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Predictability of Bond Risk Premia

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Abstract

The notion of time-varying risk premia has great implications from an economic standpoint. We study the predictability of bond risk premia in the US, Australia, Canada, Switzerland, Germany, UK, and Japan, and whether predictive models can generate real-time excess returns. We find that Cochrane and Piazzesi's (2005) single factor is a significant driver of bond risk premia variations, although its significance has weakened lately. In contrast, Dahlquist and Hasseltoft's (2013) global single factor has increased in significance, on average explaining 20% of bond risk premia variations. The global single factor appears to produce real-time excess returns when adopting a simple trading setup with direction accuracy as the objective function.

Acknowledgments

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This thesis is the culmination of our formal education at BI and a product of insightful lectures by inspiring professors and educative discussions with fellow students. To them, we are thankful and enchantedly wish the best of luck in the forthcoming.

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1 Introduction and Motivation

The notion of time-varying risk premia[1] has great implications from an economic standpoint. For instance, actively managed funds (e.g., sovereign wealth funds, pension funds, and insurance firms, etc.) investing in bonds across the maturity spectrum would benefit from being able to shift its portfolio composition to the long end when long-term bond risk premia are expected to be positive, and vice versa. Similarly, actively managed stock funds would preferably over-/underweight the stock index depending on expected future stock risk premia.

The focus of this thesis is whether time-varying government bond risk premia are predictable and, if so, whether it can be exploited.[2] To explore this, we draw on insights from literature that find convincing evidence of time-varying bond risk premia predictability (e.g., Campbell & Shiller, 1991; Cochrane & Piazzesi, 2005; Dahlquist & Hasseltoft, 2013; Fama & Bliss, 1987). Cochrane and Piazzesi (2005) find that a single return-forecasting factor explains time-variation in annual excess returns of all bonds in the US with an R^2 up to 44%. Induced by the integration of world financial markets, Dahlquist and Hasseltoft (2013) form a global single factor and find evidence for predictability in annual excess bond returns in several countries.[3] Motivated by these, we define **research question one** as follows: Are the results for the single factor and the global single factor still valid? Particularly, do these factors significantly explain bond risk premia variations during 1992–2017? Additionally, we assess

[1] We use *risk premia* and *excess returns*, interchangeably, referring to returns in excess of the risk-free rate.

[2] Governments bonds in developed nations generally assume negligible default risk (because of stable currencies, ability to print money, etc). However, changing interest rates make investing in government bonds risky, and this risk source may be time-varying (unless adopting a buy-and-hold-to-maturity strategy).

[3] These countries are USA, Australia, Canada, Switzerland, Germany, UK, Japan, New Zealand, Norway, and Sweden.

whether the single factor and global single factor have forecasting power for one- to five-year stock risk premia, motivated by Fama and French (1989).[4]

To see if the potential predictability can be exploited by investors we try to answer **research question two**, defined as follows: Do the single factor or the global single factor have predictive power in real-time? Our results indicate that bond risk premia are predictable and that generating real-time excess returns seems possible. Most interesting, the global single factor has become more relevant in explaining excess bond return variations, whereas the single factor's relevance has weakened.

We ask these questions in an international context. Specifically, we assess the predictability of time-varying bond risk premia in the US, Australia, Canada, Switzerland, Germany, UK, and Japan.[5,6] Undeniably, the literature offer most insights from U.S. markets, the reason being that the US has the most liquid capital markets in the world and most data available.[7] Therefore, throughout the thesis we present findings, tables and figures for the US, and include results for DEU in Section 4.3, regarding the global single factor, to show how the factor works in an additional country. The tables in the main text are excerpts from the full tables, which, together with figures for all countries, are in the Appendices.

The thesis continues as follows: In Section 2, we present the data we use. In Section 3 we outline basics of fixed income securities, including how government bond yield data is constructed, before briefly reviewing literature on the term structure of interest rates. In Section 4, we review the findings of our main

[4]They find that the term spread of interest rates tracks a component of expected excess returns that is similar for all risky assets.

[5]These countries are chosen because they are developed nations and span widely the global economic market.

[6]Later in the thesis, country names are abbreviated: Australia (AUS), Canada (CAN), Germany (DEU), Switzerland (CHE), UK (GBR), and Japan (JPN).

[7]Data from SIFMA (2018) show that outstanding one- to ten-year maturity government bonds in the US amount to roughly $9,000 billion, nearly 25% of the total gross domestic product of the countries we examine. Each day, on average $400 billion are traded, nearly 1% of the total gross domestic product.

sources (Cochrane & Piazzesi, 2005; Dahlquist & Hasseltoft, 2013; Fama & Bliss, 1987) and answer research question one by replicating their methods and applying these to extended data samples. We assess research question two in Section 5 and conclude in Section 6.

2 Data

In this section we outline the data we use. We aim to give a detailed representation of sources and other prominent features to accurately conceive the data reliability, as well as its fit for our empirical investigation.

2.1 Gross Domestic Product and Recession Dates

We collect quarterly gross domestic product (GDP) data for the US, Switzerland, Germany, and UK from OECD (2018). Figure 2.1 shows each country's GDP-weight from 1980 to 2017. The data is in US dollars and purchasing power parity-adjusted. We collect recession data for the US from National Bureau of Economic Research (NBER, 2010) and for the other countries from Economic Cycle Research Institute (ECRI, 2018).

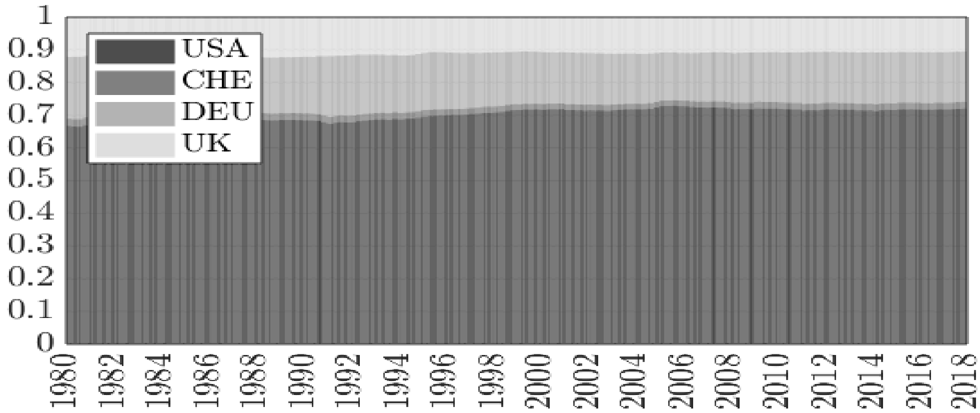


Figure 2.1: Monthly GDP-weights.
Time-series of monthly purchasing power parity-adjusted GDP weights of USA, CHE, DEU, and UK. Sample period: 1980-2018. These are the weights in the GCP factor (Dahlquist & Hasseltoft, 2013).

2.2 Government Bond Yields

We use end-of-month zero-coupon government bond yields with one- to five-years to maturity.[8] We obtain this data from various sources. Yield data ending in May 2009 is from Wright (2011). Yield data up to and including

[8]If the last day of a given month is on weekends or calendar holidays (when bond markets are closed), yields are from the last opening day.

2017 is from the countries' central banks. For the US, we use two data sets: the Fama-Bliss Discount Bond Rates from CRSP (2018a) and Treasury yields estimated by Gürkaynak, Sack, and Wright (2007). The yields are estimated with various methods.[9] Table 2.1 depicts the countries we examine in this thesis, including the estimation method of each data set as well as start and end dates.

Country	Identifier	Source	Start	End	#Obs.	Est. method.
USA	USA	CRSP (2018a)	1964.01	2017.12	648	Fama-Bliss
USA	USA^2	Gürkaynak et al. (2007)*	1964.01	2017.12	648	Svensson
Australia	AUS	RBA (2018)	1992.07	2017.12	306	Spline (MLES)
Australia	AUS^2	Wright (2011)	1987.02	2009.05	268	Nelson-Siegel
Canada	CAN	BOC (2018)*	1986.01	2017.12	384	Spline (MLES)
Switzerland	CHE	SNB (2018)	1988.01	2017.12	360	Ext.Nelson-Siegel
Switzerland	CHE^2	Wright (2011)	1988.01	2009.05	257	Svensson
Germany	DEU	Bundesbank (2018)*	1973.01	2017.12	540	Svensson
UK	GBR	BOE (2018)*	1972.12	2017.12	541	Spline (VRP)
Japan	JPN	MOF (2018)	1980.08	2017.12	449	Spline (Cubic)
Japan	JPN^2	Wright (2011)	1985.01	2009.05	293	Svensson

Table 2.1: Bond Data Details.
*Details and sources of end-of-month bond yields. CRSP: Center for Research in Security Prices, FED: Federal Reserve, RBA: Reserve Bank of Australia, BOC: Bank of Canada, SNB: Swiss National Bank, MOF: Ministry of Finance. *: Updated version of Wright (2011).*

2.3 Stock Returns

We gather end-of month value-weighted stock returns for the US from CRSP (2018b), and for the other countries from French's Data Library.[10] U.S. stock returns are value-weighted returns for firms listed on AMEX, NYSE, and NASDAQ. French's data is from Morgan Stanley Capital International for 1975–2006 and from Bloomberg for 2007–2017. Table 2.2 depicts details and sources of the stock data we use.[11]

[9] See Section 3.3 for an outline of estimation methods in general.
[10] Returns are in local currency unit, that is, no foreign exchange affects the portfolio return.
[11] See Appendix A on how we compute returns and dividend-price ratios.

Country	Identifier	Source	Start	End	#Obs.	Currency
USA	USA	CRSP (2018b)	1963.01	2017.12	660	USD
Australia	AUS	French (2018)	1975.01	2017.12	516	AUD
Canada	CAN	French (2018)	1977.01	2017.12	492	CAD
Switzerland	CHE	French (2018)	1975.01	2017.12	516	CHF
Germany	DEU	French (2018)	1975.01	2017.12	516	EUR
UK	GBR	French (2018)	1975.01	2017.12	516	GBP
Japan	JPN	French (2018)	1975.01	2017.12	516	JPY

Table 2.2: Stock Data Details. *Details and sources of end-of-month value-weighted local stock returns.*

2.4 Descriptive Statistics and Diagnostics

For our sample, average realized excess bond returns are significantly positive and time-varying, with standard deviation of around double the unconditional average. Bond yields are significantly positively correlated across maturities and across countries, as are the realized excess bond returns. This is also the case for excess stock returns.[12]

Furthermore, bond yields are non-stationary series that seem to inherit geometrically decreasing autocorrelations: One-month, one-year, and five-year autocorrelations lies in the intervals of around [0.96–0.99], [0.59–0.86], and [-0.13–0.33], respectively. As for annual excess bond returns, the respective autocorrelations lie in the intervals of around [0.90–0.95], [-0.28–0.20], and [-0.06–0.10], thus showing tendency of stationarity. However, from stationarity tests of Kwiatkowski, Phillips, Schmidt, and Shin (1992) and Dickey and Fuller (1979) the results are twofold: Some countries' realized annual excess bond returns are stationary, while some are not.[13] The same is true for realized annual excess stock returns. We keep this in mind when interpreting parameter estimates throughout the thesis.[14]

[12] Descriptive statistics and correlations of realized excess bond returns during 1992.12–2017.12 are in Appendix B.1 and B.3, respectively. Correlations of yields during 1992.12–2017.12 are in Appendix B.3. Descriptive statistics and correlations of realized excess stock returns and dividend-price ratios during 1992.12–2017.12 are in Appendix B.2 and Appendix B.3, respectively.

[13] Bond yield and excess bond and stock return diagnostics are in Appendix B.4.

[14] Non-stationary regression variables implode statistical inferences, consequentially making parameter estimates unreliable.

3 Basics of Fixed Income

In this section, we review aspects of fixed income markets relevant to our investigation. First, we outline how prices, yields, forwards, and returns of government bonds are computed and related. Second, we outline some government bond market dynamics and its link to other asset markets. Third, we describe how the bond yield data we use are constructed, before briefly reviewing the literature on term structure of interest rates in Section 3.4.

3.1 Prices, Yields, Forwards, and Returns

The issuer of a zero-coupon bond promises to pay the bond's face value at its maturity. We denote the price of a time t τ-year maturity zero-coupon bond as $B_t^{(\tau)}$.[15] By assuming the face value to be one unit of account, $B_t^{(0)} = 1$. $B_t^{(\tau)}$ is the *market discount factor* and reflects how the aggregated investor values the face value at time t. Theoretically, since lenders will demand to receive a higher amount than they provide, the value of bonds decrease with time to maturity (i.e., $\tau \geq 0$ leads to $B_t^{(\tau)} \leq 1$), ceteris paribus.[16] The *market discount function* is the bond price, $B_t^{(\tau)}$, as a function of time to maturity ($\tau \mapsto B_t^{(\tau)}$). By convention, $B_t^{(\tau)}$ is quoted in annual yields (Brown, 1998, p. 23). A graph that plots $B_t^{(\tau)}$ as a function of τ is called the *term structure of discount factors.*

At time t, a τ-year maturity bond's continuously compounded yield, $y_t^{(\tau)}$, and price is related by,

$$B_t^{(\tau)} = e^{-y_t^{(\tau)} \cdot \tau} \qquad \Leftrightarrow \qquad y_t^{(\tau)} = -\frac{1}{\tau} \cdot \ln B_t^{(\tau)}. \tag{1}$$

[15]The notation we use is inspired by Munk (2011) and Cochrane (2005).

[16]However, this is can be violated in practice. The impact of unconventional monetary policy implementations world-wide witnessed after the global financial crisis have given rise to negative yields.

Thus, a spot rate is the annual return an investor would earn on the zero-coupon bond from t to $t+\tau$. The time t *term structure of interest rates*[17] is a graph that plots spot rates as a function of τ ($\tau \mapsto y_t^{(\tau)}$), and it conveys the same information as the market discount function. Figure 3.1 shows the one- to five-year yield curve each month from 1964–2017 in the US. Clearly, the yield curve changes shape and level over time. Forward rates are time

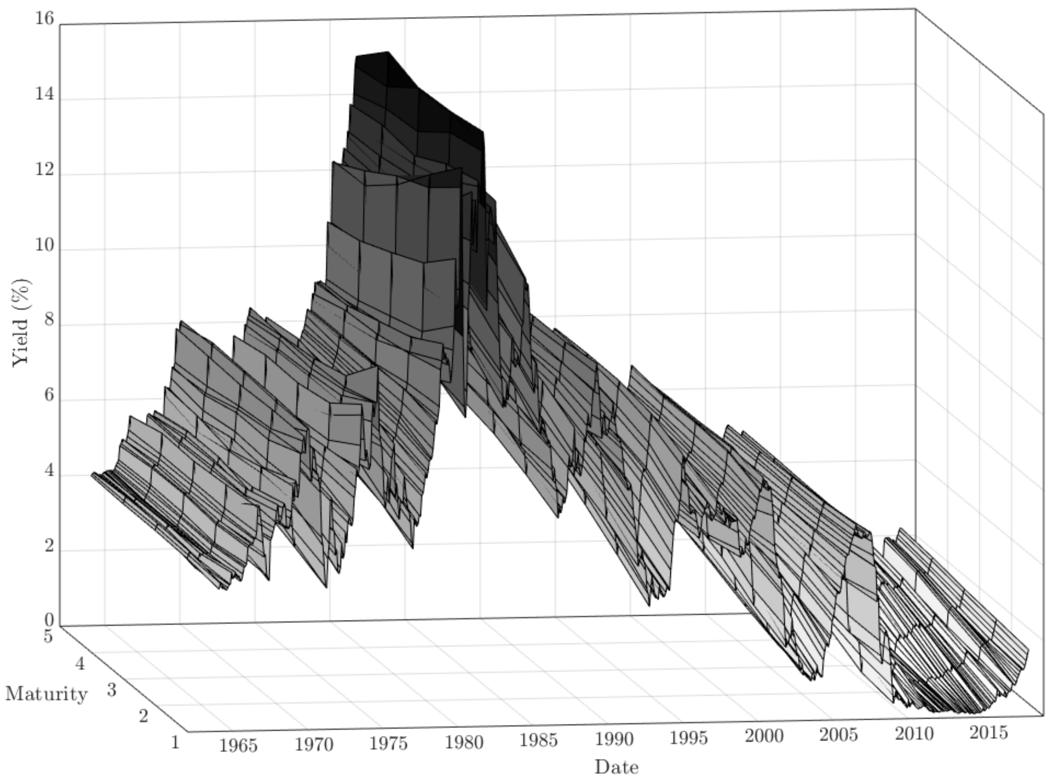


Figure 3.1: U.S. Term Structure of Interest Rates.
Monthly one- to five-year term structure of interest rates. Yields are the Fama-Bliss Discount Bond data from CRSP (2018a). Sample period: 1964.01–2017.12.

t annual interest rates on loans that begins at τ_1 and matures at τ_2 ($\geq \tau_1$). Continuously compounded forward rates are given by

$$B_t^{(\tau_2)} = B_t^{(\tau_1)} e^{-f_t^{(\tau_1,\tau_2)} \cdot (\tau_2 - \tau_1)} \quad \Leftrightarrow \quad f_t^{(\tau_1,\tau_2)} = \frac{y_t^{(\tau_2)}\tau_2 - y_t^{(\tau_1)}\tau_1}{\tau_2 - \tau_1}.$$

Here we see the relation between spot and forward rates. Forward rates reflect the slope of the yield curve between two maturities. Assuming a fully

[17] Also referred to as the (zero-coupon) yield curve, or spot rate curve.

differentiable yield curve, spot rates equal the average of connecting forward rates:

$$y_t^{(\tau)} = \frac{1}{\tau} \int_{T-\tau}^{\tau+t} f_t^{(T-\tau,u)} du, \tag{2}$$

where $\tau = (T - t)$ is time to maturity and u is the maturity increment on the yield curve.

Buying a τ-year zero-coupon bond at price $B_t^{(\tau)}$ and selling it at $B_{t+1}^{(\tau)}$ yields the holding period return[18]

$$r_{t+1}^{(\tau)} = \ln B_{t+1}^{(\tau)} - \ln B_t^{(\tau)}.$$

The one-year realized excess return (or risk premium) is then

$$rx_{t+1}^{(\tau)} = r_{t+1}^{(\tau)} - y_t^{(1)}.$$

3.2 Government Bond Markets – Stylized Facts

Nominal yields on short-term bonds[19] are believed to be solely affected by central banks' monetary policy implementations. Bernanke (2013) states that short-term nominal yields are even "controlled" by a central bank's actions. In contrast, long-term nominal yields are believed to be determined by factors outside central banks' control.[20] Fundamentally, long-term nominal yields are believed to be composed of the expected real yield (r), expected inflation (π), and a risk premium (RP) (Veronesi, 2016, p. 9).[21] In equation form,

$$\text{Nominal yield} = \mathbb{E}_t[r] + \mathbb{E}_t[\pi] + \mathbb{E}_t[RP]. \tag{3}$$

[18] We use $B_{t+1}^{(\tau)}$ to indicate the same bond, although it matures in $(\tau - 1)$-years at time $t + 1$.
[19] Bonds which mature in less than one year.
[20] However, unconventional monetary policy actions such as quantitative easing attempts to influence factors affecting nominal yields on long-term bonds in order to spur economic activity (Krishnamurthy & Vissing-Jorgensen, 2011, p. 215).
[21] This is a modified version of the Fisher Equation.

The shape of the yield curve can be explained by any combination of the three economic drivers in Equation (3).

Table 3.1 depicts mean, standard deviation, and correlations of end-of-month nominal yields on one- to five-year maturity government bonds in the US during 1992–2017.[22] From row two and three, we see that the yield curve shape

	$y_t^{(1)}$	$y_t^{(2)}$	$y_t^{(3)}$	$y_t^{(4)}$	$y_t^{(5)}$
Mean	2.76	3.01	3.26	3.49	3.67
S.D.	2.21	2.18	2.10	2.01	1.92
			Correlations		
$y_t^{(1)}$	**1.00**				
$y_t^{(2)}$	0.99	**1.00**			
$y_t^{(3)}$	0.98	1.00	**1.00**		
$y_t^{(4)}$	0.97	0.99	1.00	**1.00**	
$y_t^{(5)}$	0.95	0.98	0.99	1.00	**1.00**
USA	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
AUS	0.75	0.79	0.82	0.84	0.86
CAN	0.91	0.92	0.93	0.94	0.95
CHE	0.76	0.82	0.85	0.87	0.89
DEU	0.79	0.84	0.87	0.89	0.91
GBR	0.91	0.93	0.94	0.94	0.95
JPN	0.44	0.55	0.63	0.70	0.75

Table 3.1: Descriptive Statistics - U.S. Bond Yields.
Mean, standard deviation, and correlation of one- to five-year maturity bond yields in the US. Numbers in the last seven rows are correlations with yields in other countries. The full bond yield correlations table is in Appendix B.3. Sample period: 1992.12–2017.12.

changes significantly over time but is on average upward sloping. Further, the correlation between yields on two- to five-year maturity bonds are almost perfectly positively correlated. Figure 3.2, depicts the time series of two- to five-year yield spread in the US for the time period 1964–2017.[23] Yield spreads excerpt part of the term structure of interest rates and give some information about its shape.[24] Minding Equation (3), r is believed to be affected by the general real investment return on assets in the economy (Hamilton, Harris, Hatzius, & West, 2016); π is what bond investors demand today to avoid

[22] The full bond yield correlations table is in Appendix B.3.
[23] Figures for other countries are in Appendix C.1.
[24] The shape of the function that maps the term structure of interest rates is theoretically continuous and has infinitely many function values.

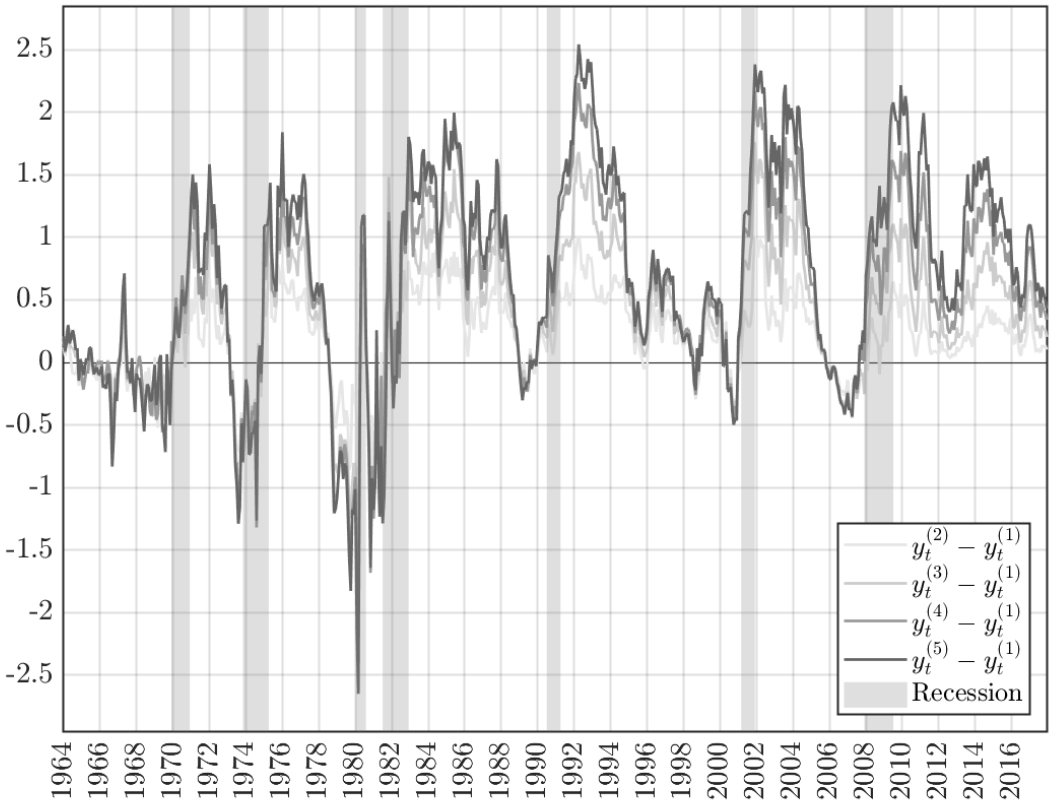


Figure 3.2: U.S. Yield Spreads.
Two-, three-, four-, and five-year yield spreads (in percent) in the US. Yields are the Fama-Bliss Discount Bond data from CRSP (2018a). Shaded areas are NBER (2010) recession periods. Sample period 1964.01–2017.12.

reduced purchasing power over the investment horizon, while RP[25] act as compensation for being exposed to specific bond risks, like the risk of changing interest rates. Interest rate risk depends on the interest rate-sensitivity[26] of longer-maturity bonds, illustrating that the capital gain/loss risk of liquidating a long-term bond position before maturity can be significant. Even though bond investors don't expect to liquidate before maturity, situations can arise where they are forced. For instance, insurance companies may need to liquidate positions to raise cash if insurance claims become unanticipatedly high. Furthermore, regulatory restrictions could force insurance companies and pension funds to offload negative mark-to-market positions, consequentially pushing prices down further.

[25] Also referred to as the *term premium*.
[26] Also referred to as *duration*.

Table 3.2 contains descriptive statistics of realized one-year risk premia on two- to five-year maturity bonds in the US for 1992–2017.[27] The

	Mean	I.	II.	SR	I.	II.	Obs.	I.	II.
$rx_{t+1}^{(2)}$	0.59**	1.57**	0.49**	0.52	2.19	0.44	289	26	263
$rx_{t+1}^{(3)}$	1.22**	3.04**	1.04**	0.55	2.42	0.47	289	26	263
$rx_{t+1}^{(4)}$	1.81**	3.96**	1.59**	0.57	1.89	0.50	289	26	263
$rx_{t+1}^{(5)}$	2.18**	4.68**	1.94**	0.54	1.91	0.47	289	26	263

Table 3.2: Descriptive Statistics - U.S. Bond Risk Premia.
*One-year mean excess bond return, Sharpe ratio (SR) and observations on two- to five-year maturity bonds in the US. Mean, Sharpe ratio and number of observations in columns I and II are conditioned on buying in recession and non-recession periods (defined by NBER (2010)), respectively. **: p-value < 0.01, *: p-value < 0.05. Sample period: 1992.12–2017.12.*

unconditional historical average (in percent) of one-year risk premium on the two-year maturity bond is 0.59% while the standard deviation is 1.14%, resulting in a Sharpe ratio of 0.52.[28] Both the unconditional mean and the standard deviation is monotonically increasing with the maturity of the bond, illustrating the concept of increased duration risk of longer maturity bonds.

Numbers in columns I and II in Table 3.2 are average one-year excess returns and Sharpe ratios in recession and non-recession periods, respectively. We see that the ex post one-year average excess returns in recession periods are between 3 and 5 times higher than the unconditional averages and statistically significant. Interestingly, the Sharpe ratios are around 4–5 times higher for the 26 monthly recession observations in the US in 1992–2017. Thus, the historical one-year reward to risk of investing in risky (long-term) bonds is much higher in recession periods.

In Table 3.3, we see that the one-year bond risk premia on two- to five-year maturity bonds in the US, and across countries, are significantly positively correlated.[29] We see from Figure 3.2 that, historically, bond yield spreads in recessions in the US have increased almost universally, meaning that the yield

[27] The table for all countries is in Appendix B.1.
[28] Sharpe Ratio is defined as the excess return as a proportion of the risk measured in standard deviation (Sharpe, 1994).
[29] This is consistent for the other countries as well, see Appendix B.3.

	$rx^{(2)}_{t+1}$	$rx^{(3)}_{t+1}$	$rx^{(4)}_{t+1}$	$rx^{(5)}_{t+1}$
$rx^{(2)}_{t+1}$	**1.00**			
$rx^{(3)}_{t+1}$	0.98	**1.00**		
$rx^{(4)}_{t+1}$	0.94	0.98	**1.00**	
$rx^{(5)}_{t+1}$	0.89	0.95	0.99	**1.00**
USA	**1.00**	**1.00**	**1.00**	**1.00**
AUS	0.52	0.57	0.63	0.67
CAN	0.72	0.74	0.76	0.77
CHE	0.66	0.68	0.69	0.69
DEU	0.60	0.63	0.67	0.70
GBR	0.67	0.71	0.75	0.77
JPN	0.29	0.33	0.36	0.40

Table 3.3: Correlation - U.S. Bond Risk Premia.
Bond risk premia correlations for the US. Numbers in right-hand columns are correlations with bond risk premia in other countries. The full bond risk premia correlation table is in Appendix B.3. Sample period: 1993.12–2017.12.

curve steepens.[30] By minding Equation (3) when analyzing Figure 3.2, which driver can we say is the dominant factor affecting nominal yields (prices) to increase (decrease) during recession and decrease (increase) during expansions? Cochrane and Piazzesi (2005) document that risk premia are driving nominal yield variation on long-term bonds in the US. Dahlquist and Hasseltoft (2013) confirm that this is also the case for long-term bonds in other markets.[31]

To spot potential inconclusiveness of our research investigation, we dedicate Section 3.3 to briefly outline how the yield data that we use are constructed. Further, we dedicate the last subsection of 4 to a discussion on how the data affect the predictive regressions in Section 4 and 5.

3.3 Bond Yield Data Construction Methods

In section 3.1, we showed the mathematical relations governing bond prices and spot and forward rates. It is paramount to understand how zero-coupon bond data are constructed when pursuing empirical analysis in bond markets.

[30] This is also the case for long-term bond yields the other countries, see Appendix C.1.
[31] Lettau and Wachter (2011) argue that upward-sloping yield curves indicate that bond investors require compensation for holding high-duration assets in the form of a positive risk premium, and that time-varying preferences for risk are driving bond yield variations.

The market zero-coupon yield curve connects spot rates on bonds directly read from the market, either by observing spot rates on traded zero-coupon bonds or coupon bonds (the former being uncommon in practice because of insufficient outstanding zero-coupon bonds). As the market for government coupon bonds is vast, one can use the prices of these to derive implicit discount rates (and thus zero-coupon yields) that are consistent with prevailing market prices.

Denote bond payment i $(i = 1, \ldots, M)$ at time $t + j$ $(j = 1, \ldots, T)$ by C_i^{t+j}. In a frictionless market, and by no-arbitrage, the simplest pricing equation of a risk-free coupon bond, $P_{i,t}$, is the sum of discounted cash flows, thus

$$P_{i,t} = \sum_{j}^{T} C_i^{(t+j)} \cdot B_t^{(t+j)} = \sum_{j}^{T} C_i^{(t+j)} \cdot e^{-y_t^{(t+j)} \cdot (t+j)}. \tag{4}$$

Given a collection of traded coupon-bonds, $\boldsymbol{P_t} = (P_{1,t}, P_{2,t}, \ldots, P_{M,t})^T$, that pays coupons, $\boldsymbol{C_t}$, at distinct future dates from today, $t + j$ $(j = 1, \ldots, M)$, by Equation (4), the discount factors, $\boldsymbol{B_t}$, must satisfy

$$\boldsymbol{P_t} = \boldsymbol{C_t B_t} \quad \Leftrightarrow \quad \begin{pmatrix} P_{1,t} \\ P_{2,t} \\ \vdots \\ P_{M,t} \end{pmatrix} = \begin{pmatrix} C_1^{(t+1)} & C_1^{(t+2)} & \cdots & C_1^{(t+T)} \\ C_2^{(t+1)} & C_2^{(t+2)} & \cdots & C_2^{(t+T)} \\ \vdots & \vdots & \ddots & \vdots \\ C_M^{(t+1)} & C_M^{(t+2)} & \cdots & C_M^{(t+T)} \end{pmatrix} \begin{pmatrix} B_t^{(t+1)} \\ B_t^{(t+2)} \\ \vdots \\ B_t^{(t+T)} \end{pmatrix}.$$

The discount factors are found by solving the linear system,

$$\boldsymbol{B_t} = \boldsymbol{C_t^{-1} P_t}. \tag{5}$$

Thus, in deriving the implicit discount rates, the cash flow matrix of the traded bonds must be invertible. In practice, this method is impractical. Finding the necessary traded coupon bonds with distinct coupon dates that are independent of each other[32] is certainly unfeasible. Further, the bootstrapping coupon procedure[33] relies on that there exist at least one traded zero-coupon

[32] That is, one bond cannot be expressed as a linear combination of the others.
[33] Which is an iterative procedure using Equation (4) to compute implicit discount factors.

bond and coupon bonds that matures in a regular interval from the first discount factor and the second (Veronesi, 2010, p. 47). If these do not exist, the iterative process stops. Consequently, the implied discount function that is consistent with market prices cannot be inferred from the traded bonds.

By relaxing the assumption of no-arbitrage, we can estimate implied discount functions, although inconsistent with market prices. Bliss (1996) outlines a general framework for estimating the term structure of interest rates:

1. A pricing equation that relates the price of a coupon-bond, $P_{i,t}$, to the discount rate function, $\bar{y}_t(\tau) \equiv y_t^{(\tau)}$.[34]

2. A functional form to approximate the discount rate function, $\bar{y}_t(\tau)$.

3. An econometric method for estimating the parameters of the term structure function.

In practice, the market is characterized by frictions and other real-world features. The literature accounts for these features by incorporating an error term $\boldsymbol{\epsilon_t}$ into Equation (4), thus

$$\boldsymbol{P_t} = \boldsymbol{C_t}\boldsymbol{B_t} + \boldsymbol{\varepsilon_t}. \tag{6}$$

The error term accounts for influences that generate mispricing, such as illiquidity and other real-life factors (Veronesi, 2010, p. 67).

The term structure of discount rates is given by searching for values of $\boldsymbol{B_t}$ such that the pricing error, $\boldsymbol{\varepsilon_t}$, is minimized. To perform this optimisation exercise, one must decide the functional form acting as an approximate of the discount rate function and then estimate the parameters that minimize the pricing error (Bliss, 1996, p. 4).[35]

[34]Which is outlined in section 3.1: the discount rate function is a transformation of the market discount function via: $y_t^{(\tau)} = -\frac{1}{\tau}\ln B_t^{(\tau)}$

[35]See Appendix D for details on the functional forms that are used to construct the data we use.

3.4 Literature Review

Equation (3) depicts three components grounded on macroeconomic fundamentals believed to affect nominal yields on long-term government bonds. The Expectations Hypothesis (EH) of interest rates is the classic theory that relates to investors' expectations and preferences.

Expectations Hypothesis

Lutz (1940) postulated that investors, under certain assumptions, for a given investment horizon are indifferent to the structure of a government bond investment (e.g., with a one-year investment horizon they are indifferent to buying a 10-year maturity bond and selling it after one year and buying a one-year maturity bond). This postulation formed the EH, with three equivalent statements about the pattern of nominal yields (Cochrane, 2005, p. 355):

1. The annual yield on the τ-period maturity zero-coupon bond is equal to the average expected future one-period yields, plus a risk premium

$$y_t^{(\tau)} = \frac{1}{\tau} \cdot E_t \left(y_t^{(1)} + y_{t+1}^{(1)} + y_{t+2}^{(1)} + \cdots + y_{t+\tau-1}^{(1)} \right) + RP. \tag{7}$$

2. The forward rate on a synthetic one-period loan beginning in period τ equals the expected future one-period yield, plus a risk premium

$$f_t^{(\tau,\tau+1)} = E_t \left(y_{t+\tau}^{(1)} \right) + RP. \tag{8}$$

3. The expected one-period return on any government bond equals the current one-period yield, plus a risk premium

$$E_t \left(r_{t+1}^{(\tau)} \right) = y_t^{(1)} + RP. \tag{9}$$

By Equation (7), if the yield curve is upward sloping, the EH predicts expectation of rising future short-term yields, suggesting shorting short-term bonds.[36] But by Equation (9), any bond investment is predicted to yield the same return. Thus, the *equalization of bond returns* makes any bond investment equivalent.[37]

The EH restricts the risk premium to equal zero (Pure EH) or be constant over time. Hence, investors should not care about the structure of bond investments (i.e., be indifferent to roll-over and buy-and-hold strategies)[38] because of equal expected returns. However, if investors care about the structure, a bond's future price may generate time-varying risk premia, thus invalidating EH predictions. Since risks in different investment strategies may be time-varying, excess returns can be generated if these risks covary with the stochastic discount factor (Cochrane, 2005, p. 357). This is clear from Equation (11).

The *Discount Factor Existence Theorem*[39] states that there exists a stochastic discount factor m such that for any asset price p the relationship between p and payoff x of that asset obey

$$p = E[mx] \quad \Leftrightarrow \quad p = E[m] \cdot E[x] + cov(m, x). \tag{10}$$

Written in the *Expected Return-Beta representation*,[40] with gross return R as the proportion of x in p, Equation (10) becomes

$$E[R] - rf = \beta_{R,m} \cdot \lambda_m = \left(\frac{cov(R, m)}{var(m)} \right) \cdot \left(- \frac{var(m)}{E[m]} \right). \tag{11}$$

$E[R] - rf$ is the expected asset excess return, λ_m is the market price of risk and $\beta_{R,m}$ is the asset's market risk exposure. Thus, as long as $\beta_{R,m}$ is non-zero, so too will the expected excess return of that asset be (if $\lambda_m \neq 0$).

[36] Because rising yields means falling bond prices. See Section 3.1.
[37] Note: The RP's in Equation (7)–(9) are not necessarily equal.
[38] That is, buying new one-year bonds each year for T years vs. buying and holding T-year bonds to maturity.
[39] By Rubinstein (1976), Ross (1978) and Harrison and Kreps (1979). See Cochrane (2005, Chapter 4) for proof and details.
[40] See Cochrane (2005, p. 16).

Several researchers document strong empirical evidence against the EH (e.g., Cochrane & Piazzesi, 2005; Dahlquist & Hasseltoft, 2013; Fama & Bliss, 1987), suggesting modifications to Equation (7) to account for time-varying risk premia:

$$y_t^{(\tau)} = \frac{1}{\tau} \cdot E_t\left(\sum_{i=0}^{\tau-1} y_{t+i}^{(1)}\right) + RP_t. \tag{12}$$

By Equation (12), two components explain the yield curve: The expected path of short-term nominal yields and risk premia. Rising yield curves can therefore signal either rising expected future short-term nominal yields, high risk premia, or a combination of both. Looking back to Figure 3.2 and the steepening of the historical yield curve during U.S. recessions, which component dominantly drove nominal yields higher during these times? Was it higher expected future short-term yields or higher risk premia demands for holding long-term bonds under uncertain future economic prospects? Considering the recession following the recent financial crisis, it is easy in hindsight to say that higher risk premia demands probably were the dominant force. This documents consistency with assumptions about investors' risk aversion in prominent asset pricing models.[41] Hence, risk and expected (excess) returns are positively related: The risk and expected return trade-off governing investment decisions in foresight.

[41] Asset pricing models featuring habit persistence such as Campbell and Cochrane (1999) suggest that risk premia move counter-cyclically.

4 Predictive Regressions of Excess Returns

In this section, we review literature on excess bond return predictability with emphasis on Fama and Bliss (1987), Cochrane and Piazzesi (2005) and Dahlquist and Hasseltoft (2013). We replicate their methods and apply them to updated data to investigate whether risk premia are predictable. If so, we conclude on research question one that their result are still valid, and further by Equation (12), that expected bond risk premia are driving the level of nominal long-term bond yields. Furthermore, we examine whether their predictive variables explain a significant part of one-year excess bond and one- to five-year excess stock return variations. Finally, we discuss how data construction methods may affect the results.

4.1 Forward-Spot Spread Regressions

Fama and Bliss (1987) test the EH by running predictive regressions on U.S. Treasury Bonds, regressing one-year excess returns of τ-year maturity bonds on the spread between one-year forward rates commencing in $(\tau-1)$-years and the one-year spot interest rate,[42]

$$rx_{c,t+1}^{(\tau)} = \alpha_{c,t+1}^{(\tau)} + b_c^{(\tau)} \left(f_{c,t}^{(\tau-1,\tau)} - y_{c,t}^{(1)} \right) + \varepsilon_{c,t+1}^{(\tau)}, \tag{R.1}$$

$$\text{for } \tau = 2, 3, 4, 5.$$

They forecast annual excess returns of τ-year bonds with R^2 up to 18% with significant coefficient estimates, concluding that expected one-year excess returns for U.S. Treasury Bonds vary through time. By this, they find evidence against EH. However, they also find that the forward-spot spread seems to forecast short-term yield changes at longer horizons, in line with the EH (see Equation (8)).

[42] Also referred to the *forward-spot spread*.

Cochrane and Piazzesi (2005) apply their methodology on yields in 1964–2003 with the same conclusion. We apply their methodology on data up to and including 2017, with different sample periods. Results are in Table 4.1.[43] The

	(1)		(2)		(3)		(4)	
	1964.01–2003.12		**1964.01–2017.12**		**1992.12–2009.05**		**1992.12–2017.12**	
τ	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2
2	0.99**	0.16	0.83**	0.11	-0.09	0.00	0.03	0.00
	(4.27)		*(3.58)*		*(-0.18)*		*(0.07)*	
3	1.35**	0.17	1.13**	0.13	0.02	-0.01	0.26	0.01
	(4.39)		*(3.83)*		*(0.03)*		*(0.47)*	
4	1.61**	0.18	1.36**	0.15	0.01	-0.01	0.39	0.01
	(4.05)		*(3.95)*		*(0.01)*		*(0.74)*	
5	1.27**	0.08	1.12**	0.09	0.11	0.00	0.58	0.03
	(2.39)		*(2.87)*		*(0.16)*		*(1.18)*	

Table 4.1: Regression Results - Bonds - Forward-Spot Spread - USA.
*Estimates of Regression (R.1) in the US for four sample periods. T-statistics in parentheses use Newey and West (1987) standard error-correction with 18 lags. Adjusted R^2. Constant estimates are excluded. **: p-value $<$ 0.01, *: p-value $<$ 0.05.*

results confirm that forward-spot spreads in the period 1964–2003 statistically significantly predict one-year excess bond returns on two- to five-year maturity bonds with positive magnitudes (i.e., increases in forward-spot spreads increase one-year risk premia). However, the results by Fama and Bliss (1987) and Cochrane and Piazzesi (2005) weakens slightly for (2) and completely vanish in (3) and (4), showing R^2 of around 0% with non-significant estimated coefficients.

We conclude that the forward-spot spreads did not statistically significantly predict one-year bond risk premia in the US during these periods and cannot reject the constant risk premia predicted by the EH.[44]

4.2 Single-Factor Regressions

Cochrane and Piazzesi (2005) study variations in expected excess returns of U.S. Treasury bonds. They find that a single return-forecasting factor (CP

[43] See Appendix E.1 for the other countries' results during 1992–2017.

[44] Results for the other countries' in 1992.12–2017.12 our conclusion is mixed: forward-spot spreads did statistically significantly (though, some show low t-stats) influence the one-year bond risk premia on some bonds, see Appendix E.1.

factor) of forward rates explains variations in annual excess returns on *all* bonds, and predicts excess returns with an R^2 up to 44%, intensifying the evidence against the EH.

An important aspect of the CP factor is that it seems to predict annual excess bond returns of not only a specific τ-year maturity bond but of different maturity bonds. This finding is complementary to the factors Fama and Bliss (1987) and Campbell and Shiller (1991) construct, which only predict annual excess return on a specific τ-year bond. Moreover, the CP factor seems to capture information relevant in predicting annual excess bond returns unrelated to the factors that capture virtually all variation in excess bond returns: The level, slope, and curvature factors (Litterman & Scheinkman, 1991). Additionally, Cochrane and Piazzesi (2005) document that the CP factor has forecasting power for expected excess stock returns. In their sample, they document an R^2 of 15% when regressing excess stock returns on factors including moving average values of CP factor realizations.

According to Cochrane and Piazzesi (2005), the CP factor in a country (indicated by c) is formed by estimating the linear combinations of forward rates:

$$CP_t^{(c)} = \hat{\boldsymbol{\gamma}}_{\boldsymbol{c}}^{\intercal} \boldsymbol{f_{c,t}}$$

where

$$\boldsymbol{f_{c,t}} = \begin{bmatrix} 1 & y_{c,t}^{(1)} & f_{c,t}^{(1,2)} & f_{c,t}^{(2,3)} & f_{c,t}^{(3,4)} & f_{c,t}^{(4,5)} \end{bmatrix}^{\intercal},$$
$$\boldsymbol{\gamma_c} = \begin{bmatrix} \gamma_0^c & \gamma_1^c & \gamma_2^c & \gamma_3^c & \gamma_4^c & \gamma_5^c \end{bmatrix}^{\intercal}.$$

The coefficient vector $\hat{\boldsymbol{\gamma}}_{\boldsymbol{c}}^{\intercal}$ is estimated by the regression:

$$\frac{1}{4}\sum_{\tau=2}^{5} rx_{c,t+1}^{(\tau)} = \gamma_0^c + \gamma_1^c y_{c,t}^{(1)} + \gamma_2^c f_{c,t}^{(1,2)} + \gamma_3^c f_{c,t}^{(2,3)} + \gamma_4^c f_{c,t}^{(3,4)} + \gamma_5^c f_{c,t}^{(4,5)} + \bar{\varepsilon}_{c,t+1}$$

$$\Updownarrow$$

$$\overline{rx}_{c,t+1} = \boldsymbol{\gamma}_{\boldsymbol{c}}^{\intercal} \boldsymbol{f_{c,t}} + \bar{\varepsilon}_{c,t+1}.$$

They then run the restricted predictive regression of annual excess returns on two- to five-year maturity bonds,

$$rx_{c,t+1}^{(\tau)} = \alpha_{c,t+1}^{(\tau)} + b_c^{(\tau)} CP_t^{(c)} + \varepsilon_{c,t+1}^{(\tau)}. \tag{R.2}$$

According to Cochrane and Piazzesi (2005), the restricted model has empirically only a minor impact on the forecasting ability of excess bond returns in the U.S. market compared to the unrestricted model,[45] given by

$$rx_{c,t+1}^{(\tau)} = \beta_{c,0}^{(\tau)} + \beta_{c,1}^{(\tau)} y_{c,t}^{(1)} + \beta_{c,2}^{(\tau)} f_{c,t}^{(1,2)} + \beta_{c,3}^{(\tau)} f_{c,t}^{(2,3)} + \beta_{c,4}^{(\tau)} f_{c,t}^{(3,4)} + \beta_{c,5}^{(\tau)} f_{c,t}^{(4,5)} + \varepsilon_{c,t+1}^{(\tau)},$$

or in vector form:

$$rx_{c,t+1}^{(\tau)} = \boldsymbol{\beta_c} \boldsymbol{f_{c,t}} + \varepsilon_{c,t+1}^{(\tau)}. \tag{R.3}$$

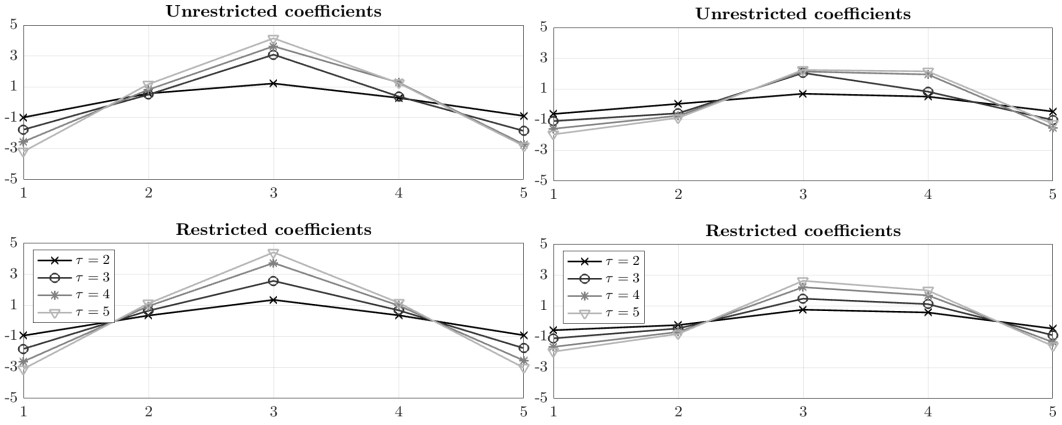
Cochrane and Piazzesi hypothesized that the CP factor is a state variable[46] in the stochastic discount factor (i.e., $m_t^{(c)} = g_t[f_t(\ldots, CP_t^{(c)}, \ldots)]$). After a thorough statistical analysis and testing whether $\boldsymbol{b_c}\boldsymbol{\gamma}_{\boldsymbol{c}}^{\intercal} = \boldsymbol{\beta_c}$ they reject this hypothesis. Furthermore, they document that the estimated coefficients unveil a "tent shape", peaking at $\beta_{c,3}^{(\tau)}$ in Regression (R.3). Figure 4.1 plots the unrestricted and restricted coefficients for the US in 1964–2003 (a) and 1964–2017 (b).[47] There is no distinct coefficient tent shape for 1964–2017. Additionally, the difference between the unrestricted and restricted coefficients

[45] The parameters in Regression (R.3) and (R.2) are related by $\hat{\boldsymbol{\beta}}_{\boldsymbol{c}} = \hat{\boldsymbol{b}}_{\boldsymbol{c}} \hat{\boldsymbol{\gamma}}_{\boldsymbol{c}}^{\intercal}$.

[46] A variable indicating the state of the economy (e.g., wealth, consumption, etc.), consequentially affecting investors' consumption and portfolio decision (Cochrane, 2005, p. 165).

[47] Plots for the other countries are in Appendix E.12.

are larger.[48] This might indicate errors in Regression (R.2), though, comparing Regression (R.2) and (R.3)'s adjusted R^2 in Table 4.2, this seems not to be the case. We apply Regression (R.2) to data for 1964–2017. The results are in Table 4.2.[49]



(a) *USA: 1964.01–2003.12* (b) *USA: 1964.01–2017.12*

Figure 4.1: Unrestricted vs. Restricted Coefficient Plot - USA.
Unrestricted vs. restricted estimated coefficients for the US. Coefficients are estimated from Regression (R.3) *and* (R.2) *and are related by* $\hat{\boldsymbol{\beta}}_{\boldsymbol{c}} = \hat{\boldsymbol{b}}_{\boldsymbol{c}}\hat{\gamma}_{\boldsymbol{c}}^{\intercal}$. *Cochrane and Piazzesi (2005) use 1964–2003 data.*

	(1)		**(2)**		**(3)**		**(4)**	
	1964.01–2003.12		**1964.01–2017.12**		**1992.12–2009.05**		**1992.12–2017.12**	
τ	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2
2	0.45**	0.31	0.43**	0.19	0.55	0.11	0.39	0.05
	(8.85)	*[0.31]*	*(5.47)*	*[0.20]*	*(1.88)*	*[0.10]*	*(1.93)*	*[0.07]*
3	0.85**	0.34	0.83**	0.21	0.99	0.09	0.80*	0.06
	(8.51)	*[0.33]*	*(5.31)*	*[0.21]*	*(1.80)*	*[0.07]*	*(1.97)*	*[0.06]*
4	1.24**	0.37	1.25**	0.25	1.20	0.07	1.17*	0.06
	(8.57)	*[0.36]*	*(5.67)*	*[0.25]*	*(1.61)*	*[0.05]*	*(2.13)*	*[0.05]*
5	1.46**	0.34	1.49**	0.23	1.26	0.05	1.64**	0.08
	(7.90)	*[0.34]*	*(5.41)*	*[0.23]*	*(1.37)*	*[0.03]*	*(2.40)*	*[0.07]*

Table 4.2: Regression Results - Bonds - CP factor in the US.
Estimates of Regression (R.2) *in the US for four sample periods. T-statistics in parentheses use Newey and West (1987) standard error-correction with 18 lags. Adjusted* R^2 *and adjusted* R^2 *of Regression* (R.3) *in square brackets. Constant estimates are excluded.**: p-value* $<$ *0.01, *: p-value* $<$ *0.05.*

Regression outputs for (1) are identical to Cochrane and Piazzesi (2005). The CP factor statistically significantly predicts one-year excess bond returns on two- to five-year maturity bonds and coefficients are monotonically increasing with adjusted R^2 up to 37%. Regressing on data for (2) give almost identical

[48]Although, by construction they are on average equal by the restriction: $\hat{\boldsymbol{\beta}}_{\boldsymbol{c}} = \hat{\boldsymbol{b}}_{\boldsymbol{c}}\hat{\gamma}_{\boldsymbol{c}}^{\intercal}$.
[49]See Appendix E.2 for the other countries' results during 1992–2017.

results but with lower R^2's and significance. The same regression for (3) and (4) give significantly lower R^2's and t-statistics. Thus, we conclude that the CP factor's significance in predicting annual bond risk premia the US has weakened during these time periods, and has marginally been a statistically significant driver of one-year excess bond returns.[50]

Further, Cochrane and Piazzesi (2005) add lagged forward rates to Regression (R.3) and run the following regression,

$$\overline{rx}_{c,t+1} = MA\left(CP_t^{(c)}, k\right) + \bar{\varepsilon}_{c,t+1} \tag{R.4}$$

where

$$MA\left(CP_t^{(c)}, k\right) \equiv \alpha_{c,0} CP_t^{(c)} + \alpha_{c,1} CP_{t-\frac{1}{12}}^{(c)} + \ldots + \alpha_{c,k} CP_{t-\frac{k}{12}}^{(c)}.$$

Adding lags increases adjusted R^2 to 44%, and thereby also the models fit of explaining variations in average annual excess bond return. We run Regression (R.4) on the same subsamples as above. The results are in Table 4.3.[51] The increasing adjusted R^2 is also the case for (2), where three

Lags	**0**	**1**	**2**	**3**	**4**	**5**	**6**
(1) 1964.01–2003.12	0.35	0.41	0.42	0.44	0.44	0.44	0.44
(2) 1964.01–2017.12	0.23	0.25	0.26	0.27	0.27	0.26	0.26
(3) 1992.12–2009.05	0.07	0.06	0.06	0.05	0.05	0.06	0.08
(4) 1992.12–2017.12	0.07	0.06	0.06	0.06	0.07	0.09	0.10

Table 4.3: Regression Results - Bonds - MA(CP, k) in the US.
Adjusted R^2 for Regression (R.4) with k lags in the US for four sample periods. Shaded cells indicate which k that results in maximum R^2.

monthly lagged values of the CP factor in Regression (R.4) increase the R^2 to 27% (from 23% when zero lags). However, for (3) and (4), the results are not as

[50] In contrast, results for the other countries show that the CP factor predicts one-year excess bond returns with statistical significance (although the t-statistics for DEU are borderline low) for 1992–2017. Particularly noticeable is JPN, where the CP factor predicts one-year expected risk premia on two-year maturity bonds with R^2 of 72%. See Appendix E.2.

[51] See Appendix E.3 for other countries' results for 1992–2017.

evident. We conclude that including lags of the CP factor marginally increases the models fit of explaining average one-year bond risk premia variations.[52]

Stock Return Predictability

Cochrane and Piazzesi (2005) document that the CP factor has forecasting power for expected excess stock returns with the regression,

$$sx_{c,t}^{(\tau)} = \alpha_{c,t}^{(\tau)} + b_c^{(\tau)} CP_t^{(c)} + \varepsilon_{c,t}^{(\tau)}. \tag{R.5}$$

With motivation from Fama and French (1989), we extend their model slightly to assess the CP factor's influence on excess stock returns up to five years (i.e., we run Regression (R.5) for $\tau = 1, 2, 3, 4, 5$). Results are in Table 4.4.[53]

	(1)		(2)		(3)		(4)	
	1964.01–2003.12		**1964.01–2017.12**		**1992.12–2009.05**		**1992.12–2017.12**	
τ	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2
1	1.53	0.05	1.03	0.01	2.52	0.01	-3.36	0.01
	(1.85)		*(1.09)*		*(0.37)*		*(-1.03)*	
2	2.68**	0.07	2.35	0.03	1.85	0.00	-2.32	0.00
	(2.41)		*(1.71)*		*(0.19)*		*(-0.33)*	
3	2.84**	0.05	3.23*	0.03	9.51	0.02	10.64	0.03
	(2.68)		*(2.18)*		*(0.75)*		*(0.87)*	
4	3.53*	0.05	4.89**	0.05	18.11	0.06	22.91	0.09
	(2.27)		*(2.48)*		*(1.05)*		*(1.32)*	
5	5.63**	0.08	6.73**	0.06	25.92	0.06	25.94	0.07
	(2.73)		*(2.53)*		*(1.16)*		*(1.10)*	

Table 4.4: *Regression Results - Stocks - CP Factor in the US.*
Estimates of Regression (R.5) in the US in four sample periods. Estimates for one-year excess returns for 1964–2003 differ slightly from Cochrane and Piazzesi (2005) because of different stock returns.
T-statistics in parentheses use Hansen-Hodrick standard error-correction with 12 lags. Adjusted R^2.
*Constant estimates are excluded. **: p-value < 0.01, *: p-value < 0.05.*

In (1), we see that the CP factor statistically significantly influences the excess one-year stock return at the 10% level, as documented by Cochrane and Piazzesi (2005). A 1% change in the CP factor is associated with 1.53% change in one-year excess stock return in this period. Our extended analysis

[52] With the exception of JPN.
[53] See Appendix E.4 for other countries' results for 1992–2017.

reveals that the CP factor significantly influences two- to five-year excess stock returns at the 1% level (except for $\tau = 4$) in (1). In (2), the CP factor influences the three-, four-, and five-year excess stock returns at the five, one, and 1% level, respectively. In (3) and (4), the CP factor's significance vanishes.[54]

Further, assessing the CP factor's forecasting ability of excess stock return, Cochrane and Piazzesi (2005) run the following regression for one-year excess return:

$$sx_{c,t}^{(\tau)} = \alpha_{c,t}^{(\tau)} + b_{c,1}^{(\tau)} MA\left(CP_t^{(c)}, 3\right) + b_{c,2}^{(\tau)} \left(\frac{d}{p}\right)_{c,t} + b_{c,3}^{(\tau)} \left(y_{c,t}^{(5)} - y_{c,t}^{(1)}\right) + \varepsilon_{c,t}^{(\tau)}. \quad \text{(R.6)}$$

We extend their model slightly to assess the CP factor's influence on excess stock returns up to five years (i.e., we run Regression (R.6) for τ = 1, 2, 3, 4, 5). Correlation among the regressors for sample period 1992.12–2017.12 in the US are depicted in Table 4.5 while regression results of Regression (R.6) are in Table 4.6.[55]

	$MA(CP_t, 3)$	$(D/P)_t$	$y_t^{(5)} - y_t^{(1)}$
$MA(CP_t, 3)$	**1.00**	0.06	0.26
$(D/P)_t$	0.06	**1.00**	0.23
$y_t^{(5)} - y_t^{(1)}$	0.26	0.23	**1.00**

Table 4.5: Correlation Table - MA(CP, 3), D/P, and Term Spread in the US.
Correlation among the regressors in Regression (R.6) *in the US. Sample period: 1992.12–2017.12.*

From the low correlations among the regressors, we are not too concerned about multicollinearity.

[54] The same holds for the other countries' in 1992–2017, except for JPN. See Appendix E.4.
[55] See Appendix E.5 for the other countries' results for 1992–2017.

	(1)		(2)		(3)		(4)	
	1964.01–2003.12		1964.01–2017.12		1992.12–2009.05		1992.12–2017.12	
τ	$b_{c,1}^{(\tau)}$	R^2	$b_{c,1}^{(\tau)}$	R^2	$b_{c,1}^{(\tau)}$	R^2	$b_{c,1}^{(\tau)}$	R^2
1	1.92**	0.11	-0.39	0.05	2.01	0.14	-3.37	0.19
	(3.06)	*[0.00]*	*(-0.31)*	*[0.30]*	*(0.33)*	*[0.34]*	*(-1.60)*	*[0.03]*
2	2.90**	0.12	-0.09	0.07	1.13	0.44	-4.43	0.36
	(3.30)	*[0.00]*	*(-0.04)*	*[0.11]*	*(0.22)*	*[0.03]*	*(-1.05)*	*[0.00]*
3	1.13	0.09	-2.44	0.16	10.85	0.61	1.04	0.51
	(1.17)	*[0.01]*	*(-1.27)*	*[0.00]*	*(1.83)*	*[0.00]*	*(0.15)*	*[0.00]*
4	0.68	0.13	-2.52	0.21	19.85*	0.71	11.24	0.64
	(0.43)	*[0.01]*	*(-0.97)*	*[0.00]*	*(1.97)*	*[0.00]*	*(1.20)*	*[0.00]*
5	1.63	0.17	-1.78	0.22	28.58**	0.68	9.09	0.60
	(0.66)	*[0.01]*	*(-0.47)*	*[0.00]*	*(2.78)*	*[0.00]*	*(0.78)*	*[0.00]*

Table 4.6: Regression Results Excerpt - Stocks - MA(CP, 3), D/P, and Term Spread in the US. *Estimates of Regression* (R.6) *in the US for four sample periods. T-statistics in parentheses use Hansen-Hodrick standard error-correction with 12 lags. Estimates for one-year excess returns for 1964–2003 differ slightly from Cochrane and Piazzesi (2005) because of different stock returns. P-value of F-statistics in brackets. Adjusted R^2. Constant estimates, coefficient estimates for D/P and Term Spread are excluded. Full regression results table is in Appendix* E.5. ***: p-value < 0.01, *: p-value < 0.05.*

In (1), MA(CP, 3) statistically significantly influences one-year excess stock returns at the 1% level, as documented by Cochrane and Piazzesi (2005). For our updated analysis, this is also the case for the excess two-year stock return. In (2)–(4), MA(CP, 3) is only significant for four- and five-year excess stock returns in (3), and insignificant otherwise.[56]

Summary

We successfully replicate the work of Cochrane and Piazzesi (2005) and confirm their empirical findings about the CP factor in the US for our updated data set. The CP factor is still a statistically significant driver of one-year excess return variations on two- to five-year maturity bonds, although the significance seems to have weakened. In other bond markets, the CP factor's influence is more convincing.[57] For one-year stock excess returns, the significance of the

[56]The same conclusion holds for the other countries', except for excess one-year stock return in DEU where MA(CP,3) is significant at the 1% level. See Appendix E.5.

[57]Although, generally, the estimated coefficients do not show a distinct tent shape but rather a 'W' shape, suggesting a greater degree of multicollinearity (Cochrane & Piazzesi, 2008, p. 13). See Appendix E.12 for the coefficient plots.

CP factor for explaining annual stock risk premia variations in the US vanishes in our more recent sample. For two- to five-year horizons, we find no statistical significance.

We conclude on our first research question that the findings of Cochrane and Piazzesi (2005) are still valid and that the CP factor is a significant driver of one-year excess bond return variations and are still valid in the US as well as in the other countries. Further, by Equation (12), we conclude that expected bond risk premia are an important determinant of long-term nominal bond yields.

4.3 Global Single-Factor Regressions

Dahlquist and Hasseltoft (2013) find evidence for predictability in annual excess bond returns in several international bond markets.[58] Motivated by the increasing integration of world financial markets, they extend the work of Cochrane and Piazzesi (2005) by forming a global CP factor (GCP) comprised of the GDP-weighted average[59] of local CP factors in the US, Switzerland, Germany, and UK:

$$GCP_t = \sum_{c=1}^{C} w_{c,t} CP_t^{(c)} \qquad \text{where} \qquad w_{c,t} = \frac{GDP_{c,t}}{\sum_{c=1}^{C} GDP_{c,t}}$$

and $C = [USA, CHE, DEU, GBR]$. They run Regression (R.7) to assess the extent to which this factor explains variations in time-varying bond risk premia across international markets:

$$rx_{c,t+1}^{(\tau)} = \alpha_c^{(\tau)} + b_c^{(\tau)} GCP_t + \varepsilon_{c,t+1}^{(\tau)} \tag{R.7}$$

They find that bond risk premia across international markets are closely related to U.S. bond risk premia and international business cycles. Both being

[58] They examine the same countries as we do, including Sweden, Norway and New Zealand.
[59] Similar to Dahlquist and Hasseltoft (2013), since GDP data is reported quarterly, we assume constant GDP weight for each month from and up to each reporting.

significant, the CP factor and the GCP factor have strong forecasting power for one-year excess bond returns across countries and linked to overall business conditions. They document that rising global risk premia are associated with a contemporaneous drop in leading economic indicators.

Before running regressions, we analyze the similarity between the GCP_t and local CP factors in the US and Germany ($CP_t^{(USA)}$ and $CP_t^{(DEU)}$, respectively). We expect minor differences between GCP_t and $CP_t^{(USA)}$, as the weight of the US in the GCP is around 70% (see Figure 2.1). However, for DEU, where the weight is around 20%, we expect a greater difference. By analyzing panel (b) in Figure 4.2 we confirm our expectation: GCP_t and $CP_t^{(USA)}$ reveal minor differences in the period 1992.12–2017.12 and have a high positive 24-month rolling correlation. In contrast, significant differences can be observed between GCP_t and $CP_t^{(DEU)}$. For instance, at the start of the last U.S. recession the 24-month correlation turns negative for about one year before turning positive in 2009. At the end of 2017, the correlation is slightly negative.

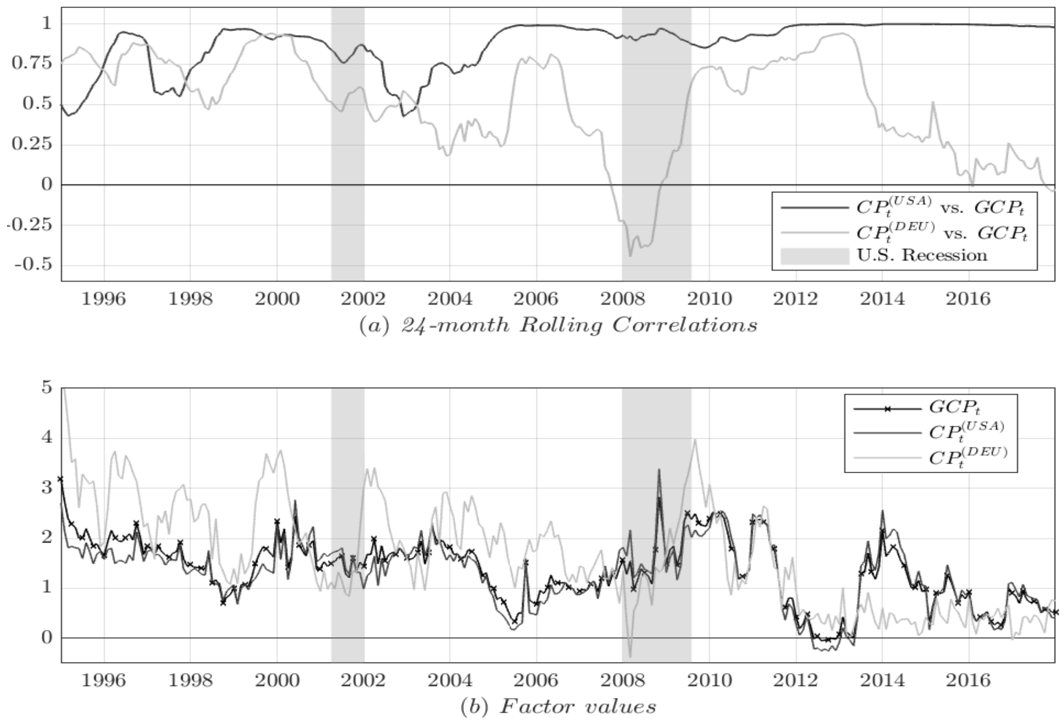


Figure 4.2: CP and GCP 24-month rolling correlation - USA and DEU.
Panel (a) depicts 24-month rolling correlation between CP and GCP factor for the US and DEU. Panel (b) depicts CP factor realizations in the US and DEU as well as GCP factor realizations. Sample period: 1992.12–2017.12.

We apply Regression (R.7) to the same data as Dahlquist and Hasseltoft (2013) and additional data going up to and including 2017. The results for the US and Germany are in Table 4.7.[60] The results confirm the findings of Dahlquist

	(1)		(2)		(3)		(4)	
	1975.01–2009.12		1975.01–2017.12		1992.12–2009.05		1992.12–2017.12	
τ	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2
USA								
2	0.56**	0.14	0.54**	0.12	0.59**	0.13	0.52**	0.09
	(2.78)		*(3.01)*		*(2.47)*		*(3.10)*	
3	1.04**	0.13	1.03**	0.13	1.07**	0.11	1.06**	0.10
	(2.60)		*(2.95)*		*(2.34)*		*(3.21)*	
4	1.52**	0.15	1.55**	0.15	1.43*	0.10	1.62**	0.12
	(2.67)		*(3.13)*		*(2.28)*		*(3.47)*	
5	1.89**	0.15	1.99**	0.16	1.74*	0.10	2.33**	0.15
	(2.71)		*(3.29)*		*(2.20)*		*(3.87)*	
DEU								
2	0.53**	0.19	0.55**	0.19	0.65**	0.24	0.71**	0.22
	(4.70)		*(5.90)*		*(2.66)*		*(4.32)*	
3	1.00**	0.20	1.05**	0.20	1.39**	0.27	1.44**	0.23
	(4.88)		*(6.01)*		*(3.21)*		*(4.37)*	
4	1.40**	0.20	1.46**	0.19	2.02**	0.27	2.04**	0.23
	(4.87)		*(5.87)*		*(3.54)*		*(4.36)*	
5	1.76**	0.20	1.82**	0.19	2.51**	0.26	2.53**	0.21
	(4.87)		*(5.69)*		*(3.69)*		*(4.28)*	

Table 4.7: Regression Results - Bonds - GCP Factor in the US and Germany
*Estimates of Regression (R.7) in the US and DEU for four sample periods. T-statistics in parentheses use Newey and West (1987) standard error-correction with 18 lags. Adjusted R^2. Constant estimates are excluded. **: p-value $<$ 0.01, *: p-value $<$ 0.05. Note: Because of lack of data, we make the GCP factor without CHE for the sample periods starting in 1975 and ending in 2009 and 2017. Hence, our results differ slightly from Dahlquist and Hasseltoft (2013).*

and Hasseltoft (2013). The GCP factor statistically significantly predicts one-year excess bond returns in the US on two- to five-year maturity bonds and the coefficients are monotonically increasing with R^2 in the interval 10–15%. The significance of the GCP factor is relatively stable across (1)-(4) but has increased, suggesting that global bond risk premia have been increasingly influencing nominal bond yields in the US.[61] The pattern repeats for Germany. Although the significance is not as stable as for the US, being somewhat lower in (3) and (4) compared to (1) and (2), the coefficients are still highly significant

[60] See Appendix E.6 for the other countries' results for 1992–2017.
[61] Because the significance of the GCP factor is greater than that of the CP factor.

when extending the data sets. These observations are consistent in the other countries as well, except for JPN.[62]

We follow the notion of Cochrane and Piazzesi (2005) that lagged CP factor (Regression (R.4)) improves the forecasting ability of excess bond returns and extend their model to assess if it is transferable to a model with lagged GCP factors. We run the regression,

$$\overline{rx}_{c,t+1} = MA\left(GCP_t, k\right) + \overline{\varepsilon}_{c,t+1} \tag{R.8}$$

where

$$MA\left(GCP_t, k\right) \equiv \sum_{c=1}^{C} w_{c,t} MA\left(CP_t^{(c)}, k\right)$$

and $C = [USA, CHE, DEU, GBR]$. Results for the US and Germany are in Table 4.8.[63]

Lags	**0**	**1**	**2**	**3**	**4**	**5**	**6**
				USA			
(1) 1975.01–2009.12	0.19	0.21	0.22	0.22	0.23	0.24	0.24
(2) 1975.01–2017.12	0.18	0.19	0.19	0.20	0.20	0.20	0.20
(3) 1992.12–2009.05	0.24	0.26	0.25	0.20	0.27	0.32	0.36
(4) 1992.12–2017.12	0.20	0.22	0.22	0.21	0.20	0.20	0.21
				DEU			
(1) 1975.01–2009.12	0.25	0.28	0.29	0.32	0.35	0.37	0.38
(2) 1975.01–2017.12	0.24	0.25	0.26	0.27	0.28	0.28	0.28
(3) 1992.12–2009.05	0.29	0.30	0.32	0.33	0.35	0.33	0.34
(4) 1992.12–2017.12	0.24	0.25	0.25	0.25	0.25	0.26	0.27

Table 4.8: Regression Results - Bonds - MA(GCP, k) in the US and DEU.
Adjusted R^2 for Regression (R.8) with k lags in the US and DEU for four sample periods. Shaded cells indicate which k that results in maximum R^2. Note: Because of lack of data, we make the GCP factor without CHE for the sample periods starting in 1975 and ending in 2009 and 2017.

Adding up to six lags nearly improves the adjusted R^2 in all subperiods, thus adding lags of the GCP factor seems to improve the model's fit and thereby its explanation of annual bond risk premia variations. Nevertheless, the increases

[62] One possibility for the GCP factor less significance in JPN might be the low foreign investor holdings in the Japanese government bond market. Only 9.4% of outstanding bonds were held by foreign investors (compared to OECD average of 48.8%) as of 2016 (OECD, 2016, p. 71).

[63] See Appendix E.7 for the other countries' for 1992–2017.

in Adjusted R^2 are not that convincing and we question whether increasing the model complexity has value in terms of our investigation in Section 5. Appendix E.7 depicts Table 4.8 but for the other countries' in 1992–2017. We conclude that including lags of the GCP factor marginally increases the models fit of predicting average one-year excess bond returns (except for in JPN).

Stock Return Predictability

As for the CP factor, we asses whether the GCP factor forecasts excess stock returns. We extend the model of Cochrane and Piazzesi (2005) and run Regression (R.5) and (R.6) but with the GCP factor as regressor. Thus,

$$sx_{c,t}^{(\tau)} = \alpha_{c,t}^{(\tau)} + b_c^{(\tau)} GCP_t + \varepsilon_{c,t}^{(\tau)} \tag{R.9}$$

and,

$$sx_{c,t}^{(\tau)} = \alpha_{c,t}^{(\tau)} + b_{c,1}^{(\tau)} MA\left(GCP_t, 3\right) + b_{c,2}^{(\tau)} \left(\frac{d}{p}\right)_{c,t} + b_{c,3}^{(\tau)} \left(y_{c,t}^{(5)} - y_{c,t}^{(1)}\right) + \varepsilon_{c,t}^{(\tau)}. \tag{R.10}$$

Regression results for Regression (R.9) and (R.10) for the US and Germany are in Table 4.9 and Table 4.11.[64]

From Table 4.9, we see that the GCP factor statistically significantly explains the three- to five-year excess stock return in (2) in the US. Here, a 1% change in the factor has been associated with an 8.3%, 11.5%, and 14.4% change in the three-, four-, and five-year excess stock return, respectively. As stocks are exposed to cash flow shocks in addition to discount rate shocks, this somewhat confirms the notion of Dahlquist and Hasseltoft (2013) that high global bond risk premia, while indicating short-term macroeconomic uncertainty and/or risk aversion, also signal improved economic activities ahead. However, these

[64] See Table E.8.1 and E.9.2 in Appendix E.8 and E.9, respectively, for the other countries' results for 1992–2017.

	(1)		(2)		(3)		(4)	
	1975.01–2009.12		1975.01–2017.12		1992.12–2009.05		1992.12–2017.12	
τ	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2
				USA				
1	2.61	0.04	1.71	0.01	4.17	0.03	0.11	0.00
	(1.26)		*(0.92)*		*(0.77)*		*(0.03)*	
2	4.53	0.06	4.53	0.04	6.66	0.03	3.34	0.00
	(1.42)		*(1.32)*		*(0.76)*		*(0.37)*	
3	6.36	0.06	8.33*	0.09	18.37	0.12	18.43	0.09
	(1.82)		*(2.15)*		*(1.53)*		*(1.29)*	
4	7.44	0.05	11.52*	0.11	29.70	0.18	33.43	0.19
	(1.42)		*(2.27)*		*(1.87)*		*(1.73)*	
5	11.12	0.07	14.44**	0.11	38.40	0.17	38.52	0.16
	(1.95)		*(2.37)*		*(1.66)*		*(1.48)*	
				DEU				
1	2.79	0.02	1.74	0.01	0.30	-0.01	-3.28	0.01
	(0.91)		*(0.62)*		*(0.05)*		*(-0.84)*	
2	7.36	0.07	6.95	0.05	-0.94	-0.01	-3.49	0.00
	(1.54)		*(1.54)*		*(-0.08)*		*(-0.40)*	
3	7.68	0.04	9.08	0.05	8.98	0.01	10.60	0.02
	(1.21)		*(1.60)*		*(0.53)*		*(0.76)*	
4	7.31	0.02	10.64	0.05	22.16	0.06	32.18	0.12
	(0.88)		*(1.64)*		*(1.03)*		*(1.67)*	
5	4.49	0.00	8.04	0.02	34.38	0.09	37.40	0.12
	(0.49)		*(0.92)*		*(1.12)*		*(1.46)*	

Table 4.9: Regression Results - Stocks - GCP Factor - USA and DEU.
*Estimates of Regression (R.9) in the US and DEU for four sample periods. T-statistics in parentheses use Hansen-Hodrick standard error-correction with 12 lags. Adjusted R^2. Constant estimates are excluded. **: p-value < 0.01, *: p-value < 0.05.*

results are not evident in more recent samples, nor in Germany, where the GCP factor is insignificant.[65]

Correlation among the regressors in Regression (R.10) for sample period 1992.12–2017.12 in the US are depicted in Table 4.10. From the

	$MA(GCP_t, 3)$	$(D/P)_t$	$y_t^{(5)} - y_t^{(1)}$
$MA(GCP_t, 3)$	**1.00**	-0.10	0.13
$(D/P)_t$	-0.10	**1.00**	0.23
$y_t^{(5)} - y_t^{(1)}$	0.13	0.23	**1.00**

Table 4.10: Correlation Table - MA(GCP, 3), D/P, and Term Spread in the US.
Correlation among the regressors in Regression (R.10) in the US. Sample period: 1992.12–2017.12.

low correlations among the regressors, we are not too concerned about multicollinearity.

[65] The same conclusion holds for the other countries', except for excess one-year stock return in JPN where MA(CP,3) are significant at the 1% level. See Appendix E.8.

	(1)		(2)		(3)		(4)	
	1975.01–2009.12		**1975.01–2017.12**		**1992.12–2009.05**		**1992.12–2017.12**	
τ	$b_{c,1}^{(\tau)}$	R^2	$b_{c,1}^{(\tau)}$	R^2	$b_{c,1}^{(\tau)}$	R^2	$b_{c,1}^{(\tau)}$	R^2
				USA				
1	1.35	0.03	-1.12	0.02	-4.28	0.16	-4.45*	0.20
	(0.52)	*[0.69]*	*(-0.48)*	*[0.73]*	*(-1.45)*	*[0.13]*	*(-2.23)*	*[0.01]*
2	-0.32	0.07	-2.52	0.08	-8.64*	0.48	-9.69*	0.39
	(-0.09)	*[0.33]*	*(-0.67)*	*[0.16]*	*(-2.11)*	*[0.01]*	*(-2.10)*	*[0.00]*
3	-3.22	0.14	-4.00	0.18	-1.05	0.58	-3.95	0.51
	(-0.84)	*[0.03]*	*(-0.82)*	*[0.01]*	*(-0.20)*	*[0.00]*	*(-0.51)*	*[0.00]*
4	-4.70	0.16	-3.72	0.21	11.30	0.67	6.55	0.62
	(-0.95)	*[0.15]*	*(-0.66)*	*[0.01]*	*(1.18)*	*[0.00]*	*(0.71)*	*[0.00]*
5	0.55	0.17	1.03	0.21	13.70	0.63	5.91	0.59
	(0.08)	*[0.06]*	*(0.15)*	*[0.01]*	*(1.39)*	*[0.00]*	*(0.42)*	*[0.00]*
				DEU				
1	1.20	0.04	0.59	0.04	-6.89	0.24	-9.80**	0.22
	(0.38)	*[0.48]*	*(0.19)*	*[0.50]*	*(-1.34)*	*[0.02]*	*(-2.41)*	*[0.01]*
2	4.74	0.11	5.79	0.12	-20.91**	0.59	-12.44	0.33
	(1.10)	*[0.33]*	*(1.31)*	*[0.24]*	*(-2.63)*	*[0.00]*	*(-1.71)*	*[0.02]*
3	6.59	0.08	9.84	0.13	-11.77	0.48	-0.79	0.32
	(1.17)	*[0.50]*	*(1.83)*	*[0.14]*	*(-0.86)*	*[0.00]*	*(-0.07)*	*[0.01]*
4	8.29	0.11	12.98*	0.16	-13.61	0.62	16.82	0.38
	(1.43)	*[0.40]*	*(2.30)*	*[0.03]*	*(-0.87)*	*[0.00]*	*(1.25)*	*[0.01]*
5	10.95*	0.28	15.36**	0.31	12.12	0.68	24.26	0.39
	(2.32)	*[0.01]*	*(2.97)*	*[0.00]*	*(0.57)*	*[0.00]*	*(1.49)*	*[0.01]*

Table 4.11: Regression Results Excerpt - Stocks - MA(GCP, 3), D/P, and Term Spread in the US and DEU.
*Estimates of Regression (R.10) in the US and DEU for four sample periods. T-statistics in parentheses use Hansen-Hodrick standard error-correction with 12 lags. P-value of F-statistics in brackets. Adjusted R^2. Constant estimates, coefficient estimates for D/P and Term Spread are excluded. Full regression results table in Appendix E.9. **: p-value $<$ 0.01, *: p-value $<$ 0.05.*

When adding the dividend-price ratio and the term spread as control variables as in Regression (R.10), the results in Table 4.11 reveal that the GCP factor loses its significance in (2) in the US, but becomes significant for the one- and two-year horizon in (4), but with a negative sign. Here, a 1% change in the GCP factor is associated with a -4.5% and -9.7% change in one- and two-year excess stock returns, respectively. This is also the case for Germany (except for $\tau = 2$); a 1% change in the GCP factor is associated with a -9.8% change in one-year excess stock returns.[66]

Since the CP factor seems to have lost its significance in later sample periods and the opposite seems to be true for the GCP factor, we conclude, as for

[66]However, the results for this observation are mixed in the other countries', see Appendix E.9

excess bond returns, that the relevance of the GCP factor in predicting excess stock returns has increased in later periods. However, we remain cautious about making any absolute conclusion of the GCP factors influence on excess stock returns as the significance may be a consequence of pure chance.[67]

Summary

We successfully replicate the work of Dahlquist and Hasseltoft (2013) and confirm the empirical findings about the GCP factor in the US and Germany for our updated data set. The GCP factor is a statistically significant driver of one-year excess bond return variations on two- to five-year maturity bonds, and the significance level has increased during recent years, in contrast to the CP factor. Findings in the US and Germany are consistent across the countries we examine.[68]

For one- to five-year stock excess returns, the individual significances of the GCP factor for explaining excess return variations in the US and Germany are nonexistent. However, when including dividend-price ratio and yield spread as control variables, monthly lagged realizations of the GCP factor significantly explain stock risk premia in the US and Germany at one-year horizon with a negative magnitude (i.e., increase in the GCP factor are associated with a decrease in one-year stock risk premia). As we find no clear-cut significance in the other markets, we remain cautious in making any absolute conclusion about the GCP factor's influence on stock risk premia, recommended by Harvey et al. (2015).

We conclude on our first research question that the findings of Dahlquist and Hasseltoft (2013) regarding the prediction of one-year excess bond returns are still valid. The GCP factor is a significant driver of bond risk premia variations

[67] Harvey, Liu, and Zhu (2015) recommend the literature to have a t-statistic hurdle of 3.0 before claiming significance of factors explaining excess stock returns.

[68] With the exception of JPN.

and has become more relevant for predicting excess bond returns in the US as well as the other countries in later periods. Further, by Equation (12), we conclude that global bond risk premia (with relative weights defined by the GCP factor) are important determinants of long-term nominal bond yield levels, and that it has become more important in recent periods.

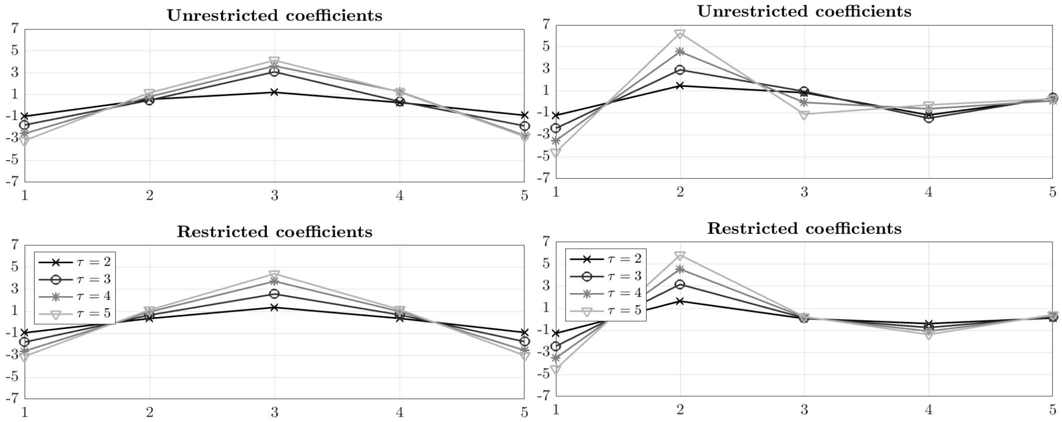
These insights are valuable to portfolio managers, especially actively managed bond funds. If expected excess bond returns are positive, the bond portfolio composition would preferably tilt towards longer-maturity bonds, and vice versa. Therefore, in section 5, we examine the extent to which an investor would generate excess returns using real-time forecasts by the CP factor and GCP factor.[69]

4.4 Data Impact on Predictive Regressions

To spot any inconclusiveness in our investigation, we dedicate this subsection to a brief outline on how the data impact our predictive regressions. See Appendix F for an outline of the difference in yields for different data sets, including an analytical outline of how data affect the estimated parameters in a regression model.

Cochrane and Piazzesi (2004a) perform several robustness checks to assess any inconclusiveness in their findings. The general message is that results persist across data sets and are stable across subsamples. We examine the impact of different yield data on the unrestricted and restricted coefficient estimates. Figure 4.3 depicts this difference for the US data sets we use (identifier: USA & USA^2). As we see, when using yield data constructed with the Svensson method, the tent shape documented by Cochrane and Piazzesi

[69] As we find no clear-cut significance of these factors in predicting excess stock returns, we do not pursue the same examination for excess stock returns.



(a) *Unsmoothed Fama-Bliss data* (b) *Svensson data*

Figure 4.3: Yield Data Comparison - Unrestricted vs. Restricted Coefficients in the US. *Unrestricted vs. restricted estimated coefficients for the US. Coefficients are estimated from Regression* (R.3) *and* (R.2) *and are related by* $\hat{\boldsymbol{\beta}}_{\mathbf{c}} = \hat{\mathbf{b}}_{\mathbf{c}}\hat{\boldsymbol{\gamma}}_{\mathbf{c}}^{\intercal}$. *Cochrane and Piazzesi (2005) use the data set from CRSP (2018a) (panel (a)). Panel (b) is data from Gürkaynak et al. (2007).*

(2005) disappears, although it seems to shift to the left.[70] Our results are in line with the findings of Dai, Singleton, and Yang (2004), who analyze the coefficient estimates for four different yield data sets and conclude that the tent shape is only distinct for unsmoothed Fama-Bliss data. Whereas for other data, it is characterized by a "wave-shape", suggesting a larger degree of multicollinearity (Cochrane & Piazzesi, 2008, p. 13).[71,72]

The upper part in Table 4.12 depicts outputs for the CP factor regressed on the two US data sets for 1964–2003 and 1964–2017. The difference in estimated coefficients are minor, but the difference in data affects the CP factor's statistical significance and R^2 significantly. For 1964–2003, t-statistics are approximately halved and R^2s are about 10 percentage points lower for the Svensson-estimated data. For 1964–2017, the reductions in significance and R^2 are not that severe, yet noticeable.[73] Nevertheless, the CP factor is

[70] This contrasts Cochrane and Piazzesi (2004a), who conclude that the tent shape is very similar across Fama-Bliss data and McCulloch-Kwon data over the sample period 1964.01–1992.12.

[71] Cochrane and Piazzesi (2004b) emphasize that there still is a single factor driving excess returns on two- to five-year maturity bonds (i.e., the coefficients for different maturity bonds have the same shape).

[72] Figure E.10.1 in Appendix E.10 highlights differences in the estimated coefficients for different yield data in the US, AUS, CHE, and JPN for 1992–2009.

[73] The reduction is less severe because the yield data difference is less in absolute value in newer sample. See Figure F.1 in Appendix F.

Identifier	USA		USA^2		USA		USA^2	
rhv	$CP_t^{(c)}$							
Sample	1964.01–2003.12				1964.01–2017.12			
lhv	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2
$rx_{t+1}^{(2)}$	0.45**	0.31	0.43**	0.20	0.43**	0.19	0.41**	0.13
	(8.85)	*[0.31]*	*(4.36)*	*[0.20]*	*(5.47)*	*[0.20]*	*(3.54)*	*[0.13]*
$rx_{t+1}^{(3)}$	0.85**	0.34	0.83**	0.23	0.83**	0.21	0.81**	0.15
	(8.51)	*[0.33]*	*(4.6)*	*[0.22]*	*(5.31)*	*[0.21]*	*(3.75)*	*[0.14]*
$rx_{t+1}^{(4)}$	1.24**	0.37	1.20**	0.24	1.25**	0.25	1.20**	0.17
	(8.57)	*[0.36]*	*(4.69)*	*[0.24]*	*(5.67)*	*[0.25]*	*(3.96)*	*[0.16]*
$rx_{t+1}^{(5)}$	1.46**	0.34	1.53**	0.26	1.49**	0.23	1.58**	0.19
	(7.90)	*[0.34]*	*(4.71)*	*[0.25]*	*(5.41)*	*[0.23]*	*(4.16)*	*[0.18]*
rhv	GCP_t							
Sample	1975.01–2009.12				1975.01–2017.12			
lhv	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2	$b_c^{(\tau)}$	R^2
$rx_{t+1}^{(2)}$	0.56**	0.14	0.55**	0.13	0.54**	0.12	0.53**	0.12
	(2.78)		*(2.60)*		*(3.01)*		*(2.87)*	
$rx_{t+1}^{(3)}$	1.04**	0.13	1.03**	0.14	1.03**	0.13	1.02**	0.13
	(2.60)		*(2.59)*		*(2.95)*		*(2.96)*	
$rx_{t+1}^{(4)}$	1.52**	0.15	1.46**	0.14	1.55**	0.15	1.50**	0.14
	(2.67)		*(2.61)*		*(3.13)*		*(3.08)*	
$rx_{t+1}^{(5)}$	1.89**	0.15	1.88**	0.15	1.99**	0.16	1.98**	0.16
	(2.71)		*(2.66)*		*(3.29)*		*(3.22)*	

Table 4.12: Data Set Comparison - CP and GCP Regression Results for the US.
Estimates of Regression (R.2) *and* (R.7) *in the US for two data sets (USA: CRSP (2018a), USA^2: Gürkaynak et al. (2007)) in two sample periods. T-statistics in parentheses use Newey and West (1987) standard error-correction with 18 lags. Adjusted R^2. Adjusted R^2 for Regression* (R.3) *in brackets. Constant estimates are excluded. See Appendix E.11 for same table for AUS, CHE, and JPN in the period 1992.12–2009.05. **: p-value < 0.01, *: p-value < 0.05.*

statistically significant at the 1% level irrespective of data set. Accordingly, we keep our conclusion that the CP factor still explains variations in annual bond risk premia on two- to five-year maturity bonds. The lower part in Table 4.12 depicts outputs for the GCP factor regressed on the two US data sets for 1975–2009 and 1975–2017. Coefficient estimates, statistical significance and R^2 are similar across data sets and sample periods. With this, we are to some degree confident that the GCP factor's significance is not driven by artificial features of the estimated bond yield data. Thus, we keep our conclusion that the GCP factor explains variations in annual bond risk premia on bonds with two- to five-years maturity, and that the GCP factor's significance has increased.[74]

[74] Appendix E.11 depicts the outputs of Cochrane and Piazzesi (2005) and Dahlquist and Hasseltoft (2013) predictive regressions for different data sets in the US, Australia, Switzerland, and Japan in 1992.12–2009.05. The conclusions for these countries are the same as for the US, strengthening our confidence in the conclusion of research question one. Moreover, the data impact on the predictive regressions seems to be greatest between the US data sets from CRSP (2018a) and Gürkaynak et al. (2007).

5 Real-Time Predictions

Bond risk premia have been time-varying and predictable during 1992–2017 and the CP and GCP factor explain a significant part of these variations. But to what extent could an investor have exploited this predictability and generated real-time excess returns? We test these models' predictive performance and whether they are superior to the simpler forward-spot spread model of Fama and Bliss (1987). We get mixed results, in line with literature on the economic value of forecasting models (e.g., Barillas, 2011; Gargano, Pettenuzzo, & Timmermann, 2017; Sarno, Schneider, & Wagner, 2016; Thornton & Valente, 2012). The GCP model's performance is better than the CP model's performance in most countries. Adding lags slightly improves the CP model results for most countries, but worsen the GCP model results.

5.1 Trading Setup

To assess whether the CP or GCP factor for expected bond risk premia are associated with real-time excess returns, we take a Gaussian[75] approach and use the models' forecast direction-accuracy (DA)[76] as the objective function. This method is inspired by Leitch and Tanner (1991), who find statistically significant correlation between trading profits and direction accuracy of models forecasting interest rates, when assuming constant bets.[77] They find no such relationship between profits and conventional error criteria, nor between DA and different error criteria.[78] Others find similar results (e.g., Gerlow, Irwin,

[75] Meaning that variables are assumed to have a normal (Gaussian) distribution.

[76] DA is the percentage a model forecasts the right direction of the actual value. See Appendix G.1 for details.

[77] Constant bet means one unit per trade, regardless preceding periods' profit/loss. Hence, the total return is the sum of returns each period. Ilmanen (1995) compares Sharpe ratios of proportional bet (bet proportional to expected profits) to constant bet (except negative forecasts means a zero position) and find that they are similar.

[78] Leitch and Tanner (1991) acknowledge that results might differ with a proportional bet strategy, where for instance MAE might have statistically significant correlation with profits.

& Liu, 1993). Therefore, we mainly rest our analysis on DA as an indication of the model's real-time economic value, with its mean absolute error (MAE) as a supplementary tool to address model estimation accuracy.[79]

Further, we make the following assumptions: no transaction costs or fees, no foreign exchange exposure, no liquidity issues, trading at end-of-month prices,[80] and the possibility to enter into short positions in the bond market.

5.2 Estimation Period for Out-of-Sample Forecasts

In real-life, trading decisions rely on information up to and including t. As such, our models only incorporate information available at time t (Ω_t) necessary for predictions. Thus,

$$E^{\mathbb{P}}[y_{t+1}|\Omega_t] \equiv \hat{y}_{t+1}.$$

We use a pseudo-out-of-sample method with an estimation period from December 1992 to May 2009.[81] As we compare the average one-year realized excess return ($\overline{rx}_{c,t+1} = \frac{1}{4}\sum_{\tau=2}^{5} rx_{c,t+1}^{(\tau)}$) against the forecast ($E^{\mathbb{P}}[\overline{rx}_{c,t+1}|\Omega_t]$), the first forecast is May 2010. Subsequently, the models recursively produce new predictions with new available information. Forecasts from May 2010 to December 2017 give 92 trades.

5.3 Out-of-Sample Results

To what extent do the CP or the GCP factor for expected bond risk premia generate real-time excess returns? Table 5.1 contains DA and MAE for all

[79] Real-life trading strategies should try to optimize a portfolio maximisation problem (Cochrane & Piazzesi, 2004a, p. 12), and our objective function for real-time excess returns does not necessarily maximize profits. Also, profits should entail arithmetic returns. Calculating real profits with these considerations is difficult and time-consuming and is beyond the scope of this thesis.

[80] Exact prices are difficult to determine. Yields in our data sets are estimated with interpolation methods and are not exact (see section 3.3), probably altering the results.

[81] Dahlquist and Hasseltoft (2013) use this as one of their sample period and May 2009 is when the initial Wright (2011) data set ends, but for all intents and purposes the period is arbitrarily chosen.

models in each country. DA numbers are bolded, and below them are the corresponding MAE. The best performing models for each country have shaded cells.

	USA	USA²	AUS	CAN	CHE	DEUW	GBRW	JPN
I	**79.3%**	**79.3%**	**78.3%**	**79.3%**	**76.1%**	**87.0%**	**78.3%**	**45.7%**
	(1.208)	*(1.201)*	*(1.424)*	*(1.135)*	*(0.790)*	*(0.939)*	*(1.282)*	*(0.460)*
II	**68.5%**	**79.3%**	**21.7%**	**67.4%**	**34.8%**	**44.6%**	**53.3%**	**42.4%**
	(1.306)	*(1.168)*	*(3.399)*	*(1.173)*	*(1.787)*	*(1.891)*	*(2.564)*	*(0.511)*
III	**77.2%**	**76.1%**	**28.3%**	**79.3%**	**42.4%**	**47.8%**	**45.7%**	**44.6%**
	(1.553)	*(1.634)*	*(2.602)*	*(1.077)*	*(1.556)*	*(1.699)*	*(2.722)*	*(0.523)*
IV	**75.0%**	**75.0%**	**57.6%**	**69.6%**	**69.6%**	**68.5%**	**71.7%**	**57.6%**
	(1.250)	*(1.252)*	*(1.981)*	*(1.244)*	*(0.927)*	*(1.501)*	*(1.885)*	*(0.840)*
V	**64.1%**	**65.2%**	**35.9%**	**72.8%**	**67.4%**	**47.8%**	**68.5%**	**37.0%**
	(1.605)	*(1.605)*	*(2.546)*	*(1.328)*	*(1.118)*	*(1.760)*	*(2.021)*	*(0.997)*

Table 5.1: Out-of-Sample Performance.
Pseudo-out-of-sample forecasting performance of each model in each country. Percentages are direction accuracy, numbers in parentheses are mean absolute errors. For both measures, the best performing model in each country is highlighted. Regressions - I: FB (R.1); II: CP (R.2); III: MA(CP, 2) (R.4); IV: GCP (R.7); V: MA(GCP, 2) (R.8). Estimation period: 1992.12–2009.05. Recursively forecasting during 2010.05–2017.12 give 92 forecasts.

The CP factor forecasts the right direction more than 50% of the time only in the US, CAN, and, slightly, GBR. DA in AUS and CHE are surprisingly low. Adding lags to the model improves the results slightly for all countries except the GBR and the US (alternative data set), where performance worsens. Still, MA(CP, 2) only has positive performance (i.e., DA $>$ 50%) in the US and CAN.

The GCP factor has a DA above 50% for all countries, yet only slightly for AUS and JPN. Adding lags to the GCP model reduces the performance in all countries but CAN, and the DA even drops below 50% for AUS, DEU, and JPN.

The pattern more or less holds for the MAE as well. The simple FB model has the lowest average absolute error in six data sets and is only higher by 0.03 and 0.06 in the US (alternative data set) and CAN, respectively. It is perhaps somewhat surprising that the MAE for FB in JPN is the lowest in the sample, given that JPN is the only country where the model does not have the highest forecast direction accuracy. As mentioned, however, Leitch and Tanner (1991) find no relationship between DA and MAE (conventional error-criteria), and we assume the same holds in our sample.[82]

Concluding on the out-of-sample results of forecasting average excess bond returns with direction accuracy as the objective function for excess returns, the CP factor produces weak results overall. On the other hand, the GCP seems to generate real-time excess returns, and more consistently than the CP factor. Yet, according to DA and MAE, these models falls short to the simpler forward-spot spread model of Fama and Bliss (1987). But how systematic is this conclusion?

A Closer Look at the Results

Measured by DA and MAE, the forward-spot spread model ("FB model") is superior in forecasting average expected excess bond return in the period 2010–2017, predicting the right direction between 76–87% for every country except Japan. However, closer examination of forecasts and realized average excess returns show that sample-specific properties seem to be driving the superior performance.

Figure 5.1 depicts the average one-year realized excess returns (AHPRX $\equiv$ $\overline{rx}_{c,t+1}$) in the US and the different models' expected risk premia forecasts. Table 5.2 holds the correlation between actual and predicted values. The FB model yields only positive predictions and they are fairly stable between 1 and 2%. Yet, the correlation between predicted and actual values is 0.42. Although the correlation is statistically significant, the FB model is not that interesting here since it exclusively forecasts positive expected risk premia. In contrast, the realized average excess returns fluctuate between positive and

[82] The correlation between out-of-sample MAE and DoC is around -0.46 for our sample, with a t-stat of -3.2. However, with only 40 observations (five models and eight data sets), we are cautious in making any inferences.

negative, so the superior DA performance by the FB model is a consequence of sample-specific properties.

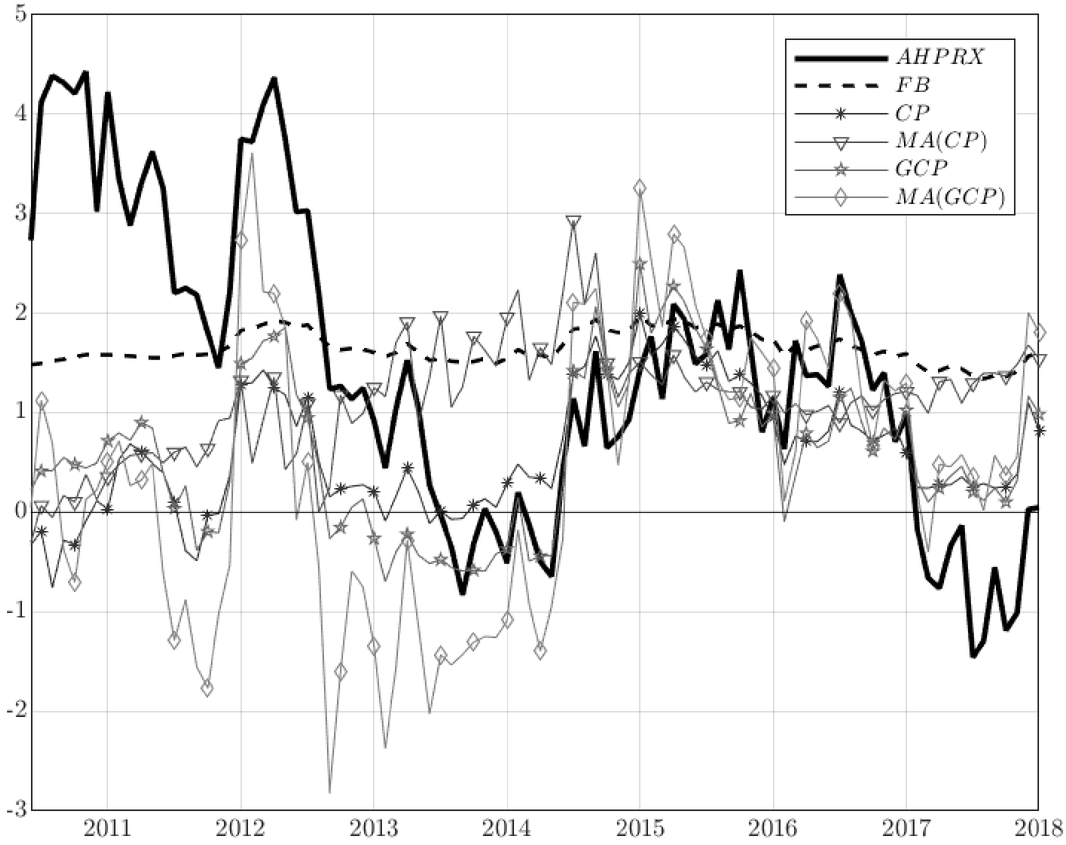


Figure 5.1: Forecasts vs. Actual Mean Excess Bond Returns in the US.
Pseudo-out-of-sample forecasts vs. actual average excess bond returns (in percent) in the US. MA(CP) and MA(GCP) are with $k = 2$. AHPRX: Average one-year excess bond returns. Estimation period: 1992.12–2009.05. Recursively forecasting during 2010.05–2017.12 results in 92 forecasts.

I	**II**	**III**	**IV**	**V**
0.42	0.09	-0.60	0.42	0.28
(0.00)	*(0.38)*	*(0.00)*	*(0.00)*	*(0.01)*

Table 5.2: Forecast-Actual Correlations in the US.
Correlation between pseudo-out-of-sample forecasts and actual average one-year excess bond returns in USA. Regressions - I: FB (R.1); II: CP (R.2); III: MA(CP, 2) (R.4); IV: GCP (R.7); V: MA(GCP, 2) (R.8). P-values of t-statistics in parentheses. Estimation period: 1992.12–2009.05. Recursively forecasting during 2010.05–2017.12 results in 92 forecasts.

As we discuss in Section 4.2, the CP factor seems to have lost some of its predictive power in recent years, and the forecasts correlate weakly with realized risk premia. More worrisome, when adding lags, the correlation coefficient becomes negative and significant, a highly undesirable feature for a forecasting model. Still, MA(CP,2) has good DA for the US, but as with the

FB model, this seems to be driven by sample-specific properties. Looking at Figure 5.1, we see that the MA(CP,2) model's forecasts are positive for the whole sample except for a few in 2010. As realized values are also mostly positive, this explains why the DA of MA(CP,2) is greater than 50%. Also discussed in Section 4.3, the GCP factor seems to have increased in significance recently, and the figure and performance seem to reflect this. The GCP model has the highest average correlation across countries and all of them are significant.[83] For the US, the GCP has the highest correlation of all models and it seems to follow the dynamics of realized values to a greater degree, relative to the other models (see Figure 5.1). Furthermore, the MAE is at 1.25, only beaten by the FB model. This makes it the best model overall.

As we saw earlier, adding lags to the GCP model worsens the DA in almost every country. Furthermore, the correlation falls to about a third of the standard GCP, even though the model seems to track actual values fairly well (see Figure 5.1). Also, from the first prediction for May 2010 to around 2012, the errors are quite large for the MA(GCP,2) model. The errors are also large for the GCP model, but the forecasts do not fluctuate as extremely as the MA(GCP,2) model's, especially around 2012–2014. This behaviour in risk premia forecasting models is much more desirable, and probably more valuable (than the FB model predictions), because it means that the model fits the fluctuating behaviour of historical realized excess bond returns better.

The corresponding figures for the other countries show the same pattern with stable forecasts by FB, and flexible, fluctuating results by CP and GCP, with and without lags.[84]

Therefore, while the performance measures and correlation declare the simpler FB model superior in almost every country, our closer examination tells a different story of the model's forecasting ability. Since the correlation

[83] See Appendix G.4 for full correlation table.
[84] See Appendix G.

coefficient is positive and the DA is greater than 50% for the GCP model for all countries, we conclude, with our assumptions, that this model of expected bond risk premia is able to produce real-time excess returns and would have been valuable for a bond investor in the sample period 2010–2017. The results for CP are more mixed and would only be valuable in certain countries. We also conclude that extending the models with lags worsens the models' forecasting fit.

Other Estimation Periods

We have performed our analyses with the estimation period ending at several dates both before and after the financial crisis. While changing the estimation period alters our results, our conclusion remains. Initially, the FB model seems to yield superior results but closer analysis reveal this is still because of sample-specific features. For instance, ending the estimation period in January 2008, the FB model has the highest DA in all countries, except Japan, but its forecasts correlate mostly little or negatively with average realized excess returns. The GCP model also has high DA in all countries, but show a relatively higher correlation between forecasted and realized values. This is the case for other estimation periods as well and we keep our conclusion that the GCP factor seem to be able to produce real-time excess returns.

6 Conclusion

We assess the predictability of annual risk premia on one- to five-year maturity government bonds in several countries and whether the predictability can be exploited by investors to generate excess returns. Particularly, we ask in research question one whether the results by Cochrane and Piazzesi (2005) and Dahlquist and Hasseltoft (2013) are still valid and if the CP factor and GCP factor significantly explain bond risk premia variations during 1992–2017. Additionally, we assess whether these factors forecast one- to five-year stock risk premia.

We find that the GCP factor has become more relevant for explaining annual excess bond returns variations in the US compared to earlier periods. Our results indicate that the factor explains a significant part of bond risk premia variations with average R^2 around 20%.[85] In contrast, the CP factor's relevance has weakened. Our results support Dahlquist and Hasseltoft's notion that asset prices globally move with more conformity as a consequence of increased integration of financial markets world wide. For stock risk premia, the CP factor and the GCP factor are insignificant. However, when including the dividend-price ratio and the one- to five-year yield spread as control variables, monthly lagged realizations of the GCP factor significantly forecasts stock risk premia at a one-year horizon in the US and Germany with a negative sign. For the other countries, the results are mixed.

We conclude on our first research question that bond risk premia are predictable and that the CP factor and GCP factor significantly explain bond risk premia variations in 1992–2017. Given our mixed results, we refrain from drawing conclusions on the factors' stock risk premia predictability.

[85] Significant at 1% for all countries, R^2 are 11%, 12%, 24%, 25%, 22%, 17%, and 32% for the US (both data sets), AUS, CAN, CHE, DEU, GBR, and JPN, respectively.

Research question two asks whether the CP factor and GCP factor have real-time predictive power. Since results for both factors in explaining stock risk premia variations are mixed and weak, we do not examine their real-time predictive power of excess stock returns. To answer research question two, we follow insights by Leitch and Tanner (1991) and use a simplified trading setup with directional accuracy (DA) as the objective function to determine the CP and GCP factor model's predictive power out of sample. In line with the literature, we find that the models that use the CP factor and GCP factor as forecast variables fall short to the simpler forward-spot spread model. However, closer analysis reveal that the correlation between the GCP factor forecasts and realized excess returns in the US is equal to the forward-spot spread forecasts at 0.42 and statistically significant in our pseudo sample (2010–2017). The CP factor model's results, however, are weak with correlation of only 0.09. By examining forecasted and realized excess returns, we observe that the seemingly superior results by the forward-spot spread model are driven by sample-specific features, while the GCP factor forecasting model seems to a greater extent mimic the fluctuating behavior of average bond risk premia. This finding is consistent across countries in the pseudo sample.

We conclude on our second research question that the CP factor has weak real-time predictive power for excess bond returns, while our findings are more convincing for the GCP factor.

We acknowledge that the predictive models we use may lack factors that could influence our results. As we focus on annual holding period returns on one- to five-year maturity bonds, a natural extension would be to test how our results stand up against other holding periods with other maturity bonds. Furthermore, will incorporating actual traded bond prices affect our results? Piazzesi and Swanson (2008) document that EH predictions of constant risk premia also fail to hold empirically for the federal funds futures market. They use historical actual traded prices on federal funds future contracts to show that excess returns on these contracts—with one- to six-month holding periods—are on average positive, time-varying and significantly predictable both in- and out-of-sample. Their evidence indicates that market participants even took advantage of the predictability in real-time.

Moreover, our results indicate that the CP factor's significance in forecasting annual excess stock return has vanished in later periods. However, Koijen, Lustig, and Van Nieuwerburgh (2017) find an interesting relationship between the CP factor and U.S. stock returns. They show that the CP factor forecasts aggregate dividend growth, particularly on value stocks, and that CP factor innovations are tightly linked to the value-minus-growth portfolio returns. Further, they document that the CP factor is a leading indicator of business cycle turning points and postulate that the business cycle is a priced state variable in the cross section of U.S. stock returns, and that the value premium reflects compensation for macroeconomic risks. Thus, bond factors, such as the CP factor, seem to some extent influence non-diversifiable risks in U.S. stock returns.

Furthermore, when assessing real-time predictive power, we assume a simplified trading setup in a Gaussian setting that has its limitations. To illustrate, bond returns are heteroskedastic, but our methods do not incorporate the conditional variance of returns, although conditional variance is paramount to reduce parameter uncertainty in a trading model. Gargano et al. (2017) take a Bayesian approach that incorporates stochastic volatility and time-varying parameters. They find significant out-of-sample economic gains when forecasting excess bond returns in the US on monthly holding periods. Their finding contrasts Thornton and Valente (2012), who do not account for these features.

To have any economic value and be useful to investors' portfolio allocation decisions, a predictive model must produce consistent and accurate results. The examples of differing results highlight the importance of incorporating more advanced statistical methods when estimating and modelling expected excess returns, and should encourage future research of bond risk premia predictability.

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APPENDIX

A Stock Data Calculations

We derive the τ-year value-weighted stock returns at t by monthly compounding the returns from $t-\tau$ to t:

$$sr_t^{(\tau)} = \left[\prod_{i=t-\tau+\frac{1}{12}}^{t} \left(1 + r_i^{(i-\frac{1}{12})}\right) - 1 \right]$$

The data is of monthly frequency, thus, $di = \frac{1}{12}$ (i.e., $t - \frac{11}{12}, \ldots, t - \frac{2}{12}, t$). The realized τ-year excess stock return at t is then the τ-year return less the $t-\tau$-year zero-coupon yield:

$$sx_t^{(\tau)} = sr_t^{(\tau)} - y_{t-\tau}^{(\tau)}.$$

We implicitly derive annual dividend-price ratios for each month by finding the ratio of monthly compounded annual returns including dividends to the corresponding returns excluding dividends and subtracting one:

$$\left(\frac{d}{p}\right)_t = \frac{\left(1 + sr_t^{(1)}[incl.div]\right)}{\left(1 + sr_t^{(1)}[excl.div]\right)} - 1.$$

B Descriptive Statistics

In this Appendix section we present the relevant descriptive statistics of the data, including diagnostics. The sample period 1992.12–2017.12 and data observations is of monthly frequency, recorded last business day.

B.1 Descriptive Statistics: Bond Risk Premia

Country	Series	Mean	I.	II.	SR[1]	I.	II.	Obs.	I.	II.
USA	$rx_{t+1}^{(2)}$	0.59**	1.57**	0.49**	0.52	2.19	0.44	289	26	263
	$rx_{t+1}^{(3)}$	1.22**	3.04**	1.04**	0.55	2.42	0.47	289	26	263
	$rx_{t+1}^{(4)}$	1.81**	3.96**	1.59**	0.57	1.89	0.50	289	26	263
	$rx_{t+1}^{(5)}$	2.18**	4.68**	1.94**	0.54	1.91	0.47	289	26	263
USA[2]	$rx_{t+1}^{(2)}$	0.57**	1.58**	0.48**	0.50	2.16	0.42	289	26	263
	$rx_{t+1}^{(3)}$	1.17**	2.94**	0.99**	0.53	2.25	0.45	289	26	263
	$rx_{t+1}^{(4)}$	1.73**	4.00**	1.51**	0.55	2.17	0.47	289	26	263
	$rx_{t+1}^{(5)}$	2.25**	4.81**	2.00**	0.56	2.03	0.49	289	26	263
AUS	$rx_{t+1}^{(2)}$	0.34**	*n.a.*	0.34**	0.27	*n.a.*	0.27	289	0	289
	$rx_{t+1}^{(3)}$	0.85**	*n.a.*	0.85**	0.35	*n.a.*	0.35	289	0	289
	$rx_{t+1}^{(4)}$	1.33**	*n.a.*	1.33**	0.37	*n.a.*	0.37	289	0	289
	$rx_{t+1}^{(5)}$	1.70**	*n.a.*	1.70**	0.37	*n.a.*	0.37	289	0	289
CAN	$rx_{t+1}^{(2)}$	0.75**	1.64**	0.69**	0.65	1.91	0.61	289	18	271
	$rx_{t+1}^{(3)}$	1.35**	2.51**	1.27**	0.64	1.68	0.60	289	18	271
	$rx_{t+1}^{(4)}$	1.87**	2.80**	1.81**	0.64	1.36	0.62	289	18	271
	$rx_{t+1}^{(5)}$	2.36**	2.93**	2.32**	0.65	1.11	0.63	289	18	271
CHE	$rx_{t+1}^{(2)}$	0.42**	1.55**	0.21**	0.47	2.28	0.27	289	46	243
	$rx_{t+1}^{(3)}$	0.97**	2.96**	0.59**	0.56	2.35	0.38	289	46	243
	$rx_{t+1}^{(4)}$	1.54**	4.10**	1.06**	0.63	2.24	0.47	289	46	243
	$rx_{t+1}^{(5)}$	2.06**	4.97**	1.51**	0.66	2.09	0.51	289	46	243
DEU	$rx_{t+1}^{(2)}$	0.66**	1.18**	0.55**	0.65	1.10	0.57	289	49	240
	$rx_{t+1}^{(3)}$	1.36**	2.06**	1.22**	0.68	0.97	0.63	289	49	240
	$rx_{t+1}^{(4)}$	2.03**	2.67**	1.90**	0.71	0.87	0.68	289	49	240
	$rx_{t+1}^{(5)}$	2.64**	3.08**	2.55**	0.72	0.79	0.71	289	49	240
GBR	$rx_{t+1}^{(2)}$	0.59**	1.96**	0.49**	0.55	1.97	0.49	289	21	268
	$rx_{t+1}^{(3)}$	1.21**	3.74**	1.01**	0.58	2.74	0.51	289	21	268
	$rx_{t+1}^{(4)}$	1.72**	4.98**	1.47**	0.58	3.00	0.51	289	21	268
	$rx_{t+1}^{(5)}$	2.18**	5.81**	1.89**	0.57	2.80	0.50	289	21	268
JPN	$rx_{t+1}^{(2)}$	0.38**	0.26**	0.44**	0.63	0.98	0.62	289	102	187
	$rx_{t+1}^{(3)}$	0.83**	0.63**	0.93**	0.66	1.02	0.63	289	102	187
	$rx_{t+1}^{(4)}$	1.39**	1.09**	1.55**	0.72	1.01	0.69	289	102	187
	$rx_{t+1}^{(5)}$	1.82**	1.42**	2.05**	0.73	0.90	0.71	289	102	187

Table B.1.1: Descriptive Statistics - Bond Risk Premia.
One-year mean excess bond returns on two- to five-year maturity bonds, Sharpe ratio (SR) and observations in international markets. Mean, Sharpe ratio and number of observations in columns I and II are condition on buying in recession and non-recession periods, respectively. [1]*: For $(d/p)_t$ standard deviation are tabulated. **: p-value $<$ 0.01, *: p-value $<$ 0.05. Sample period: 1992.12–2017.12.*

B.2 Descriptive Statistics: Stock Risk Premia and Dividend-Price Ratio

	Series	Mean	I.	II.	SR[1]	I.	II.	Obs.	I.	II.
USA	$(d/p)_t$	2.01**	1.95**	2.02**	0.42	0.56	0.41	301	26	275
	$sx_t^{(1)}$	7.93**	−4.91	9.20**	0.45	-0.16	0.61	289	26	263
	$sx_t^{(2)}$	16.29**	12.00	16.74**	0.57	0.31	0.61	277	26	251
	$sx_t^{(3)}$	24.93**	20.73**	25.39**	0.64	0.62	0.64	265	26	239
	$sx_t^{(4)}$	33.40**	32.71**	33.48**	0.66	0.77	0.65	253	26	227
	$sx_t^{(5)}$	40.00**	56.31**	38.03**	0.65	1.01	0.61	241	26	215
AUS	$(d/p)_t$	3.92**	*n.a.*	3.92**	0.58	*n.a.*	0.58	301	0	301
	$sx_t^{(1)}$	5.65**	*n.a.*	5.65**	0.38	*n.a.*	0.38	289	0	289
	$sx_t^{(2)}$	10.88**	*n.a.*	10.88**	0.51	*n.a.*	0.51	277	0	277
	$sx_t^{(3)}$	16.97**	*n.a.*	16.97**	0.62	*n.a.*	0.62	265	0	265
	$sx_t^{(4)}$	23.54**	*n.a.*	23.54**	0.71	*n.a.*	0.71	253	0	253
	$sx_t^{(5)}$	29.61**	*n.a.*	29.61**	0.84	*n.a.*	0.84	241	0	241
CAN	$(d/p)_t$	2.34**	2.83**	2.31**	0.58	0.50	0.57	301	18	283
	$sx_t^{(1)}$	7.77**	4.38	8.00**	0.45	0.14	0.50	289	18	271
	$sx_t^{(2)}$	15.11**	25.22**	14.40**	0.61	0.70	0.60	277	18	259
	$sx_t^{(3)}$	22.55**	21.50**	22.63**	0.78	0.91	0.77	265	18	247
	$sx_t^{(4)}$	31.00**	19.93*	31.85**	0.87	0.64	0.89	253	18	235
	$sx_t^{(5)}$	38.43**	35.04**	38.70**	0.93	0.88	0.94	241	18	223
CHE	$(d/p)_t$	2.14**	1.64**	2.25**	0.83	0.27	0.87	301	56	245
	$sx_t^{(1)}$	8.91**	10.29*	8.65**	0.44	0.38	0.46	289	46	243
	$sx_t^{(2)}$	17.91**	36.99**	14.11**	0.54	0.77	0.51	277	46	231
	$sx_t^{(3)}$	28.54**	62.07**	21.50**	0.61	0.97	0.55	265	46	219
	$sx_t^{(4)}$	38.38**	80.64**	28.99**	0.66	1.41	0.54	253	46	207
	$sx_t^{(5)}$	44.98**	92.11**	33.86**	0.66	1.72	0.51	241	46	195
DEU	$(d/p)_t$	2.59**	2.79**	2.54**	0.52	0.46	0.52	301	61	240
	$sx_t^{(1)}$	8.61**	−5.59	11.50**	0.38	-0.19	0.59	289	49	240
	$sx_t^{(2)}$	16.81**	2.96	19.79**	0.48	0.08	0.59	277	49	228
	$sx_t^{(3)}$	26.51**	16.56*	28.77**	0.56	0.36	0.61	265	49	216
	$sx_t^{(4)}$	35.40**	41.87**	33.84**	0.59	0.70	0.57	253	49	204
	$sx_t^{(5)}$	40.97**	60.13**	36.08**	0.59	1.08	0.50	241	49	192
GBR	$(d/p)_t$	3.53**	4.50**	3.46**	0.63	0.28	0.58	301	21	280
	$sx_t^{(1)}$	5.44**	18.33**	4.43**	0.35	0.95	0.30	289	21	268
	$sx_t^{(2)}$	10.54**	28.89**	9.03**	0.44	1.15	0.39	277	21	256
	$sx_t^{(3)}$	15.83**	30.53**	14.57**	0.51	1.65	0.46	265	21	244
	$sx_t^{(4)}$	20.74**	47.18**	18.34**	0.55	1.86	0.48	253	21	232
	$sx_t^{(5)}$	24.24**	60.40**	20.78**	0.57	2.20	0.49	241	21	220
JPN	$(d/p)_t$	1.38**	1.32**	1.42**	0.58	0.55	0.60	301	114	187
	$sx_t^{(1)}$	4.59**	6.29*	3.67*	0.20	0.23	0.18	289	102	187
	$sx_t^{(2)}$	8.04**	13.51**	4.85	0.24	0.43	0.14	277	102	175
	$sx_t^{(3)}$	12.69**	21.99**	6.88*	0.29	0.51	0.16	265	102	163
	$sx_t^{(4)}$	14.13**	26.29**	6.69	0.28	0.49	0.14	253	96	157
	$sx_t^{(5)}$	14.58**	37.88**	−0.33	0.26	0.68	-0.01	241	94	147

Table B.2.1: Descriptive Statistics - Stock Risk Premia and Dividend-Price Ratios.
One- to five-year mean excess stock returns, Sharpe ratio (SR) and observations in international markets. Mean, Sharpe ratio and number of observations in columns I and II are condition on buying in recession and non-recession periods, respectively. [1]*: For* $(d/p)_t$ *standard deviation are tabulated. **: p-value* $<$ *0.01, *: p-value* $<$ *0.05. Sample period: 1992.12–2017.12. Note: two- to five-year excess returns are not stated in annualized terms.*

B.3 Correlations

Correlations: Bond Yields

		$y_t^{(1)}$	$y_t^{(2)}$	$y_t^{(3)}$	$y_t^{(4)}$	$y_t^{(5)}$	**I.**	**II.**	**III.**	**IV.**	**V.**	**VI.**	**VII.**	**VIII.**
	$y_t^{(1)}$	**1.00**					**1.00**	1.00	0.75	0.91	0.76	0.79	0.91	0.44
	$y_t^{(2)}$	0.99	**1.00**				**1.00**	1.00	0.79	0.92	0.82	0.84	0.93	0.55
I. USA	$y_t^{(3)}$	0.98	1.00	**1.00**			**1.00**	1.00	0.82	0.93	0.85	0.87	0.94	0.63
	$y_t^{(4)}$	0.97	0.99	1.00	**1.00**		**1.00**	1.00	0.84	0.94	0.87	0.89	0.94	0.70
	$y_t^{(5)}$	0.95	0.98	0.99	1.00	**1.00**	**1.00**	1.00	0.86	0.95	0.89	0.91	0.95	0.75
	$y_t^{(1)}$	**1.00**					1.00	**1.00**	0.74	0.91	0.76	0.79	0.91	0.44
	$y_t^{(2)}$	0.99	**1.00**				1.00	**1.00**	0.79	0.92	0.82	0.84	0.93	0.55
II. USA²	$y_t^{(3)}$	0.98	1.00	**1.00**			1.00	**1.00**	0.82	0.93	0.85	0.87	0.94	0.63
	$y_t^{(4)}$	0.97	0.99	1.00	**1.00**		1.00	**1.00**	0.84	0.94	0.87	0.89	0.95	0.70
	$y_t^{(5)}$	0.95	0.98	0.99	1.00	**1.00**	1.00	**1.00**	0.86	0.95	0.89	0.91	0.95	0.75
	$y_t^{(1)}$	**1.00**					0.75	0.74	**1.00**	0.80	0.77	0.81	0.83	0.48
	$y_t^{(2)}$	0.98	**1.00**				0.79	0.79	**1.00**	0.87	0.86	0.88	0.88	0.64
III. AUS	$y_t^{(3)}$	0.96	1.00	**1.00**			0.82	0.82	**1.00**	0.90	0.90	0.92	0.91	0.72
	$y_t^{(4)}$	0.95	0.99	1.00	**1.00**		0.84	0.84	**1.00**	0.92	0.92	0.93	0.92	0.78
	$y_t^{(5)}$	0.94	0.98	1.00	1.00	**1.00**	0.86	0.86	**1.00**	0.93	0.94	0.94	0.94	0.82
	$y_t^{(1)}$	**1.00**					0.91	0.91	0.80	**1.00**	0.88	0.90	0.91	0.64
	$y_t^{(2)}$	0.99	**1.00**				0.92	0.92	0.87	**1.00**	0.93	0.93	0.94	0.71
IV. CAN	$y_t^{(3)}$	0.98	1.00	**1.00**			0.93	0.93	0.90	**1.00**	0.94	0.95	0.96	0.76
	$y_t^{(4)}$	0.96	0.99	1.00	**1.00**		0.94	0.94	0.92	**1.00**	0.95	0.96	0.97	0.80
	$y_t^{(5)}$	0.95	0.98	0.99	1.00	**1.00**	0.95	0.95	0.93	**1.00**	0.95	0.96	0.97	0.83
	$y_t^{(1)}$	**1.00**					0.76	0.76	0.77	0.88	**1.00**	0.96	0.81	0.78
	$y_t^{(2)}$	0.99	**1.00**				0.82	0.82	0.86	0.93	**1.00**	0.97	0.88	0.78
V. CHE	$y_t^{(3)}$	0.97	1.00	**1.00**			0.85	0.85	0.90	0.94	**1.00**	0.98	0.92	0.80
	$y_t^{(4)}$	0.96	0.99	1.00	**1.00**		0.87	0.87	0.92	0.95	**1.00**	0.98	0.94	0.82
	$y_t^{(5)}$	0.95	0.98	0.99	1.00	**1.00**	0.89	0.89	0.94	0.95	**1.00**	0.99	0.95	0.84
	$y_t^{(1)}$	**1.00**					0.79	0.79	0.81	0.90	0.96	**1.00**	0.91	0.71
	$y_t^{(2)}$	0.99	**1.00**				0.84	0.84	0.88	0.93	0.97	**1.00**	0.94	0.73
VI. DEU	$y_t^{(3)}$	0.98	1.00	**1.00**			0.87	0.87	0.92	0.95	0.98	**1.00**	0.96	0.76
	$y_t^{(4)}$	0.97	0.99	1.00	**1.00**		0.89	0.89	0.93	0.96	0.98	**1.00**	0.97	0.79
	$y_t^{(5)}$	0.96	0.98	0.99	1.00	**1.00**	0.91	0.91	0.94	0.96	0.99	**1.00**	0.97	0.82
	$y_t^{(1)}$	**1.00**					0.91	0.91	0.83	0.91	0.81	0.91	**1.00**	0.49
	$y_t^{(2)}$	0.99	**1.00**				0.93	0.93	0.88	0.94	0.88	0.94	**1.00**	0.61
VII. GBR	$y_t^{(3)}$	0.98	1.00	**1.00**			0.94	0.94	0.91	0.96	0.92	0.96	**1.00**	0.70
	$y_t^{(4)}$	0.96	0.99	1.00	**1.00**		0.94	0.95	0.92	0.97	0.94	0.97	**1.00**	0.77
	$y_t^{(5)}$	0.95	0.98	0.99	1.00	**1.00**	0.95	0.95	0.94	0.97	0.95	0.97	**1.00**	0.82
	$y_t^{(1)}$	**1.00**					0.44	0.44	0.48	0.64	0.78	0.71	0.49	**1.00**
	$y_t^{(2)}$	0.99	**1.00**				0.55	0.55	0.64	0.71	0.78	0.73	0.61	**1.00**
VIII. JPN	$y_t^{(3)}$	0.97	0.99	**1.00**			0.63	0.63	0.72	0.76	0.80	0.76	0.70	**1.00**
	$y_t^{(4)}$	0.95	0.98	1.00	**1.00**		0.70	0.70	0.78	0.80	0.82	0.79	0.77	**1.00**
	$y_t^{(5)}$	0.93	0.97	0.99	1.00	**1.00**	0.75	0.75	0.82	0.83	0.84	0.82	0.82	**1.00**

Table B.3.1: Correlations - Yields.
Correlation of one- to five-year maturity bond yields in international markets. Numbers in columns I.–VIII. are correlations with yields in other countries. Sample period: 1992.12–2017.12.

Correlations: Bond Risk Premia

		$rx_{t+1}^{(2)}$	$rx_{t+1}^{(3)}$	$rx_{t+1}^{(4)}$	$rx_{t+1}^{(5)}$	**I.**	**II.**	**III.**	**IV.**	**V.**	**VI.**	**VII.**	**VIII.**
I. USA	$rx_{t+1}^{(2)}$	**1.00**				**1.00**	1.00	0.52	0.72	0.66	0.60	0.67	0.29
	$rx_{t+1}^{(3)}$	0.98	**1.00**			**1.00**	1.00	0.57	0.74	0.68	0.63	0.71	0.33
	$rx_{t+1}^{(4)}$	0.94	0.98	**1.00**		**1.00**	1.00	0.63	0.76	0.69	0.67	0.75	0.36
	$rx_{t+1}^{(5)}$	0.89	0.95	0.99	**1.00**	**1.00**	1.00	0.67	0.77	0.69	0.70	0.77	0.40
II. USA²	$rx_{t+1}^{(2)}$	**1.00**				1.00	**1.00**	0.50	0.72	0.65	0.59	0.66	0.28
	$rx_{t+1}^{(3)}$	0.98	**1.00**			1.00	**1.00**	0.58	0.75	0.68	0.63	0.72	0.32
	$rx_{t+1}^{(4)}$	0.94	0.99	**1.00**		1.00	**1.00**	0.63	0.76	0.69	0.67	0.76	0.36
	$rx_{t+1}^{(5)}$	0.89	0.96	0.99	**1.00**	1.00	**1.00**	0.67	0.77	0.70	0.70	0.78	0.40
III. AUS	$rx_{t+1}^{(2)}$	**1.00**				0.52	0.50	**1.00**	0.69	0.61	0.66	0.68	0.48
	$rx_{t+1}^{(3)}$	0.97	**1.00**			0.57	0.58	**1.00**	0.76	0.68	0.71	0.73	0.47
	$rx_{t+1}^{(4)}$	0.93	0.99	**1.00**		0.63	0.63	**1.00**	0.80	0.73	0.75	0.78	0.50
	$rx_{t+1}^{(5)}$	0.91	0.98	1.00	**1.00**	0.67	0.67	**1.00**	0.83	0.75	0.79	0.81	0.53
IV. CAN	$rx_{t+1}^{(2)}$	**1.00**				0.72	0.72	0.69	**1.00**	0.78	0.72	0.68	0.50
	$rx_{t+1}^{(3)}$	0.97	**1.00**			0.74	0.75	0.76	**1.00**	0.82	0.76	0.72	0.51
	$rx_{t+1}^{(4)}$	0.92	0.98	**1.00**		0.76	0.76	0.80	**1.00**	0.82	0.78	0.74	0.52
	$rx_{t+1}^{(5)}$	0.86	0.95	0.99	**1.00**	0.77	0.77	0.83	**1.00**	0.82	0.80	0.76	0.54
V. CHE	$rx_{t+1}^{(2)}$	**1.00**				0.66	0.65	0.61	0.78	**1.00**	0.83	0.73	0.54
	$rx_{t+1}^{(3)}$	0.97	**1.00**			0.68	0.68	0.68	0.82	**1.00**	0.88	0.77	0.55
	$rx_{t+1}^{(4)}$	0.93	0.99	**1.00**		0.69	0.69	0.73	0.82	**1.00**	0.91	0.79	0.55
	$rx_{t+1}^{(5)}$	0.89	0.96	0.99	**1.00**	0.69	0.70	0.75	0.82	**1.00**	0.93	0.80	0.56
VI. DEU	$rx_{t+1}^{(2)}$	**1.00**				0.60	0.59	0.66	0.72	0.83	**1.00**	0.85	0.53
	$rx_{t+1}^{(3)}$	0.98	**1.00**			0.63	0.63	0.71	0.76	0.88	**1.00**	0.85	0.56
	$rx_{t+1}^{(4)}$	0.94	0.99	**1.00**		0.67	0.67	0.75	0.78	0.91	**1.00**	0.85	0.55
	$rx_{t+1}^{(5)}$	0.89	0.96	0.99	**1.00**	0.70	0.70	0.79	0.80	0.93	**1.00**	0.86	0.56
VII. GBR	$rx_{t+1}^{(2)}$	**1.00**				0.67	0.66	0.68	0.68	0.73	0.85	**1.00**	0.44
	$rx_{t+1}^{(3)}$	0.96	**1.00**			0.71	0.72	0.73	0.72	0.77	0.85	**1.00**	0.43
	$rx_{t+1}^{(4)}$	0.90	0.98	**1.00**		0.75	0.76	0.78	0.74	0.79	0.85	**1.00**	0.43
	$rx_{t+1}^{(5)}$	0.84	0.95	0.99	**1.00**	0.77	0.78	0.81	0.76	0.80	0.86	**1.00**	0.45
VIII. JPN	$rx_{t+1}^{(2)}$	**1.00**				0.29	0.28	0.48	0.50	0.54	0.53	0.44	**1.00**
	$rx_{t+1}^{(3)}$	0.99	**1.00**			0.33	0.32	0.47	0.51	0.55	0.56	0.43	**1.00**
	$rx_{t+1}^{(4)}$	0.96	0.99	**1.00**		0.36	0.36	0.50	0.52	0.55	0.55	0.43	**1.00**
	$rx_{t+1}^{(5)}$	0.93	0.97	0.99	**1.00**	0.40	0.40	0.53	0.54	0.56	0.56	0.45	**1.00**

Table B.3.2: Correlations - Bond Risk Premia.
Correlation of annual excess bond returns on two- to five-year maturity bonds in international markets. Numbers in columns I.–VIII. are correlations with excess returns in other countries. Sample period: 1992.12–2017.12.

Correlations: Stock Risk Premia

Country	Series	I.	II.	III.	IV.	V.	VI.	VII.
I. USA	$sx_t^{(1)}$	**1.00**	0.74	0.82	0.78	0.83	0.92	0.61
	$sx_t^{(2)}$	**1.00**	0.73	0.81	0.82	0.86	0.93	0.60
	$sx_t^{(3)}$	**1.00**	0.67	0.80	0.89	0.89	0.95	0.52
	$sx_t^{(4)}$	**1.00**	0.63	0.77	0.92	0.91	0.96	0.47
	$sx_t^{(5)}$	**1.00**	0.61	0.76	0.90	0.91	0.96	0.45
II. AUS	$sx_t^{(1)}$	0.74	**1.00**	0.73	0.75	0.73	0.83	0.61
	$sx_t^{(2)}$	0.73	**1.00**	0.83	0.74	0.79	0.81	0.73
	$sx_t^{(3)}$	0.67	**1.00**	0.87	0.72	0.76	0.75	0.71
	$sx_t^{(4)}$	0.63	**1.00**	0.85	0.68	0.70	0.70	0.62
	$sx_t^{(5)}$	0.61	**1.00**	0.84	0.64	0.64	0.65	0.53
III. CAN	$sx_t^{(1)}$	0.82	0.73	**1.00**	0.71	0.83	0.79	0.58
	$sx_t^{(2)}$	0.81	0.83	**1.00**	0.73	0.83	0.82	0.62
	$sx_t^{(3)}$	0.80	0.87	**1.00**	0.79	0.85	0.85	0.56
	$sx_t^{(4)}$	0.77	0.85	**1.00**	0.81	0.86	0.82	0.44
	$sx_t^{(5)}$	0.76	0.84	**1.00**	0.81	0.85	0.79	0.36
IV. CHE	$sx_t^{(1)}$	0.78	0.75	0.71	**1.00**	0.88	0.87	0.56
	$sx_t^{(2)}$	0.82	0.74	0.73	**1.00**	0.92	0.87	0.51
	$sx_t^{(3)}$	0.89	0.72	0.79	**1.00**	0.93	0.91	0.45
	$sx_t^{(4)}$	0.92	0.68	0.81	**1.00**	0.93	0.92	0.35
	$sx_t^{(5)}$	0.90	0.64	0.81	**1.00**	0.93	0.90	0.25
V. DEU	$sx_t^{(1)}$	0.83	0.73	0.83	0.88	**1.00**	0.86	0.63
	$sx_t^{(2)}$	0.86	0.79	0.83	0.92	**1.00**	0.90	0.59
	$sx_t^{(3)}$	0.89	0.76	0.85	0.93	**1.00**	0.93	0.56
	$sx_t^{(4)}$	0.91	0.70	0.86	0.93	**1.00**	0.93	0.46
	$sx_t^{(5)}$	0.91	0.64	0.85	0.93	**1.00**	0.94	0.37
VI. GBR	$sx_t^{(1)}$	0.92	0.83	0.79	0.87	0.86	**1.00**	0.60
	$sx_t^{(2)}$	0.93	0.81	0.82	0.87	0.90	**1.00**	0.57
	$sx_t^{(3)}$	0.95	0.75	0.85	0.91	0.93	**1.00**	0.55
	$sx_t^{(4)}$	0.96	0.70	0.82	0.92	0.93	**1.00**	0.48
	$sx_t^{(5)}$	0.96	0.65	0.79	0.90	0.94	**1.00**	0.43
VII. JPN	$sx_t^{(1)}$	0.61	0.61	0.58	0.56	0.63	0.60	**1.00**
	$sx_t^{(2)}$	0.60	0.73	0.62	0.51	0.59	0.57	**1.00**
	$sx_t^{(3)}$	0.52	0.71	0.56	0.45	0.56	0.55	**1.00**
	$sx_t^{(4)}$	0.47	0.62	0.44	0.35	0.46	0.48	**1.00**
	$sx_t^{(5)}$	0.45	0.53	0.36	0.25	0.37	0.43	**1.00**

Table B.3.3: Correlations - Stock Risk Premia.
Correlation of one- to five-year excess stock returns in international markets. Numbers in columns I.–VIII. are correlations with respective variable in other countries. Sample period: 1992.12–2017.12.

B.4 Diagnostics

Diagnostics: Bond Yields

Country	Series	*Sample autocorrelation* $\hat{\rho}(\frac{1}{12})$	$\hat{\rho}(1)$	$\hat{\rho}(5)$	*KPSS test* t-stat	p-val	*ADF test* t-stat	p-val
USA	$y_t^{(1)}$	0.99	0.84	0.25	20.9	0.01	-0.9	0.32
	$y_t^{(2)}$	0.99	0.85	-0.01	22.8	0.01	-1.1	0.25
	$y_t^{(3)}$	0.99	0.86	-0.08	24.1	0.01	-1.2	0.20
	$y_t^{(4)}$	0.99	0.85	-0.12	24.9	0.01	-1.3	0.17
	$y_t^{(5)}$	0.99	0.85	-0.12	25.5	0.01	-1.4	0.15
USA[2]	$y_t^{(1)}$	0.99	0.84	0.26	21.1	0.01	-0.9	0.31
	$y_t^{(2)}$	0.99	0.85	-0.05	22.8	0.01	-1.1	0.25
	$y_t^{(3)}$	0.99	0.85	-0.10	24.1	0.01	-1.2	0.20
	$y_t^{(4)}$	0.99	0.85	-0.12	25.0	0.01	-1.3	0.17
	$y_t^{(5)}$	0.99	0.85	-0.13	25.6	0.01	-1.4	0.15
AUS	$y_t^{(1)}$	0.98	0.66	0.11	17.4	0.01	-1.2	0.20
	$y_t^{(2)}$	0.98	0.71	0.16	19.9	0.01	-1.4	0.15
	$y_t^{(3)}$	0.98	0.73	0.14	21.0	0.01	-1.5	0.13
	$y_t^{(4)}$	0.98	0.74	0.13	21.5	0.01	-1.6	0.11
	$y_t^{(5)}$	0.98	0.75	0.12	21.9	0.01	-1.6	0.10
CAN	$y_t^{(1)}$	0.98	0.78	0.40	24.4	0.01	-1.9	0.05
	$y_t^{(2)}$	0.99	0.82	0.05	26.1	0.01	-1.8	0.07
	$y_t^{(3)}$	0.99	0.84	0.02	27.0	0.01	-1.8	0.07
	$y_t^{(4)}$	0.99	0.85	0.00	27.5	0.01	-1.8	0.07
	$y_t^{(5)}$	0.99	0.86	-0.02	27.8	0.01	-1.8	0.06
CHE	$y_{c,t}^{(1)}$	0.97	0.69	0.20	19.8	0.01	-3.3	0.00
	$y_t^{(2)}$	0.98	0.74	0.12	22.3	0.01	-3.0	0.00
	$y_t^{(3)}$	0.98	0.76	0.08	23.6	0.01	-2.8	0.01
	$y_t^{(4)}$	0.98	0.78	0.04	24.3	0.01	-2.7	0.01
	$y_t^{(5)}$	0.98	0.79	0.01	24.8	0.01	-2.6	0.01
DEU	$y_t^{(1)}$	0.98	0.75	0.29	23.7	0.01	-3.3	0.00
	$y_t^{(2)}$	0.98	0.78	0.04	24.8	0.01	-2.7	0.01
	$y_t^{(3)}$	0.98	0.80	0.00	25.7	0.01	-2.4	0.02
	$y_t^{(4)}$	0.98	0.81	-0.04	26.2	0.01	-2.3	0.02
	$y_t^{(5)}$	0.99	0.83	-0.08	26.6	0.01	-2.2	0.03
GBR	$y_t^{(1)}$	0.99	0.86	0.33	25.7	0.01	-1.7	0.08
	$y_t^{(2)}$	0.99	0.86	-0.01	26.8	0.01	-1.7	0.08
	$y_t^{(3)}$	0.99	0.86	-0.08	27.2	0.01	-1.8	0.07
	$y_t^{(4)}$	0.99	0.85	-0.12	27.3	0.01	-1.8	0.06
	$y_t^{(5)}$	0.99	0.85	-0.13	27.2	0.01	-1.9	0.06
JPN	$y_t^{(1)}$	0.96	0.56	0.00	11.5	0.01	-4.9	0.00
	$y_t^{(2)}$	0.96	0.61	0.01	13.5	0.01	-4.2	0.00
	$y_t^{(3)}$	0.96	0.65	0.06	15.3	0.01	-3.6	0.00
	$y_t^{(4)}$	0.97	0.68	0.11	17.0	0.01	-3.4	0.00
	$y_t^{(5)}$	0.97	0.72	0.15	18.4	0.01	-3.2	0.00

Table B.4.1: Diagnostics - Yields.
Yield diagnostics on one-to five-year maturity bonds, sample period: 1992.12–2017.12. $\hat{\rho}(\frac{1}{12})$, $\hat{\rho}(1)$ and $\hat{\rho}(5)$ are sample autocorrelation with lags one month, one year and five year, respectively. t-stat and p-val are T-statistics and P-value of the stationarity test by Kwiatkowski et al. (1992) and Dickey and Fuller (1979). Note: we run the KPSS test with a trend component, thus testing for trend stationarity. MatLab only reports p-values of the t-statistics between [0.01–0.10] (i.e., values lower than 0.01 shows 0.01, while values larger than 0.1 shows 0.1.).

Diagnostics: Bond Risk Premia

		Sample autocorrelation			*KPSS test*		*ADF test*	
Country	**Series**	$\hat{\rho}(\frac{1}{12})$	$\hat{\rho}(1)$	$\hat{\rho}(5)$	**t-stat**	**p-val**	**t-stat**	**p-val**
USA	$rx_{t+1}^{(2)}$	0.94	0.13	0.05	0.78	0.01	-2.72	0.01
	$rx_{t+1}^{(3)}$	0.93	0.04	0.05	0.80	0.01	-2.86	0.00
	$rx_{t+1}^{(4)}$	0.92	-0.05	0.05	0.87	0.01	-3.09	0.00
	$rx_{t+1}^{(5)}$	0.92	-0.11	0.05	1.01	0.01	-3.22	0.00
USA^2	$rx_{t+1}^{(2)}$	0.95	0.14	0.06	0.80	0.01	-2.58	0.01
	$rx_{t+1}^{(3)}$	0.94	0.04	0.06	0.85	0.01	-2.82	0.00
	$rx_{t+1}^{(4)}$	0.93	-0.04	0.06	0.96	0.01	-3.03	0.00
	$rx_{t+1}^{(5)}$	0.92	-0.11	0.06	0.98	0.01	-3.19	0.00
AUS	$rx_{t+1}^{(2)}$	0.92	-0.19	0.01	1.11	0.01	-3.58	0.00
	$rx_{t+1}^{(3)}$	0.92	-0.26	0.01	0.54	0.03	-3.64	0.00
	$rx_{t+1}^{(4)}$	0.92	-0.28	0.01	0.42	0.07	-3.59	0.00
	$rx_{t+1}^{(5)}$	0.92	-0.28	0.01	0.40	0.08	-3.54	0.00
CAN	$rx_{t+1}^{(2)}$	0.92	0.06	0.10	2.21	0.01	-3.07	0.00
	$rx_{t+1}^{(3)}$	0.91	-0.02	0.10	1.12	0.01	-3.25	0.00
	$rx_{t+1}^{(4)}$	0.91	-0.08	0.10	0.73	0.01	-3.34	0.00
	$rx_{t+1}^{(5)}$	0.90	-0.11	0.10	0.57	0.03	-3.38	0.00
CHE	$rx_{t+1}^{(2)}$	0.94	0.09	-0.06	2.98	0.01	-2.89	0.00
	$rx_{t+1}^{(3)}$	0.94	0.02	-0.06	1.59	0.01	-2.84	0.00
	$rx_{t+1}^{(4)}$	0.94	-0.05	-0.06	0.88	0.01	-2.78	0.01
	$rx_{t+1}^{(5)}$	0.94	-0.10	-0.06	0.58	0.02	-2.74	0.01
DEU	$rx_{t+1}^{(2)}$	0.95	-0.03	-0.04	1.07	0.01	-2.48	0.01
	$rx_{t+1}^{(3)}$	0.94	-0.11	-0.04	0.77	0.01	-2.63	0.01
	$rx_{t+1}^{(4)}$	0.94	-0.16	-0.04	0.53	0.04	-2.70	0.01
	$rx_{t+1}^{(5)}$	0.93	-0.19	-0.04	0.41	0.07	-2.76	0.01
GBR	$rx_{t+1}^{(2)}$	0.94	-0.02	0.01	0.53	0.04	-2.80	0.01
	$rx_{t+1}^{(3)}$	0.94	-0.10	0.01	0.75	0.01	-2.92	0.00
	$rx_{t+1}^{(4)}$	0.93	-0.14	0.01	1.05	0.01	-3.00	0.00
	$rx_{t+1}^{(5)}$	0.93	-0.16	0.01	1.20	0.01	-3.10	0.00
JPN	$rx_{t+1}^{(2)}$	0.92	0.20	-0.02	8.86	0.01	-3.63	0.00
	$rx_{t+1}^{(3)}$	0.92	0.10	-0.02	8.04	0.01	-3.51	0.00
	$rx_{t+1}^{(4)}$	0.91	0.06	-0.02	7.80	0.01	-3.59	0.00
	$rx_{t+1}^{(5)}$	0.91	0.04	-0.02	7.31	0.01	-3.60	0.00

Table B.4.2: Diagnostics - Bond Risk Premia.
Annual excess bond return diagnostics on two-to five-year maturity bonds, sample period: 1992.12–2017.12. $\hat{\rho}(\frac{1}{12})$*,* $\hat{\rho}(1)$ *and* $\hat{\rho}(5)$ *are sample autocorrelation with lags one month, one year and five year, respectively. t-stat and p-val are T-statistics and P-value of the stationarity test by Kwiatkowski et al. (1992) and Dickey and Fuller (1979). Note: MatLab only reports p-values of the t-statistics between [0.01–0.10] (i.e., values lower than 0.01 shows 0.01, while values larger than 0.1 shows 0.1.).*

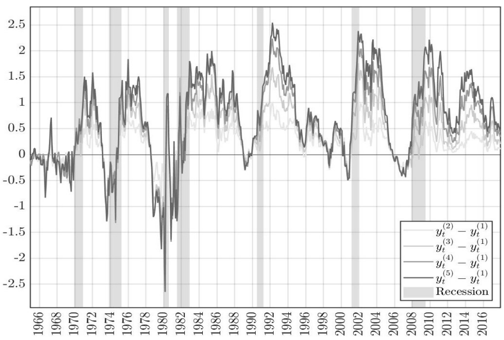
Diagnostics: Stock Risk Premia and Dividend-yield

		Sample autocorrelation			*KPSS test*		*ADF test*	
Country	**Series**	$\hat{\rho}(\frac{1}{12})$	$\hat{\rho}(1)$	$\hat{\rho}(5)$	**t-stat**	**p-val**	**t-stat**	**p-val**
USA	$(d/p)_t$	0.99	0.75	-0.17	5.43	0.01	-1.42	0.14
	$sx_t^{(1)}$	0.93	0.05	-0.37	0.87	0.01	-2.85	0.00
	$sx_t^{(2)}$	0.96	0.45	-0.35	1.59	0.01	-1.87	0.06
	$sx_t^{(3)}$	0.97	0.64	-0.33	2.60	0.01	-1.60	0.10
	$sx_t^{(4)}$	0.98	0.68	-0.34	3.21	0.01	-1.41	0.15
	$sx_t^{(5)}$	0.98	0.62	-0.36	3.42	0.01	-1.39	0.15
AUS	$(d/p)_t$	0.99	0.73	0.29	18.99	0.01	-0.01	0.65
	$sx_t^{(1)}$	0.92	-0.17	-0.13	0.43	0.06	-3.41	0.00
	$sx_t^{(2)}$	0.96	0.30	-0.24	0.85	0.01	-2.17	0.03
	$sx_t^{(3)}$	0.97	0.50	-0.23	1.66	0.01	-1.84	0.06
	$sx_t^{(4)}$	0.97	0.46	-0.27	2.22	0.01	-1.77	0.07
	$sx_t^{(5)}$	0.97	0.43	-0.48	3.16	0.01	-1.63	0.10
CAN	$(d/p)_t$	0.99	0.80	0.20	12.52	0.01	-0.89	0.32
	$sx_t^{(1)}$	0.93	-0.20	-0.28	0.41	0.07	-3.03	0.00
	$sx_t^{(2)}$	0.95	0.19	-0.23	0.93	0.01	-2.19	0.03
	$sx_t^{(3)}$	0.96	0.44	-0.17	2.26	0.01	-1.85	0.06
	$sx_t^{(4)}$	0.96	0.45	-0.25	3.11	0.01	-1.79	0.07
	$sx_t^{(5)}$	0.97	0.32	-0.47	3.61	0.01	-1.72	0.08
CHE	$(d/p)_t$	0.99	0.87	0.42	24.53	0.01	-0.10	0.61
	$sx_t^{(1)}$	0.94	0.10	-0.34	1.46	0.01	-2.85	0.00
	$sx_t^{(2)}$	0.97	0.54	-0.40	2.55	0.01	-1.76	0.07
	$sx_t^{(3)}$	0.98	0.64	-0.37	4.03	0.01	-1.55	0.11
	$sx_t^{(4)}$	0.98	0.69	-0.37	5.33	0.01	-1.46	0.14
	$sx_t^{(5)}$	0.98	0.62	-0.35	5.88	0.01	-2.31	0.02
DEU	$(d/p)_t$	0.95	0.52	0.00	5.57	0.01	-1.25	0.19
	$sx_t^{(1)}$	0.93	0.01	-0.41	0.67	0.02	-3.05	0.00
	$sx_t^{(2)}$	0.96	0.45	-0.39	1.16	0.01	-2.11	0.03
	$sx_t^{(3)}$	0.97	0.58	-0.37	1.92	0.01	-1.71	0.08
	$sx_t^{(4)}$	0.98	0.61	-0.41	2.71	0.01	-1.58	0.11
	$sx_t^{(5)}$	0.97	0.52	-0.45	3.10	0.01	-1.73	0.08
GBR	$(d/p)_t$	0.98	0.65	0.06	7.30	0.01	-0.55	0.45
	$sx_t^{(1)}$	0.93	0.03	-0.29	0.84	0.01	-3.05	0.00
	$sx_t^{(2)}$	0.96	0.43	-0.28	1.16	0.01	-1.96	0.05
	$sx_t^{(3)}$	0.97	0.59	-0.30	1.73	0.01	-1.75	0.08
	$sx_t^{(4)}$	0.98	0.61	-0.38	2.23	0.01	-1.60	0.10
	$sx_t^{(5)}$	0.97	0.54	-0.46	2.58	0.01	-1.63	0.10
JPN	$(d/p)_t$	0.99	0.88	0.43	25.72	0.01	0.86	0.89
	$sx_t^{(1)}$	0.94	-0.03	-0.30	1.50	0.01	-2.72	0.01
	$sx_t^{(2)}$	0.97	0.49	-0.31	3.05	0.01	-1.88	0.06
	$sx_t^{(3)}$	0.98	0.57	-0.32	4.67	0.01	-1.49	0.13
	$sx_t^{(4)}$	0.98	0.68	-0.38	6.49	0.01	-1.22	0.20
	$sx_t^{(5)}$	0.97	0.59	-0.43	7.79	0.01	-0.26	0.56

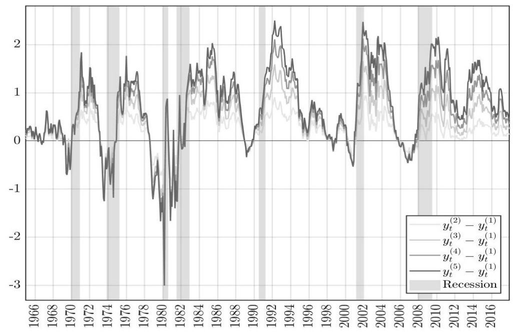
Table B.4.3: Diagnostics - Stock Risk Premia and Dividend-Price Ratios.
One- to five-year excess stock return and dividend-price ratio diagnostics, sample period: 1992.12–2017.12. $\hat{\rho}(\frac{1}{12})$, $\hat{\rho}(1)$ and $\hat{\rho}(5)$ are sample autocorrelation with lags one month, one year and five year, respectively. t-stat and p-val are T-statistics and P-value of the stationarity test by Kwiatkowski et al. (1992) and Dickey and Fuller (1979). Note: MatLab only reports p-values of the t-statistics between [0.01–0.10] (i.e., values lower than 0.01 shows 0.01, while values larger than 0.1 shows 0.1.).

C Time-Series Graphs

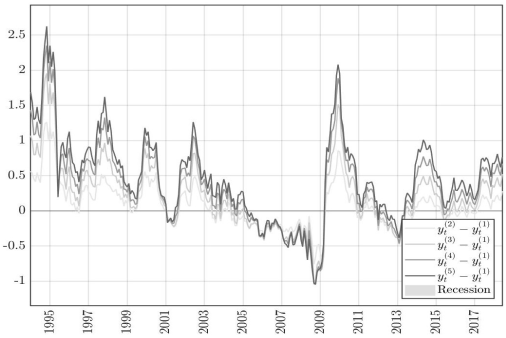
C.1 Bond Yield Spreads



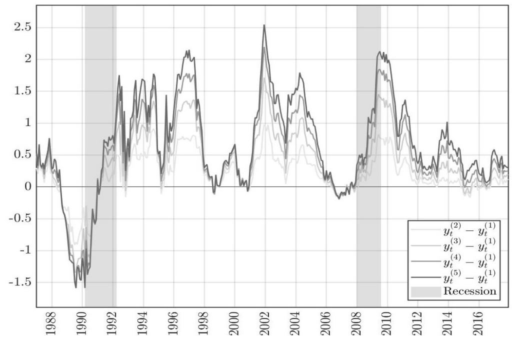
(a) *USA (1964.01–2017.12)*



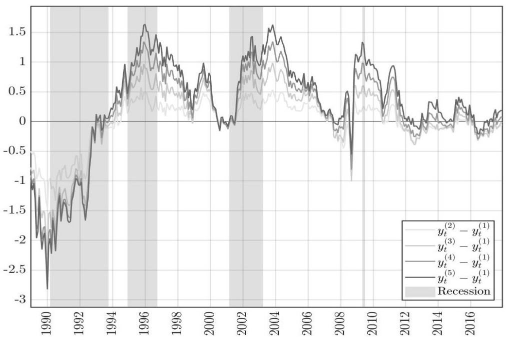
(b) *USA² (1964.01–2017.12)*



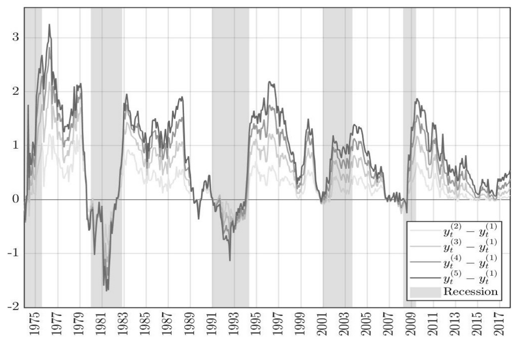
(c) *AUS² (1992.07–2017.12)*



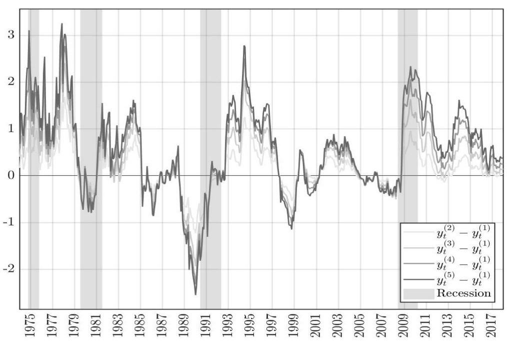
(d) *CAN (1986.01–2017.12)*



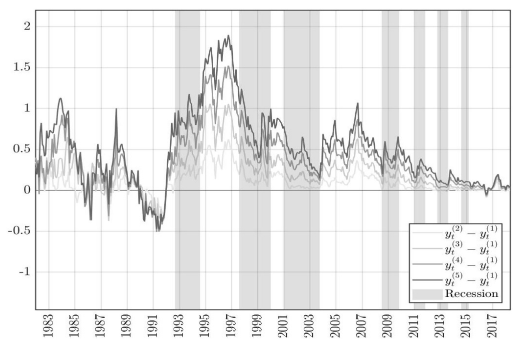
(e) *CHE² (1988.01–2017.12)*



(f) *DEU (1973.01–2017.12)*



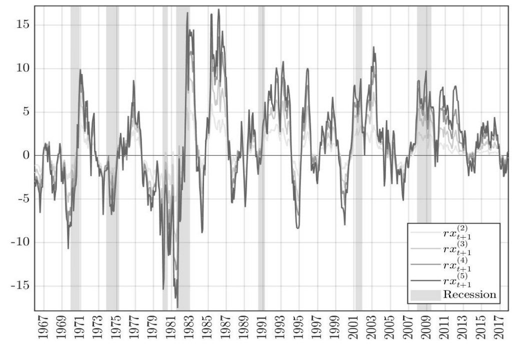
(g) *GBR (1972.12–2017.12)*



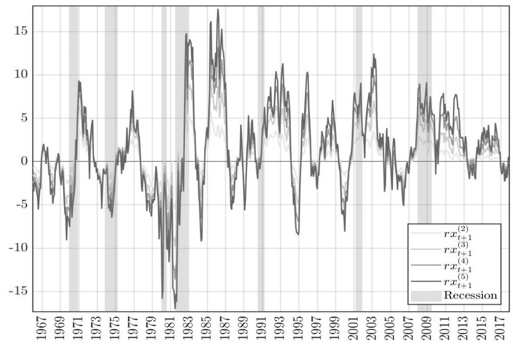
(h) *JPN (1980.08–2017.12)*

Figure C.1.1: Yield Spreads.
Two-, three-, four-, and five-year yield spreads (in percent). Shaded areas are recession periods defined by ECRI (2018) (NBER (2010) for the US). Sample period in subcaption. For data source, see Table 2.1.

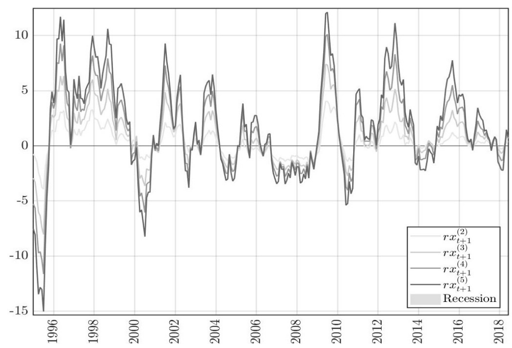
C.2 One-Year Bond Risk Premia



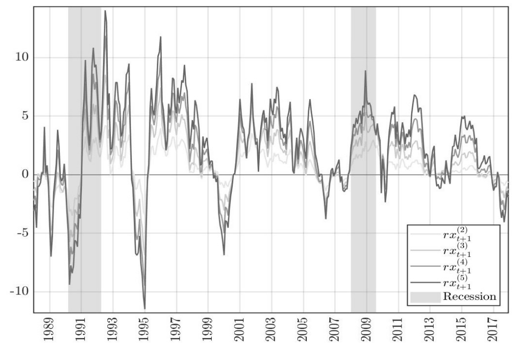
(a) *USA (1964.01–2017.12)*



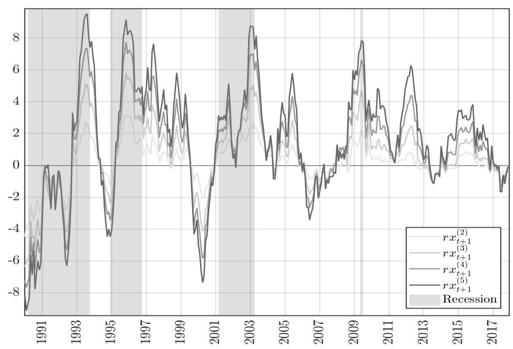
(b) *USA² (1964.01–2017.12)*



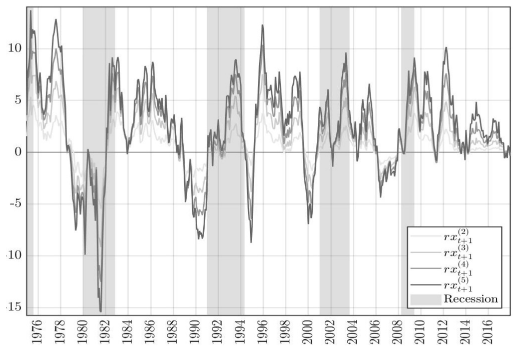
(c) *AUS² (1992.07–2017.12)*



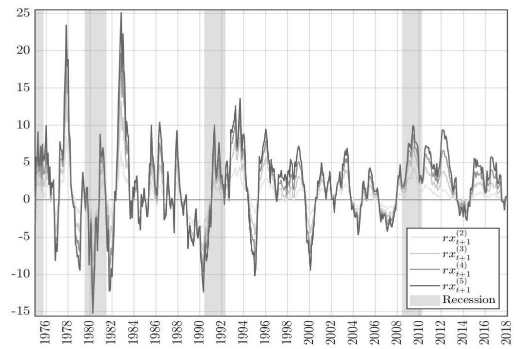
(d) *CAN (1986.01–2017.12)*



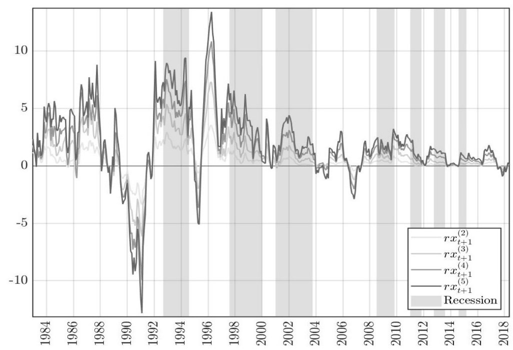
(e) *CHE² (1988.01–2017.12)*



(f) *DEU (1973.01–2017.12)*



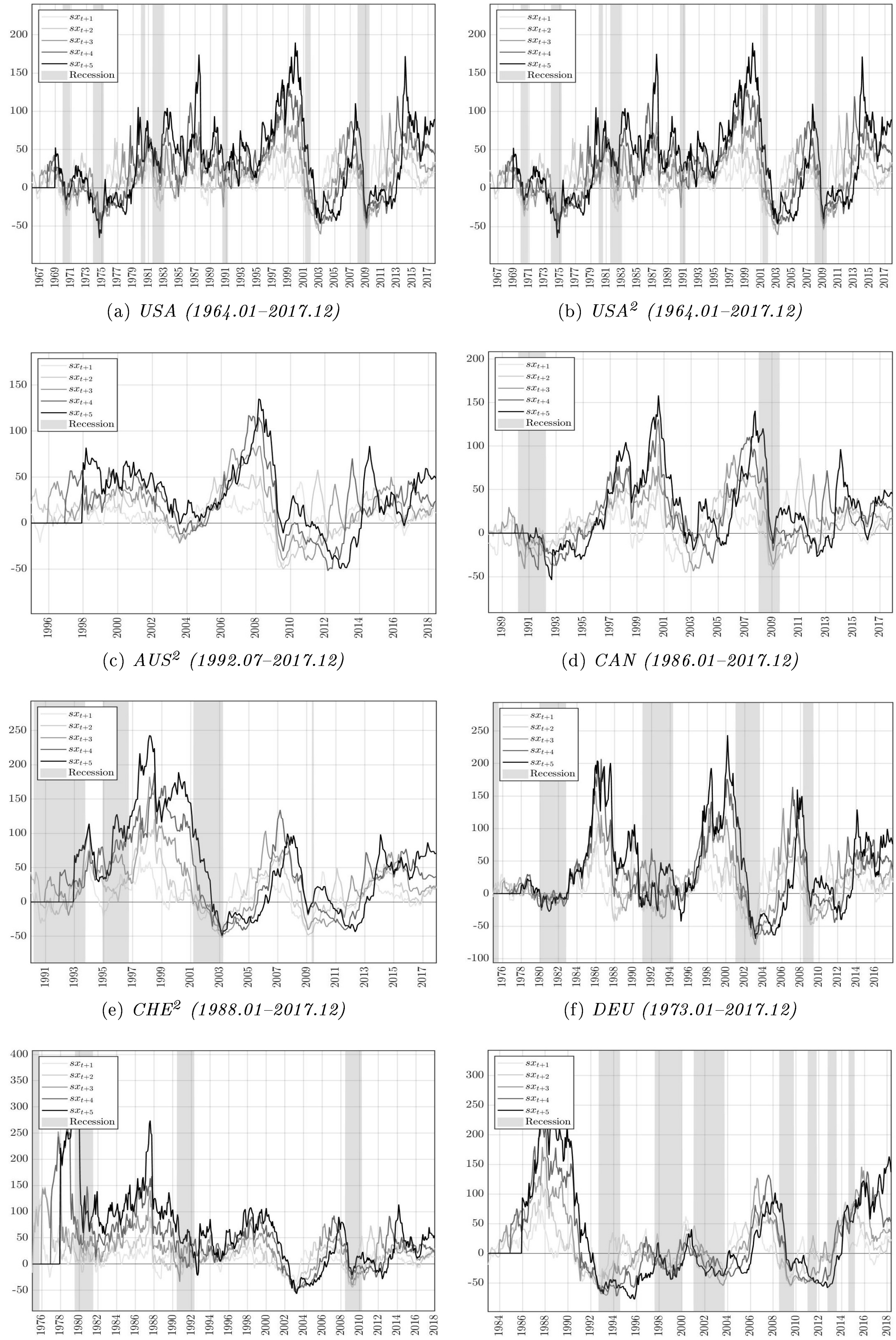
(g) *GBR (1972.12–2017.12)*



(h) *JPN (1980.08–2017.12)*

Figure C.2.1: Bond Risk Premia.
Annual excess bond returns (in percent) on two- to five-year maturity bonds. Shaded areas are recession periods defined by ECRI (2018) (NBER (2010) for the US). Sample period in subcaption. For data source, see Table 2.1.

C.3 One- to Five-Year Stock Risk Premia



(a) *USA (1964.01–2017.12)* (b) *USA²* *(1964.01–2017.12)*

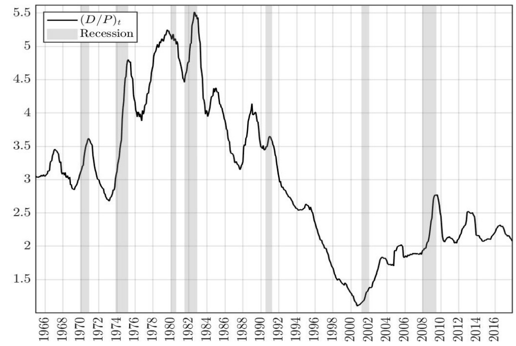
(c) *AUS²* *(1992.07–2017.12)* (d) *CAN (1986.01–2017.12)*

(e) *CHE²* *(1988.01–2017.12)* (f) *DEU (1973.01–2017.12)*

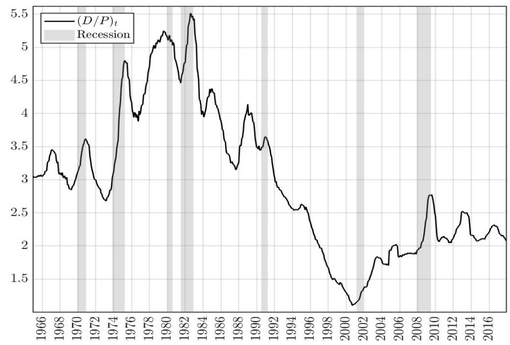
(g) *GBR (1972.12–2017.12)* (h) *JPN (1980.08–2017.12)*

Figure C.3.1: Stock Risk Premia.
One- to five-year excess stock returns (in percent). Shaded areas are recession periods defined by ECRI (2018) (NBER (2010) for the US). Sample period in subcaption. For data source, see Table 2.2. Note: two- to five-year excess returns are not stated in annualized terms.

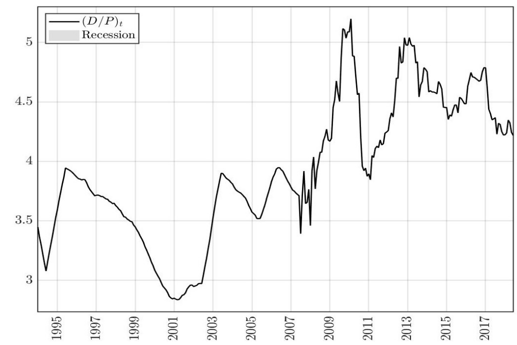
C.4 Dividend-Price Ratio



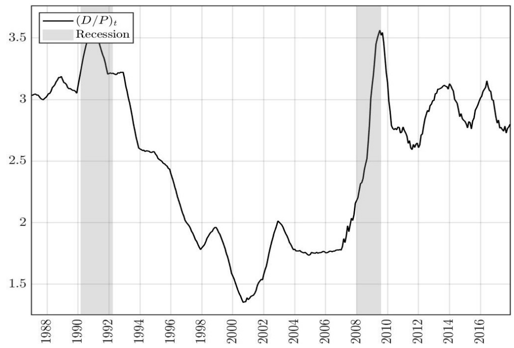
(a) *USA (1964.01–2017.12)*



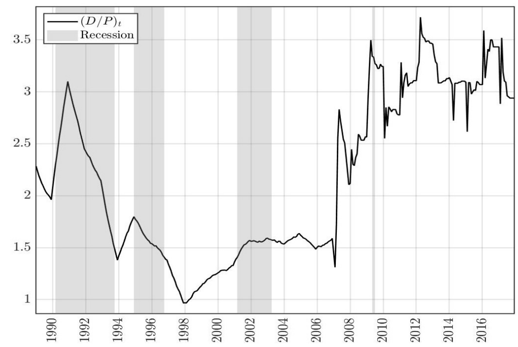
(b) *USA² (1964.01–2017.12)*



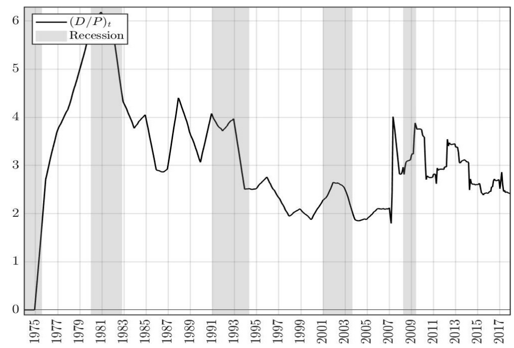
(c) *AUS² (1992.07–2017.12)*



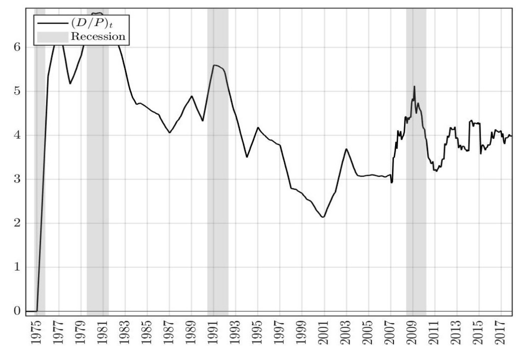
(d) *CAN (1986.01–2017.12)*



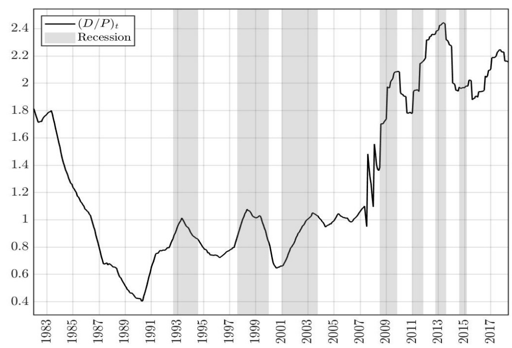
(e) *CHE² (1988.01–2017.12)*



(f) *DEU (1973.01–2017.12)*



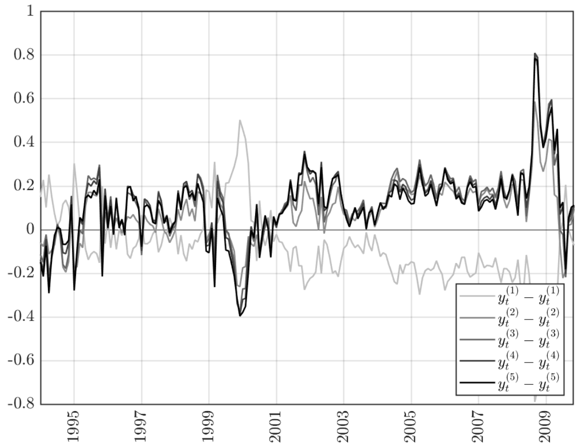
(g) *GBR (1972.12–2017.12)*



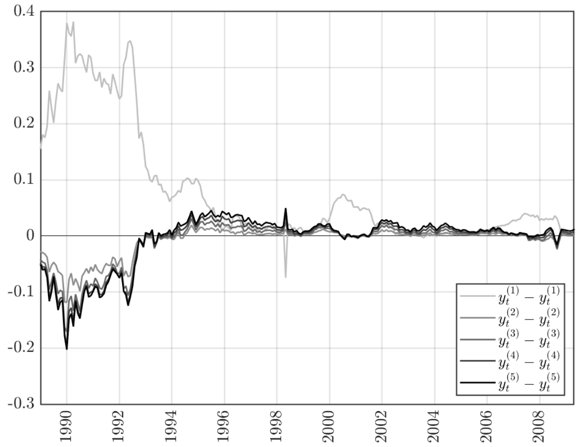
(h) *JPN (1980.08–2017.12)*

Figure C.4.1: Dividend-Price Ratios.
Annual Dividend-price ratio (in percent). Shaded areas are recession periods defined by ECRI (2018) (NBER (2010) for the US). Sample period in subcaption. For data source, see Table 2.2.

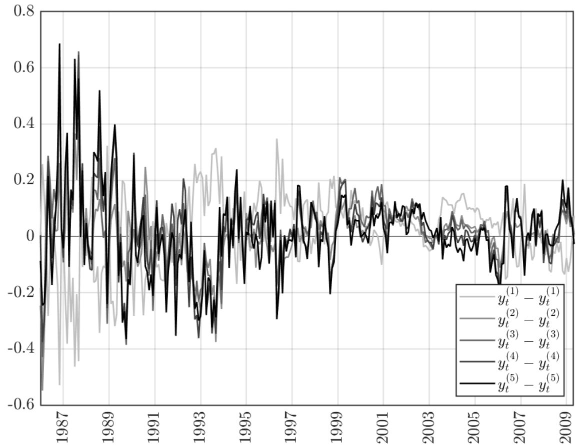
C.5 Yield Differences by Estimation Method



(a) *AUS (1992–2009): Spline (MLES) vs. Nelson-Siegel*



(b) *CHE (1988–2009): Ext. Nelson Siegel vs. Svensson*



(c) *JPN (1985–2009): Spline (Cubic) vs. Svensson*

Figure C.5.1: Yield Data Difference in AUS, CHE, and JPN.
Percentage point difference in yields for AUS (RBA, 2018; Wright, 2011), CHE (SNB, 2018; Wright, 2011), and JPN (MOF, 2018; Wright, 2011).

D Yield Data Construction Methods

D.1 Unsmoothed Fama-Bliss Method

The bond yield data from CRSP (2018a) that Cochrane and Piazzesi (2005) use are constructed using the unsmoothed Fama-Bliss method. It is an iterative method of forward rate extraction generally known as "bootstrapping" (Bliss, 1996, p. 12), and "unsmoothed" refers to the resulting piecewise linear (jagged) discount rate function. This method constructs yields from estimated forwards at observed maturities rather than discount functions (Li & Diebold, 2006). The discount rate function is constructed by iteratively computing forward rate linking the fitted discount rate values on previous maturity bonds with successively longer-maturity bonds.

To obtain the approximate discount rate function, one needs as many estimated parameters as bonds included in the approximation (Bliss, 1996, p. 10). By this, the resulting discount rates will exactly price the included bonds and there is no pricing error by construction (i.e., consistent with market prices. See Equation (4)). According to CRSP (2018a), when selecting which bonds to include in this method, each bond goes through a series of filters.[86]

D.2 Splines

The bond yield data used in Dahlquist and Hasseltoft (2013) for AUS, CAN, GBR and JPN[2] are constructed using a Spline method. 'Spline' refers to that different functions (of the same type) are used to model the discount

[86]Refer to the Fama-Bliss Discount Bond Data in "Data File Layout" (Chapter 2) in CRSP US Treasury Database Guide for exact definition of the filter applied when selecting bonds to calculate the discount rate function.

functions on intervals dividing the maturity axis (Munk, 2011, p. 30). A spline approximation of $\bar{B}_t(\tau)$ is based on the expression

$$\bar{B}_t(\tau) = \sum_{j=0}^{k-1} G_j(\tau) \cdot I_j(\tau)$$

The maturity subintervals are defined by the 'knot' points $0 = \tau_0 < \tau_1 < \ldots < \tau_k = T_M$ given by the M traded bonds with time-to-maturities $T_1 \leq T_2 \leq \cdots \leq T_M$. $I_j(\tau)$ is a step function, taking value of 1 if $\tau \geq \tau_j$ and zero otherwise. $G_j(\tau)$ is a basis function. The basis function can be arbitrarily defined and there are several documented types[87]. The cubic spline is one method to model the discount function, $\bar{B}_t(\tau)$. Here, the approximate function is given by a third-degree polynomial, introduced by McCulloch (1971) and later modified by McCulloch (1975) and Litzenberger and Rolfo (1984). In this method,

$$G_j(\tau) = \alpha_j + \beta_j(\tau - \tau_j) + \gamma_j(\tau - \tau_j)^2 + \delta_j(\tau - \tau_j)^3.$$

By imposing certain conditions to ensure a continuous and smooth discount function, and solving it algebraically[88], the cubic spline approximation $\bar{B}_t(\tau)$ is

$$\bar{B}_t(\tau) = 1 + \beta_0\tau + \gamma_0\tau^2 + \delta_0\tau^3 + \sum_{j=1}^{k-1} \delta_j(\tau - \tau_j)^3 \cdot I_j(\tau).$$

The parameters β_0, γ_0, δ_0, ..., δ_{k-1} are estimated by minimizing the sum of squared errors (OLS) of the pricing relation in Equation (6).

As with all estimation methods, the splines are associated with several undesirable features although being considered the superior in terms of flexibility because of the large number of parameters that has to be estimated

[87] There is a large class of spline based interpolation methods, we only consider the general framework. The CAN and GBR data set uses the Merrill Lynch Exponential spline (MLES) and variable roughness penalty method, respectively. See BIS (2005) for more details.

[88] For the algebraic computations, see Munk (2011, p. 31).

(Gürkaynak et al., 2007). For cubic splines, there is no feature of the method imposing the estimated discount function to have an economically credible form. Depending on the estimated sign of the third degree terms, as maturity reaches infinity, values of the estimated discount function increase or decrease without bounds (Munk, 2011, p. 33). Another undesirable feature is that the discount function is sensitive to the number of intervals on the maturity axis ('knot' points). Small variations in bond input prices may impact the estimated values significantly, consequentially making forward rate estimates rather unstable (Svensson, 1994, p. 5).

D.3 The Nelson-Siegel Parametrization

The bond yield data used in Dahlquist and Hasseltoft (2013) for USA^2, AUS^2, GBR, JPN^2 are constructed using the Nelson-Siegel method. The bond yield data that we use in this thesis identified by USA^2, AUS^2, CHE, CHE^2, DEU, and JPY are constructed by using the parameterization method by Nelson and Siegel (1987) and Svensson (1994).

Instead of estimating discount functions, Nelson and Siegel (1987) introduced a way to estimate the forward curve, approximated by parameterizing forward rates:

$$f_t^{(t,\tau)} \equiv \bar{f}_t(\tau) = \beta_0 + \beta_1 e^{-\frac{\tau}{\theta}} + \beta_2 \frac{\tau}{\theta} e^{-\frac{\tau}{\theta}}$$

The zero-coupon yields are obtained using Equation (2), thus,

$$\bar{y}_t(\tau) = \frac{1}{\tau} \int_{\tau-T}^{\tau+t} \bar{f}_t(u)du = \beta_0 + (\beta_1 + \beta_2) \frac{1 - e^{-\frac{\tau}{\theta}}}{\frac{\tau}{\theta}} - \beta_2 e^{-\frac{\tau}{\theta}}.$$

Equivalently, the discount function $\bar{B}_t(\tau)$ is

$$\bar{B}_t(\tau) = e^{-\bar{y}_t(\tau)\cdot\tau} = e^{\left(-\beta_0\tau - (\beta_1+\beta_2)\theta\left(1-e^{-\frac{\tau}{\theta}}\right) - \beta_2 \tau e^{-\frac{\tau}{\theta}}\right)}.$$

β_0, β_1, β_2, and θ are constants that are estimated using the technique of generalized least squares when estimating the parameters of the non-linear regression equation

$$P_{i,t} = \sum_{j}^{T} C_i^{(t+j)} \cdot B_t^{(t+j)} + \varepsilon_{i,t}$$

Motivated by the increase in flexibility and improvement in fitted values, Svensson (1994) extends the approach by Nelson and Siegel (1987) by introducing a fourth term to the functional form of forward rates:

$$f_t^{(t,\tau)} \equiv \bar{f}_t(\tau) = \beta_0 + \beta_1 e^{-\frac{\tau}{\theta}} + \beta_2 \frac{\tau}{\theta} e^{-\frac{\tau}{\theta}} + \beta_3 \frac{\tau}{\theta'} e^{-\frac{\tau}{\theta'}}$$

The additional parameters θ' and β_3 need to be estimated and the estimation procedure is the same as above. Note that if $\theta' = \beta_3 = 0$, the parameterization function is that of Nelson and Siegel (1987).

The estimation method of the term structure of interest rate outlined comes with differences in terms of its flexibility (to be able to sufficiently price bonds at the whole maturity spectrum) and the degree of smoothness to account for idiosyncratic variances (e.g., hedging demand, demand for deliverability into futures contracts, etc.) in bond prices at different maturities. Bliss (1996) performs a comparison of five distinct estimation methods and concludes that the Unsmoothed Fama-Bliss does best overall. Further, the Nelson and Siegel methods is superior to more flexible methods such as Spline (Gürkaynak et al., 2007, p. 12) in fitting yields to prices.

BIS (2005, p. 10) notes that estimating nominal yields in the short-maturity end of the curve is more difficult than the long-end. We observe that from the yield difference between the two USA data set (see Figure F.1.1 in Appendix F.1), the most differing yield prominently is that of the one-year maturity bond.

E Regression Outputs

E.1 Bonds - FB Regression

	lhv	$rx_{c,t+1}^{(2)}$		$rx_{c,t+1}^{(3)}$		$rx_{c,t+1}^{(4)}$		$rx_{c,t+1}^{(5)}$	
	rhv	$f_{c,t}^{(1,2)} - y_{c,t}^{(1)}$		$f_{c,t}^{(2,3)} - y_{c,t}^{(1)}$		$f_{c,t}^{(3,4)} - y_{c,t}^{(1)}$		$f_{c,t}^{(4,5)} - y_{t}^{(1)}$	
USA	$b_c^{(\tau)}$	0.03	*(0.07)*	0.26	*(0.47)*	0.39	*(0.74)*	0.58	*(1.18)*
	R^2	0.00		0.01		0.01		0.03	
USA²	$b_c^{(\tau)}$	-0.03	*(-0.07)*	0.17	*(0.33)*	0.38	*(0.74)*	0.57	*(1.12)*
	R^2	0.00		0.00		0.01		0.03	
AUS	$b_c^{(\tau)}$	0.26	*(0.75)*	0.23	*(0.49)*	0.25	*(0.37)*	0.31	*(0.37)*
	R^2	0.02		0.00		0.00		0.00	
CAN	$b_c^{(\tau)}$	0.41	*(1.72)*	0.56	*(1.68)*	0.71	*(1.59)*	0.84	*(1.51)*
	R^2	0.04		0.04		0.05		0.06	
CHE	$b_c^{(\tau)}$	0.47	*(1.34)*	0.82**	*(2.46)*	1.09**	*(3.35)*	1.30**	*(3.74)*
	R^2	0.05		0.08		0.10		0.10	
DEU	$b_c^{(\tau)}$	0.69	*(1.86)*	1.02**	*(2.43)*	1.21**	*(2.85)*	1.38**	*(3.27)*
	R^2	0.10		0.14		0.14		0.15	
GBR	$b_c^{(\tau)}$	0.46	*(1.60)*	0.63*	*(2.05)*	0.74*	*(2.15)*	0.82*	*(2.20)*
	R^2	0.07		0.08		0.08		0.08	
JPN	$b_c^{(\tau)}$	1.57**	*(3.52)*	1.85**	*(4.29)*	1.83**	*(4.97)*	1.81**	*(6.18)*
	R^2	0.51		0.53		0.46		0.39	

Table E.1.1: Regression Results - Bonds - Forward-Spot Spread.
*Estimates of Regression (R.1) in international markets. T-statistics in parentheses use Newey and West (1987) standard error-correction with 18 lags. Adjusted R^2. Constant estimates are excluded. **: p-value < 0.01, *: p-value < 0.05.*

E.2 Bonds - CP Regression

	lhv	$rx^{(2)}_{t+1}$		$rx^{(3)}_{t+1}$		$rx^{(4)}_{t+1}$		$rx^{(5)}_{t+1}$	
	rhv	$CP^{(c)}_t$		$CP^{(c)}_t$		$CP^{(c)}_t$		$CP^{(c)}_t$	
USA	$b^{(\tau)}_c$	0.39	*(1.93)*	0.80*	*(1.97)*	1.17*	*(2.13)*	1.64**	*(2.40)*
	R^2	0.05		0.06		0.06		0.08	
USA²	$b^{(\tau)}_c$	0.38	*(1.79)*	0.74	*(1.76)*	1.18	*(1.94)*	1.70*	*(2.18)*
	R^2	0.05		0.06		0.07		0.09	
AUS	$b^{(\tau)}_c$	0.50**	*(3.85)*	0.86**	*(3.66)*	1.18**	*(3.46)*	1.46**	*(3.25)*
	R^2	0.17		0.14		0.12		0.11	
CAN	$b^{(\tau)}_c$	0.50**	*(3.83)*	0.89**	*(4.26)*	1.20**	*(4.23)*	1.42**	*(3.87)*
	R^2	0.17		0.17		0.16		0.14	
CHE	$b^{(\tau)}_c$	0.45**	*(4.00)*	0.87**	*(4.03)*	1.21**	*(3.82)*	1.47**	*(3.55)*
	R^2	0.23		0.24		0.23		0.21	
DEU	$b^{(\tau)}_c$	0.36**	*(2.71)*	0.82**	*(3.44)*	1.24**	*(3.95)*	1.58**	*(4.28)*
	R^2	0.17		0.22		0.24		0.25	
GBR	$b^{(\tau)}_c$	0.36	*(1.63)*	0.81*	*(2.02)*	1.23*	*(2.25)*	1.60**	*(2.38)*
	R^2	0.07		0.10		0.11		0.11	
JPN	$b^{(\tau)}_c$	0.41**	*(6.51)*	0.83**	*(6.56)*	1.23**	*(7.41)*	1.53**	*(7.35)*
	R^2	0.72		0.69		0.64		0.58	

Table E.2.1: Regression Results - Bonds - CP Factor.
*Estimates of Regression (R.2) in international markets, sample period: 1992.12–2017.12. T-statistics in parentheses use Newey and West (1987) standard error-correction with 18 lags. Adjusted R^2. Constant estimates are excluded.**: p-value $<$ 0.01, *: p-value $<$ 0.05.*

E.3 Bonds - MA(CP) Regression

Lags	**0**	**1**	**2**	**3**	**4**	**5**	**6**
USA	0.07	0.06	0.06	0.06	0.07	0.09	0.10
USA²	0.08	0.07	0.07	0.07	0.08	0.10	0.12
AUS	0.12	0.13	0.13	0.13	0.13	0.14	0.17
CAN	0.16	0.18	0.20	0.23	0.24	0.25	0.26
CHE	0.23	0.24	0.25	0.25	0.25	0.25	0.25
DEU	0.24	0.25	0.25	0.25	0.25	0.25	0.25
GBR	0.11	0.11	0.12	0.14	0.14	0.16	0.17
JPN	0.65	0.65	0.66	0.65	0.65	0.66	0.66

Table E.3.1: Regression Results - Bonds - MA(CP, k).
Adjusted R^2 *for Regression* (R.4) *with k lags in international markets, sample period: 1992.12–2017.12. Shaded cells indicate which k that results in maximum* R^2.

E.4 Stocks - CP Regression

	lhv	$sx^{(1)}_{c,t}$		$sx^{(2)}_{c,t}$		$sx^{(3)}_{c,t}$		$sx^{(4)}_{c,t}$		$sx^{(5)}_{c,t}$	
	rhv	$CP^{(c)}_t$		$CP^{(c)}_t$		$CP^{(c)}_t$		$CP^{(c)}_t$		$CP^{(c)}_t$	
USA	$b^{(\tau)}_c$	-3.36	*(-1.03)*	-2.32	*(-0.33)*	10.64	*(0.87)*	22.91	*(1.32)*	25.94	*(1.10)*
	R^2	0.01		0.00		0.03		0.09		0.07	
USA²	$b^{(\tau)}_c$	-2.34	*(-0.85)*	-1.42	*(-0.22)*	12.18	*(1.1)*	25.93	*(1.64)*	31.70	*(1.46)*
	R^2	0.01		0.00		0.05		0.14		0.13	
AUS	$b^{(\tau)}_c$	-2.44	*(-1.15)*	-3.70	*(-1.09)*	-2.53	*(-0.60)*	-2.12	*(-0.37)*	-0.17	*(-0.02)*
	R^2	0.03		0.03		0.00		0.00		0.00	
CAN	$b^{(\tau)}_c$	0.14	*(0.05)*	-1.28	*(-0.33)*	1.35	*(0.25)*	9.32	*(1.36)*	12.63	*(1.85)*
	R^2	0.00		0.00		0.00		0.05		0.07	
CHE	$b^{(\tau)}_c$	1.40	*(0.41)*	10.81	*(1.37)*	21.60	*(1.72)*	35.23*	*(2.08)*	39.40*	*(1.98)*
	R^2	0.00		0.09		0.16		0.24		0.20	
DEU	$b^{(\tau)}_c$	0.67	*(0.25)*	5.03	*(0.98)*	6.28	*(0.78)*	7.74	*(0.71)*	1.56	*(0.09)*
	R^2	0.00		0.02		0.02		0.02		0.00	
GBR	$b^{(\tau)}_c$	4.46	*(1.18)*	9.13	*(1.97)*	18.08**	*(4.86)*	29.81**	*(10.59)*	31.37**	*(6.76)*
	R^2	0.05		0.10		0.24		0.45		0.41	
JPN	$b^{(\tau)}_c$	-4.60*	*(-2.20)*	-9.63*	*(-2.16)*	-15.84**	*(-2.69)*	-20.12**	*(-3.03)*	-22.37*	*(-2.26)*
	R^2	0.06		0.13		0.20		0.24		0.25	

Table E.4.1: Regression Results - Stocks - CP Factor.
Estimates of Regression (R.5) *in international markets, sample period: 1992.12–2017.12. T-statistics in parentheses use Hansen-Hodrick standard error-correction with 12 lags. Adjusted* R^2*. Constant estimates are excluded. **: p-value < 0.01, *: p-value < 0.05.*

E.5 Stocks - MA(CP), D/P, and Term Spread Regression

	τ	**1**		**2**		**3**		**4**		**5**	
(1)	$b^{(\tau)}_{c,1}$	1.92**	*(3.06)*	2.90**	*(3.30)*	1.13	*(1.17)*	0.68	*(0.43)*	1.63	*(0.66)*
	$b^{(\tau)}_{c,2}$	2.20	*(0.88)*	3.43	*(0.73)*	6.01	*(0.94)*	10.00	*(1.26)*	14.65	*(1.54)*
	$b^{(\tau)}_{c,3}$	-0.69	*(-0.27)*	-1.20	*(-0.35)*	6.42	*(1.31)*	12.42	*(1.60)*	15.97	*(1.30)*
	R^2	0.11	*[0.00]*	0.12	*[0.00]*	0.09	*[0.01]*	0.13	*[0.01]*	0.17	*[0.01]*
(2)	$b^{(\tau)}_{c,1}$	-0.39	*(-0.31)*	-0.09	*(-0.04)*	-2.44	*(-1.27)*	-2.52	*(-0.97)*	-1.78	*(-0.47)*
	$b^{(\tau)}_{c,2}$	2.25	*(1.03)*	3.18	*(0.87)*	6.34	*(1.63)*	11.09**	*(2.54)*	16.47**	*(3.76)*
	$b^{(\tau)}_{c,3}$	4.67	*(1.67)*	7.92	*(1.60)*	17.47**	*(3.40)*	22.84**	*(3.24)*	24.77**	*(2.44)*
	R^2	0.05	*[0.30]*	0.07	*[0.11]*	0.16	*[0.00]*	0.21	*[0.00]*	0.22	*[0.00]*
(3)	$b^{(\tau)}_{c,1}$	2.01	*(0.33)*	1.13	*(0.22)*	10.85	*(1.83)*	19.85*	*(1.97)*	28.58*	*(2.78)*
	$b^{(\tau)}_{c,2}$	13.47	*(1.45)*	34.02**	*(2.69)*	51.98**	*(3.70)*	72.56**	*(5.57)*	78.56**	*(5.06)*
	$b^{(\tau)}_{c,3}$	3.72	*(0.76)*	12.29	*(1.69)*	22.38**	*(2.72)*	27.78**	*(2.82)*	35.30**	*(3.60)*
	R^2	0.14	*[0.34]*	0.44	*[0.03]*	0.61	*[0.00]*	0.71	*[0.00]*	0.68	*[0.00]*
(4)	$b^{(\tau)}_{c,1}$	-3.37	*(-1.60)*	-4.43	*(-1.05)*	1.04	*(0.15)*	11.24	*(1.20)*	9.09	*(0.78)*
	$b^{(\tau)}_{c,2}$	15.50**	*(2.58)*	30.12**	*(2.96)*	44.86**	*(3.24)*	69.92**	*(4.18)*	87.08**	*(3.82)*
	$b^{(\tau)}_{c,3}$	2.95	*(0.75)*	11.48	*(1.49)*	19.62**	*(2.49)*	20.30**	*(2.30)*	20.43	*(1.70)*
	R^2	0.19	*[0.03]*	0.36	*[0.00]*	0.51	*[0.00]*	0.64	*[0.00]*	0.60	*[0.00]*

Table E.5.1: Full Regression Results - Stocks - MA(CP, 3), D/P, and Term Spread - USA.
Estimates of Regression (R.6) *in USA, four sample periods: (1): 1964.01–2003.12, (2): 1964.01–2017.12, (3): 1992.12–2009.05, (4): 1992.12–2017.12. Estimates for one-year excess returns for 1964–2003 differ slightly from Cochrane and Piazzesi (2005) because of different stock returns. T-statistics in parentheses use Hansen-Hodrick standard error-correction with 12 lags. P-value of F-statistics in brackets. Adjusted* R^2*. Constant estimates are excluded. **: p-value < 0.01, *: p-value < 0.05.*

	lhv	$sx_{c,t}^{(1)}$		$sx_{c,t}^{(2)}$		$sx_{c,t}^{(3)}$		$sx_{c,t}^{(4)}$		$sx_{c,t}^{(5)}$	
	rhv	$MA(CP_t^{(c)}, 3)$, $(d/p)_{c,t}$, $y_{c,t}^{(5)} - y_{c,t}^{(1)}$									
USA	$b_{c,1}^{(\tau)}$	-3.37	*(-1.60)*	-4.43	*(-1.05)*	1.04	*(0.15)*	11.24	*(1.20)*	9.09	*(0.78)*
	$b_{c,2}^{(\tau)}$	15.50**	*(2.58)*	30.12**	*(2.96)*	44.86**	*(3.24)*	69.92**	*(4.18)*	87.08**	*(3.82)*
	$b_{c,3}^{(\tau)}$	2.95	*(0.75)*	11.48	*(1.49)*	19.62**	*(2.49)*	20.30*	*(2.30)*	20.43	*(1.70)*
	R^2	0.19	*[0.03]*	0.36	*[0.00]*	0.51	*[0.00]*	0.64	*[0.00]*	0.60	*[0.00]*
USA²	$b_{c,1}^{(\tau)}$	-4.57**	*(-2.36)*	-8.25**	*(-2.40)*	-2.11	*(-0.36)*	7.98	*(0.88)*	5.69	*(0.49)*
	$b_{c,2}^{(\tau)}$	16.43**	*(2.76)*	31.33**	*(3.32)*	44.07**	*(3.31)*	66.11**	*(3.87)*	83.94**	*(3.51)*
	$b_{c,3}^{(\tau)}$	3.30	*(0.84)*	12.82	*(1.70)*	20.81**	*(2.76)*	21.79**	*(2.56)*	22.09	*(1.78)*
	R^2	0.20	*[0.01]*	0.39	*[0.00]*	0.51	*[0.00]*	0.63	*[0.00]*	0.60	*[0.00]*
AUS	$b_{c,1}^{(\tau)}$	-1.30	*(-0.72)*	-2.56	*(-0.81)*	-2.12	*(-0.66)*	-2.28	*(-0.66)*	-2.80	*(-0.66)*
	$b_{c,2}^{(\tau)}$	4.49	*(1.56)*	4.69	*(0.69)*	2.78	*(0.34)*	6.02	*(0.76)*	-0.88	*(-0.08)*
	$b_{c,3}^{(\tau)}$	3.06	*(0.60)*	4.70	*(0.59)*	9.49	*(1.12)*	17.94*	*(1.96)*	20.94*	*(2.20)*
	R^2	0.05	*[0.12]*	0.04	*[0.49]*	0.05	*[0.72]*	0.13	*[0.24]*	0.16	*[0.16]*
CAN	$b_{c,1}^{(\tau)}$	-1.26	*(-0.48)*	-7.58*	*(-1.96)*	-9.72**	*(-2.46)*	-1.26	*(-0.18)*	2.76	*(0.46)*
	$b_{c,2}^{(\tau)}$	3.86	*(0.87)*	1.58	*(0.24)*	-1.98	*(-0.28)*	7.59	*(0.66)*	17.75	*(1.04)*
	$b_{c,3}^{(\tau)}$	4.81	*(0.84)*	15.67*	*(1.96)*	32.55**	*(5.16)*	27.93**	*(3.25)*	13.54	*(0.96)*
	R^2	0.04	*[0.72]*	0.15	*[0.22]*	0.43	*[0.00]*	0.30	*[0.00]*	0.15	*[0.14]*
CHE	$b_{c,1}^{(\tau)}$	-1.91	*(-0.70)*	6.39	*(1.11)*	17.45	*(1.29)*	34.23	*(1.75)*	43.19*	*(2.03)*
	$b_{c,2}^{(\tau)}$	4.26	*(1.09)*	10.78	*(1.14)*	15.88	*(1.34)*	17.46	*(1.43)*	18.35	*(1.64)*
	$b_{c,3}^{(\tau)}$	20.15**	*(2.46)*	33.81*	*(2.31)*	32.26	*(1.77)*	14.90	*(0.48)*	-17.18	*(-0.48)*
	R^2	0.18	*[0.09]*	0.30	*[0.08]*	0.29	*[0.02]*	0.31	*[0.00]*	0.30	*[0.01]*
DEU	$b_{c,1}^{(\tau)}$	-8.61**	*(-2.43)*	-12.48**	*(-2.77)*	-16.51	*(-1.70)*	-8.51	*(-0.83)*	-0.68	*(-0.05)*
	$b_{c,2}^{(\tau)}$	-2.64	*(-0.47)*	-0.54	*(-0.05)*	9.49	*(0.63)*	39.03	*(1.93)*	67.32**	*(2.80)*
	$b_{c,3}^{(\tau)}$	25.67**	*(3.23)*	48.03**	*(3.94)*	65.95**	*(4.20)*	56.00**	*(2.49)*	27.33	*(1.19)*
	R^2	0.20	*[0.01]*	0.34	*[0.00]*	0.39	*[0.00]*	0.35	*[0.01]*	0.33	*[0.00]*
GBR	$b_{c,1}^{(\tau)}$	-6.54	*(-1.87)*	-8.19	*(-1.50)*	-2.09	*(-0.33)*	6.01	*(1.34)*	7.72	*(1.00)*
	$b_{c,2}^{(\tau)}$	5.13	*(0.74)*	13.99	*(1.91)*	19.36**	*(2.75)*	27.21**	*(3.72)*	33.34**	*(4.43)*
	$b_{c,3}^{(\tau)}$	9.87	*(1.26)*	13.80	*(1.26)*	16.03	*(1.78)*	16.05	*(1.74)*	11.72	*(1.00)*
	R^2	0.23	*[0.00]*	0.37	*[0.00]*	0.50	*[0.00]*	0.68	*[0.00]*	0.61	*[0.00]*
JPN	$b_{c,1}^{(\tau)}$	-1.68	*(-0.63)*	-2.97	*(-0.71)*	-7.13	*(-1.34)*	-9.27**	*(-2.46)*	-8.05	*(-1.55)*
	$b_{c,2}^{(\tau)}$	8.88	*(0.82)*	17.92	*(0.96)*	25.91	*(1.04)*	40.74	*(1.63)*	63.63**	*(2.76)*
	$b_{c,3}^{(\tau)}$	-1.85	*(-0.14)*	-7.20	*(-0.49)*	-10.37	*(-0.36)*	-7.73	*(-0.21)*	-10.86	*(-0.41)*
	R^2	0.09	*[0.08]*	0.20	*[0.03]*	0.29	*[0.00]*	0.39	*[0.00]*	0.52	*[0.00]*

Table E.5.2: Full Regression Results - Stocks - MA(CP, 3), D/P, and Term Spread.
Estimates of Regression (R.6) *in international markets, sample period: 1992.12–2017.12. T-statistics in parentheses use Hansen-Hodrick standard error-correction with 12 lags. P-value of F-statistics in brackets. Adjusted* R^2. *Constant estimates are excluded. **: p-value* < 0.01, **: p-value* < 0.05.

E.6 Bonds - GCP Regression

	lhv	$rx^{(2)}_{t+1}$		$rx^{(3)}_{t+1}$		$rx^{(4)}_{t+1}$		$rx^{(5)}_{t+1}$	
	rhv	GCP_t		GCP_t		GCP_t		GCP_t	
USA	$b_c^{(\tau)}$	0.52**	*(3.10)*	1.06**	*(3.21)*	1.62**	*(3.47)*	2.33**	*(3.87)*
	R^2	0.09		0.10		0.12		0.15	
USA²	$b_c^{(\tau)}$	0.49**	*(2.99)*	1.01**	*(3.08)*	1.62**	*(3.42)*	2.30**	*(3.86)*
	R^2	0.08		0.09		0.12		0.15	
AUS	$b_c^{(\tau)}$	0.64**	*(3.07)*	1.27**	*(3.48)*	1.89**	*(3.71)*	2.49**	*(3.79)*
	R^2	0.11		0.12		0.13		0.13	
CAN	$b_c^{(\tau)}$	0.84**	*(4.67)*	1.53**	*(4.72)*	2.12**	*(4.85)*	2.66**	*(5.01)*
	R^2	0.24		0.24		0.24		0.24	
CHE	$b_c^{(\tau)}$	0.70**	*(4.53)*	1.30**	*(4.74)*	1.79**	*(4.79)*	2.23**	*(4.86)*
	R^2	0.26		0.25		0.24		0.23	
DEU	$b_c^{(\tau)}$	0.71**	*(4.32)*	1.44**	*(4.37)*	2.04**	*(4.36)*	2.53**	*(4.28)*
	R^2	0.22		0.23		0.23		0.21	
GBR	$b_c^{(\tau)}$	0.68**	*(4.92)*	1.29**	*(4.48)*	1.82**	*(4.25)*	2.31**	*(4.17)*
	R^2	0.18		0.17		0.17		0.16	
JPN	$b_c^{(\tau)}$	0.50**	*(2.42)*	1.06**	*(2.64)*	1.64**	*(2.91)*	2.13**	*(3.10)*
	R^2	0.31		0.32		0.33		0.32	

Table E.6.1: Regression Results - Bonds - GCP Factor.
Estimates of Regression (R.7) *in international markets, sample period: 1992.12–2017.12. T-statistics in parentheses use Newey and West (1987) standard error-correction with 18 lags. Adjusted* R^2*. Constant estimates are excluded. **: p-value < 0.01, *: p-value < 0.05.*

E.7 Bonds - MA(GCP) Regression

k	**0**	**1**	**2**	**3**	**4**	**5**	**6**
USA	0.20	0.22	0.22	0.21	0.20	0.20	0.21
USA^2	0.20	0.22	0.22	0.21	0.20	0.20	0.21
AUS	0.16	0.18	0.20	0.20	0.20	0.20	0.19
CAN	0.24	0.25	0.25	0.25	0.25	0.25	0.27
CHE	0.25	0.27	0.27	0.27	0.28	0.28	0.29
DEU	0.24	0.25	0.25	0.25	0.25	0.26	0.27
GBR	0.22	0.24	0.25	0.25	0.25	0.26	0.26
JPN	0.47	0.47	0.47	0.47	0.47	0.47	0.47

Table E.7.1: Regression Results - Bonds - MA(GCP, k).
Adjusted R^2 for Regression (R.8) with k lags in international markets, sample period: 1992.12–2017.12. Shaded cells indicate which k that results in maximum R^2.

E.8 Stocks - GCP Regression

	lhv	$sx^{(1)}_{c,t}$		$sx^{(2)}_{c,t}$		$sx^{(3)}_{c,t}$		$sx^{(4)}_{c,t}$		$sx^{(5)}_{c,t}$	
	rhv	GCP_t		GCP_t		GCP_t		GCP_t		GCP_t	
USA	$b^{(\tau)}_c$	0.11	*(0.03)*	3.34	*(0.37)*	18.43	*(1.29)*	33.43	*(1.73)*	38.52	*(1.48)*
	R^2	0.00		0.00		0.09		0.19		0.16	
USA^2	$b^{(\tau)}_c$	0.10	*(0.03)*	3.34	*(0.37)*	18.44	*(1.29)*	33.41	*(1.73)*	38.51	*(1.48)*
	R^2	0.00		0.00		0.09		0.19		0.16	
AUS	$b^{(\tau)}_c$	-1.58	*(-0.58)*	-3.42	*(-0.66)*	4.22	*(0.62)*	14.47	*(1.52)*	14.95	*(1.28)*
	R^2	0.00		0.01		0.01		0.08		0.07	
CAN	$b^{(\tau)}_c$	0.17	*(0.07)*	-1.54	*(-0.27)*	8.22	*(1.24)*	18.82*	*(2.16)*	21.25	*(1.88)*
	R^2	0.00		0.00		0.03		0.12		0.11	
CHE	$b^{(\tau)}_c$	-0.01	*(0.00)*	2.71	*(0.27)*	21.46	*(1.23)*	40.71	*(1.86)*	46.11	*(1.71)*
	R^2	0.00		0.00		0.08		0.21		0.19	
DEU	$b^{(\tau)}_c$	-3.28	*(-0.84)*	-3.49	*(-0.40)*	10.60	*(0.76)*	32.18	*(1.67)*	37.40	*(1.46)*
	R^2	0.01		0.00		0.02		0.12		0.12	
GBR	$b^{(\tau)}_c$	-0.37	*(-0.11)*	2.15	*(0.34)*	13.14	*(1.43)*	23.10	*(1.81)*	22.18	*(1.33)*
	R^2	0.00		0.00		0.07		0.16		0.11	
JPN	$b^{(\tau)}_c$	-13.90**	*(-2.92)*	-20.00*	*(-2.14)*	-19.22	*(-1.20)*	-9.79	*(-0.52)*	-12.74	*(-0.50)*
	R^2	0.16		0.15		0.08		0.01		0.02	

Table E.8.1: Regression Results - Stocks - GCP Factor.
*Estimates of Regression (R.9) in international markets, sample period: 1992.12–2017.12. T-statistics in parentheses use Hansen-Hodrick standard error-correction with 12 lags. Adjusted R^2. Constant estimates are excluded. **: p-value < 0.01, *: p-value < 0.05.*

E.9 Stocks - MA(GCP,3), D/P, and Term Spread Regression

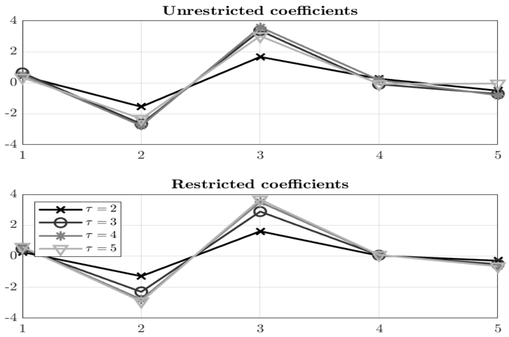
	(1)				(2)				(3)				(4)			
τ	$b_{c,1}^{(\tau)}$	$b_{c,2}^{(\tau)}$	$b_{c,3}^{(\tau)}$	R^2	$b_{c,1}^{(\tau)}$	$b_{c,2}^{(\tau)}$	$b_{c,3}^{(\tau)}$	R^2	$b_{c,1}^{(\tau)}$	$b_{c,2}^{(\tau)}$	$b_{c,3}^{(\tau)}$	R^2	$b_{c,1}^{(\tau)}$	$b_{c,2}^{(\tau)}$	$b_{c,3}^{(\tau)}$	R^2
									USA							
1	1.35	1.57	1.33	0.03	-1.12	1.79	3.73	0.02	-4.28	14.10	3.58	0.16	-4.45*	15.49**	2.96	0.20
	(0.52)	*(0.64)*	*(0.40)*	*[0.69]*	*(-0.48)*	*(0.72)*	*(1.08)*	*[0.73]*	*(-1.45)*	*(1.82)*	*(0.85)*	*[0.13]*	*(-2.23)*	*(2.52)*	*(0.75)*	*[0.01]*
2	-0.32	3.17	7.18	0.07	-2.52	3.44	10.15	0.08	-8.64*	34.85**	12.27	0.48	-9.69*	29.60**	12.43	0.39
	(-0.09)	*(0.72)*	*(1.39)*	*[0.33]*	*(-0.67)*	*(0.85)*	*(1.75)*	*[0.16]*	*(-2.11)*	*(3.00)*	*(1.76)*	*[0.01]*	*(-2.10)*	*(2.94)*	*(1.60)*	*[0.00]*
3	-3.22	6.97	14.92*	0.14	-4.00	7.06	18.49**	0.18	-1.05	54.93**	18.70*	0.58	-3.95	44.18**	20.98**	0.51
	(-0.84)	*(1.29)*	*(2.22)*	*[0.03]*	*(-0.82)*	*(1.61)*	*(2.52)*	*[0.01]*	*(-0.20)*	*(3.39)*	*(2.26)*	*[0.00]*	*(-0.51)*	*(3.14)*	*(2.58)*	*[0.00]*
4	-4.70	11.77	17.94*	0.16	-3.72	11.53*	21.69**	0.21	11.30	78.29**	18.81	0.67	6.55	68.86**	22.42**	0.62
	(-0.95)	*(1.87)*	*(2.12)*	*[0.15]*	*(-0.66)*	*(2.30)*	*(2.66)*	*[0.01]*	*(1.18)*	*(4.14)*	*(1.66)*	*[0.00]*	*(0.71)*	*(3.89)*	*(2.50)*	*[0.00]*
5	0.55	14.70*	14.84	0.17	1.03	15.28**	17.98	0.21	13.70	86.43**	23.27	0.63	5.91	86.25**	22.00	0.59
	(0.08)	*(2.06)*	*(1.17)*	*[0.06]*	*(0.15)*	*(2.78)*	*(1.68)*	*[0.01]*	*(1.39)*	*(3.83)*	*(1.61)*	*[0.00]*	*(0.42)*	*(3.61)*	*(1.77)*	*[0.00]*
									DEU							
1	1.20	1.42	5.17	0.04	0.59	1.34	5.19	0.04	-6.89	5.63	24.42**	0.24	-9.80**	5.35	20.54**	0.22
	(0.38)	*(0.48)*	*(1.21)*	*[0.48]*	*(0.19)*	*(0.48)*	*(1.33)*	*[0.50]*	*(-1.34)*	*(0.37)*	*(2.86)*	*[0.02]*	*(-2.41)*	*(0.99)*	*(2.89)*	*[0.01]*
2	4.74	4.71	9.79	0.11	5.79	4.64	9.58	0.12	-20.91**	61.59**	61.91**	0.59	-12.44	10.33	38.70**	0.33
	(1.10)	*(0.86)*	*(1.30)*	*[0.33]*	*(1.31)*	*(0.93)*	*(1.42)*	*[0.24]*	*(-2.63)*	*(3.16)*	*(5.57)*	*[0.00]*	*(-1.71)*	*(0.87)*	*(3.07)*	*[0.02]*
3	6.59	7.74	8.21	0.08	9.84	8.73	8.82	0.13	-11.77	79.04*	68.39**	0.48	-0.79	18.35	43.29**	0.32
	(1.17)	*(0.97)*	*(0.84)*	*[0.50]*	*(1.83)*	*(1.27)*	*(0.98)*	*[0.14]*	*(-0.86)*	*(2.15)*	*(4.40)*	*[0.00]*	*(-0.07)*	*(0.97)*	*(3.04)*	*[0.01]*
4	8.29	15.11	-3.52	0.11	12.98*	17.21*	-0.97	0.16	-13.61	147.46**	72.85**	0.62	16.82	37.23	34.04	0.38
	(1.43)	*(1.52)*	*(-0.28)*	*[0.40]*	*(2.30)*	*(2.13)*	*(-0.08)*	*[0.03]*	*(-0.87)*	*(5.14)*	*(4.17)*	*[0.00]*	*(1.25)*	*(1.68)*	*(1.56)*	*[0.01]*
5	10.95*	24.51**	-17.40	0.28	15.36**	26.33**	-13.50	0.31	12.12	159.01**	31.22	0.68	24.26	56.46*	12.29	0.39
	(2.32)	*(2.94)*	*(-1.45)*	*[0.01]*	*(2.97)*	*(4.30)*	*(-1.21)*	*[0.00]*	*(0.57)*	*(4.64)*	*(1.75)*	*[0.00]*	*(1.49)*	*(2.28)*	*(0.59)*	*[0.01]*

Table E.9.1: Regression Results - Stocks - MA(GCP, 3), D/P, and Term Spread in the US and DEU.
Estimates of Regression (R.10) in the US and DEU for four sample periods: (1): 1975.01–2009.12, (2): 1975.01–2017.12, (3): 1992.12–2009.05, (4): 1992.12–2017.12. T-statistics in parentheses use Hansen-Hodrick standard error-correction with 12 lags. P-value of F-statistics in brackets. Adjusted R^2. *Constant estimates are excluded. **: p-value* < 0.01, **: p-value* < 0.05.

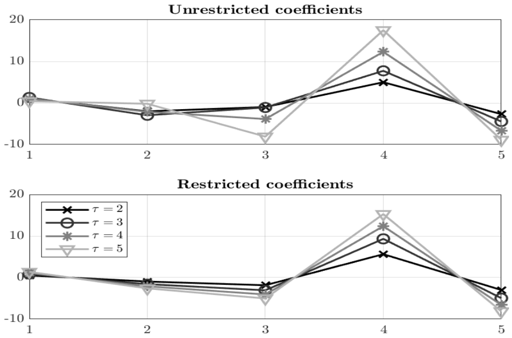
	lhv	$sx^{(1)}_{c,t}$		$sx^{(2)}_{c,t}$		$sx^{(3)}_{c,t}$		$sx^{(4)}_{c,t}$		$sx^{(5)}_{c,t}$	
	rhv	$MA(GCP_t, 3)$, $(d/p)_{c,t}$, $y^{(5)}_{c,t} - y^{(1)}_{c,t}$									
USA	$b^{(\tau)}_{c,1}$	-4.45*	*(-2.23)*	-9.69*	*(-2.10)*	-3.95	*(-0.51)*	6.55	*(0.71)*	5.91	*(0.42)*
	$b^{(\tau)}_{c,2}$	15.49**	*(2.52)*	29.60**	*(2.94)*	44.18**	*(3.14)*	68.86**	*(3.89)*	86.25**	*(3.61)*
	$b^{(\tau)}_{c,3}$	2.96	*(0.75)*	12.43	*(1.60)*	20.98**	*(2.58)*	22.42**	*(2.50)*	22.00	*(1.77)*
	R^2	0.20	*[0.01]*	0.39	*[0.00]*	0.51	*[0.00]*	0.62	*[0.00]*	0.59	*[0.00]*
USA²	$b^{(\tau)}_{c,1}$	-4.62*	*(-2.30)*	-10.23*	*(-2.20)*	-4.24	*(-0.54)*	6.72	*(0.71)*	6.30	*(0.44)*
	$b^{(\tau)}_{c,2}$	15.43**	*(2.50)*	29.12**	*(2.91)*	43.29**	*(3.07)*	67.80**	*(3.81)*	85.22**	*(3.53)*
	$b^{(\tau)}_{c,3}$	2.96	*(0.77)*	12.69	*(1.67)*	21.17**	*(2.66)*	22.77**	*(2.61)*	22.40	*(1.82)*
	R^2	0.20	*[0.01]*	0.40	*[0.00]*	0.52	*[0.00]*	0.63	*[0.00]*	0.60	*[0.00]*
AUS	$b^{(\tau)}_{c,1}$	-0.73	*(-0.25)*	-2.17	*(-0.49)*	-0.43	*(-0.07)*	-2.00	*(-0.32)*	-6.76	*(-0.73)*
	$b^{(\tau)}_{c,2}$	5.26*	*(2.04)*	6.01	*(1.02)*	4.04	*(0.54)*	7.02	*(0.91)*	0.21	*(0.02)*
	$b^{(\tau)}_{c,3}$	3.02	*(0.55)*	5.15	*(0.65)*	8.88	*(0.97)*	18.33*	*(2.03)*	24.48**	*(2.44)*
	R^2	0.05	*[0.18]*	0.03	*[0.65]*	0.04	*[0.77]*	0.13	*[0.18]*	0.16	*[0.10]*
CAN	$b^{(\tau)}_{c,1}$	-1.27	*(-0.53)*	-4.93	*(-0.91)*	-0.46	*(-0.07)*	8.84	*(1.22)*	14.93	*(1.37)*
	$b^{(\tau)}_{c,2}$	3.98	*(0.80)*	3.24	*(0.39)*	0.96	*(0.10)*	9.02	*(0.83)*	17.37	*(1.10)*
	$b^{(\tau)}_{c,3}$	4.53	*(0.88)*	12.18	*(1.51)*	25.10**	*(3.13)*	22.37**	*(3.62)*	8.75	*(0.67)*
	R^2	0.04	*[0.70]*	0.09	*[0.52]*	0.32	*[0.00]*	0.33	*[0.00]*	0.21	*[0.06]*
CHE	$b^{(\tau)}_{c,1}$	-5.15	*(-1.13)*	-0.88	*(-0.09)*	21.28	*(1.42)*	44.48**	*(2.62)*	54.68**	*(3.01)*
	$b^{(\tau)}_{c,2}$	3.34	*(0.97)*	9.21	*(0.98)*	18.01	*(1.35)*	27.33	*(1.75)*	32.90*	*(2.06)*
	$b^{(\tau)}_{c,3}$	21.92**	*(2.95)*	39.42**	*(2.63)*	32.59*	*(2.02)*	9.45	*(0.39)*	-24.49	*(-0.89)*
	R^2	0.20	*[0.03]*	0.28	*[0.06]*	0.30	*[0.05]*	0.41	*[0.01]*	0.42	*[0.00]*
DEU	$b^{(\tau)}_{c,1}$	-9.80**	*(-2.41)*	-12.44	*(-1.71)*	-0.79	*(-0.07)*	16.82	*(1.25)*	24.26	*(1.49)*
	$b^{(\tau)}_{c,2}$	5.35	*(0.99)*	10.33	*(0.87)*	18.35	*(0.97)*	37.23	*(1.68)*	56.46*	*(2.28)*
	$b^{(\tau)}_{c,3}$	20.54**	*(2.89)*	38.70**	*(3.07)*	43.29**	*(3.04)*	34.04	*(1.56)*	12.29	*(0.59)*
	R^2	0.22	*[0.01]*	0.33	*[0.02]*	0.32	*[0.01]*	0.38	*[0.01]*	0.39	*[0.01]*
GBR	$b^{(\tau)}_{c,1}$	-2.79	*(-1.12)*	-3.95	*(-1.30)*	-3.18	*(-0.62)*	-4.58	*(-1.20)*	-3.58	*(-0.60)*
	$b^{(\tau)}_{c,2}$	7.70	*(1.15)*	17.29**	*(2.56)*	19.94**	*(3.01)*	23.15**	*(4.56)*	28.76**	*(3.98)*
	$b^{(\tau)}_{c,3}$	4.58	*(0.70)*	7.46	*(1.16)*	16.07**	*(3.58)*	26.57**	*(7.34)*	23.33**	*(3.68)*
	R^2	0.19	*[0.03]*	0.34	*[0.00]*	0.50	*[0.00]*	0.68	*[0.00]*	0.61	*[0.00]*
JPN	$b^{(\tau)}_{c,1}$	-13.78**	*(-2.81)*	-15.00	*(-1.53)*	-20.23	*(-1.64)*	-13.47	*(-1.27)*	-2.47	*(-0.24)*
	$b^{(\tau)}_{c,2}$	1.48	*(0.14)*	10.04	*(0.57)*	15.64	*(0.64)*	34.33	*(1.25)*	63.11**	*(2.44)*
	$b^{(\tau)}_{c,3}$	11.91	*(1.28)*	5.43	*(0.38)*	0.62	*(0.03)*	-9.18	*(-0.29)*	-23.41	*(-0.82)*
	R^2	0.17	*[0.01]*	0.25	*[0.03]*	0.33	*[0.00]*	0.38	*[0.00]*	0.50	*[0.00]*

Table E.9.2: Regression Results - Stocks - MA(GCP, 3), D/P, and Term Spread.
*Estimates of Regression (R.10) in international markets, sample period: 1992.12–2017.12. T-statistics in parentheses use Hansen-Hodrick standard error-correction with 12 lags. P-value of F-statistics in brackets. Adjusted R^2. Constant estimates are excluded. **: p-value < 0.01, *: p-value < 0.05.*

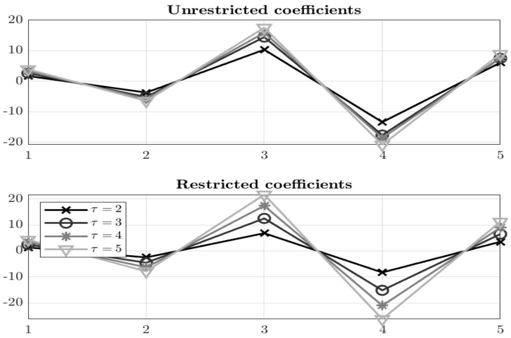
E.10 Yield Data Impact - Estimated Coefficients



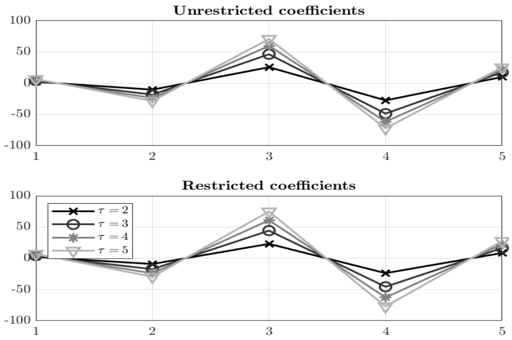
(a) *USA: CRSP (2018a)*



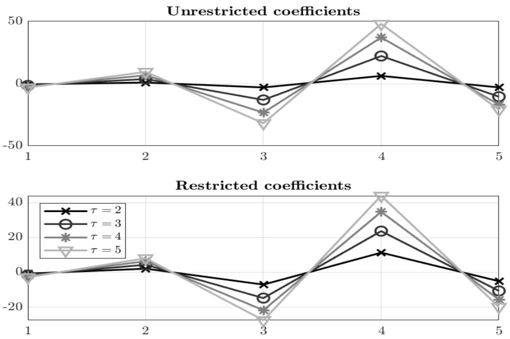
(b) *USA²: Gürkaynak et al. (2007)*



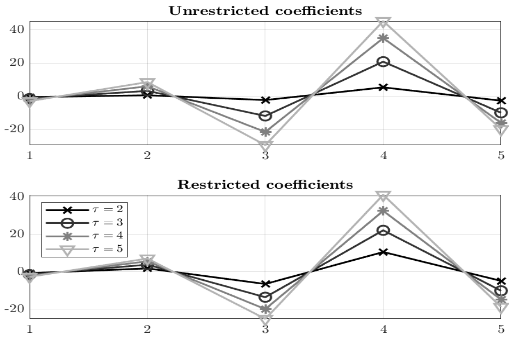
(c) *AUS: RBA (2018)*



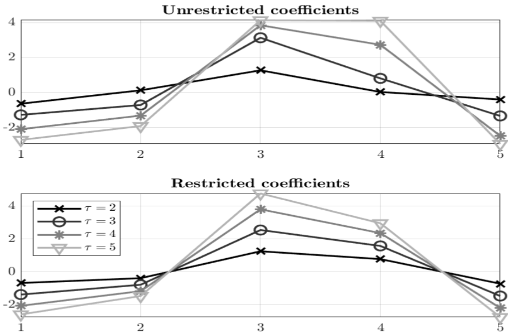
(d) *AUS²: Wright (2011)*



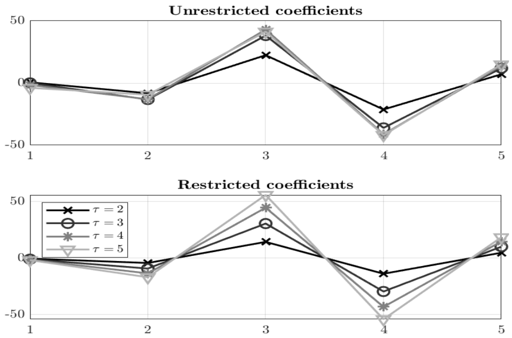
(e) *CHE: SNB (2018)*



(f) *CHE²: Wright (2011)*



(g) *JPN: MOF (2018)*



(h) *JPN²: Wright (2011)*

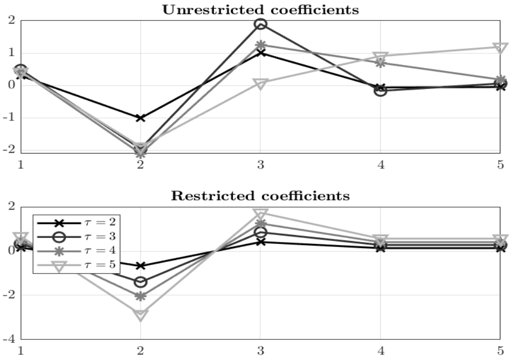
Figure E.10.1: Yield Data Comparison - Unrestricted vs. Restricted Coefficients in the US, AUS, CHE, and JPN.
Coefficients are estimated from Regression (R.3) *and* (R.2) *and are related by* $\hat{\boldsymbol{\beta}}_{\mathbf{c}} = \hat{\boldsymbol{b}}_{\mathbf{c}} \hat{\boldsymbol{\gamma}}_{\mathbf{c}}^{\intercal}$. *Sample period: 1992.12–2009.05.*

E.11 Yield Data Impact - Predictive Regressions

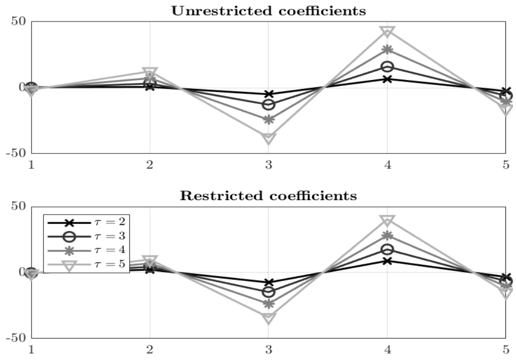
lhv		$rx^{(2)}_{c,t+1}$		$rx^{(3)}_{c,t+1}$		$rx^{(4)}_{c,t+1}$		$rx^{(5)}_{c,t+1}$	
rhv				$CP^{(c)}_t$					
USA	$b^{(\tau)}_c$	0.55	*(1.88)*	0.99	*(1.80)*	1.20	*(1.61)*	1.26	*(1.37)*
	R^2	0.11	*[0.10]*	0.09	*[0.07]*	0.07	*[0.05]*	0.05	*[0.03]*
USA²	$b^{(\tau)}_c$	0.53	*(1.45)*	0.88	*(1.31)*	1.16	*(1.30)*	1.43	*(1.35)*
	R^2	0.06	*[0.06]*	0.04	*[0.03]*	0.04	*[0.02]*	0.04	*[0.02]*
AUS	$b^{(\tau)}_c$	0.47**	*(5.82)*	0.86**	*(5.52)*	1.19**	*(5.47)*	1.48**	*(5.47)*
	R^2	0.44	*[0.44]*	0.41	*[0.39]*	0.38	*[0.36]*	0.35	*[0.34]*
AUS²	$b^{(\tau)}_c$	0.46**	*(6.60)*	0.87**	*(6.14)*	1.20**	*(5.77)*	1.47**	*(5.48)*
	R^2	0.46	*[0.45]*	0.42	*[0.41]*	0.39	*[0.38]*	0.36	*[0.34]*
CHE	$b^{(\tau)}_c$	0.40**	*(5.20)*	0.83**	*(6.01)*	1.22**	*(6.38)*	1.55**	*(6.44)*
	R^2	0.33	*[0.34]*	0.39	*[0.38]*	0.41	*[0.40]*	0.41	*[0.41]*
CHE²	$b^{(\tau)}_c$	0.40**	*(5.13)*	0.83**	*(5.91)*	1.22**	*(6.25)*	1.55**	*(6.31)*
	R^2	0.33	*[0.33]*	0.38	*[0.37]*	0.41	*[0.39]*	0.41	*[0.40]*
JPN	$b^{(\tau)}_c$	0.40**	*(6.43)*	0.82**	*(6.32)*	1.23**	*(7.33)*	1.54**	*(7.59)*
	R^2	0.71	*[0.73]*	0.68	*[0.68]*	0.64	*[0.63]*	0.59	*[0.59]*
JPN²	$b^{(\tau)}_c$	0.39**	*(9.49)*	0.84**	*(12.75)*	1.23**	*(16.30)*	1.54**	*(18.41)*
	R^2	0.81	*[0.84]*	0.80	*[0.80]*	0.76	*[0.75]*	0.70	*[0.70]*
rhv				GCP_t					
USA	$b^{(\tau)}_c$	0.59**	*(2.47)*	1.07**	*(2.34)*	1.43*	*(2.28)*	1.74*	*(2.20)*
	R^2	0.13		0.11		0.10		0.10	
USA²	$b^{(\tau)}_c$	0.55*	*(2.25)*	1.01*	*(2.18)*	1.41*	*(2.21)*	1.80*	*(2.30)*
	R^2	0.11		0.10		0.10		0.10	
AUS	$b^{(\tau)}_c$	0.91**	*(3.29)*	1.65**	*(3.33)*	2.32**	*(3.37)*	2.98**	*(3.47)*
	R^2	0.26		0.24		0.22		0.22	
AUS²	$b^{(\tau)}_c$	0.78**	*(2.83)*	1.57**	*(3.04)*	2.26**	*(3.24)*	2.89**	*(3.37)*
	R^2	0.21		0.21		0.21		0.21	
CHE	$b^{(\tau)}_c$	0.60**	*(3.31)*	1.16**	*(3.43)*	1.65**	*(3.53)*	2.07**	*(3.64)*
	R^2	0.23		0.23		0.23		0.23	
CHE²	$b^{(\tau)}_c$	0.58**	*(3.28)*	1.12**	*(3.39)*	1.58**	*(3.48)*	1.99**	*(3.60)*
	R^2	0.23		0.23		0.22		0.22	
JPN	$b^{(\tau)}_c$	0.63**	*(3.77)*	1.32**	*(4.15)*	2.07**	*(5.13)*	2.76**	*(6.22)*
	R^2	0.55		0.56		0.58		0.61	
JPN²	$b^{(\tau)}_c$	0.59**	*(3.50)*	1.33**	*(4.30)*	2.03**	*(5.19)*	2.65**	*(6.22)*
	R^2	0.53		0.58		0.60		0.60	

Table E.11.1: Data Set Comparison - CP and GCP Regression Results for the US, AUS, CHE, and JPN. *Estimates of Regression* (R.2) *and* (R.7) *in the US, AUS, CHE, and JPN for two data sets (USA: CRSP (2018a), USA²: Gürkaynak et al. (2007), AUS: RBA (2018), AUS²: Wright (2011), CHE: SNB (2018), CHE²: Wright (2011), JPN: MOF (2018) and JPN²: Wright (2011)). T-statistics in parentheses use Newey and West (1987) standard error-correction with 18 lags. Adjusted R^2. Adjusted R^2 for Regression* (R.3) *in brackets. Constant estimates are excluded. Sample period: 1992.12–2009.05. **: p-value $<$ 0.01, *: p-value $<$ 0.05*

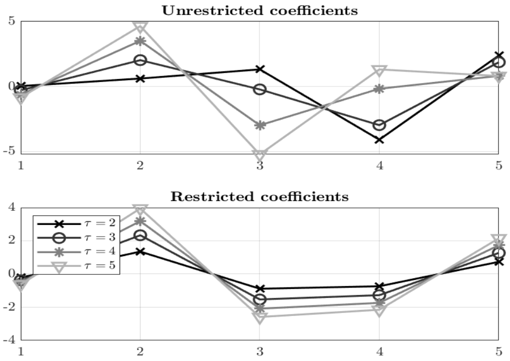
E.12 Unrestricted vs. Restricted Coefficients Plots



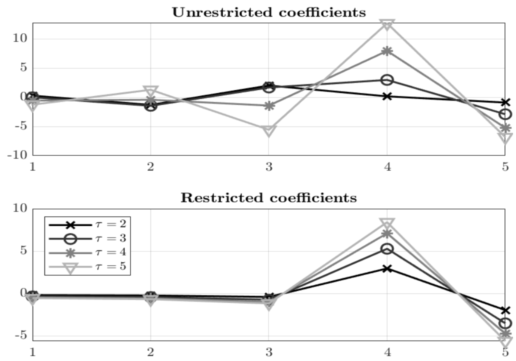
(a) *USA*



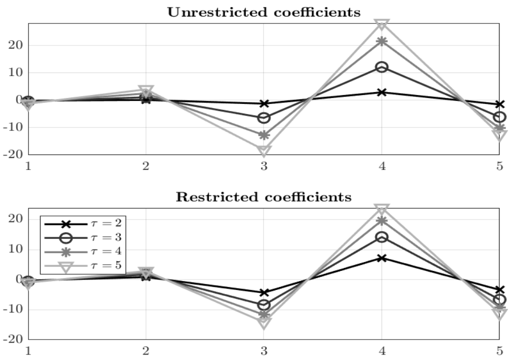
(b) *USA*^{2}



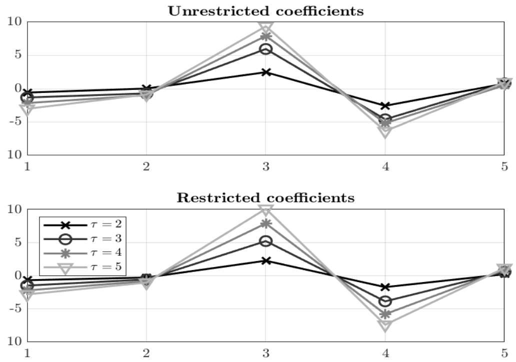
(c) *AUS*



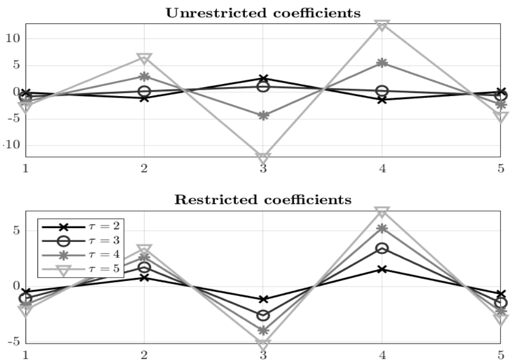
(d) *CAN*



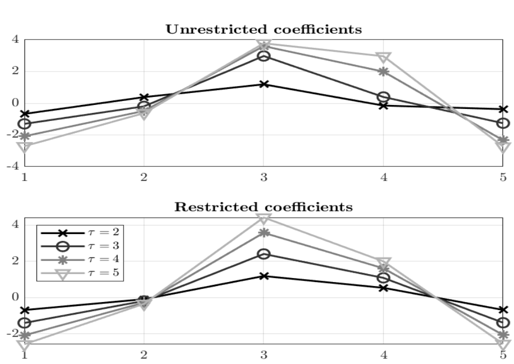
(e) *CHE*^{2}



(f) *DEU*



(g) *GBR*



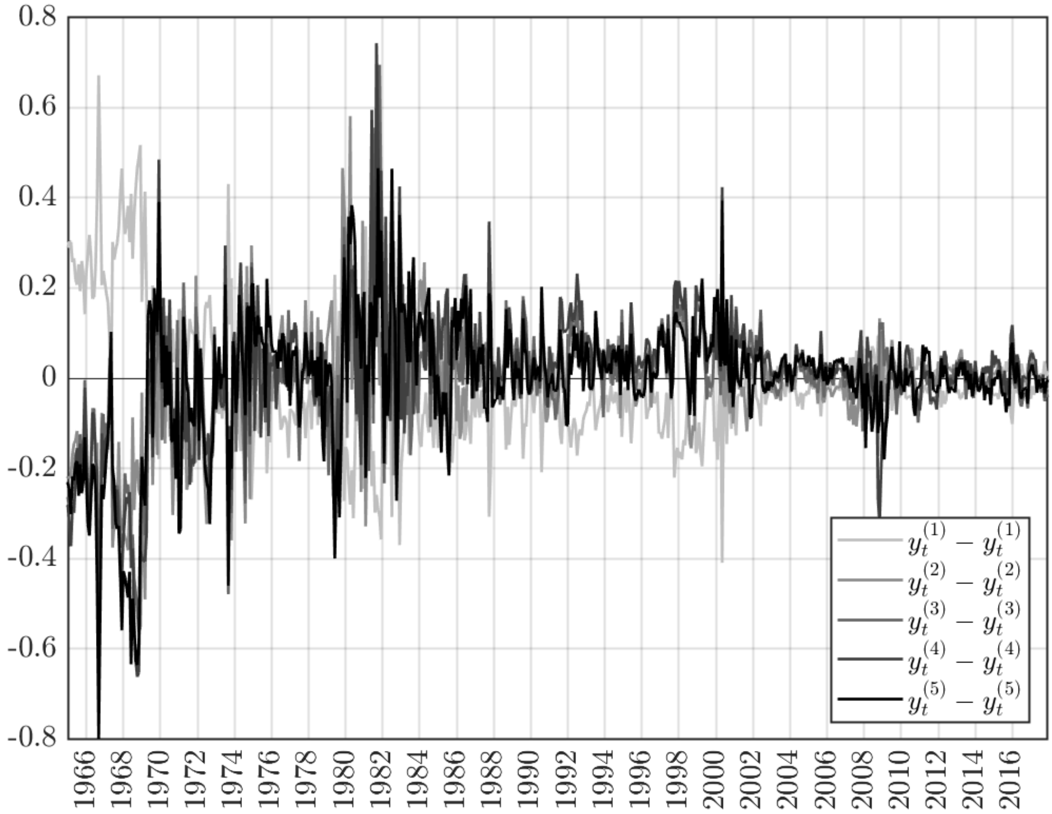
(h) *JPN*^{2}

Figure E.12.1: Unrestricted vs. Restricted Coefficient Plot.
Coefficients are estimated from Regression (R.3) and (R.2) and are related by $\hat{\boldsymbol{\beta}}_{\mathbf{c}} = \hat{\boldsymbol{b}}_{\mathbf{c}} \hat{\boldsymbol{\gamma}}_{\mathbf{c}}^{\intercal}$. *Sample period: 1992.12–2017.12.*

F Data Impact

F.1 Yield Difference

Figure (F.1.1) depicts percentage point differences between yield data constructed with the Unsmoothed Fama-bliss (CRSP, 2018a) and Svensson (Gürkaynak et al., 2007) methods in the US for 1964–2017. From 2001



(a) *USA (1964–2017): Fama-Bliss vs. Svensson*

Figure F.1.1: Yield Data Difference in the US.
Percentage point difference in yields estimated with the unsmoothed Fama-Bliss- and Svensson-method (CRSP, 2018a; Gürkaynak et al., 2007) for the US.

onwards, the average yield differences are close to zero. However, up to 2001, the differences are more dispersed, particularly in periods of bond market turmoil (e.g., around 1980, 2000, and 2008). Moreover, as the yield difference of the one-year maturity bond is prominent in Figure (F.1.1), this confirms that nominal yields in the short-maturity-end of the curve are more difficult to estimate than the long-end, as we outline in section 3.3.[89] Appendix C.5

[89] See BIS (2005, p. 10).

highlights yield data differences in Australia (AUS vs AUS[2]), Switzerland (CHE vs CHE[2]) and Japan (JPN vs JPN[2]) of other construction methods.

F.2 Analytical Difference

Bekaert, Hodrick, and Marshall (1997) document that small-sample bias and measurement errors of estimated yield data make the coefficient estimates biased, and associated statistical tests based on asymptotic distribution theory unreliable. Backus, Foresi, Mozumdar, and Wu (2001, p. 285) run the regression

$$f_{t+1}^{(t+1,\tau-1)} - f_t^{(t,0)} = constant + b_\tau \left(f_t^{(t,\tau)} - f_t^{(t,0)} \right) + residual,$$

and concretize the impact of measurement error on the estimated coefficient by supposing that the observations of forward rates $\hat{f}$ differ from the "true" forward rate f in having measurement error η:

$$\hat{f}_t^{(t,\tau)} = f_t^{(t,\tau)} + \eta_t^{(t,\tau)}$$

Where $\eta_t^{(t,\tau)}$ is assumed to be independent of "true" forward rates, has variance $\sigma^2_{t,\tau}$, is uncorrelated with errors at different dates and has arbitrary correlation with contemporaneous errors $\left[Corr\left(\eta_t^{(t,\tau_1)}, \eta_t^{(t,\tau_2)}\right) = \rho_{\tau_1 \tau 2} \right]$. They show that the estimated coefficient for the true forward rates is given by:

$$\begin{aligned} b_\tau &= \frac{cov\left(f_{t+1}^{(t+1,\tau-1)} - f_t^{(t,0)}, f_t^{(t,\tau)} - f_t^{(t,0)}\right)}{var\left(f_t^{(t,\tau)} - f_t^{(t,0)}\right)} \\ &= \frac{cov\left(\hat{f}_{t+1}^{(t+1,\tau-1)} - \hat{f}_t^{(t,0)}, \hat{f}_t^{(t,\tau)} - \hat{f}_t^{(t,0)}\right) - \left[\sigma^2_{(t,0)} - \rho_{0\tau}\sigma_0\sigma_\tau\right]}{var\left(\hat{f}_t^{(t,\tau)} - \hat{f}_t^{(t,0)}\right) - \left[\sigma^2_{(t,0)} + \sigma^2_{(t,\tau)} - 2\rho_{0\tau}\sigma_0\sigma_\tau\right]} \end{aligned}$$

The unsmoothed Fama-Bliss method estimates the discount function with zero errors (i.e., consistent with market prices).[90] Thus, Bekaert et al. (1997) regard the covariance matrix of bond yield data differences estimated by the

[90] See section 3.3.

unsmoothed Fama-bliss method and other methods as the upper bound of plausible measurement errors (Bekaert et al., 1997, p. 339). Hence, they regard unsmoothed Fama-Bliss yield data as the "true" term structure of interest rates. Therefore, we interpret the estimates from regressions using unsmoothed Fama-Bliss yield data as data with no measurement error. Unfortunately, to our knowledge, this data type is only available for the US.

G Out-of-Sample Exercise

G.1 Performance Measures

We consider the Direction Accuracy and Mean Absolute Error measure when assessing model performance, and below are the mathematical derivations.

Direction Accuracy

Direction accuracy (DA, henceforth) measures how often the model predicts the right direction of the actual outcome, that is, the percentage of trades with positive returns. Mathematically, the DA-formula is:

$$\text{DA} = \frac{1}{N}\sum_{j=1}^{N} B_j \qquad \text{where} \qquad B_j = \begin{cases} 1 & \text{if } y_j \cdot \hat{y}_j > 0 \\ 0 & \text{otherwise} \end{cases}$$

and N is the number of forecasts.

Mean Absolute Error

The mean absolute error (MAE, henceforth) is the mean absolute value of the error between actual and predicted excess return. Mathematically, the MAE-formula is:

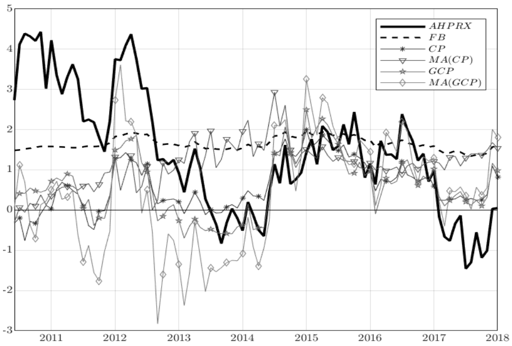
$$\text{MAE} = \frac{1}{N}\sum_{j=1}^{N} |y_j - \hat{y}_j|.$$

G.2 Performance Results

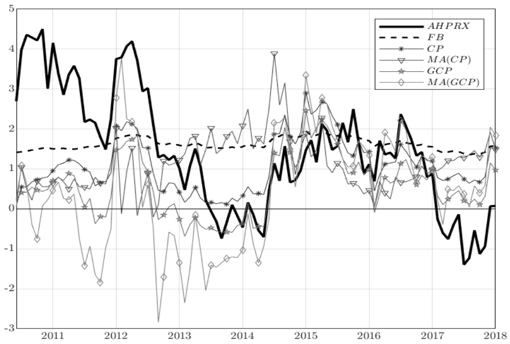
		USA	USA²	AUS	CAN	CHE	DEUW	GBRW	JPN
In-sample									
DOC	I	*79.3%*	*79.3%*	*78.3%*	*79.3%*	*76.1%*	*87.0%*	*78.3%*	*64.1%*
DOC	II	*83.7%*	*85.9%*	*52.2%*	*78.3%*	*67.4%*	**88.0%**	*78.3%*	*70.7%*
DOC	III	*81.5%*	*83.7%*	*52.2%*	*76.1%*	*66.3%*	*87.0%*	*78.3%*	*62.0%*
DOC	IV	**88.0%**	**88.0%**	**80.4%**	**82.6%**	*84.8%*	*78.3%*	*84.8%*	**81.5%**
DOC	V	*83.7%*	*83.7%*	*79.3%*	*75.0%*	**87.0%**	*81.5%*	**92.4%**	*66.3%*
MAE	I	*+0.34*	*+0.33*	*+0.01*	*+0.24*	*+0.07*	**0.92**	*+0.23*	**0.28**
MAE	II	*+0.12*	*+0.06*	*+0.28*	*+0.17*	*+0.16*	*+0.10*	*+0.23*	*+0.03*
MAE	III	*+0.16*	*+0.10*	*+0.29*	*+0.16*	*+0.19*	*+0.10*	*+0.20*	*+0.05*
MAE	IV	**0.71**	**0.72**	**1.36**	**0.76**	*+0.03*	*+0.14*	*+0.30*	*+0.50*
MAE	V	*+0.19*	*+0.17*	*+0.01*	*+0.05*	**0.65**	*+0.07*	**0.89**	*+0.20*
Out-of-sample									
DOC	I	**79.3%**	**79.3%**	**78.3%**	**79.3%**	**76.1%**	**87.0%**	**78.3%**	*45.7%*
DOC	II	*68.5%*	**79.3%**	*21.7%*	*67.4%*	*34.8%*	*44.6%*	*53.3%*	*42.4%*
DOC	III	*77.2%*	*76.1%*	*28.3%*	**79.3%**	*42.4%*	*47.8%*	*45.7%*	*44.6%*
DOC	IV	*75.0%*	*75.0%*	*57.6%*	*69.6%*	*69.6%*	*68.5%*	*71.7%*	**57.6%**
DOC	V	*64.1%*	*65.2%*	*35.9%*	*72.8%*	*67.4%*	*47.8%*	*68.5%*	*37.0%*
MAE	I	**1.21**	*+0.03*	**1.42**	*+0.06*	**0.79**	**0.94**	**1.28**	**0.46**
MAE	II	*+0.10*	**1.17**	*+1.98*	*+0.10*	*+1.00*	*+0.95*	*+1.28*	*+0.05*
MAE	III	*+0.35*	*+0.47*	*+1.18*	**1.08**	*+0.77*	*+0.76*	*+1.44*	*+0.06*
MAE	IV	*+0.04*	*+0.08*	*+0.56*	*+0.17*	*+0.14*	*+0.56*	*+0.60*	*+0.38*
MAE	V	*+0.40*	*+0.44*	*+1.12*	*+0.25*	*+0.33*	*+0.82*	*+0.74*	*+0.54*

Table G.2.1: Performance Results - In-Sample vs. Out-of-Sample.
In-sample vs. pseudo-out-of-sample forecasting performance of each model in each country. Percentages are direction accuracy, numbers in parentheses are mean absolute errors. For both measures, the best performing model in each country is highlighted. For MAE, non-highlighted numbers show the difference from the best performing model in each country. Regressions - I: FB (R.1); II: CP (R.2); III: MA(CP, 2) (R.4); IV: GCP (R.7); V: MA(GCP, 2) (R.8). Recursively forecasting 2010.05–2017.12 give 92 forecasts.

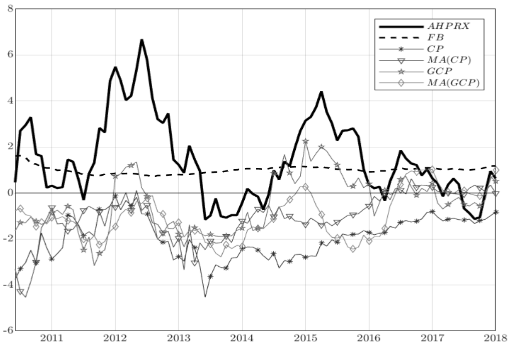
G.3 Average Realized vs. Forecasted Risk Premia



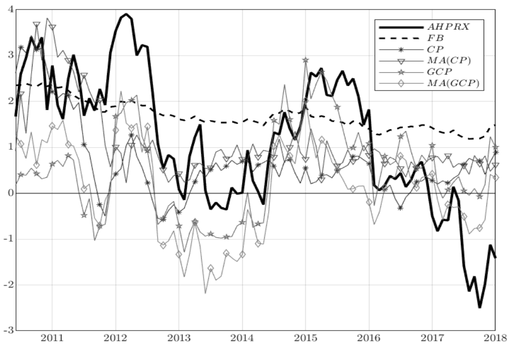
(a) *USA*



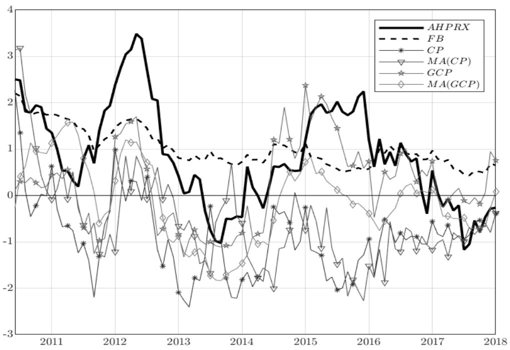
(b) USA^2



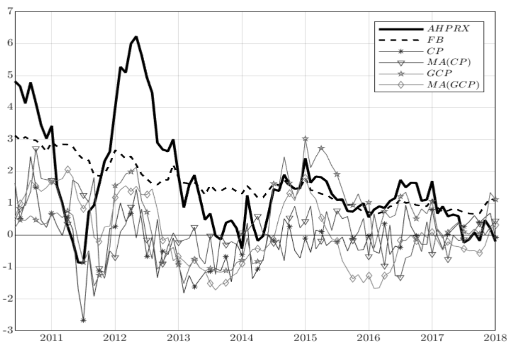
(c) *AUS*



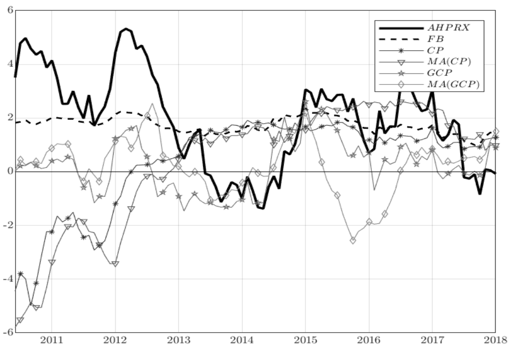
(d) *CAN*



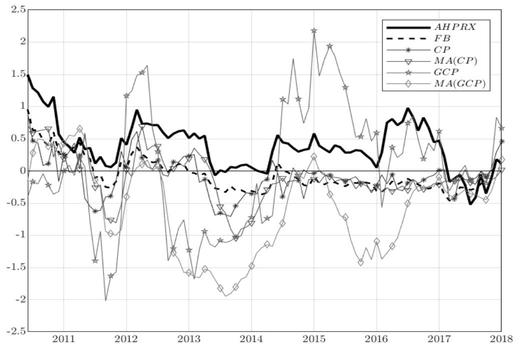
(e) *CHE*



(f) *DEU*



(g) *GBR*



(h) *JPN*

Figure G.3.1: Forecasts vs. Actual Mean Excess Bond Returns in international markets. *Pseudo-out-of-sample forecasts vs. actual average excess bond returns (in percent) in international markets. MA(CP) and MA(GCP) are with $k = 2$. AHPRX: Average one-year excess bond returns. Estimation period: 1992.12–2009.05. Recursively forecasting 2010.05–2017.12 results in 92 forecasts.*

G.4 Correlations - Average Realized and Forecasted Risk Premia

		USA	USA²	AUS	CAN	CHE	DEU	GBR	JPN	Mean
					In-sample					
Correlation & Significane	**I**	**0.92**	**0.91**	**0.25**	**0.73**	**0.63**	**0.59**	**0.80**	**0.68**	**0.69**
		(0.00)	*(0.00)*	*(0.02)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	
	II	**0.86**	**0.84**	**0.51**	**0.63**	**0.53**	**0.71**	**0.82**	**0.66**	**0.69**
		(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	
	III	**0.81**	**0.81**	**0.28**	**0.64**	**0.47**	**0.68**	**0.76**	**0.63**	**0.64**
		(0.00)	*(0.00)*	*(0.01)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	
	IV	**0.89**	**0.89**	**0.58**	**0.80**	**0.72**	**0.62**	**0.82**	**0.59**	**0.74**
		(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	
	V	**0.83**	**0.83**	**0.51**	**0.86**	**0.76**	**0.64**	**0.81**	**0.54**	**0.72**
		(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	
					Out-of-sample					
Correlation & Significane	**I**	**0.42**	**0.30**	**-0.16**	**0.75**	**0.57**	**0.57**	**0.66**	**0.70**	**0.48**
		(0.00)	*(0.00)*	*(0.13)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	
	II	**0.09**	**0.34**	**0.35**	**0.38**	**0.40**	**0.50**	**-0.57**	**0.58**	**0.26**
		(0.38)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	
	III	**-0.60**	**-0.44**	**-0.09**	**0.43**	**0.32**	**0.14**	**-0.55**	**0.56**	**-0.03**
		(0.00)	*(0.00)*	*(0.41)*	*(0.00)*	*(0.00)*	*(0.18)*	*(0.00)*	*(0.00)*	
	IV	**0.42**	**0.42**	**0.41**	**0.46**	**0.53**	**0.32**	**0.49**	**0.21**	**0.41**
		(0.00)	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.04)*	
	V	**0.28**	**0.27**	**0.10**	**0.65**	**0.61**	**0.55**	**0.33**	**0.34**	**0.39**
		(0.01)	*(0.01)*	*(0.36)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	*(0.00)*	

Table G.4.1: Forecast-Actual Correlations in international markets.
Correlation between pseudo-out-of-sample forecasts and actual average one-year excess bond returns in international markets. In-sample and out-of-sample. Models - I: FB; II: CP; III: MA(CP, 2); IV: GCP; V: MA(GCP, 2). P-values of t-statistics in parentheses. Estimation period: 1992.12–2009.05. Recursively forecasting in 2010.05–2017.12 results in 92 forecasts.