1)} + \gamma_{c,2} f_{c,t}^{(2)} + \ldots + \gamma_{c,5} f_{c,t}^{(5)} + \bar{\varepsilon}_{c,t+1} \tag{8}$$

where,

$$\bar{rx}_{c,t+1} = \frac{1}{4} \sum_{n=2}^{5} rx_{c,t+1}^{(n)}, \quad n = 2, 3, 4, 5 \tag{9}$$

If we rewrite this in vector form, we get:

$$\bar{rx}_{c,t+1} = \boldsymbol{\gamma}_c^T \boldsymbol{f}_{c,t} + \bar{\varepsilon}_{c,t+1} \tag{10}$$

Having estimated the CP factor, $\boldsymbol{\gamma^T_{c,t}} \boldsymbol{f}_{c,t}$, Cochrane and Piazzesi (2005) estimate factor loadings, $b_c^{(n)}$, for each forward rate by regressing annual excess returns for all n-year maturity bonds on the CP factor, as below:

$$rx^{(n)}_{c,t+1} = b^{(n)}_c \left(\gamma_{c,0} + \gamma_{c,1} y^{(1)}_{c,t} + \gamma_{c,2} f^{(2)}_{c,t} + \ldots + \gamma_{c,5} f^{(5)}_{c,t} \right) + \varepsilon^{(n)}_{c,t+1} \tag{11}$$

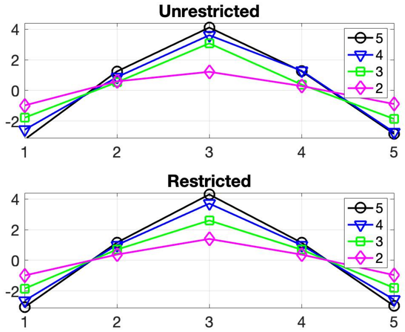
Where the left-hand side represents a vector of two-to-five-year annual excess returns. Which can be written in vector form as:

$$rx^{(n)}_{c,t+1} = b^{(n)}_c \left(\boldsymbol{\gamma}^T_c \boldsymbol{f}_{c,t} \right) + \varepsilon^{(n)}_{c,t+1} \ , \ n = 2,\ 3,\ 4,\ 5 \tag{12}$$

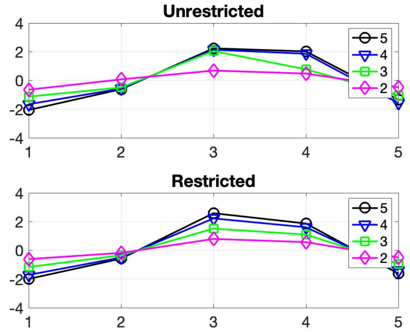
The single factor model is a tool used to describe expected excess returns over multiple maturities in terms of one single factor and is based on the results of an unrestricted regression of annual excess returns on the same set of yields and forward rates:

$$rx^{(n)}_{c,t+1} = \beta^{(n)}_{c,0} + \beta^{(n)}_{c,1} y^{(1)}_{c,t} + \beta^{(n)}_{c,2} f^{(2)}_{c,t} + \ldots + \beta^{(n)}_{c,5} f^{(5)}_{c,t} + \varepsilon^{(n)}_{c,t+1} \tag{13}$$

Cochrane and Piazzesi (2005) found that this unrestricted regression yields slope parameters that follow a tent-shaped pattern across maturities, on which they concluded that forward rates incorporate predictive information about one-year excess returns at all maturities, and that longer maturities only have greater loadings.



(a) USA 1964.01 - 2003.12



(b) USA 1964.01 - 2020.12

Figure 2. *Single factor regression coefficients subject to (13) and (11)*

The left side of Figure 2 presents the results of equation (11) and (13) using the same sample as Cochrane and Piazzesi (2005). The tent-shape to the bottom left in Figure 2 is given by the product of factor loading, $b_c^{(n)}$, and the gamma coefficients, γ_c^T, and captures almost exactly the parameters from the unrestricted regression (13). Due to the similarities between the restricted and unrestricted regressions Cochrane and Piazzesi speculate on whether the single factor is a state variable[1] However, although the models provide parameters that are equal individually, they find that they are not jointly equal to each other - That is, $b_{c,n}\gamma_c^T \neq \beta_c$, thereby rejecting this hypothesis.

When extending the sample to December 2020, we find that the tent shape is no longer present due to the two-year maturity coefficient (right side of Figure 2). There might be multiple reasons for this result. Dai et al. (2004) argue that the distinctive tent-shape in the findings of Cochrane and Piazzesi (2005) is not a robust feature of zero coupon bond yields. Dai et al. (2004) state that these very different patterns could be explained by even minor variations in the zero yields caused by different degrees of smoothing from the spline methodologies. As we see from our extended sample the pattern load positively on the three- and four-year forward rates, and slightly negative on two- and five-year forward rates producing more of a wave-shaped pattern. This pattern, and others, are also found in Dai et al. (2004) where they estimate four different data sets of zero-coupon bond yields derived from the same set of underlying coupon bond prices and run the same regression as we conducted above (tent shape regression). Their slope coefficients can be found in Figure 7 in the Appendix.

[1]A variable that can forecast changes in the distribution of future returns (such as wealth, consumption, ect.), that ultimately affects the investor's consumption-portfolio decision. (Cochrane, 2009)

Panel A: Estimates of the return-forecasting factor $\bar{rx}_{c,t+1} = \boldsymbol{\gamma}_c^T \boldsymbol{f}_{c,t} + \bar{\varepsilon}_{c,t+1}$							
	γ_0	γ_1	γ_2	γ_3	γ_4	γ_5	R^2
1964.01 - 2003.12	-3.24	-2.14	0.81	3.00	0.80	-2.08	0.35
1964.01 - 2020.12	-0.75	-1.39	-0.16	1.68	1.20	-1.20	0.20
1975.01 - 2009.12	-1.03	-1.35	-0.53	3.03	0.85	-1.81	0.23
1999.01 - 2020.12	-0.95	0.77	-2.21	1.18	0.76	0.11	0.15

Panel B: Restricted bond regression $rx_{c,t+1}^{(n)} = b_{c,n}\left(\boldsymbol{\gamma}_c^T \boldsymbol{f}_{c,t}\right) + \varepsilon_{c,t+1}^{(n)}$								
	1964.01-2003.12		1964.01-2020.12		1975.01-2009.12		1999.01-2020.12	
Maturity	$b_c^{(n)}$	R^2	$b_c^{(n)}$	R^2	$b_c^{(n)}$	R^2	$b_c^{(n)}$	R^2
2	0.47	0.31	0.45	0.17	0.47	0.19	0.39	0.14
	[14.55]		*[10.35]*		*[11.93]*		*[6.13]*	
3	0.87	0.34	0.85	0.19	0.87	0.22	0.84	0.16
	[40.14]		*[27.78]*		*[29.85]*		*[13.48]*	
4	1.24	0.37	1.25	0.22	1.25	0.25	1.23	0.15
	[84.70]		*[61.49]*		*[65.68]*		*[59.45]*	
5	1.43	0.34	1.45	0.20	1.41	0.21	1.54	0.14
	[35.52]		*[25.61]*		*[26.03]*		*[13.89]*	

Table 5. *Estimates Of The Single-Factor Model. The 1-percent, 5-percent and 10-percent critical values for $\chi^2(5)$ are 15.1, 11.1, and 9.2. [ ] provides the test statistics using GMM standard errors. Regressions are run using both Hansen-Hodrick with twelve lags to accout for the overlapping data, and Newey-West with eighteen lags to handle conditional heterosecedasticity and serial correlation.*

We examine the performance of the single factor model for four samples representing different time periods. The results are found in Table 5. The first row in Panel A and the left column in Panel B are pure replications of the result from the original paper and is included to compare the models' significance over time (note that differences in values from the original paper are due to data differences - we get identical results when we use same data). In line with what we found for our FB regression, we find that the performance of the single factor changes over time and that it seems to have lost some of its explanatory power since it was first introduced. Even so, for much of our sample, it provides estimates that are far greater than the 1 percent critical value. Considering Panel B, both the second and the third column shows very significant parameter estimates, where the two-year bond has somewhat weakened in significance relative to longer-maturity bonds. This is interesting as it explains the changes in the tent shape presented to the lower right in Figure 2 - The tent shape seems to prevail for all maturities except for the two-year bond.

Even though the parameter values remain relatively intact across sub-samples, the significance seems to fade when we shorten the data to only cover the last two decades. The forward rates still jointly predict average excess holding period return with a Chi-square statistic of 23.90 which also exceeds the 1 percent critical value, but looking at each bond separately, we see that the significance weakens both for individual parameters and jointly for each maturity. The fact that we find similar weakening performance tendencies between the CP factor and the forward-spot spread of Fama and Bliss suggests that modern risk premia is less explained by the term structure. One potential explanation to our results was suggested by Sekkel (2011) who related a weakening CP factor during the 2007 financial crisis to extraordinary monetary policy implementations and changes in liquidity funding that might go unrecognized by the CP factor. Nevertheless, the CP factor still outperforms the forward-spot spread which is most likely related to the factor contain more information about the term structure than the forward-spot spread does.

To summarize, we successfully replicate the methodology of Cochrane and Piazzesi (2005) and use different subsamples to test model performance for different periods and assess updated evidence of time-varying risk premia in the US. We have documented that both the forward-spot spread and CP factor significantly predict excess returns for our full sample (1964-2020), but that their performance weakens compared to when they were first introduced, which provides an answer to our first research question. However, although the model has lost some of its predictive power in recent data, the result outputs are still significant and thereby also still relevant, and we can confidently continue to extend our analysis.

4.3 Introducing Lags

Taking the single factor one step further, Cochrane and Piazzesi (2005) find that adding multiple lags of forward rates provides extra explanatory power. We run the regression by normalizing the alpha coefficients to $\sum_{j=0}^{k} \alpha_j = 1$, such that the gammas are unaffected, and then regress the average excess holding period return on the CP factor:

$$\bar{rx}_{t+1} = \alpha_{c,0}(\gamma^T f_{c,t-(1/12)}) + \ldots + \alpha_{c,k}(\gamma^T f_{c,t-(k/12)}) + \bar{\varepsilon}_{c,t+1} \tag{14}$$

By rearranging the variables from the regression above we can rewrite this as:

$$\bar{rx}_{t+1} = \boldsymbol{\gamma}^T[\alpha_{c,0} f_{c,t-(1/12)} + \alpha_{c,1} f_{c,t-(2/12)} + \ldots + \alpha_{c,k} f_{c,t-(k/12)}] + \bar{\varepsilon}_{c,t+1} \tag{15}$$

Using these alpha estimates, the second step involves running a second regression on excess return for all maturities. Equation 15 introduces another single variable, alpha, for every new lag applied to the regression, and tests them jointly. Table 6 presents the results of eq. 15. In addition to finding that the R^2 increases for each additional lag, they find that adding lags gives a minor right shift to gamma coefficients, which is due to the factor not being Markovian[2]. The fact that the CP factor is not Markovian implies that autocorrelation disturbs the parameter values and ultimately affects the pattern of coefficients. This makes it hard to add a large number of lags to our model as this will ruin the tent-shape. They find that the increase in R^2 is most severe up to the third lag before it stabilizes at approximately 45 percent for additional lags. However, due to the increasing number of parameters for every lag, we consider the adjusted R^2 in Table 6 below.

[2]A Markov Process is a stochastic process where only the present value is relevant for predicting the future. Neither the historical values nor the path up to the present is relevant - Hull (2012). Thus, no autocorrelation applies in the process

Panel A: γ estimates							
Maturity	const	$y^{(1)}$	$f^{(2)}$	$f^{(3)}$	$f^{(4)}$	$f^{(5)}$	R^2
0	-0.75	-1.39	-0.16	1.68	1.20	-1.20	0.20
	(-0.73)	*(-3.21)*	*(-0.23)*	*(2.33)*	*(2.69)*	*(-2.55)*	
1	-0.67	-1.45	-0.22	1.78	1.72	-1.72	0.23
	(-0.66)	*(-2.89)*	*(-0.23)*	*(1.69)*	*(3.08)*	*(-2.70)*	
2	-0.70	-1.46	-0.13	1.38	2.32	-2.01	0.23
	(-0.68)	*(-2.65)*	*(-0.12)*	*(1.19)*	*(3.48)*	*(-2.74)*	
3	-0.74	-1.42	-0.15	1.14	2.75	-2.21	0.24
	(-0.76)	*(-2.39)*	*(-0.12)*	*(0.89)*	*(3.94)*	*(-2.78)*	
4	-0.76	-1.40	-0.16	1.04	2.90	-2.28	0.24
	(-0.72)	*(-2.30)*	*(-0.12)*	*(0.77)*	*(4.01)*	*(-2.79)*	

Panel B: $\boldsymbol{\alpha}$ estimates for different lags						
Lags	α_0	α_1	α_2	α_3	α_4	$R^2(adj.)$
0	1.00					0.20
	(5.00)					
1	0.53	0.47				0.22
	(4.87)	*(3.56)*				
2	0.41	0.30	0.29			0.23
	(4.45)	*(3.96)*	*(2.70)*			
3	0.31	0.27	0.21	0.21		0.24
	(3.08)	*(4.14)*	*(2.95)*	*(1.89)*		
4	0.30	0.24	0.20	0.18	0.07	0.24
	(3.18)	*(3.80)*	*(3.03)*	*(2.39)*	*(0.70)*	

Table 6. *Regression 15 estimates on 1964.01 - 2020.12 data. "()" provides the test statistics using Newey-West standard errors with twelve lags to handle conditional heterosecedasticity and serial correlation.*

Cochrane and Piazzesi (2005) found that additional lags increase the R^2 from 35 percent to 44 percent, implying that there is additional forecasting power in lagged forward rates. We draw the same conclusion for our subsamples. Our R^2s are generally lower than what Cochrane and Piazzesi (2005) found which should not be too surprising given our conclusion in section 4.2 about the weakening of the single-factor model, but all of them are higher than they were without lags. However, as one continues to introduce more lags, the alpha estimates become less significant.

We see from Panel B in Table 6 that the last coefficient for lags exceeding the third lag is not significant at a 5 percent confidence level, making the model less attractive beyond this number of lags. Nevertheless, p-values for joint significance are still far below the 1 percent critical value for all our tested lags, which is up to seven lags. However, it seems reasonable to restrict the number of lags to the point where they no longer are significant, especially when the additional parameters do not contribute to a better model fit.

4.4 FB regressions & CP factors for non-US countries

We apply the methodologies of Fama and Bliss (1987) and Cochrane and Piazzesi (2005) on data for other economies to test how well these models predict excess returns for Germany, UK, Switzerland, and Japan. First, we run the FB regressions:

n	2		3		4		5	
Country	$\boldsymbol{\beta}_c^{(n)}$	R^2	$\boldsymbol{\beta}_c^{(n)}$	R^2	$\boldsymbol{\beta}_c^{(n)}$	R^2	$\boldsymbol{\beta}_c^{(n)}$	R^2
Germany	0.34	0.02	0.62	0.04	0.83*	0.06	1.02**	0.08
UK	0.43	0.04	0.79**	0.12	0.99***	0.15	1.04***	0.15
US	-0.09	0.00	0.20	0.01	0.31	0.01	0.44	0.03
Switzerland	0.27	0.02	0.58	0.06	0.83**	0.07	1.04***	0.08
Japan	0.90***	0.44	1.10***	0.42	1.24***	0.37	1.24***	0.32

Table 7. *Fama-Bliss regression estimates 1999.01 - 2020.12 corresponding to regression 4.Significance is indicated by '*', where ***, ** and * indicate p-values lower than the 1%, 5% and 10% significance levels respectively.*

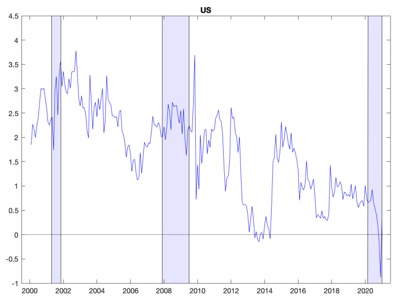
Table 7 represents the results. While the model no longer provides significant estimates for the US, we find significant parameters for the non-US countries, but primarily for longer maturities. While the European countries receive somewhat similar estimates, Japan is the only country that is subject to statistically significant coefficients across all maturities. Furthermore, high R^2s suggests that much of the variation in Japan's bond returns are explained by variations in yields, implying that the forward-spot spread is a significant driver of risk premia. Hence, our result for Japan disagrees with previous conclusions on FB regressions as we find that the forward-spot spread can be applied for non-US economies.

	CP factors									
	Germany		UK		US		CHE		JPN	
n	$b_c^{(n)}$	R^2	$b_c^{(n)}$	R^2	$b_c^{(n)}$	R^2	$b_c^{(n)}$	R^2	$b_c^{(n)}$	R^2
2	0.35	0.07	0.36	0.13	0.39	0.14	0.35	0.24	0.34	0.60
	[5.09]		*[4.67]*		*[6.13]*		*[5.07]*		*[21.80]*	
3	0.78	0.09	0.82	0.20	0.84	0.16	0.80	0.28	0.76	0.55
	[13.45]		*[13.79]*		*[13.48]*		*[14.73]*		*[41.83]*	
4	1.22	0.09	1.23	0.23	1.23	0.15	1.24	0.27	1.23	0.49
	[92.77]		*[59.29]*		*[59.45]*		*[55.86]*		*[134.49]*	
5	1.64	0.09	1.58	0.23	1.54	0.14	1.61	0.23	1.67	0.45
	[14.18]		*[13.42]*		*[13.89]*		*[15.55]*		*[59.31]*	

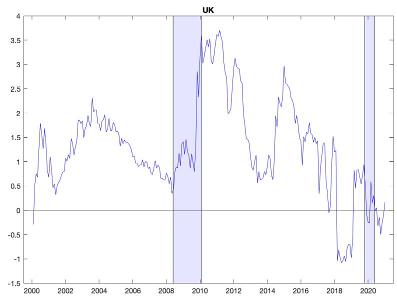
Table 8. *Estimates Of The Single-Factor Model for additional countries. This table provides estimates for data covreing 1999.01-2020.12. The 1-percent, 5-percent and 10-percent critical values for $\chi^2(5)$ are 15.1, 11.1, and 9.2. [ ] provides the test statistics using GMM standard errors. Regressions are run using both Hansen-Hodrick with twelve lags to accout for the overlapping data, and Newey-West with eighteen lags to handle conditional heterosecedasticity and serial correlation.*

Now considering the CP factor - How well does the single factor model hold outside the US? Table 8 presents our results for the 1999-2020 sample which, as discussed earlier, tends to provides the weakest parameter estimates for the US (results for 1975-2020 and 1988-2020 can be found in 16 and 17 in the Appendix). However, the results are clear; the CP factor works well for all countries. The parameter significance also seems to be fairly equal and follows the same pattern across maturities and their values still increase smoothly with maturities. One concern lies with the insignificant two-year bond which is far below the 10-percent critical value, indicating that the two-year forward rate does a poor job in explaining one-year excess returns, one year from now.

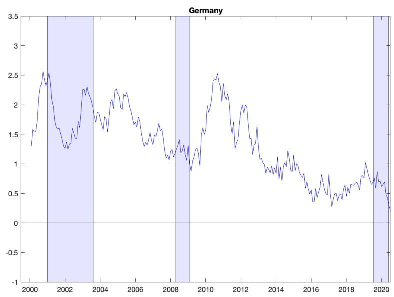
Additionally, our CP factor results for Japan are similar to the FB regressions - Japan has at least double R^2 values and far greater Chi-stats than any of the other countries for all maturities. These results are even larger than what Cochrane and Piazzesi found for the US. The fact that Japan's CP factor performs so well relative to the US and Europe might indicate an inverse relationship between risk premia in the respective economies. Figure 3 plots the CP factors (or local factors) for all five countries. The grey areas represent economic contractions. In Figure 3e we find lower sample variance for Japan than in any other country with values ranging between approximately 1.8 (in 2000 and 2007-2009) to -0.25 (in 2017). Another interesting remark is that while the CP factor seems to increase in periods of financial contractions for most countries, we find that the risk premia shrinks in Japan. This contradicts general academic evidence which suggests that risk premia on nominal bonds tend to increase in recessions due to economic uncertainty, which arguably will make investors require more compensation. Other reasons for this opposing trend might lie in market inefficiencies or irrational investor behavior, which according to behavioral finance, occurs when there are expectational errors in bond returns that deviate from rational expectations (Veronesi, 2016).



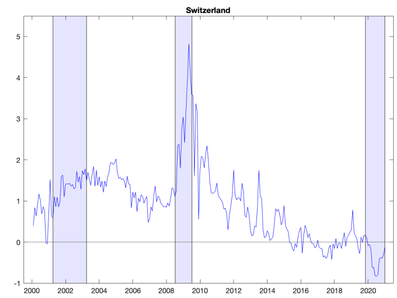
(a) *US*



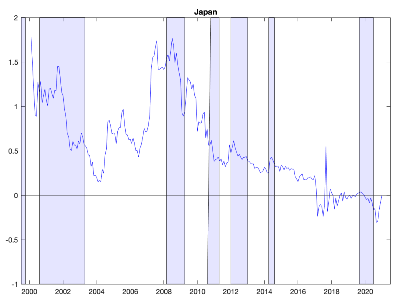
(b) *UK*



(c) *GER*



(d) *CHE*



(e) *JAP*

Figure 3. *Local CP factors (in %) for US, Germany, UK, Switzerland, and Japan, 1999.01 - 2020.12. The blue-shaded areas indicate economic contractions gathered from NBER (2021) for the US and Economic Cycle Research Institute (2021) for the remaining countries.*

The application of lags to the model has a various impact for each country (see Table 19 in the appendix). For our 1999.01-2020.12 sample, we only find significant parameters with one additional lag for US and Switzerland. While the US does not gain additional explanatory power, we find that the R^2 for Switzerland increases from 0.26 to 0.29. By extending the sample to cover data back to 1975 we find significant alpha estimates for both Germany and the US. The higher significance stems from the fact that the sample includes a period where the CP factor performed very well. While the benefits of lagged variables only have a marginal impact on German parameters, we find that the adjusted R^2 for the US increases to 0.34 with five lags.

4.5 Summary - CP factors and FB regressions

Up to this point, we have managed to replicate the predictive regression approach of both Fama and Bliss (1987) and Cochrane and Piazzesi (2005) and extend their methodologies to account for multiple countries and updated data. We found that the forward spot-spread factor has lost almost all predictive power for US bond returns in modern data, but that it performes well in Japan with R^2 up to 44 percent. For the US, the CP factor still incorporates predictive power for excess bond returns although it too has weakened over time. We find the CP factor also weakens over time for all non-US countries except forn Japan who receives significant coefficient estimates and R^2 up to 60 percent. Additionally, depending on the data sample, we find that adding lags to the single factor model provides a new set of results for each country implying large variations in performance for different periods. For our 1975-2020 sample, US and Germany receive increased predictive power, while for the 1999-2020 sample, only the US has significant lags. This finding suggests that there are other factors that drive risk premia that go uncaptured by the term structure, such as extraordinary monetary policy and liquidity risk (Sekkel, 2011).

4.6 The Global CP factor

Having established the importance of the CP factor and the existence of time-varying risk prima for other economies than the US, our next step is to study the international bond risk premia following the procedure of Dahlquist and Hasseltoft (2013). The increased integration of world financial markets and the fact that bond risk premia seem to be positively correlated across countries makes it interesting to define a global common factor that might explain international risk premia. They contribute to the literature and extend the work of Cochrane and Piazzesi (2005) by defining a global CP factor (GCP factor hereafter) as a GDP-weighted average of each local CP factor for every period t.

$$GCP_t = \sum_{c=1}^{C} w_{c,t} CP_{c,t} \tag{16}$$

Where $w_{c,t}$ is the weighted GDP-average of country $c = [US, DEU, UK, JP, CHE]$ for every period t: $w_{c,t} = \frac{GDP_{c,t}}{\sum_{c=1}^{C} GDP_{c,t}}$. The average weights for each country in our sample are 0.57 for the US, 0.13 for Germany, 0.09 for UK, 0.19 for Japan, and 0.02 for Switzerland.[3] Dahlquist and Hasseltoft (2013) found that a global CP factor is highly correlated with the US bond risk premia and international business cycles, and that increased correlations between the local factors and the global factor over the last decades indicate a stronger integration across markets. Additionally, they find that R^2s are equal or somewhat higher for the European countries than their corresponding CP factors provide. Another key observation is that the correlation with US risk premia suggests that shocks to the US will have greater predictive power on non-US countries' risk premia. For the US, the R^2 remains relatively unaffected to the results provided by the CP factor, which makes it natural to assume that non-US countries incorporate less important information for US risk premia prediction.

[3] Figure 1 show these weights over time.

Before running the regressions, we analyze the relationship between the global factor and the local factors for US, UK, and Germany.

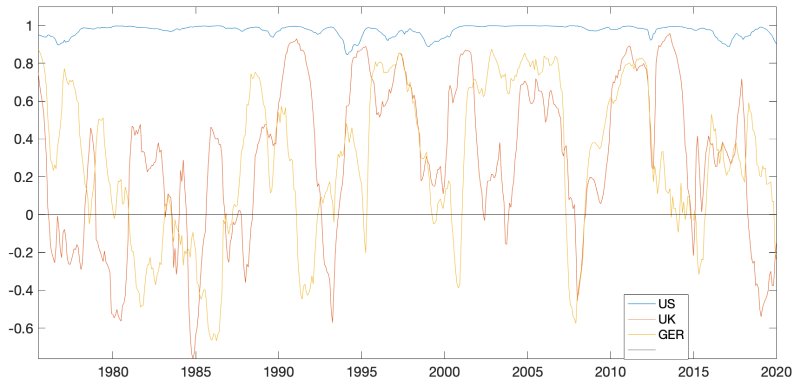


Figure 4. *24-month rolling correlations between CP^{US}, CP^{DE}, CP^{UK} and GCP Estimated on 1975.01 - 2020.12 data*

Figure 4 plots a 24-month rolling correlation between the GCP factor and each country's local factor. By definition, the GCP factor is a function of the underlying local factors, and we must bear in mind that this representation is a simplification as it represents a world with only three countries in it. The high correlation between the US and the global factor is due to the greater weighting of the US economy. Unsurprisingly, this strong relationship between the global factor and the US local factor also implies that they follow each other closely over time, relative to UK and Germany. Figure 5 plots the GCP and CP factors over time. The plot suggests that the only major difference between the US local factor and the GCP factor seems to be their volatility (the US local factor goes both higher and lower, but the patterns are the same).

We run both CP- and GCP regressions for our 1975-2020 sample, and 1988-2020[4] sample to test the model for recent data. One implication of running two separate regressions with both different samples and a different composition of countries is that they produce different global and local factors.

[4]We use both the sample 1975-2020 and 1988-2020 because there is no data on government bond yields for Japan and Switzerland going back to 1975. 1988-2020 includes testing for all the countries we wish to test for.

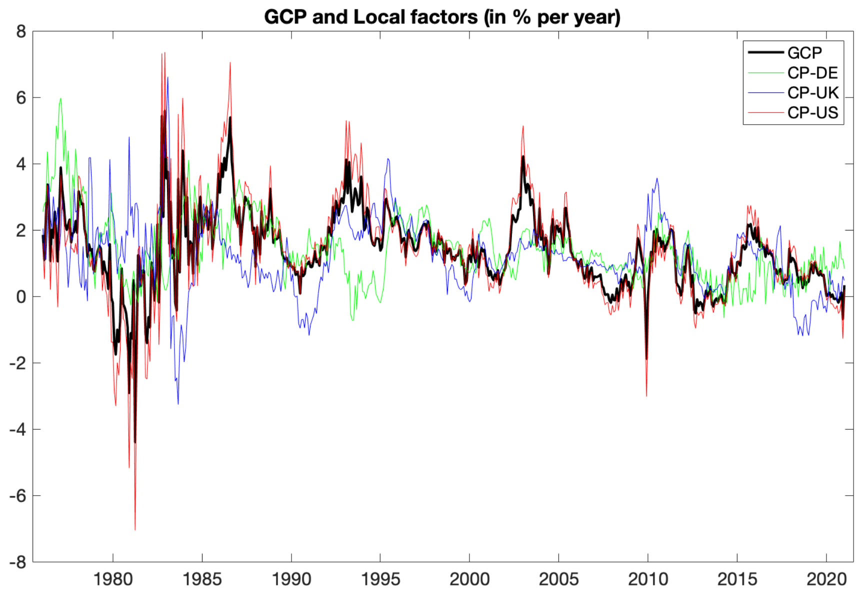


Figure 5. *CP^{US}, CP^{DE}, CP^{UK} and the global CP factor 1975.01 - 2020.12*

	Germany	UK	US	Global
1975-2009				
Germany	1.00			
UK	0.14	1.00		
US	0.24	0.06	1.00	
Global	0.40	0.20	0.98	1.00

Table 9. *Correlation between local and Global CP factors, 1975 - 2009*

	Germany	Japan	Switzerland	UK	US	Global
1988-2020						
Germany	1.00					
Japan	0.52	1.00				
Switzerland	0.58	0.59	1.00			
UK	0.54	0.10	0.36	1.00		
US	0.67	0.62	0.61	0.38	1.00	
Global	0.77	0.68	0.67	0.50	0.98	1.00

Table 10. *Correlation between local and Global CP factors (all countries), 1988 - 2020*

Gamma coefficients are estimated on the entire sample and will affect the local factors which ultimately affect the GCP factors. Additionally, introducing other countries to the model will both affect the weights and the local factor on which the GCP factor is based. Thus, the GCP can be altered in many ways based on what you are studying. On the other hand, by running the regression for multiple periods, we can assess information about when the model performs well and when it performs worse. Once we can trace model performance over time, we might uncover other elements that drive risk premia. For instance, Dahlquist and Hasseltoft (2013) found that the global factor tends to increase in US recessions. Additionally, Figure 3 suggests that local risk premia tend to increase in recessions, which is in line with rational risk-aversion theory [5]

We start running our regressions on our full sample (1975-2020) analysis which includes Germany, UK, and the US. The average GDP weights are 0.17 for Germany, 0.12 for UK and 0.71 for US. We regress country-specific excess return on the GCP factor to assess the magnitude of explanatory power of the factor internationally:

$$rx^n_{c,t+12} = a^n_c + b^n_{c,GCP} GCP_t + \varepsilon^n_{c,t+12} \tag{17}$$

Table 11 presents the results. When we compare the results from regression (17) to each country's corresponding local factor, we find that the global factor does not provide any additional explanatory power for UK or US.

Local and Global CP regressions

	Germany				UK				US			
n	$b^{(n)}_{c,CP}$	R^2	$b^{(n)}_{c,GCP}$	R^2	$b^{(n)}_{c,CP}$	R^2	$b^{(n)}_{c,GCP}$	R^2	$b^{(n)}_{c,CP}$	R^2	$b^{(n)}_{c,GCP}$	R^2
2	0.41	0.09	0.55	0.22	0.41	0.08	0.42	0.09	0.45	0.16	0.58	0.16
	(0.09)		*(0.08)*		*(0.10)*		*(0.13)*		*(0.09)*		*(0.15)*	
3	0.84	0.11	1.01	0.21	0.84	0.11	0.77	0.09	0.86	0.18	1.14	0.18
	(0.17)		*(0.15)*		*(0.19)*		*(0.23)*		*(0.17)*		*(0.32)*	
4	1.21	0.12	1.37	0.20	1.22	0.11	1.10	0.09	1.25	0.20	1.66	0.19
	(0.24)		*(0.23)*		*(0.28)*		*(0.31)*		*(0.23)*		*(0.46)*	
5	1.53	0.12	1.66	0.19	1.53	0.10	1.42	0.10	1.43	0.17	1.91	0.17
	(0.30)		*(0.31)*		*(0.35)*		*(0.38)*		*(0.28)*		*(0.59)*	

Table 11. *Table illustrates the CP- and GCP regressions for data covering 1975.01 - 2020.12. We use Newey-West standard errors accounting for conditional heteroskedasticity and serial correlation up to twelve lags are presented in paranthesis.*

[5]Rational risk theory suggests that risk compensation moves countercyclically to investors' well-being, implying that it is low in good times, and high in bad times (Stambaugh, 1988), (Fama and French, 1989).

However, the global factor roughly doubles the R^2 for Germany with a similar level of significance as the local factors. All parameters are highly significant with p-values far below the 1 percent significance level. For this composition of countries, the US economy drives a large portion of the global factor, implying that the US ultimately will carry great predictive power internationally. Considering that we use a longer data set than Dahlquist and Hasseltoft (2013), we confirm that their results still apply as our results are similar - The GCP factor is a significant predictor of international risk premia.

Next, we consider the second sample from 1988-2020, thereby including Japan and Switzerland. Results are presented in Table 12.

Local factors										
	Germany		UK		US		CHE		JPN	
n	$b^{(n)}_{c,CP}$	R^2	$b^{(n)}_{c,CP}$	R^2	$b^{(n)}_{c,CP}$	R^2	$b^{(n)}_{c,CP}$	R^2	$b^{(n)}_{c,CP}$	R^2
2	0.34	0.05	0.42	0.15	0.44	0.10	0.40	0.20	0.36	0.24
	(0.15)		*(0.10)*		*(0.12)*		*(0.10)*		*(0.08)*	
3	0.79	0.08	0.85	0.16	0.85	0.09	0.81	0.24	0.81	0.29
	(0.28)		*(0.20)*		*(0.22)*		*(0.16)*		*(0.15)*	
4	1.23	0.10	1.21	0.15	1.24	0.10	1.21	0.24	1.23	0.31
	(0.39)		*(0.29)*		*(0.29)*		*(0.20)*		*(0.19)*	
5	1.64	0.11	1.52	0.14	1.47	0.08	1.57	0.24	1.60	0.32
	(0.47)		*(0.36)*		*(0.33)*		*(0.23)*		*(0.23)*	
Global factors										
	Germany		UK		US		CHE		JPN	
n	$b^{(n)}_{c,GCP}$	R^2	$b^{(n)}_{c,GCP}$	R^2	$b^{(n)}_{c,GCP}$	R^2	$b^{(n)}_{c,GCP}$	R^2	$b^{(n)}_{c,GCP}$	R^2
2	0.55	0.11	0.60	0.09	0.50	0.08	0.51	0.07	0.60	0.23
	(0.18)		*(0.25)*		*(0.23)*		*(0.23)*		*(0.16)*	
3	1.12	0.12	1.09	0.09	0.92	0.07	0.99	0.09	1.33	0.27
	(0.35)		*(0.44)*		*(0.43)*		*(0.39)*		*(0.32)*	
4	1.56	0.12	1.45	0.08	1.32	0.07	1.36	0.09	1.98	0.28
	(0.47)		*(0.57)*		*(0.62)*		*(0.51)*		*(0.44)*	
5	1.88	0.10	1.73	0.07	1.58	0.07	1.65	0.09	2.57	0.29
	(0.56)		*(0.67)*		*(0.77)*		*(0.61)*		*(0.53)*	

Table 12. *Estimates Of the local and global factor model for additional countries. The table provides estimates for data covering 1988.01-2020.12. Regressions are run using Newey-West with twelve lags to handle conditional heterosecedasticity and serial correlation.*

Compared to our results in Table 11, we see that a general weakening in explanatory power from the global factor, combined with higher standard errors. For the US and Germany, the R^2s from equation (17) are roughly half of what they were in the full sample, while they remain almost unchanged for the UK. Local factors are also explaining less in both Germany and the US for this sample, while it captures more of the excess return variance for the UK.

Results for Switzerland are similar to those of the UK - the local factor is superior to the global factor with much larger R^2s for all maturities, indicating that risk premia for this period has been driven much more by local factors. For Japan we get somewhat similar results for both the local and the global factor where both are highly significant and have very high R^2s. Again, our estimate for Japan far exceeds the significance of any other country, implying that risk premia in Japan is largely driven by term structure dynamics.

Finding that both the local and the global factors are driving country-specific risk premia, we extend the model and test local factors and the global factor jointly. We orthogonalize the local factor onto the global factor by using the residuals as the "true" local factors, to prevent changes in the global estimates by removing any variable relation. This is essentially a two-step approach. The first step regression is given by:

$$CP_{c,t} = a_c^n + b_{c,GCP}^n GCP_t + \varepsilon_{c,t+12}^n \tag{18}$$

The residuals, $\varepsilon_{c,t+12}^n$, makes up an equally sized vector as the local factors, making them directly applicable to the second step regression:

$$rx_{c,t+12}^n = a_c^n + b_{c,CP}^n CP_{c,t} + b_{c,GCP}^n GCP_t + \varepsilon_{c,t+12}^n, \quad where\ CP_{c,t} = \varepsilon_{c,t+12}^n \tag{19}$$

First, we consider the sample from 1975-2020, and our results are provided in Table 13. We find joint significance across all countries when regressing the local and global factors, but that the significance for the US has somewhat weakened. Variations in bond returns for the UK and Germany are better explained by the joint regression than by any of the univariate, but this increase is most severe for the UK. Compared to the findings of Dahlquist and Hasseltoft (2013) we receive consistent conclusions although our results suggest lower explanatory power, in general.

	DEU			UK			US		
n	$\beta^n_{c,CP}$	$\beta^n_{c,GCP}$	R^2	$\beta^n_{c,CP}$	$\beta^n_{c,GCP}$	R^2	$\beta^n_{c,CP}$	$\beta^n_{c,GCP}$	R^2
2	0.21	0.55	0.24	0.32	0.42	0.14	0.10	0.58	0.16
	(0.12)	*(0.09)*		*(0.11)*	*(0.13)*		*(0.48)*	*(0.15)*	
3	0.48	1.01	0.24	0.69	0.77	0.16	0.56	1.14	0.18
	(0.24)	*(0.16)*		*(0.19)*	*(0.22)*		*(0.83)*	*(0.30)*	
4	0.73	1.37	0.23	0.99	1.10	0.16	0.98	1.66	0.20
	(0.35)	*(0.24)*		*(0.28)*	*(0.31)*		*(1.03)*	*(0.44)*	
5	0.93	1.66	0.22	1.16	1.42	0.15	0.80	1.91	0.17
	(0.46)	*(0.32)*		*(0.36)*	*(0.38)*		*(1.27)*	*(0.57)*	

Table 13. *Joint regression on 1975.01 - 2020.12 data. We use Newey-West standard errors accounting for conditional heteroskedasticity and serial correlation up to twelve lags are presented in paranthesis.*

Table 14 presents results for a shorter sample (1988.01-2020.12) where we also include Japan and Switzerland. The conclusion is consistent with those in Table 13 for UK, US, and Germany, but with much weaker significance for the US who receives p-values ranging from 5.7 percent up to 8.1 percent for the fifth maturity for both the GCP- and the joint regression. We also find p-values that exceed the 1 percent criteria for both Switzerland and UK for the global factor regression, where the p-value for the two-year maturity for Switzerland goes as high as 5.6 percent. Opposingly, we find higher significance for both Germany and Japan where all slope coefficients satisfy the 1 percent critical value, but the German significance is still lower than they were for the extended sample above. All joint regressions are highly significant, except for the US.

Countries	n	2	3	4	5
DEU	$\beta^n_{c,CP}$	0.12	0.44	0.81	1.20
	$s.e$	*(0.22)*	*(0.45)*	*(0.64)*	*(0.79)*
	$\beta^n_{c,GCP}$	0.55	1.12	1.56	1.88
	$s.e$	*(0.20)*	*(0.39)*	*(0.54)*	*(0.65)*
	R^2	0.12	0.14	0.15	0.15
UK	$\beta^n_{c,CP}$	0.42	0.76	1.04	1.25
	$s.e$	*(0.26)*	*(0.46)*	*(0.63)*	*(0.78)*
	$\beta^n_{c,GCP}$	0.60	1.09	1.45	1.73
	$s.e$	*(0.28)*	*(0.49)*	*(0.65)*	*(0.78)*
	R^2	0.16	0.16	0.16	0.14
US	$\beta^n_{c,CP}$	0.50	0.83	1.17	1.15
	$s.e$	*(0.39)*	*(0.68)*	*(0.93)*	*(1.14)*
	$\beta^n_{c,GCP}$	0.50	0.92	1.32	1.58
	$s.e$	*(0.2)*	*(0.48)*	*(0.68)*	*(0.86)*
	R^2	0.10	0.09	0.10	0.08
CHE	$\beta^n_{c,CP}$	0.45	0.78	1.06	1.32
	$s.e$	*(0.19)*	*(0.30)*	*(0.39)*	*(0.48)*
	$\beta^n_{c,GCP}$	0.51	0.99	1.36	1.65
	$s.e$	*(0.26)*	*(0.43)*	*(0.56)*	*(0.67)*
	R^2	0.23	0.25	0.25	0.25
JPN	$\beta^n_{c,CP}$	0.23	0.53	0.80	1.01
	$s.e$	*(0.11)*	*(0.20)*	*(0.26)*	*(0.30)*
	$\beta^n_{c,GCP}$	0.60	1.33	1.98	2.57
	$s.e$	*(0.16)*	*(0.31)*	*(0.42)*	*(0.50)*
	R^2	0.27	0.33	0.34	0.35

Table 14. *Joint regression for US, Germany, UK, Japan, and Switzerland. 1988.01 - 2020.12 data. We use Newey-West standard errors accounting for conditional heteroskedasticity and serial correlation up to twelve lags are presented in paranthesis.*

Consistent with our results for the CP factor earlier, we find much higher explanatory power for Japan than we do for any of the other economies. Similar to the UK, the global factor in itself do not perform better than the local factor but tested jointly we find R^2 values for Japan as high as 35 percent. For Switzerland, the joint regression yields much higher explanatory power than the global factor does alone but contributes less versus the Swiss local factor.

4.7 Summary - Global factor model

Following the procedure of Dahlquist and Hasseltoft (2013), we have managed to replicate their results and extend this to account for more updated data and an additional country, Japan. Similar to what we found with the CP factor, the GCP factor's predictive power has somewhat weakened, but it is still a valid model with high predictive power for some countries. We obtain higher p-values and lower explanatory power for all countries than Dahlquist and Hasseltoft reported in the original paper. Interestingly, while the model reports lower R^2s for some countries, we find quite the opposite for other countries. Japan is one example where we find that both the local and the global factor are major drivers of bond risk premia and that they jointly explain up to 35 percent of the variation in excess returns. The fact that the model can yield so different results might indicate that individual economies follow very different business cycles or be affected by other factors.

4.8 Predicting Stock Returns

If stocks can be regarded as long-term bonds with an additional cash-flow risk, a factor that can significantly estimate bond excess returns should also be able to predict excess stock returns. For instance, Fama and French (1989) found that the term structure of interest rates contains important information about stock returns, implying that the risk premia we have estimated so far is actually risk premia and not mere measurement error in bond prices. In this section, we will test whether bond return forecasting factors can be used to forecast stock returns internationally.

We regress one to five-year excess stock returns on the local and global factors individually, and then jointly. Excess stock returns are constructed by cumulating monthly log returns and subtracting the n-year treasury yields for each country, c. The right-hand side variables are the local and global factors. We will consider univariate regressions first:

$$sx_{c,t+n}^{(n)} = \alpha_{c,0} + \beta_{c,CP} CP_{c,t}^{(n)} + \varepsilon_{c,t+1}^{(n)} \tag{20}$$

and

$$sx^{(n)}_{c,t+n} = \alpha_{c,0} + \beta_{c,GCP} GCP^{(n)}_{c,t} + \varepsilon^{(n)}_{c,t+1} \tag{21}$$

Our results for the local factor regression (eq. 20) are generally weak and are therefore placed in Table 18 in the Appendix. Even so, the local factor yields significant estimates for three and four-year returns for Japan, which is the only country that has negative parameter estimates for all investment horizons, meaning that the CP factor is negatively related to stock risk premia. Furthermore, our results suggest that the local factor explains the two-year returns better than the global factor for Germany, UK, and Switzerland. While we receive highly significant estimates for the US across all investment horizons when we use the Cochrane and Piazzesi data set (beta values are 1.49, 2.45, 2.60, 2.93 and 4.09 for one-to-five-year horizons respectively), we find much weaker estimates for our 1988-2020 sample. This implies that the US CP factor has lost predictive power against US equity returns.

	GER		UK		US		CHE		JPN	
n	$\beta^n_{c,GCP}$	R^2	$\beta^n_{c,GCP}$	R^2	$\beta^n_{c,GCP}$	R^2	$\beta^n_{c,GCP}$	R^2	$\beta^n_{c,GCP}$	R^2
1	-0.04	0.00	2.39	0.01	0.88	0.00	4.22	0.01	-4.75	0.02
2	9.10	0.03	9.91	0.06	4.19	0.01	18.22*	0.08	-5.58	0.01
3	20.31*	0.11	17.78***	0.16	10.78	0.06	32.11***	0.17	-9.41	0.03
4	35.48***	0.27	25.69***	0.29	18.75**	0.15	49.75***	0.30	-8.47	0.02
5	44.88***	0.33	26.71***	0.25	20.25*	0.14	58.80***	0.32	-9.30	0.02

Table 15. *Global factor regression on one-to-five year excess stock returns. 1988.01 - 2020.12. Significance is indicated by '*', where ***, ** and * indicate p-values lower than the 1%, 5% and 10% significance levels respectively.*

Results from the global factor regression (eq. 21) are provided in Table 15. Interestingly, the results are two-folded: Estimates for Germany, UK, and Switzerland are highly significant for longer investment horizons, while estimates for the US and Japan are much weaker. Thus, international risk premia is not a universal driver of returns in local equity markets. Additionally, the global factor fails to provide significant results for shorter investment horizons.

This, however, isn't too surprising as longer holding periods returns contain more information by construction, making them more exposed to variations in the term structure. This is also shown by high R^2 values hovering around the 0.30 mark for the European countries. Furthermore, the parameters tend to be highly positive for the longer investment horizons, indicating that an increase in global bond risk premia will have a large impact on the risk premia in local equity markets. This is in line with rational risk theory which suggests that due to the additional cash-flow risk, equity investors will require more compensation for additional risk than bondholders.

Finally, we consider the joint regression. As before, we orthogonalize the local factor with respect to the global factor and use the residuals as the "true local factor". The regression is as below:

$$sx^{(n)}_{c,t+n} = \alpha_{c,0} + \beta_{c,CP} CP^{(n)}_{c,t} + \beta_{c,GCP} GCP^{(n)}_{c,t} + u^{(n)}_{c,t+1} \tag{22}$$

where $CP^{(n)}_{c,t} = \varepsilon^{(n)}_{c,t+1}$ and $\varepsilon^{(n)}_{c,t+1}$ are residuals from the orthogonalization. Our results are consistent with those of the global factor regression but with slightly higher significance and R^2s (see Table 18 in the Appendix). However, our estimates do not suggest additional evidence for stock return predictability in the US or Japan, indicating that their stock returns are driven by factors that are unrelated to the yield curve.

Conclusively, we find that the forecasting factors derived from bond returns can be used to predict stock excess returns, but that these estimates are not universally significant. While Japan and US seem to have stock returns that are driven by factors that are unrelated to the yield curve, these predictive factors capture a large portion of the stock excess return variation for Germany, UK, and Switzerland.

5 Conclusion

In this thesis, we provide empirical evidence of time-varying bond risk premia, and thereby prove the failure of the expectation hypothesis. Our methodology includes elements from Fama and Bliss (1987) but is mostly motivated by findings from Cochrane and Piazzesi (2005) and Dahlquist and Hasseltoft (2013). While we find that the procedure of Fama and Bliss (1987) no longer holds for updated data, we prove that the CP factor still yields significant results for all our samples for the US, implying that excess bond returns are still predictable by information incorporated in the yield curve. The results are further strengthened when we add lagged right-hand side variables. However, although the CP factor is still a relevant measure for the US economy, we find that it too does not fit updated financial data as well as it did when it was introduced in 2005.

We extend the work of Cochrane and Piazzesi (2005) by applying their methodology to non-US countries. Our research includes Germany, UK, Switzerland, and Japan in addition to the US. We find evidence that the term structure for non-US countries describes more of the time-varying risk premia than it does for the US. This contradicts the classic FB-regressions which indicates no predictability for non-US economies. Furthermore, the application of lagged variables tends to yield higher R^2 and more significant estimates, but the number of significant lags varies among countries. Using more recent data, Japan received the highest R^2 of up to 60 percent for two-year maturity bonds, which tends to have the weakest parameter estimates for the other countries. This might indicate that risk preferences not only vary over time but also across countries.

To capture the effects of international risk premia, we follow the procedure of Dahlquist and Hasseltoft (2013). Our results are consistent with theirs - Both the local and the global factors are statistically significant individually and jointly for non-US countries, but that the global CP factor seems to only have marginal predictability for the US. Due to the large weighting of the US local factor in the global-factor model, we find a close relationship between the global CP factor and the US economy.

Finally, we study the relationship between information within the term structure and the stock market returns, by running regressions of excess stock returns on the local and the global factor. High explanatory power and significance is granted primarily to the European nations for longer investment horizons. Our results for the US are weaker than what we expected, but we still find evidence for predictability of three-year holding period returns. Opposingly, stock returns for Japan seem to be uncaptured by both the lacal- and global CP factor.

In line with most of the literature on this topic, our study only considers in-sample regressions. Although some literature also considers out-of-sample performance of predictive factors, the results are mixed, implying that there are opportunities for additional research on this matter. Although we have confirmed that the CP factor deteriorates over time, we do not provide extensive research on the reasons behind these observations. Thus, a natural extension on the development and performance of bond risk premia models is to include measures that are not likely to be captured by yield-oriented factors, but that are likely to determine risk premia. Such factors can be central bank measures, credit risk, liquidity risk, government debt, and other macroeconomic measures, but we will leave these potential extensions to a passionate reader.

REFERENCES

Bekaert, G., and R. J. Hodrick. 2001. Expectations Hypotheses Tests. *The Journal of Finance* 56:1357–1394.

Campbell, J. Y., and R. J. Shiller. 1991. Yield Spreads and Interest Rate Movements: A Bird's Eye View. *The Review of Economic Studies* 58:495–514. doi:10.2307/2298008. Publisher: Oxford University Press, Review of Economic Studies, Ltd.

Cochrane, J. H. 2009. *Asset Pricing: Revised Edition*. Princeton University Press. Google-Books-ID: 20pmeMaKNwsC.

Cochrane, J. H., and M. Piazzesi. a. Appendix to "Bond Risk Premia" .

Cochrane, J. H., and M. Piazzesi. b. Reply to Dai, Singleton, and Yang .

Cochrane, J. H., and M. Piazzesi. 2005. Bond Risk Premia. *American Economic Review* 95:138–160. doi:10.1257/0002828053828581.

Cooper, I., and R. Priestley. 2009. Time-Varying Risk Premiums and the Output Gap. *The Review of Financial Studies* 22:2801–2833.

CRSP. 2021a. Fama-Bliss Discount Bonds. `http://www.crsp.org/products/documentation/fama-bliss-discount-bonds-%E2%80%93-monthly-only`.

CRSP. 2021b. Stock Market Indexes (NYSE/AMEX/NASDAQ/ARCA). `https://www.crsp.com`.

Dahlquist, M., and H. Hasseltoft. 2013. International Bond Risk Premia. *Journal of International Economics* 90:17–32. doi:10.1016/j.jinteco.2012.11.008.

Dai, Q., K. J. Singleton, and W. Yang. 2004. Predictability of Bond Risk Premia and Affine Term Structure Models. *Unpublished article* p. 30.

Duffee, G. R. 2011. Information in (and not in) the Term Structure. *Review of Financial Studies* 24:2895–2934. doi:10.1093/rfs/hhr033. Place: Cary Publisher: Oxford Univ Press Inc WOS:000294124100002.

Economic Cycle Research Institute. 2021. International Growth Rate and Business Cycle Chronologies. https://www.businesscycle.com.

Fama, E. F., and R. R. Bliss. 1987. The Information in Long-Maturity Forward Rates. *The American Economic Review* 77:680–692.

Fama, E. F., J. H. Cochrane, T. J. Moskowitz, J. H. Cochrane, and T. J. Moskowitz. 2017. *The Fama Portfolio: Selected Papers of Eugene F. Fama*. University of Chicago Press.

Fama, E. F., and K. R. French. 1989. Business conditions and expected returns on stocks and bonds. *Journal of Financial Economics* 25:23–49. doi:10.1016/0304-405X(89)90095-0.

French, K. R. 2021. Kenneth R. French - Data library. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/int_country_port_formed.html.

Global Financial Data. 2021. Government Bond/Note Yield (Access Date: 03/01/2021).

Gurkaynak, R. S., B. Sack, and J. H. Wright. 2007. The US. Treasury yield curve: 1961 to the present. *Journal of Monetary Economics* 54:2291–2304. doi:10.1016/j.jmoneco.2007.06.029.

Hardouvelis, G. A. 1994. The term structure spread and future changes in long and short rates in the G7 countries: Is there a puzzle? *Journal of Monetary Economics* 33:255–283. doi:10.1016/0304-3932(94)90003-5.

Hull, J. C. 2012. *Options, Futures, and Other Derivatives, Global Edition*. Pearson Education.

Ilmanen, A. 1995. Time-Varying Expected Returns in International Bond Markets. *The Journal of Finance* 50:481–506. doi:10.2307/2329416.

Ireland, P. N. 2015. Monetary policy, bond risk premia, and the economy. *Journal of Monetary Economics* 76:124–140. doi:10.1016/j.jmoneco.2015.09.003.

Koijen, R. S. J., H. Lustig, and S. Van Nieuwerburgh. 2017. The cross-section and time series of stock and bond returns. *Journal of Monetary Economics* 88:50–69. doi:10.1016/j.jmoneco.2017.05.006.

Litterman, R. B., and J. Scheinkman. 1991. Common Factors Affecting Bond Returns. *The Journal of Fixed Income* 1:54–61. doi:10.3905/jfi.1991.692347. Publisher: Institutional Investor Journals.

Ludvigson, S. C., and S. Ng. 2009. Macro Factors in Bond Risk Premia. *Review of Financial Studies* 22:5027–5067. doi:10.1093/rfs/hhp081.

NBER. 2021. US Business Cycle Expansions and Contractions. `https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions`.

OECD. 2021. Quarterly National Accounts. *OECD National Accounts Statistics (Database),* doi:https://doi.org/10.1787/data-00017-en. (Access Date: 22/03/2021)).

Sangvinatsos, A. 2010. Expectations Hypothesis. *Encyclopedia of Quantitative Finance* doi:10.1002/9780470061602.eqf03005.

Sekkel, R. 2011. International evidence on bond risk premia. *Journal of Banking & Finance* 35:174–181. doi:10.1016/j.jbankfin.2010.07.029.

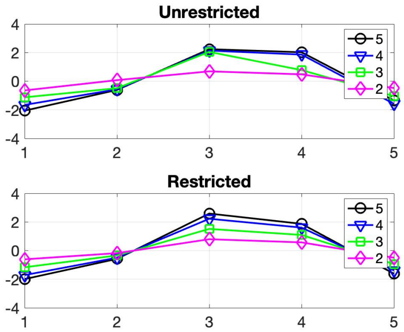
Stambaugh, R. F. 1988. The information in forward rates: Implications for models of the term structure. *Journal of Financial Economics* 21:41–70. doi:10.1016/0304-405X(88)90031-1.

Veronesi, P. 2010. *Fixed income securities : valuation, risk, and risk management*. John Wiley & Sons, Inc.

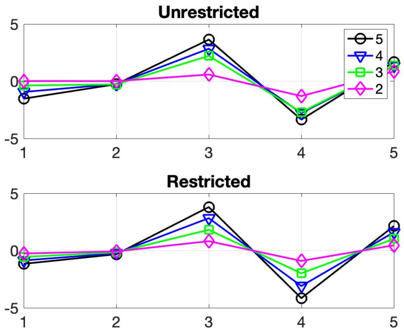
Veronesi, P. (ed.). 2016. *Handbook of fixed-income securities*. Hoboken, New Jersey: John Wiley & Sons, Inc.

Wright, J. H. 2011. Term Premia and Inflation Uncertainty: Empirical Evidence from an International Panel Dataset. *The American Economic Review* 101:1514–1534. doi:10.1257/aer.101.4.1514.

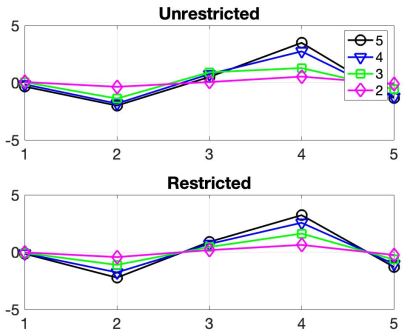
A Appendix



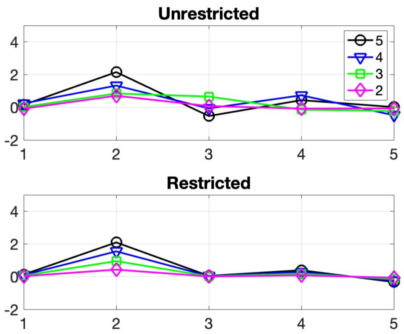
(a) USA



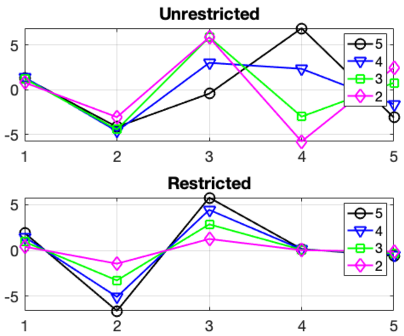
(b) GER



(c) UK



(d) JP



(e) CHE

Figure 6. *Internatrional coefficient patterns for US, Germany, UK, Japan, and Switzerland 1999.01 - 2020.12 data. Derived from Eq.13 and .11*

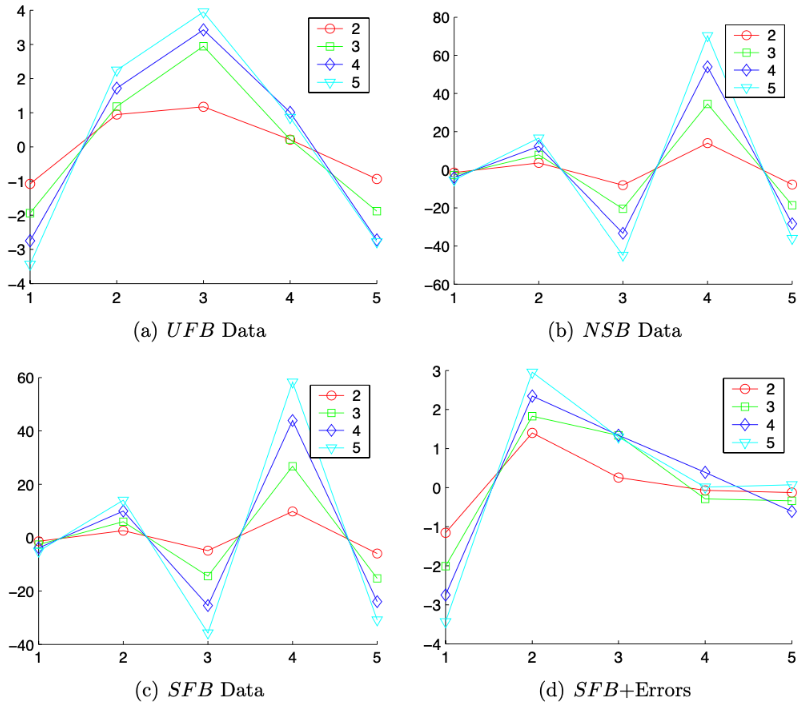
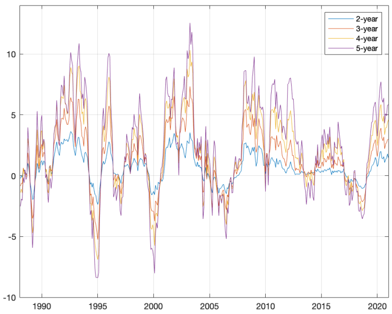
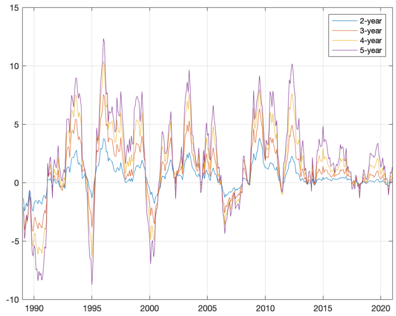


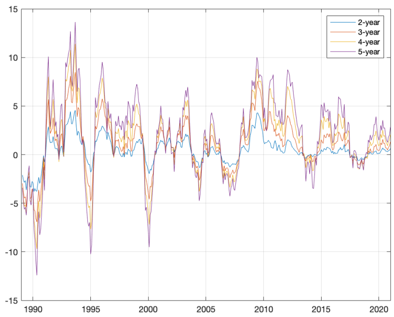
Figure 7. *Figure 2 in Dai et al. (2004)*
zero-coupon yields are estimated with well-known methods in empirical studies surrounding curve-fitting and bond yields: Unsmoothed Fama-Bliss (UFB), Smoothed Fama-Bliss (SFB), Nelson-Siegel-Bliss (NSB) and Fisher Waggoner (FW).



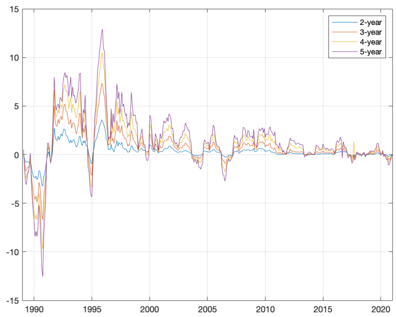
(a) US



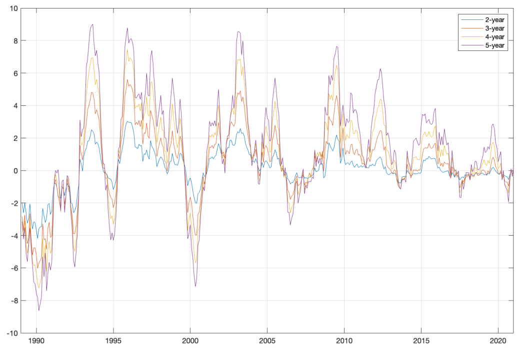
(b) GER



(c) UK



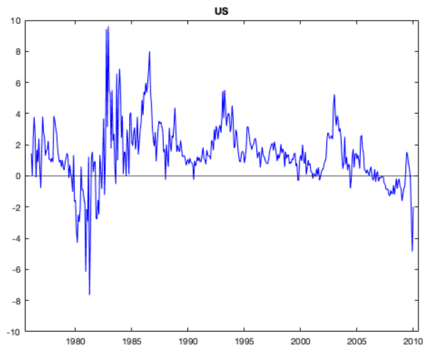
(d) JP



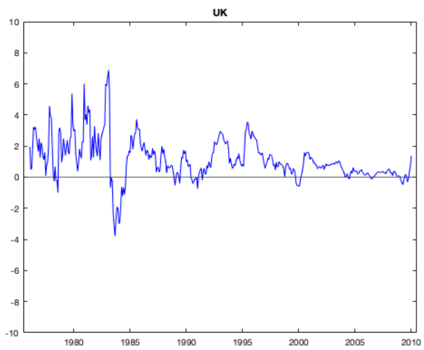
(e) CHE

Figure 8. *Bond excess returns for US, Germany, UK, Japan, and Switzerland 1988.01 - 2020.12*

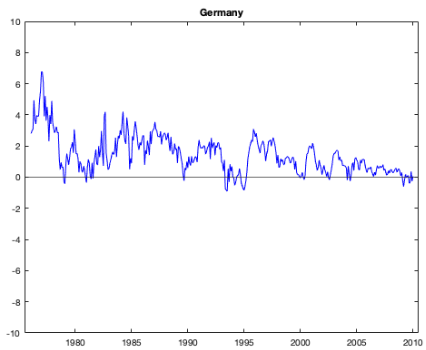
(a) *GCP*



(b) *US*



(c) *UK*



(d) *GER*

Figure 9. *Local CP factors (in %) for US, UK, Germany and the global CP factor, 1975.01 - 2009.12*

Local and Global CP regressions

Country	n	$b^{(n)}_{c,CP}$	R^2	$b^{(n)}_{c,GCP}$	R^2	$b^{(n)}_{c,CP}$	$b^{(n)}_{c,GCP}$	R^2
Germany	2	0.41	0.09	0.55	0.22	0.21	0.55	0.24
		(0.09)		*(0.08)*		*(0.12)*	*(0.08)*	
	3	0.84	0.11	1.01	0.21	0.48	1.01	0.24
		(0.17)		*(0.15)*		*(0.24)*	*(0.16)*	
	4	1.21	0.12	1.37	0.20	0.73	1.37	0.23
		(0.24)		*(0.23)*		*(0.35)*	*(0.24)*	
	5	1.53	0.12	1.66	0.19	0.93	1.66	0.22
		(0.30)		*(0.31)*		*(0.46)*	*(0.32)*	
UK	2	0.41	0.08	0.42	0.09	0.32	0.42	0.14
		(0.10)		*(0.13)*		*(0.11)*	*(0.13)*	
	3	0.84	0.11	0.77	0.09	0.69	0.77	0.16
		(0.19)		*(0.23)*		*(0.19)*	*(0.22)*	
	4	1.22	0.11	1.10	0.09	0.99	1.10	0.16
		(0.28)		*(0.31)*		*(0.28)*	*(0.31)*	
	5	1.53	0.10	1.42	0.10	1.16	1.42	0.15
		(0.35)		*(0.38)*		*(0.36)*	*(0.38)*	
US	2	0.45	0.16	0.58	0.16	0.10	0.58	0.16
		(0.09)		*(0.15)*		*(0.48)*	*(0.15)*	
	3	0.86	0.18	1.14	0.18	0.56	1.14	0.18
		(0.17)		*(0.32)*		*(0.83)*	*(0.30)*	
	4	1.25	0.20	1.66	0.19	0.98	1.66	0.20
		(0.23)		*(0.46)*		*(1.03)*	*(0.44)*	
	5	1.43	0.17	1.91	0.17	0.80	1.91	0.17
		(0.28)		*(0.59)*		*(1.27)*	*(0.57)*	

Table 16. *This table illustrates the CP- and GCP regressions as well as the joint regressions for data covering 1975.01 - 2020.12. We use Newey-West standard errors accounting for conditional heteroskedasticity and serial correlation up to twelve lags are presented in paranthesis.*

Local and Global CP regressions

Country	n	$b^{(n)}_{c,CP}$	R^2	$b^{(n)}_{c,GCP}$	R^2	$b^{(n)}_{c,CP}$	$b^{(n)}_{c,GCP}$	R^2
US	2	0.44	0.10	0.50	0.08	0.50	0.50	0.10
		(0.12)		*(0.23)*		*(0.39)*	*(0.25)*	
	3	0.85	0.09	0.92	0.07	0.83	0.92	0.09
		(0.22)		*(0.43)*		*(0.68)*	*(0.48)*	
	4	1.24	0.10	1.32	0.07	1.17	1.32	0.10
		(0.29)		*(0.62)*		*(0.93)*	*(0.68)*	
	5	1.47	0.08	1.58	0.07	1.15	1.58	0.08
		(0.33)		*(0.77)*		*(1.14)*	*(0.86)*	
Germany	2	0.34	0.05	0.55	0.11	0.12	0.55	0.12
		(0.15)		*(0.18)*		*(0.22)*	*(0.20)*	
	3	0.79	0.08	1.12	0.12	0.44	1.12	0.14
		(0.28)		*(0.35)*		*(0.45)*	*(0.39)*	
	4	1.23	0.10	1.56	0.12	0.81	1.56	0.15
		(0.39)		*(0.47)*		*(0.64)*	*(0.54)*	
	5	1.64	0.11	1.88	0.10	1.20	1.88	0.15
		(0.47)		*(0.56)*		*(0.79)*	*(0.65)*	
UK	2	0.42	0.15	0.60	0.09	0.42	0.60	0.16
		(0.10)		*(0.25)*		*(0.26)*	*(0.28)*	
	3	0.85	0.16	1.09	0.09	0.76	1.09	0.16
		(0.20)		*(0.44)*		*(0.46)*	*(0.49)*	
	4	1.21	0.15	1.45	0.08	1.04	1.45	0.16
		(0.29)		*(0.57)*		*(0.63)*	*(0.65)*	
	5	1.52	0.14	1.73	0.7	1.25	1.73	0.14
		(0.36)		*(0.67)*		*(0.78)*	*(0.78)*	
Japan	2	0.36	0.24	0.60	0.23	0.23	0.60	0.27
		(0.08)		*(0.16)*		*(0.11)*	*(0.16)*	
	3	0.81	0.29	1.33	0.27	0.53	1.33	0.33
		(0.15)		*(0.32)*		*(0.20)*	*(0.31)*	
	4	1.23	0.31	1.98	0.28	0.80	1.98	0.34
		(0.19)		*(0.44)*		*(0.26)*	*(0.42)*	
	5	1.60	0.32	2.57	0.29	1.01	2.57	0.35
		(0.23)		*(0.53)*		*(0.30)*	*(0.50)*	
Switzerland	2	0.40	0.20	0.51	0.07	0.45	0.51	0.23
		(0.10)		*(0.23)*		*(0.19)*	*(0.26)*	
	3	0.81	0.24	0.99	0.09	0.78	0.99	0.25
		(0.16)		*(0.39)*		*(0.30)*	*(0.43)*	
	4	1.21	0.24	1.36	0.09	1.06	1.36	0.25
		(0.20)		*(0.51)*		*(0.39)*	*(0.56)*	
	5	1.57	0.24	1.65	0.09	1.32	1.65	0.25
		(0.23)		*(0.61)*		*(0.48)*	*(0.67)*	

Table 17. *Regression Estimates 1988.01 - 2020.12. We use Newey-West standard errors accounting for conditional heteroskedasticity and serial correlation up to twelve lags are presented in paranthesis.*

	Germany						
n	$\beta^n_{c,CP}$	R^2	$\beta^n_{c,GCP}$	R^2	$\beta^n_{c,CP}$	$\beta^n_{c,GCP}$	R^2
1	3.57	0.01	-0.04	0.00	4.48	-0.04	0.02
2	12.90**	0.10	9.10	0.03	11.94	9.00	0.10
3	13.16*	0.07	20.31*	0.11	7.73	20.19	0.13*
4	16.26	0.09	35.48***	0.27	6.08	35.44	0.28**
5	9.35	0.03	44.88***	0.33	-4.41	44.87	0.34**
	United Kingdom						
n	$\beta^n_{c,CP}$	R^2	$\beta^n_{c,GCP}$	R^2	$\beta^n_{c,CP}$	$\beta^n_{c,GCP}$	R^2
1	2.72	0.02	2.39	0.01	2.86	2.39	0.02
2	6.55***	0.08	9.91	0.06	4.87	9.67	0.09**
3	10.08***	0.16	17.78***	0.16	6.41	17.51	0.20***
4	11.72**	0.17	25.69***	0.29	5.03	26.02	0.31***
5	10.05	0.11	26.71***	0.25	2.33	26.72	0.26***
	United States						
n	$\beta^n_{c,CP}$	R^2	$\beta^n_{c,GCP}$	R^2	$\beta^n_{c,CP}$	$\beta^n_{c,GCP}$	R^2
1	-1.65	0.01	0.88	0.00	-10.28	0.88	0.06**
2	0.09	0.00	4.19	0.01	-11.91	3.97	0.06
3	6.30	0.03	10.78	0.06	-5.44	10.63	0.07
4	12.33*	0.09	18.75**	0.15	-3.07	18.67	0.15
5	15.25*	0.12	20.25*	0.14	4.19	20.40	0.14
	Switzerland						
n	$\beta^n_{c,CP}$	R^2	$\beta^n_{c,GCP}$	R^2	$\beta^n_{c,CP}$	$\beta^n_{c,GCP}$	R^2
1	3.34	0.02	4.22	0.01	2.90	4.22	0.02
2	10.44**	0.10	18.22*	0.08	7.89	18.64	0.13**
3	12.23*	0.09	32.11***	0.17	7.02	32.56	0.19**
4	9.75	0.05	49.75***	0.30	1.00	49.84	0.30***
5	2.75	0.00	58.80***	0.32	-7.16	57.69	0.34***
	Japan						
n	$\beta^n_{c,CP}$	R^2	$\beta^n_{c,GCP}$	R^2	$\beta^n_{c,CP}$	$\beta^n_{c,GCP}$	R^2
1	-2.02	0.01	-4.75	0.02	0.14	-4.75	0.02
2	-4.64	0.03	-5.58	0.01	-4.94	-5.45	0.03
3	-9.61***	0.09	-9.41	0.03	-12.30	-8.74	0.10**
4	-9.64**	0.09	-8.47	0.02	-13.58	-7.06	0.10
5	-7.59	0.05	-9.30	0.02	-8.48	-8.29	0.05

Table 18. *Local, Global and joint regression on excess stock returns for one-to-five year returns. Significance are given by '*', where ***, ** and * represent p-values lower than the 1%, 5% and 10% significance value. We use Newey-West standard errors accounting for conditional heteroskedasticity and serial correlation up to twelve lags are presented in paranthesis.*

Germany							
lags	const	y1	f2	f3	f4	f5	R2
1.00	0.41	-0.70	-0.19	2.32	-2.54	1.31	0.09
s.e	(0.85)	(-0.53)	(-0.06)	(0.55)	(-0.73)	(0.72)	
2.00	0.42	-0.56	-0.60	2.83	-2.85	1.38	0.09
s.e	(0.85)	(-0.37)	(-0.16)	(0.53)	(-0.63)	(0.64)	
3.00	0.41	-0.58	-0.38	2.39	-2.54	1.32	0.10
s.e	(0.86)	(-0.45)	(-0.12)	(0.63)	(-0.83)	(0.79)	
4.00	0.37	-0.50	-0.27	1.69	-1.79	1.10	0.10
s.e	(0.77)	(-0.42)	(-0.11)	(0.51)	(-0.64)	(0.74)	
5.00	0.38	-0.69	0.14	2.15	-3.27	1.90	0.11
s.e	(0.90)	(-0.60)	(0.05)	(0.63)	(-1.17)	(1.28)	
6.00	0.42	-0.70	0.22	2.19	-3.51	2.04	0.13
s.e	(1.08)	(-0.75)	(0.10)	(0.80)	(-1.33)	(1.39)	
7.00	0.50	-0.71	0.36	1.52	-2.43	1.49	0.14
s.e	(1.34)	(-0.94)	(0.22)	(0.83)	(-1.39)	(1.34)	

United Kingdom							
lags	const	y1	f2	f3	f4	f5	R2
1.00	-0.45	-0.27	-1.49	0.19	3.25	-1.37	0.22
s.e	(-0.58)	(-0.20)	(-0.54)	(0.08)	(2.99)	(-1.82)	
2.00	-0.49	-0.16	-1.61	0.09	3.40	-1.41	0.21
s.e	(-0.61)	(-0.10)	(-0.50)	(0.04)	(2.93)	(-1.72)	
3.00	-0.52	-0.17	-1.47	-0.14	3.51	-1.39	0.21
s.e	(-0.65)	(-0.11)	(-0.45)	(-0.05)	(2.89)	(-1.66)	
4.00	-0.54	-0.20	-1.33	-0.33	3.59	-1.38	0.21
s.e	(-0.69)	(-0.13)	(-0.41)	(-0.12)	(2.94)	(-1.67)	
5.00	-0.60	-0.20	-1.27	-0.50	3.73	-1.39	0.22
s.e	(-0.78)	(-0.13)	(-0.37)	(-0.17)	(2.89)	(-1.60)	
6.00	-0.61	-0.19	-1.27	-0.58	3.84	-1.43	0.22
s.e	(-0.79)	(-0.12)	(-0.36)	(-0.19)	(2.77)	(-1.61)	
7.00	-0.55	-0.23	-1.25	-0.39	3.63	-1.40	0.22
s.e	(-0.71)	(-0.15)	(-0.38)	(-0.14)	(2.87)	(-1.69)	

United States							
lags	const	y1	f2	f3	f4	f5	R2
1.00	-0.95	0.77	-2.21	1.18	0.76	0.11	0.15
1.00	(-0.72)	(0.71)	(-1.39)	(0.82)	(0.77)	(0.18)	
2.00	-0.95	0.96	-2.60	1.45	0.86	-0.04	0.16
2.00	(-0.70)	(0.81)	(-1.42)	(0.95)	(0.81)	(-0.06)	
3.00	-0.95	1.16	-2.98	1.69	0.95	-0.17	0.17
3.00	(-0.69)	(0.92)	(-1.50)	(1.03)	(0.83)	(-0.23)	
4.00	-0.97	1.48	-3.44	1.89	0.91	-0.15	0.19
4.00	(-0.73)	(1.19)	(-1.69)	(1.07)	(0.82)	(-0.19)	
5.00	-0.84	1.77	-3.81	2.17	0.69	-0.12	0.22
5.00	(-0.69)	(1.66)	(-2.03)	(1.12)	(0.75)	(-0.16)	
6.00	-0.66	1.86	-3.74	2.19	0.43	-0.03	0.23
6.00	(-0.59)	(1.98)	(-2.02)	(1.04)	(0.52)	(-0.04)	
7.00	0.19	1.38	-1.82	1.06	-0.28	0.29	0.28
7.00	(0.23)	(3.38)	(-1.75)	(0.77)	(-0.73)	(0.70)	

Switzerland							
lags	const	y1	f2	f3	f4	f5	R2
1.00	0.07	1.11	-3.68	2.43	1.71	-1.16	0.27
s.e	(0.10)	(1.18)	(-0.90)	(0.21)	(0.10)	(-0.14)	
2.00	0.05	1.39	-4.24	2.86	1.66	-1.22	0.30
s.e	(0.07)	(1.34)	(-0.90)	(0.21)	(0.09)	(-0.13)	
3.00	0.00	1.47	-4.17	2.48	1.95	-1.25	0.31
s.e	(0.00)	(1.32)	(-0.81)	(0.17)	(0.09)	(-0.12)	
4.00	-0.08	1.60	-4.55	3.78	-0.20	-0.11	0.32
s.e	(-0.10)	(1.46)	(-0.91)	(0.27)	(-0.01)	(-0.01)	
5.00	-0.13	1.85	-6.00	7.89	-5.53	2.34	0.33
s.e	(-0.17)	(1.73)	(-1.27)	(0.59)	(-0.29)	(0.25)	
6.00	-0.16	2.02	-7.25	11.53	-10.25	4.50	0.35
s.e	(-0.21)	(1.93)	(-1.67)	(0.96)	(-0.60)	(0.52)	
7.00	-0.17	2.08	-7.69	12.89	-12.06	5.33	0.37
s.e	(-0.23)	(2.02)	(-1.83)	(1.12)	(-0.73)	(0.63)	
Japan							
lags	const	y1	f2	f3	f4	f5	R2
1.00	0.17	0.08	1.25	0.03	0.23	-0.20	0.50
s.e	(1.70)	(0.12)	(1.08)	(0.05)	(1.00)	(-0.92)	
2.00	0.17	0.11	1.22	-0.01	0.27	-0.21	0.49
s.e	(1.69)	(0.16)	(0.99)	(-0.01)	(1.12)	(-0.95)	
3.00	0.17	0.15	1.17	-0.00	0.26	-0.18	0.48
s.e	(1.70)	(0.21)	(0.98)	(-0.01)	(1.10)	(-0.85)	
4.00	0.17	0.12	1.20	-0.01	0.27	-0.19	0.48
s.e	(1.68)	(0.17)	(0.99)	(-0.01)	(1.11)	(-0.90)	
5.00	0.17	0.04	1.31	-0.03	0.30	-0.24	0.49
s.e	(1.67)	(0.05)	(0.99)	(-0.04)	(1.14)	(-1.05)	
6.00	0.18	-0.05	1.47	-0.04	0.31	-0.28	0.49
s.e	(1.70)	(-0.06)	(1.02)	(-0.05)	(1.11)	(-1.19)	
7.00	0.19	-0.10	1.64	-0.11	0.31	-0.31	0.49
s.e	(1.75)	(-0.13)	(1.11)	(-0.13)	(1.11)	(-1.25)	

Table 19. *Lagged regression on excess bond returns. We use Newey-West standard errors accounting for conditional heteroskedasticity and serial correlation up to twelve lags are presented in paranthesis..*