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Robeco Institutional Asset Management

Master Thesis

Factor Investing in Emerging Market Local Currency Bonds

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Abstract

This paper investigates whether factor investing can be extended to emerging market local currency (EM-LC) bonds. Existing literature has proved the existence of factors in the developed market fixed income universe, and more recently, in emerging market hard currency (EM-HC) bonds. We focus on the factors defined in developed market bonds rather than EM-HC bonds, which generally contain countries with higher credit risks rather than the rate risk. We first show that factor investing works in a simple method that has been applied in previous literature, resulting in significant alpha in Carry, Change-in-carry, and Momentum factor based portfolios. However, this method does not deal with the diverting behaviour of beta, volatility, and default risk among countries, which are peculiar characteristics of the EM-LC universe. Thereby the portfolio shows significant beta and high concentration risk. We systematically approach the potential risks by proposing advanced factor portfolio construction methods of adjusted factors, optimisation, and grouping with enhanced beta and covariance estimators and K-means clustering. Our results indicate that beta and concentration risk have been reduced using our proposed methods. Furthermore, we find promising performance with strongly significant alpha.

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1 Introduction

Factor investing is one of the most popular quantitative investment strategies due to its intuitive characteristic of categorising and assigning scores on assets based on a certain style such as size, value, and momentum from Fama & French (2012). Moreover, promising results of factor-based portfolios proven in the existing literature make it more attractive. Factors are investigated for decades in a variety of asset classes. The existence of factors in multiple asset classes lead to active factor investing in both developed and emerging equity markets. More recently, research on style investing with various factors extends to developed market government bonds, corporate bonds and emerging market hard currency (EM-HC) bonds. On the other hand, factor investing in emerging market local currency (EM-LC) bonds has not been investigated yet. EM-LC bonds have a smaller universe than EM-HC bonds, which is issued by a broad range of countries due to the accessibility as dollar-denominated debts, because countries need to meet some criteria such as currency stability and market size to issue EM-LC bonds. There might be a potential for factor investing in EM-LC bonds since they could provide a diversified portfolio from developed market securities and EM-HC bonds, with a lower credit risk than EM-HC bonds. EM-HC bonds are more related to the credit risk component, contrasting to EM-LC bonds, which has a similar rate risk component to the bonds from developed sovereigns (Brooks et al., 2020). However, the characteristics between EM-LC bonds and developed market bonds differ because countries have diverting behaviours in the EM-LC universe. For instance, the universe includes both stable and volatile countries, such as Malaysia and Turkey, respectively. In contrast, countries in developed markets behave similarly. This makes previous research on factor investing in developed market bonds insufficient. Therefore this paper investigates factor investing in EM-LC bonds by adjusting the standard factors studied in developed market bonds.

The approach to factor investing in EM-LC bonds should differ from the existing one in developed markets due to the following two aspects of EM-LC bonds. First, the pure bond risk and the co-movement, 'beta' with the market, contains notable differences over time between countries. The beta shows how each asset is volatile compared to the overall market. A higher beta means that the asset has more volatile co-movement. This can result in a portfolio which is highly exposed to beta rather than the factor itself. Second, some EM-LC bonds include non-negligible default risk, while others behave more like developed markets. It can cause the volatility of returns to vary a lot across countries, which can be risky since one highly volatile country can blow up the portfolio driven by its sensitivity to default risk during crisis periods. The classic factors focus on not potential default risk but interest rates. Methodological challenges caused by the combination of these differences have not been thoroughly explored in the existing literature. Hence, this paper investigates whether factor investing also works in EM-LC bonds and whether advanced versions of the portfolio can be constructed to take into account beta and risk differences between the countries.

The main contributions of this paper lie in systematically managing the two main attributes of EM-LC bonds. The most common way to define a factor is to rank the assets on their factor measures, and then going long and short the top and bottom-ranked assets using linear declining weights (Asness et al., 2013). We propose three advanced factor portfolio construction structures to control the above potential risks. First, we introduce advanced versions of signal measures by adjusting the standard factor measures. It includes dividing the factor measure by the beta and removing the beta exposure by orthogonalising the factor measure on the beta. Second, we propose optimising the portfolio using linear programming and quadratic programming. We construct an objective function which maximises the factor exposure subject to the zero beta exposure in linear programming. In addition, we try to reduce the impact of volatile countries by adding a weight restriction according to each country's volatility level to linear programming and considering the risk trade-off using quadratic programming. Third, we suggest systematically grouping the universe that can cluster countries into two comparable groups. Figuring out whether each market behaves like the developed market or is relatively in line with the emerging market might allow us to control different movements in each market. To achieve this, we consider dividing countries into equal-size and dynamic-size groups. We propose to use K-means clustering for dynamic-size grouping. It has the flexibility to choose the group size in real-time. Furthermore, we investigate various beta and covariance estimators to be plugged in the aforementioned methods. More precise input parameters ensure our systematic methods to be less error maximising caused by noisy input measures.

This research is focused on a country level with the EM-LC bond indices of each country. We consider 17 countries selected based on a recent weighting scheme for the J.P. Morgan Government Bond Index-Emerging Markets Global (GBI-EM Global) index, where they select countries on tradability with a maximum weight of 10% in one country. The countries that we consider include South Korea, China, Turkey, and Brazil. We use monthly data of local excess bond returns per unit of duration as a target series. The starting and end dates vary per country. The target series runs from June 1994 till February 2021. To construct factors, we use additional data such as yield-to-maturity and 3-month LIBOR rates on a country level and transform it to be a unit of duration.

Factors introduced in diverse other asset classes are studied in this paper. Fama & French (2012) prove the existence of factors such as size, value and momentum in the global equity markets. Recently, there have been efforts to find factors in a broader range of assets. Asness et al. (2013) show the existence of value and momentum factors across a diverse set of securities. Furthermore, the "COMBO" factor strategy, an equal combination factor of value and momentum, tends to outperform value and momentum strategies across tested asset types. However, the result regarding fixed income is not convincing compared to other asset classes. Investigated by Frazzini & Pedersen (2014), the betting-against-beta (BAB) factor provides consistent results across equity, bond and futures markets with significant positive risk-adjusted returns. Koijen et al. (2018) develop the concept of the carry to a variety of asset classes and show the presence of a carry factor. More recently, several papers study style investing in fixed income. Brooks et al. (2018) document the efficacy of style investing using value, momentum, carry and defensive factors for developed market government and corporate bonds. Brooks et al. (2020) study the same factors as in Brooks et al. (2018) with beta-neutral long-short portfolios and finds evidence of systematic investing in emerging market hard currency bonds. Kang et al. (2019) jointly analyses macro and style factors in the emerging dollar debt market and shows that value and FX momentum factors can explain country expected returns.

Our results show the following key findings. First, we demonstrate that factor investing works for EM-LC bonds, a new finding that could also be interesting for investors who have embraced factor investing in other asset classes. The out-of-sample tests of Carry, Change-in-carry, and Momentum factor-based portfolios show significant alpha in the EM-LC bond universe under the basic factor portfolio structure introduced in the existing literature. Second, the existing basic factor portfolio construction does not address the potential risks of EM-LC bonds, resulting in significant beta and high concentration risk. Third, we find that the beta estimate using different windows for correlation and volatility terms and subsequently shrinking it (Frazzini & Pedersen, 2014) and the covariance matrix under the market factor structure help to capture these risks better, with less estimation error. Fourth, our proposed advanced factor portfolios using the best beta and covariance matrix estimates are able to reduce the level of beta and concentration risk with enhanced performance. A combination of controlling beta and risk either via linear programming with weight restrictions or quadratic programming with risk trade-off and dynamic size grouping with K-means clustering is most effective in addressing the key problems of the factors whilst maintaining a good factor performance. Furthermore, we find that these advanced methods quickly respond to the increased riskiness of Turkish bonds by reducing the exposure to these bonds during the Turkish currency and debt crisis.

The remaining structure of our paper is as follows. In Section 2, we describe the data used in the analysis. In Section 3, we introduce initial factor construction and more advanced factor construction, followed by defining signal measures that are going to be tested in our paper. In Section 4, the results are presented and discussed. In Section 5, we discuss additional results of the multi-factor model and the sub-sample period during the Turkish currency and debt crisis. Finally, Section 6 concludes.

2 Data

This paper aims to analyse factor investing in the EM-LC universe. Hence, we use EM-LC bond indices at the overall country level as target series. To construct factors, we have additional data of yield, duration and the risk-free rate. For the country-level analysis, 17 countries are considered using its index of overall government bonds. It consists of J.P. Morgan (JPM) total return indices in local currency. Further data to calculate factors and compute local hedged excess returns are used, such as JPM index yield-to-maturity and modified duration, three-month LIBOR, two and ten-year yields. Obtained from Bloomberg, the data cover the period 1994/06/30 to 2021/02/26, where the start and end dates may vary per country depending on the availability of government bonds. Table 1 presents the starting date for each of the series.

Table 1: Used data sets and the corresponding starting date

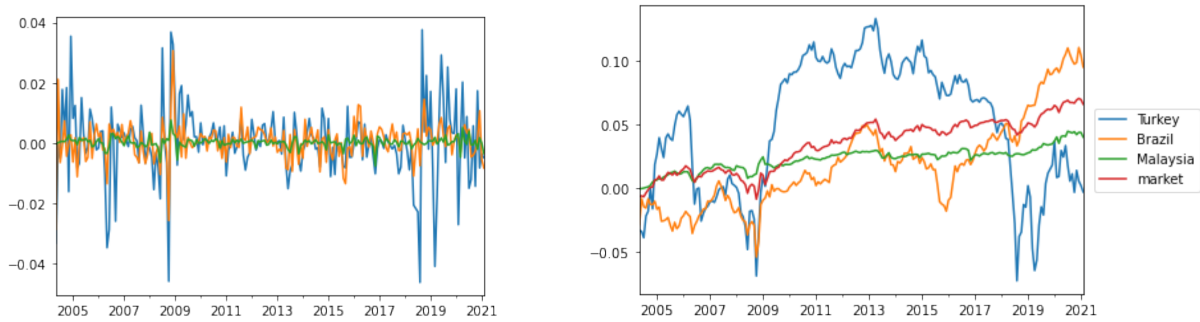
Countries	JPM total return	JPM YLD	JPM DUR	3M LIBOR	2Y YLD	10Y YLD
Brazil	2001-12-31	2002-01-01	2002-01-01	1994-07-04	2000-04-03	2009-09-21
Mexico	2001-12-31	2002-01-01	2002-01-01	1997-01-15	2001-04-26	2001-08-22
Colombia	2002-12-31	2003-01-01	2003-01-01	1991-01-01	2001-03-01	2009-12-11
Indonesia	2003-01-01	2003-01-01	2003-01-01	1997-04-10	2003-01-01	2003-07-22
Malaysia	2001-12-31	2002-01-01	2002-01-01	1991-01-01	2005-06-21	2005-06-21
Thailand	2001-12-31	2001-12-31	2001-12-31	2002-05-30	2000-08-07	2000-08-07
South Korea	2000-12-29	2001-12-11	2001-12-11	2000-08-07	2000-08-07	2000-12-19
Turkey	2004-03-31	2004-04-01	2004-04-01	2002-08-01	2006-06-06	2010-01-27
South Africa	1994-06-30	2001-12-31	2001-12-31	1999-02-01	1999-12-06	1997-01-01
Poland	2000-12-29	2001-01-01	2001-01-01	1996-08-12	1999-03-04	1999-05-21
Hungary	2000-12-29	2001-01-01	2001-12-31	1997-05-05	1997-10-09	1999-01-20
India	2001-12-31	2001-12-31	2001-12-31	1998-12-01	2001-01-01	1998-11-25
China	2004-01-01	2004-01-01	2004-01-01	2000-01-04	2010-12-16	2011-02-11
Russia	2005-01-31	2005-02-01	2005-02-01	2005-04-18	2010-03-23	2010-03-23
Chile	2010-08-31	2010-09-01	2010-09-01	2000-07-21	2013-11-12	2014-06-02
Peru	2006-10-02	2006-10-02	2006-10-02	2000-07-25	2007-10-02	2007-10-02
Philippines	2010-09-30	2010-10-01	2010-10-01	1998-12-11	-	-

Notes: The end dates of JPM total return, JPM YLD, and JPM DUR for Chile are 2019-07-30. The end date for the rest of the series is 2021-02-26.

Several errors are found in the index data, which are not in line with the maturity bucket data. It is expected that bonds are not issued at some point of time in some countries. This could cause data fields to be filled with previous values while the data is not available. To find potential errors in data, we plot both raw price data and return data to find huge outliers or repetitive values. The found errors are replaced with NA or filled with the previous value. When repetitive values or outliers are found, we replaced ten and two-year yield data with the 7-10 and 1-3 years maturity bucket data. A more detailed description of adjusted data points can be found in Appendix A.

We use monthly local excess bond returns per unit of duration of each country's EM-LC bond index for factor construction and measures. Therefore the time t denotes each month in the following sections. Using monthly data might be costly since we are not making use of all the available information. However, there are considerable differences in trading times per country. Using the daily data may harm the co-movement of the long-short portfolio. Besides, daily updating the portfolio weights may not be feasible, for example, due to transaction costs. Local excess bond returns are calculated by subtracting 3-month LIBOR rates from the bond returns. It is a proxy for currency-hedged returns (Ilmanen, 1995). Subsequently, it is divided by duration. This way, we can look at factor investing related to the bond returns without being affected by currency returns, thus excluding exchange rate risk and by the duration of bonds issued. We take the average of the monthly local excess bond returns per unit of duration to produce a global market return series.

The plot of monthly local excess bond returns per unit of the duration of few countries is shown in Figure 1a. It shows that some markets are highly volatile. For example, in 2008, Turkey and Brazil fluctuate a lot while Malaysia is relatively stable. Furthermore, Table 2 presents descriptive statistics when the data from all countries are available. The last three rows are developed markets for comparison with the EM-LC universe. We observe that the volatility and beta deviate a lot across countries, where some countries are more than three times more volatile than developed markets while other countries have a similar volatility level to developed markets. The correlations with its equity market returns, currency returns and the US bond returns also show large variations across countries. The rolling volatility shown in Figure 2 suggests that the volatility of bond returns fluctuate a lot over time. We observe huge deviations across countries during the crises, while they are similar to each other in the rest of the period. Hence we expect that factors might generally work but can suffer in crisis periods. To better understand the performance of the bonds in each country and the overall market, the cumulative performance of excess bond return per unit of duration is given in Figure 1b. It is observed that EM-LC bonds have performed quite well over the sample period. We expect that the factor performance might be driven by the overall market when positive beta presents. Therefore, controlling for the beta effect is essential to obtain the return solely from the factor.



(a) Excess return per unit of duration (b) Cumulative return per unit of duration

Figure 1: JPM bond return data

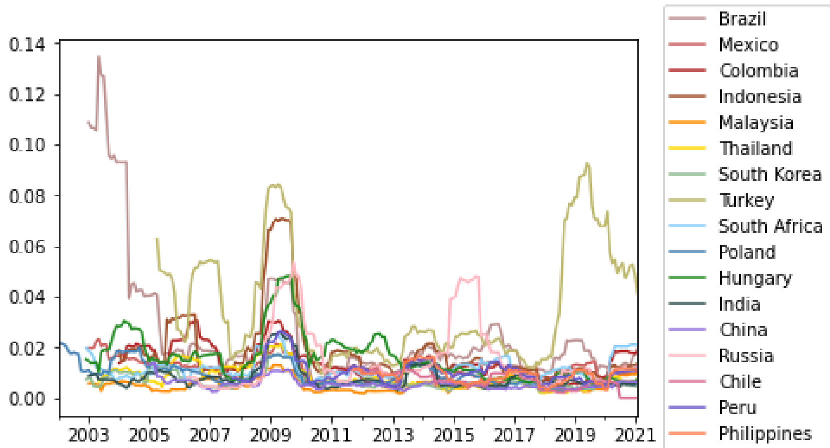


Figure 2: One-year rolling volatility of bond returns over time

Table 2: Descriptive Statistics

	vol (%)	beta	EQT corr	FX corr	US bond corr
Turkey	3.70	3.63	0.50	0.71	0.13
Russia	1.89	1.10	0.43	0.62	-0.03
Brazil	1.75	1.75	0.48	0.51	0.27
Indonesia	1.36	1.42	0.60	0.58	0.33
Hungary	1.31	1.07	0.31	0.59	0.17
South Africa	1.09	1.14	0.31	0.62	0.39
Mexico	1.03	0.96	0.25	0.52	0.52
Peru	1.03	1.09	0.47	0.52	0.31
Colombia	1.01	1.05	0.39	0.49	0.33
Philippines	0.97	0.91	0.56	0.43	0.28
Chile	0.80	0.57	0.05	0.09	0.28
India	0.73	0.28	0.09	0.22	0.15
Poland	0.72	0.71	0.17	0.32	0.39
Thailand	0.54	0.47	0.11	0.30	0.44
South Korea	0.50	0.30	-0.22	-0.01	0.62
China	0.49	0.19	-0.11	-0.13	0.20
Malaysia	0.47	0.37	0.27	0.46	0.48
US	0.60	-	-0.39	-	1.00
EMU	0.59	-	-0.28	-	0.76
Japan	0.22	-	-0.36	-	0.50

Notes: The excess bond returns per unit of duration are used. The sample period runs from 2010-11-30 to 2019-07-31, where data from all countries are available. The annualised volatility of the excess bond returns, bond beta with respect to the market is reported. The market is the average of the 17 countries. The correlation of the excess bond returns to their own equity and currency markets' returns is presented for equity correlation and currency return correlation. The last column is the correlation of each country's excess bond returns with the US bond return.

3 Methodology

We introduce methodologies to answer the research questions of whether factor investing works on EM-LC bonds and if advanced factor construction can manage the potential risks in the EM-LC universe. In Section 3.1, we explain standard factor construction introduced in the existing literature. Afterwards, we propose our advanced factor construction method, which is more suitable for characteristics of EM-LC bonds proposed in Section 2. In Section 3.2, we introduce adjusted factor measures. In Section 3.3, optimisation methods for portfolio construction are described. In Section 3.4, we propose methods regarding grouping countries into emerging market (EM) and developed market (DM)-like countries. Subsequently, we introduce factor measures introduced in the previous literature in Section 3.5. We suggest various input measures such as beta and covariance estimators for the advanced factor construction in Section 3.6 and Section 3.7. Section 3.8 introduces evaluation methods for the resulting input measures. Section 3.9 documents performance evaluation metrics to compare each factor portfolio construction methods which are used in this paper. Lastly, we introduce statistical tests to investigate the significance of differences in each input estimator and factor portfolio construction strategy in Section 3.10 and 3.11, respectively.

3.1 Koijen weighting scheme

To test if the factor investing works on EM-LC bonds, we initially use a long-short factor construction following the popular rank-based weighting scheme by Koijen et al. (2018), which is used as a carry trade specification motivated by Asness et al. (2013). This approach ranks each of the factor measures to compute the portfolio weight for factor strategies such as

$$w_{c,t}^{signal} = z_t \left(\text{rank}(S_{c,t}) - \frac{N_t + 1}{2} \right), \tag{1}$$

where $S_{c,t}$ is a country c's signal measure, N_t is the number of countries and z_t is a scalar which forces the sum of the long and short positions to be 1 and -1. Countries with higher factor scores have larger and positive weights, while countries with lower factor scores have lower and negative weights. Subsequently, the portfolio return of each signal is calculated by

$$R_{t+1}^{signal} = \sum_c w_{c,t}^{signal} R_{c,t+1}^{JPM}, \tag{2}$$

where $R_{c,t}^{JPM}$ is EM-LC excess return per unit of duration calculated by deducting 3-month LIBOR rates, $r_{c,t}$, from EM-LC bond index return and subsequently dividing by its duration, $D_{c,t}$.

Even though the weighting scheme in Equation (1) is intuitive and straightforward, it does not capture two main characteristics of EM-LC bonds that are distinct from developed market (DM) bonds: (i) Large differences in market volatility across the countries; and (ii) Some EM countries are relatively safe (DM-like) while others may be more prone to default risk (EM-like), since it only ranks the factor measures without adjusting for these risks. It may manifest itself in how bond returns are related to currency and equity returns. For example, the bond market's behaviour compared to the equity market might be different in crises. Bonds of DM-like universe are likely to perform well in crisis periods when equities do poorly. However, bonds of EM-like universe, which is a more risky bond, may perform poorly. This diverting behaviour could negatively affect the performance of long-short portfolios. More generally, the long-short portfolios' returns may be driven by differences between DM-like and EM-like bonds rather than factor characteristics like carry, change-in-carry, value, momentum and BAB. Therefore, we propose several methods to improve upon the simple long-short portfolios in Equation (1) in the following sections.

3.2 Residualisation and Division

The naive scheme in Equation (1) might lead to portfolios with bond betas that deviate quite a lot from zero, meaning the performance might be more driven by the market, which is the overall EM-LC bonds, than factor exposures. Also, countries with very high volatility can dominate the results. One way to reduce the effect of bond beta is adjusting the factor measure definition. It could be done by 'residualising' the factor exposures. The concept of residualisation is proposed by Blitz et al. (2011), where momentum factors constructed from reisidual returns are used. In our analysis, we regress the signal on the betas and use the residuals such as

$$\boldsymbol{S}_t = a + b\hat{\boldsymbol{\beta}}_t + \varepsilon_t \tag{3}$$

where $\hat{\boldsymbol{\beta}}_t$ contains $\beta_{c,t}$ for every country c obtained from ex-ante beta estimation, which is a predicted beta before realisation, with respect to the market where we consider several ex-ante beta measures in Section 3.6, and $\boldsymbol{S}_t$ contains signals for each country at time t. Each component of the residual, $\boldsymbol{S}_t - \hat{b}\hat{\boldsymbol{\beta}}_t$, which corresponds to each country, replaces $S_{c,t}$ in Equation (1). Alternatively, we could look at signal measures divided by beta as a simple way to adjust the level of signal measures caused by the bond beta, which is given as

$$\frac{S_{c,t}}{\hat{\beta}_{c,t}}. \tag{4}$$

Subsequently, we adjust the weights by replacing $S_{c,t}$ with scaled signal measures in Equation (1).

3.3 Optimisation

Another way of reducing the impact of countries with high beta or volatility and default risk is to solve the optimisation problem of maximising the factor exposures while controlling for the risks using proper measures to capture the characteristics. Linear or Quadratic programming can consider the constraints directly. Also, the advantage of solving the optimisation problem compared to the methods in Section 3.2 is its flexibility to add more constraints customised to the problem.

3.3.1 Linear programming

Linear programming maximises the factor exposures subject to constraints aimed at limiting the impact of the cited problems - for example, (i) requiring a bond beta to be zero; or (ii) restricting the maximum weights specific to each country according to its volatility. In the portfolio optimisation problem, it is conventional to maximise the expected return, where we use the factor exposure for its estimator as in Kang et al. (2019).

Here, we directly get the weights for each country from the optimisation function, thus not using the weighting scheme in Equation (1). The minimum number of assets at each point of time is set to six so that the optimisation problem can be feasible. The linear programming equation is given as

$$\begin{aligned}
\max_{\boldsymbol{w}_t^{signal}} \quad & {\boldsymbol{w}_t^{signal}}^\top \boldsymbol{S}_t \\
\text{s.t.} \quad & {\boldsymbol{w}_t^{signal}}^\top \boldsymbol{\beta}_t = 0 \\
& -\sum_{w_{c,t}^{signal}<0} w_{c,t}^{signal} = \sum_{w_{c,t}^{signal}>0} w_{c,t}^{signal} = 1, \\
& |w_{c,t}^{signal}| \leq z_t \left(\frac{1-N_t}{2}\right)
\end{aligned} \tag{5}$$

where $\boldsymbol{w}_t^{signal}$ is signal weight vector in which each element consists of the weight for each country. The bond beta $\boldsymbol{\beta}_t$ is decided in Section 3.6 where we consider several ex-ante beta measure. The third restriction imposes individual weights to be less or equal to the maximum weighting scheme in Equation (1). The advantage of this maximum weighting scheme is its flexibility to the number of assets at each point of time, which varies according to the data availability.

In order to directly restrict the effect of volatile countries, we introduce another linear programming problem with limited weights based on the volatility of each country. We divide the maximum Koijen weight restriction by each country's volatility relative to the median of the cross-sectional volatility for the past 12 months, such as

$$\begin{aligned}
\max_{\boldsymbol{w}_t^{signal}} \quad & \boldsymbol{w}_t^{signal\top} \boldsymbol{S}_t \\
\text{s.t.} \quad & \boldsymbol{w}_t^{signal\top} \boldsymbol{\beta}_t = 0 \\
& -\sum_{w_{c,t}^{signal}<0} w_{c,t}^{signal} = \sum_{w_{c,t}^{signal}>0} w_{c,t}^{signal} = 1, \\
& |w_{c,t}^{signal}| \leq z_t \left(\frac{1-N_t}{2}\right)\left(\frac{\sigma_{M,t-11:t}}{\sigma_{c,t-11:t}}\right)
\end{aligned} \tag{6}$$

where $\sigma_{c,t-11:t}$ is the standard deviation of country c with 12-month estimation window, and $\sigma_{M,t-11:t}$ is the cross-sectional median of the standard deviation of each country at time t. This allows higher maximum weight to less volatile countries while imposing tighter maximum weight restrictions on the volatile countries.

3.3.2 Quadratic programming

Quadratic programming maximises the factor exposures, directly considering the trade-off between the factor exposure and risk, subject to requiring a bond beta to be zero. This is done by deducting the variance of the long-short portfolio multiplied by the risk-aversion parameter. In order to apply the identical risk-aversion parameter to different factor measures, we compute the z-score such as

$$Z_{c,t} = \frac{S_{c,t} - \mu_t}{\sigma_t}, \tag{7}$$

where $S_{c,t}$ is the factor score of country c at time t, μ_t is a cross-sectional average, and σ_t is a cross-sectional standard deviation of each country's factor score at time t. With the vector of resulting z-scores, we optimise the following quadratic programming given as

$$
\begin{aligned}
\max_{\boldsymbol{w}_t^{signal}} \quad & \boldsymbol{w}_t^{signal^\top} \boldsymbol{Z}_t - \lambda \boldsymbol{w}_t^{signal^\top} \boldsymbol{Q}_t \boldsymbol{w}_t^{signal} \\
\text{s.t.} \quad & \boldsymbol{w}_t^{signal^\top} \boldsymbol{\beta}_t = 0 \\
& -\sum_{w_{c,t}^{signal}<0} w_{c,t}^{signal} = \sum_{w_{c,t}^{signal}>0} w_{c,t}^{signal} = 1, \\
& |w_{c,t}^{signal}| \leq z_t \left(\frac{1-N_t}{2} \right)
\end{aligned}
\tag{8}
$$

where $\boldsymbol{Z}_t$ is a vector of $Z_{c,t}$ containing every country c, λ is a risk aversion parameter and $\boldsymbol{Q}_t$ is a covariance matrix of the bond returns at time t. We consider various covariance estimators in Section 3.7. The risk aversion parameter is first chosen upon the scale differences between the z-score and the bond returns. Subsequently, it is decided by comparing the effect of λ on the volatility of resulting portfolio return compared to the global minimum variance portfolio and the linear programming solution from Equation (5).

3.4 Systematic choices regarding the Universe

We propose to create homogeneous groups of EM-LC countries, i.e. EM-like and DM-like, to reduce the impact of differences across markets on the portfolio. We look here at beta to the market as a metric for clustering countries. Several ex-ante beta measures are investigated in Section 3.6. In this section, equal-size grouping and dynamic-size grouping are introduced.

3.4.1 Equal-size grouping

We use simple grouping depending on the predicted beta estimation, known as ex-ante beta, at each point in time. Countries are divided into two groups where the size of each group is half of the universe based on the level of the ex-ante beta. Due to its simplicity, it might reduce possible estimation errors and facilitate interpretation. The factor signals set in the EM-LC universe are assigned into EM and DM-like behaving universes such as

$$
EM = \{S_{c,t} | \beta_{c,t} \geq \beta_{M,t}\}, \quad DM = \{S_{c,t} | \beta_{c,t} < \beta_{M,t}\}, \tag{9}
$$

where $\beta_{c,t}$ is estimated beta of country c, and $\beta_{M,t}$ is the cross-sectional median of the beta at time t. Subsequently, the factor signals of EM and DM-like countries are separately plugged into the Koijen weighting scheme in Equation (1). We combine the resulting two portfolio returns by taking the average of them.

3.4.2 Dynamic-size grouping

Equal-size grouping does not take into account the possible size differences for each group. To allow flexibility of each group size, we use K-means clustering, which is one of the popular clustering algorithms. It partitions the sample into K groups such that countries within a cluster have minimised dissimilarity. It is based on squared Euclidean distance,

$$d(x_i, x_{i'}) = \sum_{j=1}^{p} (x_{ij} - x_{i'j})^2 = ||x_i - x_{i'}||^2, \tag{10}$$

as the dissimilarity measure. The algorithm is given as

Algorithm 1 K-means Clustering	
1	Select K random points as the initialisation of the centroids
2	**Repeat**
3	Calculate the squared Euclidean distance for all points
4	Form K clusters by assigning each point to the closest centroids
5	Reassign groups
6	**Until** centroids converges

To establish the real-time membership, we use a rolling estimation of the model at each point in time. The resulting groups are labelled to EM or DM-like, based on the mean of the bond beta in each cluster. Cluster with higher average beta is classified into EM-like group and the lower cluster into DM-like group. Subsequently, the Koijen weighting scheme in Equation (1) is applied to each group.

We combine the resulting groups according to the following equation,

$$R_{t+1} = w_{EM,t} R^{signal}_{EM,t+1} + w_{DM,t} R^{signal}_{EM,t+1}, \tag{11}$$

where $w_{EM,t}$ and $w_{DM,t}$ are the weights which considers the size of EM and DM cluster respectively at time t. Two methods are considered for the weights $w_{EM,t}$ and $w_{DM,t}$. One is considering the size of the group, and the other considers the risk of each group. First, two portfolios are combined using the weight, which is the proportion of each group's size with respect to the entire universe, such as

$$w^{size}_{EM,t} = \frac{N_{EM,t}}{N_{EM,t} + N_{DM,t}}, \quad w^{size}_{DM,t} = \frac{N_{DM,t}}{N_{EM,t} + N_{DM,t}}, \tag{12}$$

where $N_{EM,t}$ and $N_{DM,t}$ denote the number of assets included in EM and DM cluster, respectively.

Furthermore, we investigate if assigning the weights to combine two portfolios from grouping countries using the inverse of the risk can be helpful for further reducing the potential risk. Size-proportional weight might be harmful since the volatility of the EM-like group's portfolio performance can be dominant compared to the DM-like group. Adjustments on the weights are considered by using the inverse of the risk. We use the volatility of each universe calculated from the return series containing the past 12 months multiplied by the current weight at each point of time, such as

$$\boldsymbol{R}^{risk}_{t-11:t} = \begin{bmatrix} \boldsymbol{w}_t^{signal^\top} R_{t-11}^{signal} \\ \boldsymbol{w}_t^{signal^\top} R_{t-10}^{signal} \\ \vdots \\ \boldsymbol{w}_t^{signal^\top} R_t^{signal} \end{bmatrix}, \tag{13}$$

thereby measuring the risk of the returns based on the current universe. Using the volatility of the resulting return series in individual groups, the inverse risk weight is calculated by

$$w^{risk}_{EM,t} = \frac{\frac{1}{\sigma_{EM,t-11:t}}}{\frac{1}{\sigma_{EM,t-11:t}} + \frac{1}{\sigma_{DM,t-11:t}}}, \quad w^{risk}_{EM,t} = \frac{\frac{1}{\sigma_{DM,t-11:t}}}{\frac{1}{\sigma_{EM,t-11:t}} + \frac{1}{\sigma_{DM,t-11:t}}}, \tag{14}$$

where $\sigma_{EM,t-11:t}$ and $\sigma_{DM,t-11:t}$ are the standard deviation of each EM and DM-like universe with estimation window of 12 months, at time t. The standard deviation of each universe is calculated from the return series containing the past 12 months multiplied by the current weight at each point of time. Subsequently, we use these weights in Equation (11). This imposes a group with higher volatility to have lower weight than the other.

There are some well-known drawbacks of K-means clustering to be considered: (i) the number of clusters should be determined in advance; (ii) convergence to a local optimum; (iii) sensitive to the scale of the features. The number of clusters K can be chosen using statistical measures, elbow plot of each K with respect to within-cluster dissimilarity values, or more sophisticated information as suggested by Pham et al. (2005). However, the universe in our research is relatively small, having limited degrees of freedom in choosing the number of clusters. Hence, we specify the number of clusters is $K = 2$, each standing for EM and DM-like groups. To prevent convergence to a local optimum, we implement the algorithm with 1000 random initialisations of the centroids, meaning repeating 1000 times of the algorithm, and choose the best output in terms of Euclidean distance to the centroids. This way, we expect to reach the global optimum better. Lastly, we standardise the sample features before running the algorithm to reduce the effect of scaling.

3.5 Factors

In this section, we introduce carry, change-in-carry, value, momentum, and betting-against-beta measures on a country level. These measures are from the existing literature tested on other markets. To make bonds comparable, we adjust every signal measure with duration by dividing by duration or using the duration adjusted returns. We define various signal measures which is plugged in the portfolio construction methods introduced in Section 3.1 to Section 3.4.

3.5.1 Carry

Carry is defined as the expected return when the price remains the same. There is no neighbouring maturity on the country level, making it impossible to compute carry with the exact formula. However, Koijen et al. (2018) suggest that bond carry can be approximated by the slope of the term structure plus the roll-down, where the slope component is the bond's yield spread to the risk-free rate. As shown in Koijen et al. (2018), the correlation between carry and the yield spread is very high, which is about 94%. Thus, the yield spread can be a proxy for carry in fixed income. Instead of the risk-free rate, which can be replaced by 3-month LIBOR rates when t-bill rates are unavailable, we use a 2-year bond yield. LIBOR rate is an inter-bank offered rate that also addresses the stress on the market, possibly causing noises to capture the slope component. Thus, we define carry for each country as

$$Carry_{c,t} = (Y^{10}_{c,t} - Y^{2}_{c,t})/D_{c,t}, \tag{15}$$

where $Y^{10}_{c,t}$ and $Y^{2}_{c,t}$ are 10-year and 2-year bond yields for country c at time t, respectively.

3.5.2 Change-in-Carry

Using the carry measured in Equation (15), we estimate the change in carry with the moving average of carry for one year[1]. This approach considers the country with low relative carry compared to its history as less attractive than the country with high relative carry compared to its history. The moving average of carry of country c at time t is the average of carry from Equation (15) for the previous 12 months. Then the change in carry for country c at time t is

$$Change\text{-}in\text{-}Carry_{c,t} = Carry_{c,t} - Carry^{MA}_{c,t-1}, \tag{16}$$

where the duration is already adjusted in the carry measure.

3.5.3 Value

Value, the tendency that the underpriced stocks compared to their fundamentals outperform expensive ones, is a popular factor studied in many literatures. It is measured by the book-to-market ratio in the stock market. As there is no book-to-market ratio for EM-LC bonds, we use two value measures: (1) 5-year change in yields of 10-year maturity bonds and (2) term spread to the risk-free rate, both introduced by Asness et al. (2013). For the risk-free rate, we use the 3-month LIBOR rate. The purpose of Asness et al. (2013) is to test the value factor across different asset classes. Hence they use the former value measure, which is similar to the negative of the past 5-year return, shown to be replaceable of the book-to-market ratio (Fama & French, 1996). The value spread measure is given as an alternative, and it provides better results in the literature. The value measures for country c at time t are

$$Value^{MR}_{c,t} = \left(\frac{Y^{10}_{c,t} - Y^{10}_{c,t-60}}{Y10^{MA}_{c,t}}\right)/D_{c,t} \tag{17}$$

$$Value^{spread}_{c,t} = (Y^{10}_{c,t} - r_{c,t})/D_{c,t}. \tag{18}$$

For the 5-year change in yields, we scale the absolute change in yield it by 5-year moving average of yields at time t to remove the effect caused by differences in yield levels between countries.

[1] From "Harvesting Risk Premia in Interest Rate Market" by UBS Quantitative Investment Solutions, 2020

3.5.4 Momentum

Momentum captures the persistence of the asset's performance that the currently outperforming asset keeps on winning. It is one of the widely used factors, with the advantages of intuitiveness and convenient computation across various asset classes. Most of the previous studies compute momentum as a 12-month return by equally weighting each month's return observations (Jegadeesh & Titman, 1993). However, this method can be primarily affected by the disappearing month rather than the new data. To prevent this, we use the change in total return to the moving average of past periods. It is essentially imposing linearly declining weight to the change in total return. Furthermore, it can also be of interest for fixed income to use changes in the bond index yield in addition to the total return. The excess bond return per unit of duration is approximated by carry and yield change such as

$$R_{c,t}^{JPM} \approx Carry_{c,t} - (Y_{c,t}^{JPM} - Y_{c,t-1}^{JPM}), \tag{19}$$

where $Y_{c,t}^{JPM}$ is a yield of JPM bond indices. The carry part of the return can cause the momentum measure based on total returns correlated with the carry measure. We expect that the momentum measure using yield can prevent this problem. Thus, we construct momentum measures based on both bond returns and yield changes. The momentum measures for country c at time t are

$$Momentum_{c,t}^{yield} = -\left(Y_{c,t} - Y_{c,t-1}^{MA}\right)/D_{c,t} \tag{20}$$

$$Momentum_{c,t}^{return} = \frac{P_{c,t} - P_{c,t-1}^{MA}}{P_{c,t-1}^{MA}}, \tag{21}$$

where $Y_{c,t}$ and $P_{c,t}$ are the yield and the cumulative excess return per unit of duration of JPM government bond for country c at time t, respectively. $Y_{c,t}^{MA}$ and $P_{c,t}^{MA}$ are the moving average of the yield and cumulative excess return per unit of duration at time t for past T months. We analyse look-back window of $T = 12$ months.

3.5.5 Betting-Against-Beta

Betting-against-beta (BAB) implies that low beta assets outperform high beta assets on a risk-adjusted basis. It has been proven to exist in diverse types of assets by Frazzini & Pedersen (2014). We use the beta estimation by Frazzini & Pedersen (2014). It estimates correlation and volatility separately using different estimation windows and subsequently shrinks the estimate toward the shrinkage target. For simplicity, we use the same monthly data to predict correlation and volatility instead of 3-day cumulative overlapping data for correlation estimation in Frazzini & Pedersen (2014).

Betas are computed from rolling estimations of EM-LC excess returns on market excess returns such as

$$\hat{\beta}_{c,t}^{TS} = \hat{\rho}_{t-59:t}\frac{\hat{\sigma}_{t-11:t}^{c}}{\hat{\sigma}_{t-11:t}^{mkt}}, \tag{22}$$

where $\hat{\beta}_{c,t}^{TS}$ is the rolling beta estimation of country c at time t, with the estimated volatilities for the country's bond return and the market $\hat{\sigma}^{c}_{t-11:t}$ and $\hat{\sigma}^{mkt}_{t-11:t}$ using 1-year rolling estimation window, and their correlation $\hat{\rho}_{t-59:t}$ using 5-year rolling estimation window.

Subsequently, we shrink betas toward the cross-sectional mean (β^{XS}) to avoid outlier effect, suggested by Frazzini & Pedersen (2014), which is motivated by Vasicek (1973). The resulting beta measure is

$$\hat{\beta}_{c,t} = w_i \hat{\beta}^{TS}_{c,t} + (1 - w_i)\hat{\beta}^{XS}. \tag{23}$$

We use the simplified version as introduced in Frazzini & Pedersen (2014) by setting the weight, and cross-sectional mean as constants, such as $\beta^{XS} = 1$, and the weight is decided among $w = 0.4, 0.6, 0.8$.

3.5.6 Beta-neutral portfolio

For the BAB factor, we compute long-short weight using the Koijen weighting scheme and subsequently make it beta neutral (Frazzini & Pedersen, 2014). It produces a portfolio going long low-beta countries and short high-beta countries, where the long and short side is divided by its beta. Specifically,

$$R^{BAB}_{t+1} = \frac{1}{\beta^L_t} \sum_{w^{BAB}_{c,t} > 0} |w^{BAB}_{c,t}| R^{JPM}_{c,t+1} - \frac{1}{\beta^H_t} \sum_{w^{BAB}_{c,t} < 0} |w^{BAB}_{c,t}| R^{JPM}_{c,t+1}, \tag{24}$$

where β^L_t and β^H_t are the betas of low-beta portfolio and high-beta portfolio, calculated by summing ex-ante beta at each country multiplied by the weights. The weight $w^{BAB}_{c,t}$ is calculated from the Koijen weighting scheme.

3.6 Ex-ante betas

We consider several methods to estimate inputs for the advanced factor construction. The inputs to be predicted are beta to the benchmark for individual countries. A good prediction of ex-ante betas, which are predicted beta before being observed, close to ex-post betas, which are realised betas, helps to achieve our objective to build a beta-neutral portfolio by removing the unnecessary exposure to the market. We need a real-time beta estimation for the advanced portfolios introduced in Section 3.2, Section 3.3, and Section 3.4. Hence we consider several methods to estimate betas using rolling estimation each month with the look-back window of one, three, and five years.

First, the OLS estimations in Equation (25) using each look-back window are considered using

$$\hat{\beta}^{OLS,T}_{c,t} = \hat{\rho}_{t-T+1:t} \frac{\hat{\sigma}^{c}_{t-T+1:t}}{\hat{\sigma}^{mkt}_{t-T+1:t}}, \tag{25}$$

where $\hat{\beta}^{OLS,T}_{c,t}$ is the rolling beta estimation of country c at time t with the size of the window $T = 1, 3, 5$ years. The estimated volatility for the country's bond return and the market are denoted as $\hat{\sigma}^{c}_{t-T+1:t}$ and $\hat{\sigma}^{mkt}_{t-T+1:t}$, and their correlation is $\hat{\rho}_{t-T+1:t}$. It is obtained by regressing the bond returns onto the market, such as

$$\boldsymbol{R}^{JPM}_{c,t-T+1:t} = \alpha + \beta_{c,t-T+1:t} \boldsymbol{R}^{mkt}_{t-T+1:t} + \varepsilon, \quad T = 11, 35, 59, \tag{26}$$

where $\boldsymbol{R}^{mkt}_{t-T+1:t}$ and $\boldsymbol{R}^{JPM}_{c,t-T+1:t}$ are vectors including market excess returns and EM-LC excess returns, both per unit of duration, at $t-T+1,...,t$. Taking the mean of estimations using the three look-back windows is also considered to give more weights to the recent observations, which is given as

$$\hat{\beta}^{AVG}_{c,t} = \frac{1}{3} \sum_{T \in \{11,35,59\}} \hat{\beta}^{OLS,T}_{c,t}. \tag{27}$$

Second, we apply the beta estimation by Frazzini & Pedersen (2014) introduced in Equation (22), which estimates correlation and volatility separately using a one-year and five-year horizon for volatility and correlation, respectively. The corresponding beta estimator is given as

$$\hat{\beta}^{FP}_{c,t} = \hat{\rho}_{t-59:t} \frac{\hat{\sigma}^{c}_{t-11:t}}{\hat{\sigma}^{mkt}_{t-11:t}}, \tag{28}$$

where $\hat{\beta}^{FP}_{c,t}$ is the rolling beta estimation of country c at time t, with the estimated volatility for the country's bond return and the market $\hat{\sigma}^{c}_{t-11:t}$ and $\hat{\sigma}^{mkt}_{t-11:t}$ using 1-year rolling estimation window, and their correlation $\hat{\rho}_{t-59:t}$ using 5-year rolling estimation window.

Subsequently, we shrink the estimated beta using each method, $\hat{\beta}^{TS}_{c,t}$ in Equation (29), as suggested in Frazzini & Pedersen (2014) such as,

$$\hat{\beta}_{c,t} = w\hat{\beta}^{TS}_{c,t} + (1-w)\hat{\beta}^{XS}, \tag{29}$$

where the shrinkage parameters in consideration are $w = 1, 0.8, 0.6, 0.4$. The cross-sectional mean $\hat{\beta}^{XS} = 1$ is used as a shrinkage target. The reasoning behind shrinking betas towards the shrinkage target is to reduce estimation error. Proper shrinkage target achieves it by introducing a bias into the estimates.

3.7 Ex-ante covariance

We analyse various covariance estimators to be used as an input for the quadratic programming. Using an incorrect covariance estimator in quadratic programming can be error-maximising due to the noise in the risk trade-off term in Equation (8). Kan & Zhou (2007) find that estimation errors in the sample covariance matrix can cause a high loss in expected out-of-sample performance of the portfolio. Furthermore, when we use equal weight on each observation in the moving window, the ghost effect of disappearing observation can dominate covariance estimates. This effect intensifies when the estimation window is shorter. Therefore we investigate introducing structure onto the covariance estimators using observed and unobserved factors with different estimation windows of three and five years. An equicorrelated version of individual covariance estimators is analysed to reduce potential estimation errors for each estimation window.

First, we consider the sample covariance matrix with each look-back window. Based on the sample covariance matrix, factor structure imposed covariance matrices are constructed using observed and unobserved factors. Imposing a factor structure enables to reduce the estimation error by setting the correlation of the unexplained component as zero. We use market factor as an observed factor. To obtain a market factor covariance, we regress the excess return onto the market factor as follows,

$$R_t = a + Bf_t + \epsilon_t, \tag{30}$$

and use estimated B and ϵ_t to impose structure on the covariance matrix such as

$$\Sigma_{mkt} = B\Sigma_f B' + \Sigma_\epsilon, \tag{31}$$

where Σ_ϵ is a diagonal residual covariance matrix with $\sigma^2_{\varepsilon,i} = var[\varepsilon_{i,t}]$.

Next, we combine the market factor and unoberved factors extracted by principal components. Principal components might help detecting additional characteristics besides the market factor. To combine the observed market factor and unobserved factors, we first estimate observed factor model with Equation (30). Using estimated B, principal component analysis by eigenvalue decomposition is applied on the residual covariance matrix, which is

$$\Sigma - B\Sigma_f B'. \tag{32}$$

To avoid possible estimation errors, we restrict the number of the principal components to two. Subsequently, we construct the market with two principal components covariance as follows,

$$\Sigma_{mkt,2PC} = \Lambda D \Lambda' + \Sigma_\epsilon, \tag{33}$$

where D is a diagonal matrix of the two largest eigenvalues d_i, and Λ is a matrix of corresponding eigenvectors λ_i from the resulting residual covariance matrix given in Equation (32). Specifically, $\Lambda = [\lambda_1 \quad \lambda_2]$ and $D = \text{diag}(d_1, d_2)$. Diagonal residual covariance matrix is denoted as Σ_ϵ, which extracts diagonal elements of $\Sigma - B\Sigma_f B' - \Lambda D \Lambda'$.

Factor structured covariance matrix only with unobserved factors from eigenvalue decomposition is considered. We use three principal components by estimating $B\Sigma_f B'$ in Equation (30) from the eigenvalue decomposition of the sample covariance matrix of returns. The resulting covariance matrix is as follows,

$$\Sigma_{3PC} = \Lambda D \Lambda' + \Sigma_\epsilon, \tag{34}$$

where D is a diagonal matrix of the three largest eigenvalues d_i, and Λ denotes a matrix of corresponding eigenvectors λ_i of the sample covariance matrix. A residual covariance matrix Σ_ϵ is the diagonal matrix of $\Sigma - \Lambda D \Lambda'$.

We consider assigning higher weights to more recent observations using exponentially weighted moving covariance. This reduces the ghost effect by putting a lower weight on disappearing observation and adapts to the newer information quickly compared to using the same weight for the entire observations. We set the span of the observation to each window size, three and five years. It corresponds to the decay parameter $\alpha = 0.05, 0.03$ for three and five years of moving window, respectively. To compute exponentially weighted moving covariance, we first calculate weight using the decay parameter such as

$$\boldsymbol{w} = \begin{bmatrix} (1-\alpha)^{t-1} \\ (1-\alpha)^{t-2} \\ \vdots \\ 1 \end{bmatrix}, \tag{35}$$

where $t = 36, 60$ for three and five years of moving window. Next, we calculate exponentially weighted moving average as follows,

$$\boldsymbol{\mu}_{EWM} = \frac{\iota_n \boldsymbol{w'} \cdot \boldsymbol{r}}{\iota_t' \boldsymbol{w}} = \frac{(1-\alpha)^{t-1}\boldsymbol{r}_1 + (1-\alpha)^{t-2}\boldsymbol{r}_2 + \ldots + \boldsymbol{r}_t}{(1-\alpha)^{t-1} + (1-\alpha)^{t-2} + \ldots + (1-\alpha) + 1}, \tag{36}$$

where $\boldsymbol{r}$ is a n by t matrix where each row consists of a vector of n assets at each point of time, which is $\boldsymbol{r}_1, \boldsymbol{r}_2, \ldots, \boldsymbol{r}_t$. Subsequently, the exponentially weighted moving covariance is given as

$$\Sigma_{EWM} = bias \times \frac{\iota_n \boldsymbol{w'} \cdot (\boldsymbol{r} - \boldsymbol{\mu}_{EWM}\iota_t')(\boldsymbol{r} - \boldsymbol{\mu}_{EWM}\iota_t')'}{\iota_t' \boldsymbol{w}}, \tag{37}$$

where *bias* is a term which corrects for estimation bias given as

$$bias = \frac{(\iota' \boldsymbol{w}) \cdot (\iota_t' \boldsymbol{w})}{(\iota_t' \boldsymbol{w}) \cdot (\iota_t' \boldsymbol{w}) - \iota_t'(\boldsymbol{w} \cdot \boldsymbol{w})}. \tag{38}$$

In the above equations, $\cdot$ is a dot product and ι_t and ι_n are vectors of ones with length of t and n, respectively.

Finally, we analyse equicorrelated covariance matrices by imposing equal correlation on the introduced covariance estimators. The correlation part is set to the average of pairwise correlations resulting from individual covariance estimators. By averaging the correlation component, we expect to reduce the estimation error caused in the correlation terms. First, we compute the equicorrelation from each of the introduced covariance estimators such as

$$\rho = \frac{2}{n(n-1)} \sum_{i>j} \frac{q_{ij}}{\sqrt{q_{ii} q_{jj}}}, \tag{39}$$

where q_{ij} is the *i,j*th element of each covariance estimator Σ. Subsequently, the correlation matrix is computed by

$$R = (1-\rho)I + \rho J, \tag{40}$$

where I and J denote identity matrix and matrix of ones, respectively. The equicorrelated covariance matrix is calculated by multiplying the diagonal element of the original covariance matrix as follows,

$$\Sigma_{EQ} = DRD, \tag{41}$$

where D is a diagonal matrix of the original covariance estimators.

3.8 Input estimator evaluation

We introduce evaluation metrics to compare various input estimators proposed in Section 3.6 and 3.7. We select the best ex-ante beta estimator based on BAB strategy. BAB has a beta-neutral long-short portfolio by construction, as can be seen in Equation (24). Therefore, it is logical to test which ex-ante beta measure can effectively remove the ex-post beta of the BAB strategy. We use the full sample beta and the rolling beta statistics of BAB strategies with different ex-ante beta estimators. To choose the best covariance estimator, we construct the global minimum variance (GMV) portfolio using the weight given as

$$w_{gmv} = \frac{\Sigma\iota'}{\iota\Sigma\iota'}, \tag{42}$$

where ι is a vector of ones, and Σ is each covariance estimator. This way, we can compare the resulting portfolio, which is only based on the covariance estimator. Subsequently, we select the covariance estimator with the lowest standard deviations of portfolio return.

3.9 Performance evaluation

There are several evaluation metrics to be considered to examine the performance of different factor construction strategies. The main question is if the analysed methods can mitigate the expected problems in the EM-LC universe. First, we measure how different methods deal with the beta exposures. Together with the level of maximum and minimum beta, the significance of the beta is tested, using the ex-post beta over time. The market beta part of the cumulative return calculated using the ex-post beta is examined as a proxy for the return affected by the beta exposure. The mean squared error (MSE) and mean absolute error (MAE) from zero using three-year rolling OLS beta are used for each factor strategy to see if the beta is close to zero over time. MSE gives a higher penalty on outliers by squaring the loss, while MAE is convenient for having an overview of the level of deviations. Second, we investigate how successfully individual methods control the concentration risk. To evaluate if a few volatile markets dominate, we use each country's risk and return contributions on the portfolio return. It enables us to compare how few countries drive the portfolio risk and return. Afterwards, the resulting performance is compared using the Sharpe ratio and Appraisal ratio. The Appraisal ratio is calculated by alpha divided by unsystematic risk, where alpha is from regressing the portfolio return onto the market, and unsystematic risk is the standard deviation of the residual from the regression. It measures the performance excluding the beta exposure by using the alpha instead of the average portfolio return as the Sharpe ratio.

3.10 Predictive ability testing

We analyse the predictability of ex-ante beta estimators introduced in Section 3.6. To compare the significance of the differences in predictability in the results for BAB strategy, predictive ability testing proposed by Giacomini & White (2006) is used in this paper[2]. It does not require normality assumption and non-nested models, unlike well-known predictive ability testings by

[2] The MATLAB code of predictive ability testing from http://www.runmycode.org/companion/view/88 is used.

Diebold & Mariano (1995) and West (1996). It is proper testing in our analysis since some suggested ex-ante beta estimators are non-nested, while others such as OLS estimates using different rolling windows are nested models. Furthermore, Giacomini & White (2006) focuses on rolling window forecasts, which is in line with our analysis.

3.11 Robust test statistics

The resulting performances of each strategy are compared in terms of the standard deviation and Sharpe ratio. To investigate if the gains or losses of advanced factor portfolios from the initial portfolio in Section 3.1 are statistically significant, we use robust test statistics with the studentised bootstrap procedure introduced in Ledoit & Wolf (2018). It compares the Sharpe ratio, variance, mean, skewness, and kurtosis without making normality or time-independent assumptions [3].

4 Results

In Section 4.1, we present the result of ex-ante beta estimation. Based on this, an ex-ante beta estimator for further analysis is decided. In Section 4.2, we compare the result of various ex-ante covariance estimators and choose the best performing one for quadratic programming. In Section 4.3, the result of the simple Koijen weighting scheme from Equation (1) is discussed. Afterwards, we show the results of enhanced factor portfolio strategies introduced in Section 3. Section 4.4 focuses on the market beta characteristics, Section 4.5 discuses how well each strategy deal with concentration risk, and Section 4.6 shows the overall performance of each strategy.

4.1 Estimating ex-ante betas

To evaluate beta estimations, it is logical to test it on the BAB factor, as it is supposed to be beta neutral by construction. Table 3 presents beta results of five different ex-ante beta estimation methods from Section 3.6 for four choices of shrinkage weights, 1, 0.8, 0.6, and 0.4. The table reports the full sample beta, its t-statistics, and mean squared error, mean and standard deviations of 3-year rolling ex-post betas for each weight and method combination. Each weight and method combination is tested on the BAB factor strategy with the simple rank-based weighting scheme given in Equation (1), subsequently constructing a beta-neutral portfolio using Equation (24). The table reports the full sample beta, its t-statistics, and mean squared error, mean and standard deviations of 3-year rolling ex-post betas. We observe that the smaller the estimation window is, the higher the shrinkage parameter is preferred. It is due to the higher estimation error when the sample size is small. For instance, $w = 0.6$ is optimal for the OLS 1Y beta estimate, while $w = 0.8$ gives the best ex-post beta results for the OLS 3Y and 5Y beta estimates.

Overall, the best estimator is FP 1Y5Y with the shrinkage parameter $w = 0.8$, which differs from the ex-ante beta used in Frazzini & Pedersen (2014) where the shrinkage parameter of

[3]The MATLAB code for comparing the Sharpe ratio and variance is accessible in https://www.econ.uzh.ch/en/people/faculty/wolf/publications.html.

$w = 0.6$ is used with the 3-day overlapping daily data instead of the monthly data used in our paper. It outperforms other estimators in terms of the full sample ex-ante beta, 3-year rolling ex-ante beta MSE with the target of 0 and the mean, followed by OLS AVG. It is tested using the predictive ability testing introduced in Section 3.10 whether the best estimator gives significantly better results than the other estimators. The result shows that the forecasts of FP 1Y5Y with $w = 0.8$ outperforms all the other estimators. The test statistics are reported in Table 33 in Appendix C. Therefore we use FP 1Y5Y with the shrinkage parameter $w = 0.8$ as our BAB measure in Section 3.5.5 and ex-ante beta estimate in further analysis. Pre-filled beta using the first existing value is used before 2007 to avoid losing the sample period due to a five-year correlation estimation period.

Table 3: Beta statistics

	$w = 1$					$w = 0.8$				
Beta measure	β	t-stat	MSE	Mean	StDev	β	t-stat	MSE	Mean	StDev
OLS 1Y	1.34	2.42	3.06*	1.48	0.94	0.92	5.15	0.63*	0.58	0.55
OLS 3Y	-1.22	2.98	1.57*	**-0.21**	1.24	0.13	0.92	0.16*	-0.07	0.40
OLS 5Y	**0.58**	3.43	**0.31***	0.31	0.47	-0.14	1.25	0.15*	-0.22	0.32
OLS AVG	0.86	4.60	0.46*	0.46	0.50	-0.04	0.33	0.09*	-0.16	0.26
FP 1Y5Y	0.81	4.70	0.47*	0.60	**0.33**	**-0.02**	0.22	**0.03**	**-0.06**	**0.17**
	$w = 0.6$					$w = 0.4$				
Beta measure	β	t-stat	MSE	Mean	StDev	β	t-stat	MSE	Mean	StDev
OLS 1Y	**-0.12**	1.24	**0.07***	**-0.13**	0.24	**-0.57**	6.80	**0.33***	**-0.52**	0.24
OLS 3Y	-0.43	4.16	0.30*	-0.48	0.25	-0.79	8.73	0.67*	-0.79	0.24
OLS 5Y	-0.51	5.59	0.39*	-0.55	0.30	-0.79	9.59	0.76*	-0.82	0.30
OLS AVG	-0.45	5.10	0.32*	-0.51	0.23	-0.75	9.60	0.70*	-0.80	0.24
FP 1Y5Y	-0.42	5.20	0.21*	-0.43	**0.15**	-0.71	9.97	0.55*	-0.72	**0.17**

Notes: The summary statistics of the BAB factor strategy using different ex-ante betas with the simple rank-based weighting scheme using different beta estimation methods are reported. The first two columns in each shrinkage parameter w report the ex-post beta of the whole sample period and its $t-$statistics. The rest of the metrics are calculated from the 3-year rolling OLS beta over time. MSE is the mean squared error compared to 0. For each shrinkage parameter and each metric, the closest value to 0 is in bold. The closest value to 0 across all the shrinkage parameters is in blue colour. The sample period is 2007-01 to 2021-02. * indicate that MSE is significantly different from the MSE of FP 1Y5Y with $w = 0.8$.

4.2 Estimating ex-ante covariance

We evaluate covariance estimators introduced in 3.7 using the global minimum variance portfolio. For the global minimum variance portfolio return of each covariance estimator and estimation window combination, Table 4 shows full sample standard deviations and mean squared error of 3-year rolling standard deviations compared to 0. We observe that the sample covariance matrix results in higher standard deviations than the other estimators. Increasing the size of the estimation window does not seem to improve the results. Notably, the equicorrelated covariance estimator improves the sample and exponentially weighted moving (EWM) covariance estimators, giving lower standard deviations. This can be due to higher estimation errors in correlation terms than in volatility since imposing factor structure removes some estimation errors in correlation terms by ignoring the off-diagonal element of the residual covariance matrix. It is also in line with the analysis of Frazzini & Pedersen (2014), suggesting that the correlation term in beta needs a longer estimation window than the volatility term. Overall, the best covariance estimator is the market factor structured covariance matrix with the 3-year estimation window, scoring the lowest standard deviation and MAE to zero. Therefore we use it as an ex-ante covariance estimator for quadratic programming in further analysis.

Table 4: Covariance statistics

	3Y window		5Y window	
Estimator	StDev (%)	MAE (%)	StDev (%)	MAE (%)
Sample	0.66**	0.58*	0.57	0.51
Market Factor	**0.47**	**0.43**	0.51	0.45
Market+2PC Factor	0.49	0.44	0.58	0.49
3PC Factor	0.49	0.45	0.59	0.51
EWM	0.70	0.59	0.61	0.53
	3Y window with equicorrelation		5Y window with equicorrelation	
Estimator	StDev (%)	MAE (%)	StDev (%)	MAE (%)
Sample	0.49	0.44	0.51	0.45
Market Factor	0.50	0.44	0.52	0.46
Market+2PC Factor	0.50	0.45	0.51	0.46
3PC Factor	0.49	0.44	0.51	0.45
EWM	0.49	0.44	0.51	0.45

Notes: The summary statistics of the global minimum variance portfolio constructed from different covariance estimators are reported. The first part of the table shows the results using 3-year and 5-year look-back windows, and the second part reports 3-year and 5-year estimation window result under equicorrelation structure. The mean absolute error (MAE) is calculated from the 3-year rolling ex-post standard deviations over time compared to 0. The smallest value across all the covariance estimators is in blue colour. The sample period is 2007-02 to 2021-02. * and ** indicate that the strategy's standard deviation is significantly different from the market factor covariance estimator at 10% and 5% levels, respectively.

4.3 Koijen weighting scheme

In this section, we first answer the research question of whether factor investing works on the EM-LC bond universe, which has not been investigated in the existing literature. To answer this question, we use the basic Koijen weighting scheme introduced in Equation (1) and present the performance. Afterwards, potential expected risk drivers are analysed. Based on the correlation of each factor and its performance, we exclude a few factors in the main analysis.

Figure 3 and Table 5 summarize the performance of each factor strategy. As shown in Figure 3, most of the factors give quite stable cumulative returns over the sample period. On the other hand, Value-MR is highly sensitive when the market is volatile, especially during the 2008 financial crisis and the 2018-2021 Turkish currency and debt crisis. Table 5 reports α and β obtained from a full-sample regression of the individual factor strategies onto the market. Carry, Change-in-carry, and both of the Momentum factors are able to generate significant alpha to the market at a 5% level. Sharpe ratios vary from 0.18 for BAB to 0.62 for the Carry factor. In line with the analysis in the developed market bond universe (Koijen et al., 2018), the Carry factor generates a favourable Sharpe ratio. Value-spread gives a lower Sharpe ratio and insignificant alpha, which is opposed to the result in (Asness et al., 2013). This might be due to the characteristic of the emerging market, which can have sensitive 3-month LIBOR rates when markets are unstable. Value-MR and BAB show poor performance with insignificant alpha, in line with the results for developed markets (Asness et al., 2013; Frazzini & Pedersen, 2014). On the other hand, both of the momentum factors have relatively better performance than in the developed market bond universe, where an insignificant alpha has been observed in Asness et al. (2013), showing significant alpha and higher Sharpe ratio for both in the EM-LC bond universe.

Therefore factor investing works in general in terms of the portfolio performance in the EM-LC bond universe.

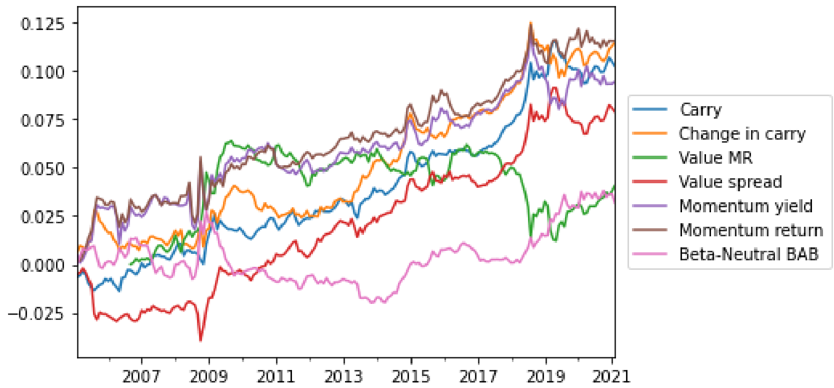


Figure 3: Cumulative return of factors using Koijen weighting scheme

Table 5: Portfolio performance of Koijen weighting scheme

Factor strategy	α (%)	β	SR	AR	Mean (%)	StDev (%)
Carry	0.62	-0.02	0.62	0.63	0.61	0.98
	(2.50)	(0.29)				
Change-in-Carry	0.76	-0.23	0.61	0.69	0.68	1.12
	(2.74)	(2.56)				
Value-MR	0.09	0.51	0.22	0.07	0.28	1.26
	(0.28)	(5.03)				
Value-spread	0.39	0.25	0.43	0.36	0.48	1.10
	(1.42)	(2.88)				
MOM-YLD	0.82	-0.68	0.37	0.57	0.57	1.55
	(2.27)	(5.80)				
MOM-RET	0.95	-0.73	0.48	0.73	0.69	1.45
	(2.91)	(6.88)				
BAB	0.27	-0.19	0.18	0.25	0.20	1.11
	(0.98)	(2.11)				

Notes: The t-statistics are shown below the alpha and beta coefficients. The alpha, Sharpe Ratio (SR), Appraisal Ratio (AR), Mean and Standard deviations (StDev) are annualised values. The sample period runs from 2006-09 for Value-MR and 2005-02 for others, and to 2021-02.

Figure 4 reports the correlation of the returns of each factor strategy. Intuitively, factor strategies that are based on a similar series show high correlations. Carry and Value-spread only differ on whether they use 2-year yield or 3-month LIBOR rates according to Equation (15) and Equation (17). However, we observe that their correlation with other factors shows quite different aspects. Carry is positively correlated with Momentum and BAB, while Value-spread is negatively correlated with them. Therefore it might be beneficial to include Value-spread in the multi-factor model for a diversified portfolio. On the other hand, Momentum-return and Momentum-yield are also highly correlated but show a similar pattern of correlations with the other factors. The only difference is whether it includes the carry part, as explained in Equation (19). As expected, Momentum-return is more correlated with the Carry compared to the Momentum-yield. However, Momentum-return has a lower correlation with Value-MR and Change-in-carry.

Besides the portfolio performance, we encounter two main features from the result of the

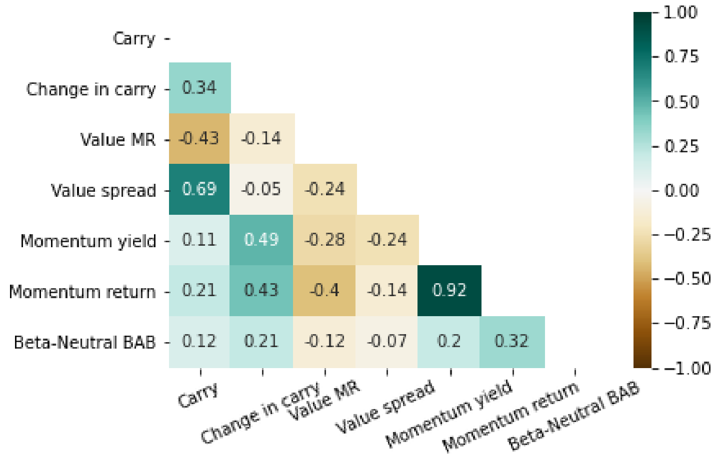


Figure 4: Correlation of factors using Koijen weighting scheme

simple rank-based weighting scheme of Equation (1) that can be potential risk drivers. The first problem is significant ex-post betas from most of the factor strategies as shown in Table 5, which can cause high risk when the market becomes volatile. Especially, BAB has highly significant betas while it is supposed to be beta-neutral by construction. Moreover, Table 6 shows that ex-ante and ex-post beta at a certain time can be even higher than the realised beta over the whole sample period. Figure 5 also suggests that the rolling ex-post beta can have highly positive and negative values. The performance of each factor strategy can be separated into the market beta part, which is calculated by $R_t^{mkt} \sum_c \beta_{c,t} w_{c,t}^{signal}$, and the rest of it, which is the pure return coming from the factor strategy itself. Ex-ante return composition of Table 6 shows a proxy of the composition of cumulative return for each strategy, which is split into the market beta part and pure factor performance. We observe that the performance of some strategies is highly driven by the market beta, which can be risky when the market crashes. Therefore, adjusting for the beta using the methods introduced in Section 3 to make the portfolio have insignificant betas is expected to be the key to the problem.

Table 6: Beta statistics of the basic Koijen weighting scheme

	Ex-ante				Ex-ante return composition		Ex-post rolling			
Factor strategy	MSE	MAE	min	max	market (%)	factor (%)	MSE	MAE	min	max
Carry	0.16	0.30	-1.40	0.81	-21.7	121.7	0.20	0.30	-1.51	0.35
Change-in-carry	0.28	0.38	-1.70	1.84	36.0	64.0	0.22	0.35	-1.37	0.42
Value-MR	0.46	0.50	-1.06	1.95	64.4	35.6	0.98	0.78	-0.56	2.18
Value-spread	0.23	0.36	-1.44	1.07	-31.7	131.7	0.37	0.53	-1.58	0.77
MOM-YLD	0.57	0.63	-1.66	1.77	129.7	-29.7	0.63	0.67	-1.35	0.63
MOM-RET	0.53	0.60	-1.59	1.78	90.2	9.8	0.74	0.74	-1.52	0.61
BAB	0.00	0.00	0.00	0.00	0.0	100.0	0.06	0.21	-0.90	0.41

Notes: The summary statistics of ex-ante betas over time for each factor strategy with the basic Koijen rank-based weighting scheme is reported. The ex-ante beta is a one and five-year rolling window FP beta with a shrinkage parameter of 0.8, multiplied by the portfolio weights at each point of time. The ex-post beta is 3-year rolling OLS beta using the factor return series. The return composition is a proxy of how the total cumulative return is separated into the market and factor part. The market part is the cumulative return of the market multiplied by the ex-ante beta. The sample period runs from 2006-09 for Value-MR and 2005-02 for others, and to 2021-02.

Second, a few markets drive the portfolio performance due to its high volatility during

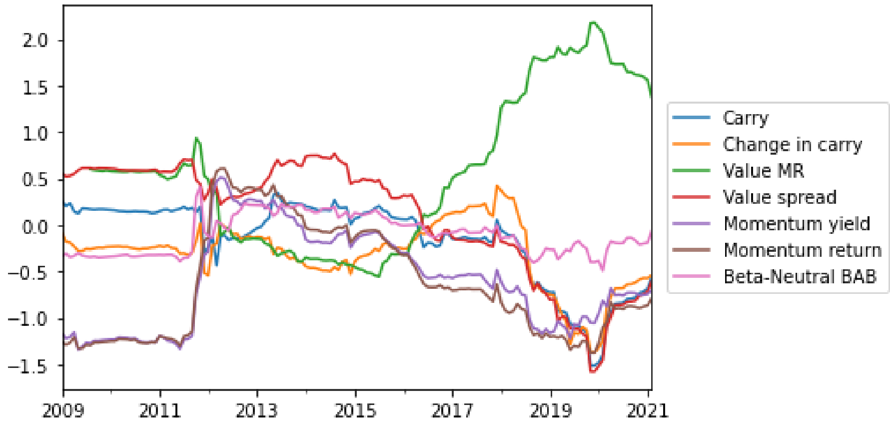


Figure 5: 3-year rolling OLS ex-post beta

crises, such as the Turkish currency and debt crisis in 2018-2021. Table 7 shows the statistics of risk and return contribution for individual factor strategies. The risk contribution is the percentage of marginal risk contribution, which sums to the total standard deviation. The return contribution is computed by the absolute return of each country over the absolute sum of return over countries. Each measure is computed at each point in time. We observe the average maximum risk contribution above 40% across all the factor strategies. Especially, Momentum strategies have an average maximum risk contribution above 80%, which means that, on average, one market drives more than 80% of the volatility at each point of time. The return contribution shows what percentage of the return at each point of time is explained by each market. The mean of the maximum return contribution of each factor strategy is around 40% except for BAB, meaning that a large proportion of the return is explained by only one market. These results suggest that the dominant market drives the performance. Also, we observe in Figure 2 that the volatility is time-varying, where a previously volatile country is no longer volatile. Hence predicting volatility in real-time and considering it for portfolio construction is essential.

Table 7: Concentration risk of the basic Koijen weighting scheme

	Risk contribution			Return contribution		
Factor strategy	Min (%)	Max (%)	StDev (%)	Min (%)	Max (%)	StDev (%)
Carry	-3.30	53.88	16.85	0.20	41.39	11.3
Change-in-carry	-3.44	61.03	20.29	0.17	43.27	12.45
Value-MR	-3.29	43.73	14.61	0.04	42.24	11.93
Value-spread	-5.82	44.67	14.17	0.17	39.26	10.36
MOM-YLD	-2.01	81.06	20.30	0.07	41.48	10.54
MOM-RET	-1.89	82.83	20.59	0.09	40.13	10.3
BAB	-1.05	47.32	11.85	0.05	29.93	8.07

Notes: Risk and return contribution show the average of minimum, maximum, and standard deviation of the risk and return contribution at each point of time. The higher the maximum contribution is, the more dominant one market contribution is on average. Higher standard deviation means that there are large deviations across countries regarding contribution on risk and return, which can be a proxy for how much it is concentrated to one market. The sample period runs from 2006-09 for Value-MR and 2005-02 for others, and to 2021-02.

These two features are closely related to the expected aspects of EM-LC bonds in Section 1. Even though factor investing might generally work, it is exposed to significant beta and risks driven by few dominating markets. In the following section, we analyse if advanced factor strategies proposed in Section 3 can minimise the aforementioned potential risk drivers. Considering the correlation between factors and their performance, we focus on Change-in-carry, Value-spread, and Momentum-return factors in further analysis.

4.4 Beta result of portfolio construction strategies

In this section, we analyse if the proposed advanced factor portfolio construction methods in Section 3 help to reduce the beta exposure of each factor strategy, which is one of the potential risks in the EM-LC bond universe. We use the ex-ante beta measure of FP 1Y5Y with the shrinkage parameter $w = 0.8$ chosen in Section 4.1. We consider three structures of portfolio construction, which are Koijen, Optimisation and Group. For Koijen, we consider the Basic Koijen weighting scheme, which ranks on the original factor measure, Division which ranks on each measure divided by the beta, and Residualisation, which ranks on each measure orthogonal to the market beta. We use the Basic Koijen weighting scheme as a benchmark. Under optimisation structure, LP is maximising the factor exposure subject to having zero betas, LP-limit is LP with country-specific maximum weight restrictions inversely related to its volatility, and QP is maximising the factor exposure with a risk trade-off subject to zero beta exposure. Group structure has Equal size grouping by real-time beta ranking and K-means grouping, which allows group size to be non-identical. To combine two groups from K-means, we consider combining based on the size and risk of each group.

Table 8 shows the statistics of the market beta exposure. We use several measures such as ex-ante, ex-post rolling and ex-post whole sample betas to investigate if betas exposures have been removed. Ex-ante beta shows how effectively each method removes beta exposure using indirect beta neutralisation methods such as grouping, residualisation and division. Ex-post rolling beta captures the time-varying characteristics of the realised beta, which can be underestimated in the ex-post full sample beta. Ex-post full sample beta gives a comprehensive insight during the entire period. For ex-ante and ex-post rolling beta, MSE and MAE to the target of zero are reported. The proportion of market beta contribution on each factor's cumulative return is also reported as an ex-ante measure.

A naive way to adjust the factor measure with dividing by the beta fails to reduce the beta exposure compared to the basic Koijen weighting scheme. It shows similar beta exposures to the Basic Koijen portfolio in general. Simply dividing the factor score by the beta is not able to adjust the ranking effectively. In Panel B, we find the lowest ex-post full sample beta from Division method. However, it is underestimated as the MSE and MAE of the ex-post rolling beta are quite high, showing a similar level to the Basic Koijen method.

In Panel A and B, the Grouping K-means-risk effectively minimises MSE of both ex-ante and ex-post rolling beta. It achieves to remove the ex-post rolling beta by estimating ex-ante beta close to it. Also, in Panel A to C, we observe that K-means groupings more effectively reduce the beta exposure than the Equal-size grouping. Simply clustering countries into equal-sized two groups cannot capture few countries that highly deviate from the other countries. Table 9 shows the overview of the group's composition using Equal size and K-means clustering, respectively. As seen in the last column of each table, equal size grouping assigns half of the countries into the emerging market group, while K-means clustering assigns only three countries into the emerging

Table 8: Market beta exposure

Structure	Methods	Ex-ante MSE	Ex-ante MAE	Ex-ante beta return	Ex-post rolling MSE	Ex-post rolling MAE	Ex-post full sample beta	Ex-post full sample $t-$stat
Panel A: Change-in-carry								
Koijen	Basic	0.28	0.38	0.36	0.22	0.35	-0.23	-2.56
	Div	0.29	0.40	0.55	0.13	0.31	-0.26	-3.26
	Resid	0.05	0.15	**-0.02**	0.11	0.24	**-0.01**	**-0.14**
Optimisation	LP	0.00	0.00	0.00	0.13	0.28	-0.16	-1.93
	LP-limit	0.00	0.00	0.00	0.06	0.21	-0.12	-1.91
	QP	0.00	0.00	0.00	0.08	0.22	-0.13	-1.98
Group	Equal	0.17	0.26	0.25	0.15	0.30	-0.20	-2.50
	K-means-size	0.04	0.14	-0.05	0.04	0.15	-0.06	-0.93
	K-means-risk	**0.03**	**0.13**	-0.06	**0.02**	**0.10**	-0.02	-0.39
Panel B: Value-spread								
Koijen	Basic	0.23	0.36	-0.32	0.37	0.53	0.25	2.88
	Div	0.28	0.40	-0.79	0.36	0.46	**0.00**	**-0.01**
	Resid	**0.04**	**0.15**	0.07	0.16	0.31	0.13	1.64
Optimisation	LP	0.00	0.00	0.00	0.12	0.28	0.20	2.57
	LP-limit	0.00	0.00	0.00	**0.04**	**0.15**	0.07	1.05
	QP	0.00	0.00	0.00	0.11	0.28	0.22	3.27
Group	Equal	0.12	0.23	-0.31	0.28	0.40	0.13	1.65
	K-means-size	**0.04**	0.16	-0.03	0.09	0.24	0.25	3.87
	K-means-risk	**0.04**	**0.15**	**0.00**	0.06	0.21	0.21	3.36
Panel C: MOM-RET								
Koijen	Basic	0.53	0.60	0.90	0.74	0.74	-0.73	-6.88
	Div	0.33	0.44	-0.16	0.69	0.70	-0.70	-8.41
	Resid	0.35	0.44	**-0.04**	**0.07**	**0.22**	**-0.17**	**-2.02**
Optimisation	LP	0.00	0.00	0.00	0.25	0.40	-0.40	-4.63
	LP-limit	0.00	0.00	0.00	0.12	0.29	-0.25	-3.70
	QP	0.00	0.00	0.00	0.22	0.39	-0.33	-4.76
Group	Equal	0.22	0.37	0.68	0.38	0.50	-0.52	-6.25
	K-means-size	**0.08**	0.23	0.58	0.27	0.40	-0.45	-5.14
	K-means-risk	**0.08**	**0.22**	0.48	0.24	0.40	-0.40	-4.83
Panel D: Average								
Koijen	Basic	0.37	0.46	0.44	0.53	0.56	-0.15	-1.27
	Div	0.36	0.46	0.00	0.53	0.57	-0.27	-3.20
	Resid	0.10	0.20	**-0.01**	0.15	0.29	**-0.03**	**-0.31**
Optimisation	LP	0.00	0.00	0.00	0.18	0.33	-0.07	-0.76
	LP-limit	0.00	0.00	0.00	**0.08**	**0.21**	-0.09	-1.30
	QP	0.00	0.00	0.00	0.13	0.28	-0.06	-0.78
Group	Equal	0.18	0.30	0.35	0.29	0.40	-0.12	-1.41
	K-means-size	**0.05**	0.18	0.20	0.13	0.27	-0.06	-0.45
	K-means-risk	**0.05**	**0.17**	0.18	0.12	0.25	-0.07	-0.67

Notes: The summary statistics of beta exposure for each factor strategy under Koijen, Optimisation and Group structure is reported. The ex-ante beta is a one and five-year rolling window FP beta with a shrinkage parameter of 0.8, multiplied by the portfolio weights at each point of time. The ex-post beta is 3-year rolling OLS beta using the factor return series. The beta return is a proxy of how the total cumulative return is separated into the market. The beta return is computed using the cumulative return of the market multiplied by the ex-ante beta divided by the cumulative return of the full sample period. Panel D is the average value using six factors excluding BAB. The results of the other individual factors are reported in Appendix B. The sample period runs from 2006-09 for Value-MR and 2005-02 for others, and to 2021-02.

market group for more than half of the sample period. Furthermore, Table 10 shows that the developed market group is around two times larger than the emerging market group. On the other hand, combining two groups by K-means clustering using the risk does not improve upon using the size. K-means clustering tends to classify outliers with large betas in the emerging market group, so the size of the emerging market group can be minimal at some point. Therefore the underperformance of K-means-risk can be due to the small size group's blowing up the result, which can be highly volatile, as the risk is an ex-ante measure based on the previous group result.

Table 9: Grouping strategy: Overview of EM and DM-like countries

	Equal				K-means			
	Chg-in-carry	Value-spread	MOM-RET	AVG	Chg-in-carry	Value-spread	MOM-RET	AVG
South Korea	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
China	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00
India	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00
Malaysia	0.89	0.92	0.94	0.93	0.99	0.98	0.98	0.99
Chile	0.75	0.95	0.97	0.92	1.00	1.00	1.00	1.00
Thailand	0.79	0.79	0.92	0.85	0.92	0.92	1.00	0.96
Poland	0.59	0.57	0.59	0.59	0.80	0.75	0.91	0.84
Russia	0.59	0.61	0.44	0.56	0.74	0.76	0.87	0.79
Philippines	-	-	0.55	0.52	-	-	0.89	0.90
Hungary	0.29	0.32	0.24	0.25	0.49	0.44	0.68	0.56
Mexico	0.18	0.24	0.28	0.21	0.62	0.59	0.79	0.68
South Africa	0.24	0.19	0.24	0.15	0.61	0.55	0.69	0.62
Colombia	0.28	0.18	0.06	0.07	0.63	0.40	0.64	0.55
Peru	0.03	0.10	0.02	0.30	0.62	0.50	0.68	0.59
Indonesia	0.01	0.01	0.03	0.01	0.16	0.12	0.41	0.26
Brazil	0.02	0.00	0.00	0.00	0.29	0.26	0.49	0.36
Turkey	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The proportion of DM-like membership per country using the grouping with the equal size and K-means is reported. One means that the country has been classified into the DM-like group during the full sample period. AVG is the average value using all seven factors. The results of the other individual factors are reported in Appendix B. The sample period runs from 2006-09 for Value-MR and 2005-02 for others, and to 2021-02.

Table 10: Grouping strategy: Overview of the size of EM and DM-like group

	Equal		K-means	
	EM	DM	EM	DM
Change-in-carry	0.53	0.47	0.35	0.65
Value-spread	0.52	0.48	0.37	0.63
MOM-RET	0.52	0.48	0.24	0.76

Notes: The overall proportion of each group's size using Equal and K-means grouping is reported. The results of the other individual factors are reported in Appendix B. The sample period runs from 2006-006-09 for Value-MR and 2005-02 for others, and to 2021-02.

Beta exposures of each grouping universe, reported in Table 11 and Table 12 show that EM-like universe has much higher beta exposure than DM-like universe. Interestingly, we see that the DM-like universe from the K-means grouping has a similar level of beta exposure to the overall K-means grouping method. High beta exposure in the EM-like group is compensated by the size of the group, where around 30% is EM and 70% is DM-like markets on average, given in Table 10. It suggests that beta exposure can be reduced by creating separate long-short portfolios when there are considerable differences in beta across the countries.

Optimisation methods have zero ex-ante betas by construction, and ex-post betas are reduced

Table 11: Grouping - Equal size: Beta exposure of EM and DM-like groups

Panel A: EM-like							
	Ex-ante			Ex-post rolling		Ex-post full sample	
Pf strategy	MSE	MAE	beta return	MSE	MAE	beta	$t-$stat
Change-in-carry	0.68	0.49	0.38	0.68	0.56	-0.42	-2.92
Value-spread	0.54	0.49	-0.81	1.05	0.76	0.13	0.88
MOM-RET	0.79	0.69	0.55	1.25	0.96	-0.99	-6.67
Panel B: DM-like							
	Ex-ante			Ex-post rolling		Ex-post full sample	
Pf strategy	MSE	MAE	beta return	MSE	MAE	beta	$t-$stat
Change-in-carry	0.03	0.14	-0.83	0.07	0.19	0.02	0.23
Value-spread	0.04	0.16	-0.04	0.11	0.25	0.13	2.25
MOM-RET	0.03	0.14	4.58	0.08	0.25	-0.06	-0.91

Notes: The summary statistics of beta exposure for each factor strategy under Group-Equal structure is reported. The ex-ante beta is a one and five-year rolling window FP beta with a shrinkage parameter of 0.8, multiplied by the portfolio weights at each point of time. The ex-post beta is 3-year rolling OLS beta using the factor return series. The beta return is a proxy of how the total cumulative return is separated into the market. The beta return is computed using the cumulative return of the market multiplied by the ex-ante beta divided by the cumulative return of the full sample period. The results of the other individual factors are reported in Appendix B. The sample period runs from 2005-02 to 2021-02.

Table 12: Grouping - K-means: Beta exposure of EM and DM-like groups

Panel A: EM-like							
	Ex-ante			Ex-post rolling		Ex-post full sample	
Pf strategy	MSE	MAE	beta return	MSE	MAE	beta	$t-$stat
Change-in-carry	0.15	0.28	0.03	0.29	0.46	0.21	1.35
Value-spread	0.17	0.30	-0.14	0.40	0.52	0.31	2.10
MOM-RET	0.18	0.27	0.38	0.41	0.58	-0.51	-3.57
Panel B: DM-like							
	Ex-ante			Ex-post rolling		Ex-post full sample	
Pf strategy	MSE	MAE	beta return	MSE	MAE	beta	$t-$stat
Change-in-carry	0.04	0.15	-0.24	0.04	0.17	-0.07	-1.16
Value-spread	0.07	0.22	0.04	0.08	0.22	0.16	2.83
MOM-RET	0.08	0.24	0.75	0.23	0.41	-0.24	-2.90

Notes: The summary statistics of beta exposure for each factor strategy under Group-K-means structure is reported. The ex-ante beta is a one and five-year rolling window FP beta with a shrinkage parameter of 0.8, multiplied by the portfolio weights at each point of time. The ex-post beta is 3-year rolling OLS beta using the factor return series. The beta return is a proxy of how the total cumulative return is separated into the market. The beta return is computed using the cumulative return of the market multiplied by the ex-ante beta divided by the cumulative return of the full sample period. The results of the other individual factors are reported in Appendix B. The sample period runs from 2005-02 to 2021-02.

compared to the Koijen strategy. However, ex-post betas exposures are still present, with non-zero values. It can be explained by the fast-moving beta, resulting in a mismatch between ex-ante and ex-post beta. As can be seen in Table 13, beta is highly volatile in some markets, making it hard to be precisely predicted. Furthermore, Linear and Quadratic programming can use the maximum Koijen weight for more than one country, leading to more concentrated portfolios. This could accentuate the prediction errors. On the other hand, LP-limit has different maximum weights for each country based on their volatility. It enables the prediction errors to decrease.

Residualisation gives comparable beta exposures to optimisation and grouping methods. We observe from Table 14 that the average t-statistics has the opposite relation to the level of beta exposure. When the beta is significant in factor measures, residualising can better remove the

Table 13: Beta stat

	mean	StDev	min	max
Brazil	1.66	0.35	0.35	2.48
Mexico	0.89	0.20	0.57	1.51
Colombia	1.19	0.35	0.46	2.10
Indonesia	1.59	0.65	0.49	2.95
Malaysia	0.36	0.15	-0.03	0.76
Thailand	0.49	0.11	0.19	1.00
South Korea	0.28	0.17	-0.07	0.74
Turkey	3.51	1.60	1.99	8.32
South Africa	0.99	0.29	0.17	1.53
Poland	0.70	0.24	0.10	1.03
Hungary	1.17	0.46	0.37	2.56
India	0.28	0.14	-0.12	0.77
China	0.13	0.10	-0.20	0.33
Russia	0.91	0.47	-0.31	2.16
Chile	0.54	0.13	0.33	0.78
Peru	1.03	0.29	0.53	1.60
Philippines	0.88	0.20	0.47	1.27

Notes: Statistics of 3-year rolling OLS beta obtained from regressing each country's bond excess return per unit of duration onto the market is reported. The sample period runs from 2005-02 to 2021-02.

beta exposure. However, the effect of removing the beta exposure by making the factor exposure orthogonal to the beta is partly off-set because we subsequently still impose a rank-based Koijen weighting scheme.

Table 14: Residualisation: cross-sectional regression statistics

	Change-in-carry	Value-spread	MOM-RET
$t-$stat	1.41	1.34	2.58
R^2	0.17	0.15	0.29

Notes: The mean of the absolute beta t-statistics and R-squared obtained from the cross-sectional regression in each month are reported. The sample period runs from 2005-02 to 2021-02.

Overall, we observe that beta exposure has been effectively reduced in most factor strategies except for the Momentum factors. For Linear programming, it might be due to the high turnover in the positioning of Momentum, which can be harmful when the beta is fluctuating a lot. Moreover, it tends to go short on Turkey, which has a beta of approximately 6.5 from 2019 to 2020. It drives the beta exposure, especially in the Grouping strategy, where only indirect adjustment on beta exposure has been made.

4.5 Concentration risk

In Section 4.3, we discuss concentration risk caused by a few volatile markets using the basic Koijen weighting scheme. In this section, we investigate if advanced methods introduced in Section 3 contributes to lower concentration risk. Table 15 reports the concentration risk statistics, which captures the characteristics of the risk and return contribution of countries at each point of time. Under Koijen structure that ranks the signal measure, Basic uses the original factor measure, Div divides the factor measure by the beta, and Resid is orthogonalising the signal measure onto the market. For the Optimisation structure, LP maximises the factor exposure subject to zero ex-ante betas, LP-limit has additional constraints of country-specific maximum weight according to its volatility, and QP maximises the factor exposure with a risk trade-off subject to zero ex-ante betas. For Group structure, Equal is clustering the universe into the two same-size groups. K-means-size and K-means-risk use K-means clustering to group countries and combines two resulting groups proportional to each group size and using the inverse of the risk of the two groups' return, respectively.

In Panel C, it is observed that LP-limit, QP, K-means-size, and K-means-risk tend to perform better at achieving lower maximum risk and return contribution. The methods under the Koijen structure show higher maximum risk contribution in Panel A to C. It is expected since those methods only adjust for the factor measure while still imposing the rank-based weighting scheme. Equal grouping also does not perform well, which can be due to imposing equal size on the two groups. It can accentuate assigning countries into the wrong group, preventing volatile assets from off-setting the risk by long-short portfolios within the group.

LP-limit generally outperforms the other methods in terms of the risk contribution across Panel A to D. It tightens up the maximum weight for high volatility countries while permitting higher maximum weight for low volatility countries. Therefore it effectively adjusts for the marginal risk contribution during the optimisation process. QP uses the risk trade-off, which is more flexible than the direct restriction on the risky countries such as LP-limit. Thereby it less effectively reduces the risk contribution.

Interestingly, K-means-risk is able to score the lowest maximum and standard deviation of the return contribution. However, we do not observe much differences from K-means-risk, which has only 0.44% higher maximum return contribution. Precisely clustering the universe makes it possible to reduce the maximum return contribution. On the other hand, considering the risk level of each group does not improve upon the concentration risk of considering the group size.

Table 15: Concentration risk statistics

Structure	Methods	Risk contribution Min (%)	Risk contribution Max (%)	Risk contribution StDev (%)	Return contribution Min (%)	Return contribution Max (%)	Return contribution StDev (%)
Panel A: Change-in-carry							
Koijen	Basic	-5.76	56.76	18.62	0.38	38.27	12.08
	Div	-4.60	51.54	16.89	0.39	37.00	11.84
	Resid	-5.76	56.76	18.62	0.37	36.24	11.42
Optimisation	LP	-3.32	47.84	16.05	0.00	39.03	13.23
	LP-limit	-3.37	**42.00**	**14.35**	0.03	34.54	11.95
	QP	-3.64	44.83	14.92	0.46	35.45	11.67
Group	Equal	-4.65	56.11	18.14	0.24	36.91	11.77
	K-means-size	-4.91	47.38	15.95	0.35	34.25	11.10
	K-means-risk	-4.99	47.87	15.84	0.35	**33.83**	**11.03**
Panel B: Value-spread							
Koijen	Basic	-6.44	51.96	15.64	0.22	33.37	9.84
	Div	-4.26	44.44	13.27	0.23	32.02	9.61
	Resid	-6.44	51.96	15.64	0.22	31.99	9.47
Optimisation	LP	-3.98	41.56	12.96	0.00	34.65	10.96
	LP-limit	-4.29	41.85	12.95	0.00	31.52	10.25
	QP	-4.08	**38.49**	**11.98**	0.15	31.94	9.91
Group	Equal	-5.61	52.75	15.42	0.13	32.57	9.59
	K-means-size	-5.99	47.67	14.22	0.15	30.60	9.18
	K-means-risk	-7.19	47.49	14.31	0.16	**29.93**	**9.10**
Panel C: MOM-RET							
Koijen	Basic	-5.70	50.52	14.38	0.05	31.49	8.70
	Div	-6.34	50.54	14.42	0.05	30.61	8.52
	Resid	-5.70	50.52	14.38	0.05	29.72	8.18
Optimisation	LP	-3.38	41.91	12.12	0.00	31.47	9.35
	LP-limit	-3.41	**33.02**	**10.46**	0.00	28.91	8.77
	QP	-2.71	35.95	10.63	0.12	30.94	9.11
Group	Equal	-4.80	52.20	14.57	0.04	31.08	8.55
	Kmeans-size	-5.28	42.02	12.47	0.02	**28.38**	**8.05**
	K-means-risk	-6.03	45.35	13.17	0.02	28.77	8.11
Panel D: Average							
Koijen	Basic	-5.95	54.22	16.74	0.23	35.06	10.50
	Div	-5.19	48.64	15.07	0.24	33.39	10.14
	Resid	-5.95	54.22	16.74	0.23	33.37	10.02
Optimisation	LP	-3.95	46.19	14.47	0.00	35.77	11.49
	LP-limit	-3.90	**39.74**	13.05	0.02	32.50	10.68
	QP	-3.50	40.28	**12.79**	0.26	33.43	10.51
Group	Equal	-5.23	54.68	16.61	0.14	34.02	10.25
	K-means-size	-5.21	45.13	14.28	0.18	31.74	9.74
	K-means-risk	-5.73	46.16	14.44	0.18	**31.30**	**9.66**

Notes: The concentration risk statistics for each factor strategy under Koijen, Optimisation and Group structure is reported. The risk contribution is computed by the 3-year rolling estimation of the marginal risk contribution divided by the marginal contribution and subsequently dividing it by the total standard deviation. Afterwards, the minimum, maximum, and standard deviation across the countries are calculated at each time, and the average of them is reported. The return contribution is measured by the absolute return of each country divided by the sum of the absolute returns at each point in time. Subsequently, the minimum, maximum, and standard deviation across the countries are calculated at each time, and the average of them is reported. Panel D is the average value using six factors excluding BAB. The results of the other individual factors are reported in Appendix B. The sample period runs from 2006-09 for Value-MR and 2005-02 for others, and to 2021-02.

4.6 Performance

In Section 4.4 and Section 4.5, we note that the advanced portfolio structures of Koijen, Optimisation, and Group manage to deal with the potential risk drivers of beta exposure and concentration risk, discussed in Section 4.3. Ideally, the advanced structure might achieve to outperform or maintain the portfolio performance of the Basic Koijen weighting scheme. In this section, we study if the advanced portfolio structures still attain good performances.

Table 16: Portfolio performance

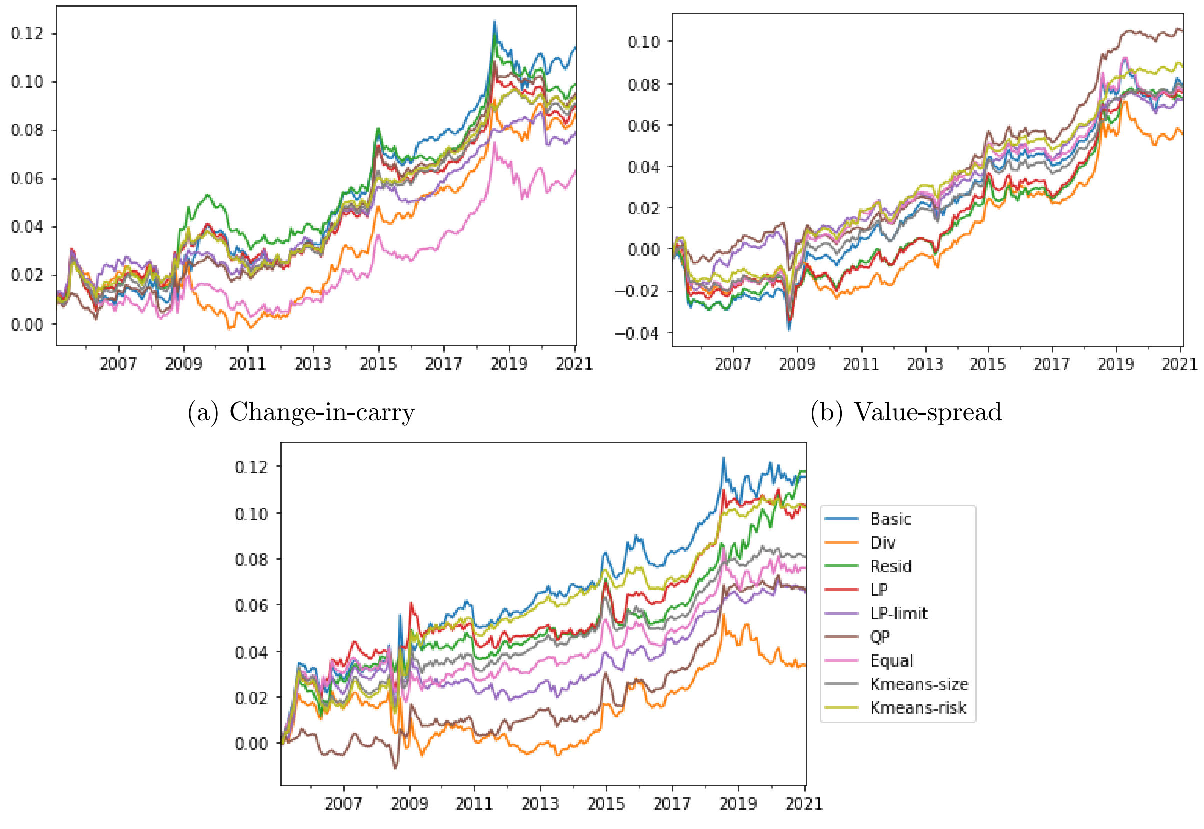
Structure	Methods	α (%)	t-stat	β	SR	AR	Mean (%)	StDev (%)	Skewness	Kurtosis
Panel A: Change-in-carry										
Koijen	Basic	0.76	2.74	-0.23^{***}	0.61	0.69	**0.68**	1.12	0.28	2.90
	Div	0.62	2.51	-0.26^{***}	0.52	0.63	0.52	1.00^{**}	0.46	3.83
	Resid	0.60	2.31	-0.01	0.58	0.58	0.59	1.02	0.95	3.65
Optimisation	LP	0.60	2.32	-0.16^{*}	0.52	0.59	0.54	1.04	0.86	3.36
	LP-limit	0.52	2.59	-0.12^{*}	0.59	0.65	0.48	0.81^{**}	0.63	4.73
	QP	0.62	**3.03**	-0.13^{**}	0.70	**0.76**	0.57	0.81^{***}	0.65	3.78
Group	Equal	0.46	1.83	-0.20^{***}	0.38	0.46	0.39	1.01^{***}	0.33	3.26
	K-means-size	0.57	2.75	-0.06	0.66	0.69	0.54	0.82^{**}	1.06	4.99
	K-means-risk	0.57	3.01	-0.02	**0.75**	**0.76**	0.56	**0.75^{***}**	0.79	3.66
Panel B: Value-spread										
Structure	Methods	α (%)	t-stat	β	SR	AR	Mean (%)	StDev (%)	Skewness	Kurtosis
Koijen	Basic	0.39	1.42	0.25^{***}	0.43	0.36	0.48	1.10	-0.67	5.20
	Div	0.34	1.32	0.00	0.33	0.33	0.34	1.02	-0.24	4.46
	Resid	0.39	1.56	0.13	0.44	0.39	0.44	1.00^{**}	-0.95	6.73
Optimisation	LP	0.38	1.60	0.20^{***}	0.47	0.40	0.46	0.96^{*}	-0.99	6.18
	LP-limit	0.41	2.05	0.07	0.55	0.52	0.43	**0.79^{**}**	-0.94	6.04
	QP	0.55	**2.67**	0.22^{***}	**0.75**	**0.67**	**0.62**	0.83^{*}	-1.88	16.45
Group	Equal	0.41	1.70	0.13^{*}	0.48	0.43	0.46	0.97^{**}	-0.2	4.02
	K-means-size	0.38	1.88	0.25^{***}	0.57	0.48	0.47	0.83^{**}	-0.66	5.09
	K-means-risk	0.45	2.32	0.21^{***}	0.66	0.59	0.53	**0.79^{***}**	-0.65	5.28
Panel C: MOM-RET										
Structure	Methods	α (%)	t-stat	β	SR	AR	Mean (%)	StDev (%)	Skewness	Kurtosis
Koijen	Basic	0.95	2.91	-0.73^{***}	0.48	0.73	0.69	1.45	0.89	11.99
	Div	0.46	1.81	-0.70^{***}	0.18	0.46	0.21	1.19	0.03	5.41
	Resid	0.76	2.93	-0.17^{**}	**0.67**	0.74	**0.70**	1.04	0.55	1.88
Optimisation	LP	0.76	2.85	-0.40^{***}	0.55	0.72	0.61	1.11	0.88	4.47
	LP-limit	0.48	2.34	-0.25^{***}	0.47	0.59	0.39	**0.85^{*}**	-0.11	4.79
	QP	0.52	2.44	-0.33^{***}	0.45	0.62	0.40	0.89^{***}	1.57	6.89
Group	Equal	0.65	2.52	-0.52^{***}	0.41	0.64	0.46	1.11	-0.65	5.33
	K-means-size	0.65	2.43	-0.45^{***}	0.43	0.61	0.49	1.12^{**}	1.13	17.6
	K-means-risk	0.75	**2.97**	-0.40^{***}	0.57	**0.75**	0.61	1.06^{***}	2.10	17.19

Notes: The portfolio performance for each factor strategy under Koijen, Optimisation and Group structure are reported. The alpha, Sharpe Ratio (SR), Appraisal Ratio (AR), Mean and Standard deviations (StDev) are annualised values. *, **, and *** indicate that the beta is significant at 10%, 5%, and 1% level, respectively. For standard deviation, *, **, and *** denote the 10%, 5%, and 1% significance for the difference against the standard deviation of Koijen Basic method. The results of the other individual factors are reported in Appendix B. The sample period runs from 2005-02 to 2021-02.

Table 16 shows the portfolio performances under Koijen, Optimisation, and Group structure. Most of the methods are able to generate significant alpha. We observe a strongly significant alpha in QP across every factor strategy, also in K-means-risk for Change-in-carry and Momentum-return. The Sharpe ratio is also improved or maintained at a similar level to the Basic Koijen weighting scheme in most factors, except for Group-Equal and Division. After excluding the market effect, summarised as Appraisal Ratio (AR), the advanced methods still show comparable results to the Basic Koijen method.

We note that the performance of the Value-spread factor is enhanced in terms of alpha and the Sharpe ratio in every method except for Division, compared to the Basic Koijen weighting scheme. This might be due to the reduced noise in 3-month LIBOR rates, which is used for calculating the factor in Equation (17). Using advanced methods, which try to neutralise the beta and/or risk, Value-spread can better emphasise the pure factor impact. From Figure 6b, it can be seen that the Basic Koijen weighting scheme shows a considerable drop during the crisis period in 2008, while risk-adjusted methods such as LP-limit suffers less.

The standard deviation is consistently reduced across individual methods. Methods that do not directly consider the volatility, such as Division, Residualisation, and LP, can still show improvement in terms of the standard deviation. Grouping methods with K-means clustering, LP-limit, and QP, which adjust for the risk by clustering countries based on the level of beta or by considering the level of volatility, significantly reduce the standard deviation of the portfolio across all the factors.



(a) Change-in-carry

(b) Value-spread

(c) Momentum-return

Figure 6: Cumulative return of factors for individual methods

5 Additional Results

In this section, we discuss additional results of advanced factor construction strategies. Section 5.1 extends the individual factor analysis to multi-factor analysis and documents the performance of the multi-factor model in different factor construction strategies. In Section 5.2, we investigate how each method achieves reducing potential risks during the crisis period. We use the sub-sample period of 2017-2021 when the Turkish currency and debt crisis happened, including one year of the pre-crisis period.

5.1 Multi-factor

We combine the three factors discussed in previous sections: Change-in-carry, Value-spread, and Momentum-return, to construct the multi-factor model. The multi-factor return is calculated from the multi-factor score, which is the average z-score of the three factors, as introduced in Equation (7). The performance of the multi-factor model using different portfolio construction methods are reported in Table 17. Overall, we find significant alpha in every method with some different features in individual methods. As can be seen in Figure 7, factors have a quite low correlation to each other, leading to better performance in multi-factor than a single-factor model.

Notably, we observe that K-means-risk, designed to minimise beta and reduce country-specific risk, has the highest Sharpe ratio of 0.80. In Figure 8, we observe that each factor for K-means-risk has a low correlation to each other. It results in a diversified multi-factor strategy, leading to a promising performance in terms of the Sharpe ratio and alpha. However, factor exposure per standard deviation of Grouping methods is lower than the other methods under the optimisation structure. Grouping strategy has relatively lower factor exposure since it divides the universe into two groups, resulting in a lower chance of maximising the factor exposure when countries with similar levels of factor exposure are in the same group.

We observe in Table 18 that Division, LP, and Equal size grouping cannot sufficiently reduce the beta exposure with the multi-factor model, which is in line with the discussion in previous sections. On the other hand, K-means-risk performs the best at minimising beta exposure. Most methods dealing with concentration risk and beta issues, such as LP-limit, QP, K-means-size and K-means-risk, have relatively lower ex-post rolling beta. Furthermore, we observe that these methods are able to reduce the risk and return contribution more effectively, as can be seen in Table 19.

5.2 Turkish currency and debt crisis

In this section, we investigate the sub-sample period during the Turkish currency and debt crisis. The sample period runs from 2017-01-31 to 2021-02-26. We observed in Section 2 that the bond return volatility in Turkey fluctuates a lot during this period. This case study analyses more in-depth how each advanced factor portfolio construction strategy reacts to one volatile country.

The performance of the multi-factor portfolio during the Turkish crisis is given in Table 20. LP-limit, QP, K-means-size, and K-means-risk perform well in terms of the Sharpe ratio since they effectively reduce the standard deviation. We note that the level of standard deviation is

Table 17: Multi-factor Portfolio performance

Structure	Methods	α (%)	β	SR	Factor/StDev	AR	Mean (%)	StDev (%)	Skew	Kurt
Koijen	Basic	1.12	-0.46	0.73	110.23	0.90	0.95	1.31	0.65	7.65
		(3.57)	(-4.48)							
	Division	1.00	-0.45	0.73	118.45	0.92	0.84	1.15^{***}	0.23	6.01
		(3.65)	(-5.02)							
	Resid	0.84	-0.26	0.76	129.54	0.88	0.74	0.98^{*}	0.74	2.88
		(3.50)	(-3.39)							
Optimisation	LP	0.91	-0.32	0.79	135.47	0.94	0.79	1.01	0.96	3.45
		(3.72)	(-4.05)							
	LP-limit	0.60	-0.24	0.64	146.47	0.78	0.51	0.80^{**}	-0.17	4.84
		(3.08)	(-3.84)							
	QP	0.66	-0.20	0.77	144.05	0.88	0.59	0.77^{***}	0.98	3.81
		(3.50)	(-3.29)							
Group	Equal	0.91	-0.34	0.75	119.85	0.90	0.79	1.06	-0.22	3.21
		(3.56)	(-4.09)							
	K-means-size	0.79	-0.21	0.73	125.09	0.83	0.71	0.97^{***}	0.68	6.65
		(3.27)	(-2.67)							
	K-means-risk	0.81	-0.18	0.80	128.17	0.88	0.75	0.94^{***}	1.02	6.38
		(3.49)	(-2.31)							

Notes: The portfolio performance for multi-factor strategy by taking average of Change-in-carry, Value-spread, and Momentum-return z-scored factors under Koijen, Optimisation and Group structure are reported. The alpha, Sharpe Ratio (SR), Appraisal Ratio (AR), Mean and Standard deviations (StDev) are annualised values. *, **, and *** indicate the 10%, 5%, and 1% significance for the difference against the Koijen Basic method in the Sharpe ratio and standard devation, based on the robust test statistics of Ledoit & Wolf (2018). The p-value of the test is reported in Appendix D. Factor/StDev shows the factor exposure per annualised standard deviation. Factor exposure is calculated by multiplying z-score to the weight, subsequently taking the mean. The sample period runs from 2005-02 to 2021-02.

Table 18: Multi-factor Market beta exposure

		Ex-ante			Ex-post rolling		Ex-post full sample	
Structure	Methods	MSE	MAE	beta return	MSE	MAE	beta	$t-$stat
Koijen	Basic	0.76	0.64	0.04	0.43	0.56	-0.46	-4.48
	Division	0.61	0.58	0.07	0.43	0.58	-0.45	-5.02
	Resid	0.03	0.14	0.00	0.15	0.31	-0.26	-3.39
Optimisation	LP	0.00	0.00	0.00	0.16	0.33	-0.32	-4.05
	LP-limit	0.00	0.00	0.00	0.11	0.29	-0.24	-3.84
	QP	0.00	0.00	0.00	0.11	0.27	-0.20	-3.29
Group	Equal	0.53	0.58	0.03	0.23	0.37	-0.34	-4.09
	K-means-size	0.12	0.28	0.05	0.12	0.27	-0.21	-2.67
	K-means-risk	0.12	0.27	0.05	0.10	0.26	-0.18	-2.31

Notes: The summary statistics of beta exposure for multi-factor strategy under Koijen, Optimisation and Group structure is reported. The ex-ante beta is FP 1Y5Y, which uses a one and five-year rolling window for volatility and correlation respectively, with a shrinkage parameter of 0.8, multiplied by the portfolio weights at each point of time. The ex-post beta is 3-year rolling OLS beta using the factor return series. The beta return is a proxy of how the total cumulative return is separated into the market. The beta return is computed using the cumulative return of the market multiplied by the ex-ante beta divided by the cumulative return of the full sample period. The sample period runs from 2005-02 to 2021-02.

highly related to the weight given to Turkey. When there is no control for the concentration risk, such as in methods under Koijen structure, LP and equal grouping, it cannot detect a spike in volatility. Thereby, the results are still driven by one volatile market.

Regarding the beta exposure, LP has significant beta despite imposing the constraint of a beta equal to zero. As discussed in Section 4.4, LP fails to remove the beta exposure due to the fast-moving beta. Estimated ex-ante beta is already outdated, resulting in error-maximisation

Table 19: Multi-factor Concentration risk statistics

Structure	Methods	Risk contribution Min (%)	Max (%)	StDev (%)	Return contribution Min (%)	Max (%)	StDev (%)
Koijen	Basic	-5.70	52.92	14.87	0.06	31.64	8.70
	Division	-5.06	47.71	13.46	0.06	29.37	8.07
	Resid	-6.31	46.33	13.29	0.06	29.39	8.16
Optimisation	LP	-5.43	43.34	12.86	0.00	31.55	9.39
	LP-limit	-4.44	35.69	11.26	0.00	27.75	8.61
	QP	-4.62	38.32	11.39	0.15	30.11	8.85
Group	Equal	-6.56	56.39	15.60	0.03	30.83	8.48
	K-means-size	-6.82	43.78	12.94	0.01	27.82	7.90
	K-means-risk	-8.19	47.25	13.76	0.01	27.94	7.91

Notes: The concentration risk statistics for multi-factor strategy under Koijen, Optimisation and Group structure is reported. The risk contribution is computed by the 3-year rolling estimation of the marginal risk contribution divided by the marginal contribution and subsequently dividing it by the total standard deviation. Afterwards, the minimum, maximum, and standard deviation across the countries are calculated at each time, and the average of them is reported. The return contribution is measured by the absolute return of each country divided by the sum of the absolute returns at each point in time. Subsequently, the minimum, maximum, and standard deviation across the countries are calculated at each time, and the average of them is reported. The sample period runs from 2005-02 to 2021-02.

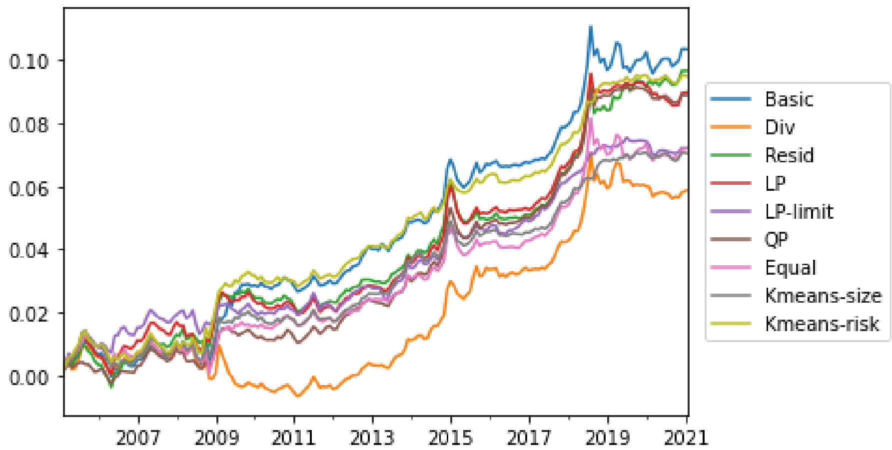
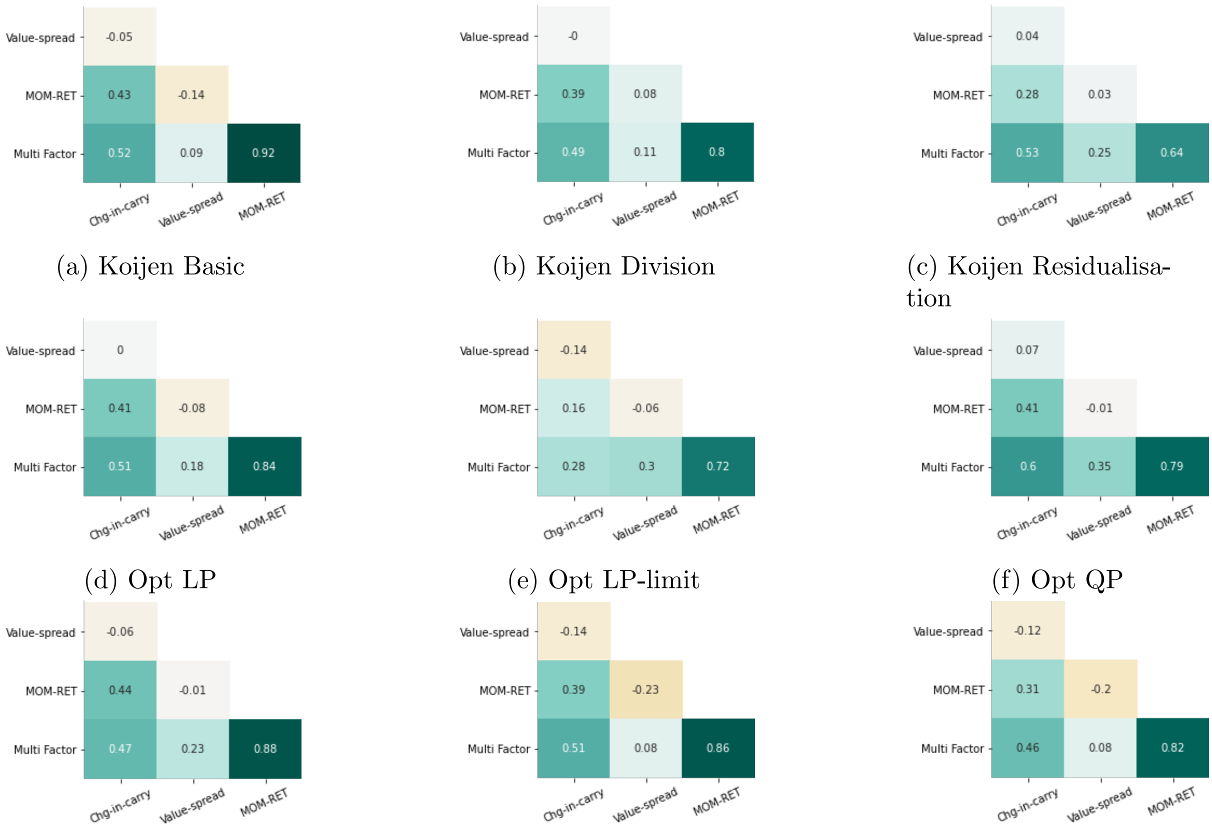


Figure 7: Cumulative return of multi-factor model for individual methods

with high ex-post beta. This beta exposure has been decreased when combined with the volatility restriction on maximum weights in LP-limit, with insignificant beta. Also, in QP, we observe that this error maximisation has been reduced because of its covariance trade-off term.

Figure 9 shows the weight of Turkey over the sub-sample period. The Basic Koijen weight only considers the factor score without dealing with the high volatility in Turkey. We can see from Figure 11 that the market beta of Turkey spikes to higher than 6.0 at the end of 2018. A naive way to adjust the factor by dividing by the beta also does not effectively reduce the weight of Turkey. Residualisation orthogonalises the factor score to the market beta, reducing the weight on Turkey. However, the Koijen weighting structure is still imposed after residualisation, reducing the effectiveness of this method.

Under the optimisation structure, we note that all three methods reduce the weight of Turkey. LP manages to achieve this by its zero beta exposure constraint. As can be seen in Figure 11a, increased market beta causes Turkey to have a lower weight. LP-limit has its additional restriction on the maximum weight on individual countries depending on their level of



(a) Koijen Basic (b) Koijen Division (c) Koijen Residualisation

(d) Opt LP (e) Opt LP-limit (f) Opt QP

(g) Group Equal (h) Group Kmeans-size (i) Group Kmeans-risk

Figure 8: Correlation of multi-factor strategy

volatility. Figure 11b shows the plot of volatility restriction, which is the cross-sectional median volatility divided by the volatility of Turkey over time, where we observe a rapid decrease in the weight restriction on Turkey. The volatility is estimated using a 12-month window. Hence it achieves to react quickly. Even though QP also reduces the weight of Turkey, but it is less effective due to its 3-year estimation window of covariance term and the off-diagonal elements, which make it less effective to reduce the weight on Turkey.

On the other hand, Table 20 shows that the Appraisal Ratio (AR) of LP-limit is much lower than LP and QP. We observe that the cumulative return earned from Turkey is much lower in LP-limit compared to other methods, as can be seen in Table 21. Even before the crisis period, LP-limit sets a lower weight on Turkey since it is a relatively more volatile country than other markets. In Figure 10a, we observe a huge spike in the cumulative return in 2018 for most of the methods except for LP-limit, K-means-size and K-means-risk. As can be seen from the cumulative return of Turkey in Figure 10b, these returns are earned from the Turkey positions, whereas LP-limit could not benefit from it due to the restricted weight on Turkey. Therefore we note that LP-limit performs the best in reducing the exposure to the risky country but could miss out on the return coming from the volatile country.

Notably, we observe huge differences in the effectiveness of reducing Turkey weight between equal and K-means groupings. Equal grouping does not have the flexibility to choose the group size over time. On the other hand, K-means grouping can vary the group size depending on the current situation. This results in meaningful differences in the two grouping methods. Figure 11c shows the number of groups assigned to the EM-like universe, where we find that Equal grouping still maintains its size when the Turkish crisis starts, causing Turkey to drive results in the EM-like universe. On the other hand, K-means clustering separates Turkey into the EM-like group from other countries when the crisis presents. It designates weights on Turkey as zero, blocking one very volatile market from affecting the portfolio.

Table 20: Multi-factor Portfolio performance during Turkish crisis

Structure	Methods	α (%)	β	SR	AR	Mean (%)	StDev (%)	Skew	Kurt
Koijen	Basic	1.31	-0.49	0.88	1.08	1.10	1.25	-0.07	0.87
		(2.12)	(-1.85)						
	Division	0.99	-0.41	0.76	0.94	0.82	1.08	-0.39	1.46
		(1.85)	(-1.77)						
	Resid	0.79	-0.41	0.67	0.89	0.62	0.92	0.20	2.62
		(1.76)	(-2.11)						
Optimisation	LP	0.97	-0.48	0.83	1.10	0.77	0.93	0.49	2.38
		(2.17)	(-2.46)						
	LP-limit	0.44	0.04	0.93	0.89	0.46	0.50	-1.23	3.78
		(1.76)	(0.36)						
	QP	0.93	-0.24	1.11	1.26	0.83	0.75	0.35	2.18
		(2.49)	(-1.49)						
Group	Equal	1.20	-0.55	0.85	1.10	0.98	1.15	-0.06	0.96
		(2.16)	(-2.29)						
	K-means-size	0.77	0.27	1.45	1.32	0.88	0.61	-0.60	3.14
		(2.60)	(2.12)						
	K-means-risk	0.75	0.26	1.39	1.27	0.86	0.62	-0.47	2.99
		(2.49)	(2.01)						

Notes: The contribution of Turkey on portfolio performance for multi-factor using Change-in-carry, Value-spread, and Momentum-return is reported. The alpha, Sharpe Ratio (SR), Appraisal Ratio (AR), Mean and Standard deviations (StDev) are annualised values. Factor/StDev shows the factor exposure per annualised standard deviation. Factor exposure is calculated by multiplying z-score to the weight, subsequently taking the mean. The sample period runs from 2017-01 to 2021-02.

Table 21: Contribution of Turkey on performance

Structure	Methods	Weight	CumReturn	Return contribution
Koijen	Basic	0.22	0.32	0.57
	Division	0.17	0.22	0.53
	Resid	0.16	0.16	0.52
Optimisation	LP	0.16	0.27	0.70
	LP-limit	0.06	0.09	0.39
	QP	0.13	0.23	0.56
Group	Equal	0.20	0.30	0.60
	Kmeans-size	0.07	0.18	0.42
	Kmeans-risk	0.06	0.17	0.40

Notes: The contribution of Turkey on portfolio performance for multi-factor using Change-in-carry, Value-spread, and Momentum-return is reported. Turkey weight shows the average absolute weight assigned to Turkey during the sample period. CumReturn reports the annualised simple cumulative return of Turkey, and Return contribution shows the proportion of simple cumulative return of Turkey out of the simple cumulative portfolio return over the sample period. The sample period runs from 2017-01 to 2021-02.

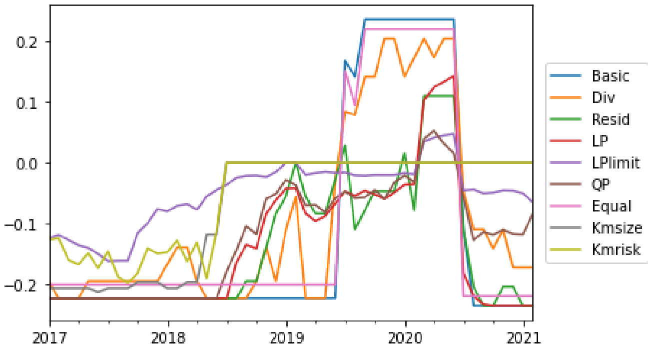
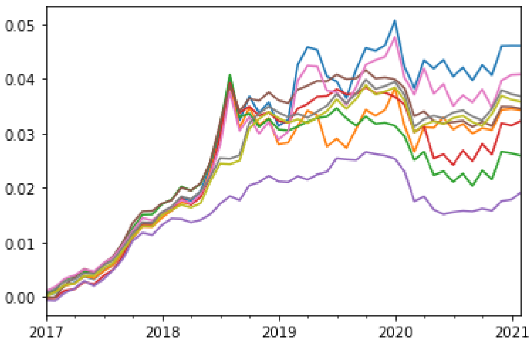
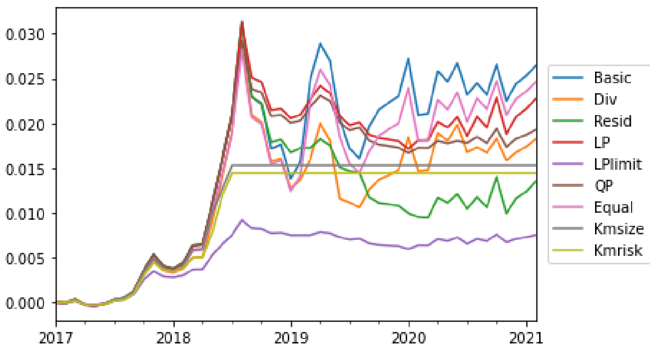


Figure 9: Turkey weight of multi-factor model for individual methods

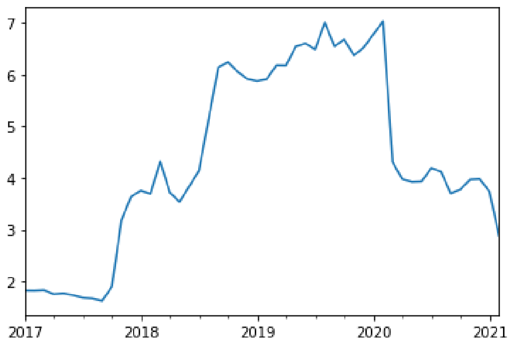


(a) Cumulative Return

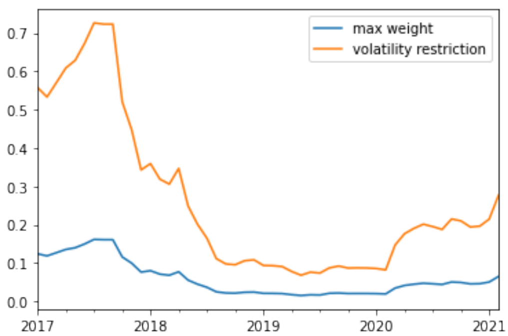


(b) Cumulative Return of Turkey

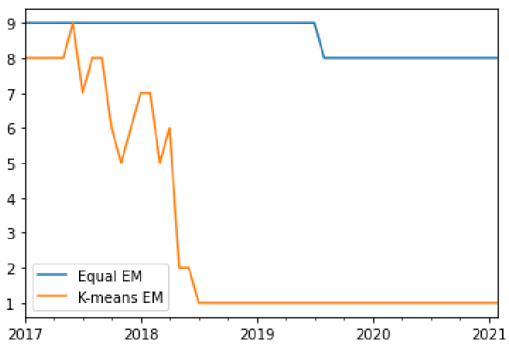
Figure 10: Cumulative return of each portfolio



(a) Market beta of Turkey



(b) Weight restriction on Turkey



(c) Number of groups assigned to EM-like

Figure 11: Input of advanced strategies during Turkish crisis

6 Conclusion

This paper investigates factor investing in emerging market local currency bonds on a country level. We consider the application of factors such as Carry, Change-in-carry, Value, Momentum and Betting-against-beta in the context of the EM-LC bond universe. These factors are first analysed using the basic Koijen weighting scheme, which is widely used in academics. Afterwards, we extend our analysis using the Koijen weighting scheme with adjusted factor scores, optimising the factor exposure subject to several constraints and grouping the universe into emerging and developed markets like countries.

The EM-LC bond universe has diverting movements in beta, volatility and default risk across both the country and time dimensions. The basic factor construction method studied in the developed market fixed income universe cannot capture these features. Therefore we propose several advanced methods to mitigate the potential risk drivers in EM-LC bonds. First, we consider adjusting the factor measure to reduce the beta effect in it. This is done by Division and Residualisation, which ranks each measure divided by the beta and measure orthogonal to the market beta, respectively. Second, we use optimisation tools to maximise factor exposure subject to the zero betas. We introduce Linear Programming, Linear Programming with restricted maximum weight according to the country's volatility, and Quadratic Programing by directly considering the risk trade-off in the objective function. Lastly, we suggest systematic choices regarding the universe by grouping countries. We consider equal-size grouping and dynamic-size grouping, by combining two groups according to either the group size or the risk.

Our research shows evidence of systematic factors in the EM-LC universe. We find significant alpha in Carry, Change-in-carry, Momentum-yield and Momentum-return factors using the basic Koijen weighting scheme. Furthermore, the extended analysis using chosen factors that perform well and have low correlation with each other gives promising results. We note that Change-in-carry and Momentum-return factors show significant alpha using the majority of the advanced methods. Value-spread factor, which shows insignificant alpha using the Basic Koijen weighting scheme, generates significant performance with LP-limit, QP, and K-means-risk. Reduced potential risk enables most advanced methods to attain a higher Sharpe ratio and more strongly significant alpha than the basic Koijen weighting scheme. The performance of the multi-factor model further shows evidence of factors in the EM-LC bond universe, with the Sharpe ratio of 0.8.

The main finding is that the advanced methods can improve upon the existing factor construction method by dealing with the potential risk drivers such as beta exposure and concentration risk. The beta exposure is effectively minimised by residualising the factor score, solving portfolio optimisation problems and grouping countries. Concentration risk measured by the risk and return contribution is reduced using optimisation and grouping. These structures have the advantage of flexibility, which allows additional conditions to be satisfied. LP-limit and K-means-size most effectively reduce the aforementioned risk drivers simultaneously. LP-limit achieves this by directly neutralising beta exposure and tightening the maximum weight for volatile countries. On the other hand, K-means-size solves these issues relatively indirectly, making each country more comparable by dividing the universe into EM and DM-like countries. Dynamically determining the group size using K-means clustering enables effectively selecting countries with diverting behaviours in real-time.

For further research, one can extend the analysis by investing in the curve using several maturity buckets for each country as introduced in Martens et al. (2019). Also, there might be a practical issue with trading EM-LC bonds due to different regulations by each country. Thus, swap data, which enables avoiding physical trading of EM-LC bonds and is rather flexible from tax regulations, can be investigated.

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Appendix A

Data processing

The data obtained from Bloomberg has some data errors. Most data errors are found in the starting dates of each series. For example, when the JPM country-level index does not exist, the data is given as 0 instead of NA. Also, for some countries, the starting value duplicates in the previous dates. Similar issues are found in the middle of the data, having duplicating values over the period. Most cases are due to public holidays, where we do not make a correction, but one of them is because the underlying bond does not exist anymore. We removed those data points and set them to NA. Another type of finding is data errors in the middle of the series. Some data points violate the pattern. For example, the JPM YLD of Chile has a huge drop for only three days. We compared it to the maturity bucket data to check if it is reasonable. We copied from the previous values as they cannot be explained by the maturity bucket data, where the index was calculated.

In two and ten-year yield data, we find similar issues as in JPM index data. We detected whether the data duplicates for more than one month or goes to zero in the middle of the series for a short period. These errors are replaced by the 1-3 and 7-10 years maturity bucket yield data when the maturity data also does not show duplicative values or outliers. If the maturity bucket data also shows duplicative values for more than one month or outliers, we set the corresponding observation of two and ten-year yield data to NA.

Table 22: Error Correction in Data

Data	Countries	Date(s)	Raw data	Corrected	Remarks
JPM return index	Brazil	31/12/2002 - 30/04/2003	110.104	NA	Underlying bond does not exist
	Indonesia	02/12/2002 - 30/12/2002	100	NA	Index does not exist
	China	01/12/2003 - 30/12/2003	100	NA	Index does not exist
	Chile	31/07/2019 - 30/03/2021	155.146	NA	Index does not exist
JPM YLD	Brazil	31/12/2002 - 30/04/2003	30.944	NA	Index does not exist
	Mexico	31/12/2001	0	NA	Index does not exist
	Indonesia	02/12/2002 - 31/12/2002	0	NA	Index does not exist
	Malaysia	31/12/2001	0	NA	Index does not exist
	South Korea	13/11/2001 - 10/12/2001	5.849	NA	Index does not exist
	Hungary	29/12/2000	0	NA	Index does not exist
	China	01/12/2003 - 31/12/2003	0	NA	Index does not exist
	Russia	03/01/2005 - 31/01/2005	0	NA	Index does not exist
	Chile	05/07/2018	2.35	3.535 [4]	Data Error
		06/07/2018	2.371	3.535	Data Error
		09/07/2018	2.334	3.535	Data Error
		31/07/2019 - 30/03/2021	0	NA	Index does not exist
JPM DUR	Brazil	31/12/2002 - 30/04/2003	0.879	NA	Index does not exist
	Mexico	31/12/2001	0	NA	Index does not exist
	Indonesia	02/12/2002 - 31/12/2002	0	NA	Index does not exist
	Malaysia	31/12/2001	0	NA	Index does not exist
	South Korea	13/11/2001 - 10/12/2001	3.382	NA	Index does not exist
	China	01/12/2003 - 31/12/2003	0	NA	Index does not exist
	Russia	03/01/2005 - 31/01/2005	0	NA	Index does not exist
	Chile	31/07/2019 - 30/03/2021	0	NA	Index does not exist
3M LIBOR	China	01/08/2000	0	2.345	Data Error

[4] It is copied from the most recent previous date, which is 04/07/2018.

Table 23: Bloomberg ticker

Countries	JPM bond total return	JPM YLD	JPM DUR	3M LIBOR	MSCI Equity
Brazil	JGENBBUL Index	JGENBBYM Index	JGENBBMD Index	BZDIOVRA Index	
Mexico	JPMTMX Index	JPETMXYM Index	JPETMXMD Index	MXIB91DT Index	
Colombia	JGENBCUL Index	JGENBCYM Index	JGENBCMD Index	DTF RATE Index	
Indonesia	JGIDULOC Index	JGIDYTOM Index	JGIDMDUR Index	JIIN3M Index	
Malaysia	JGMYULOC Index	JGMYYTOM Index	JGMYMDUR Index	KLIB3M Index	
Thailand	JGTHULOC Index	JGTHYTOM Index	JGTHMDUR Index	BOFX3M Index	
South Korea	JPMTKR Index	JPMYKR Index	JPMDKR Index	KRBO3M Index	
Turkey	JGENTBLO Index	JGENTBYM Index	JGENTBMD Index	TRLIB3M Index	
South Africa	JPMTSAF Index	JPETSAYM Index	JPETSAMD Index	JIBA3M Index	
Poland	JGENPDUL Index	JGENPDYM Index	JGENPDMD Index	WIBO3M Index	
Hungary	JPMTHU Index	JPMYHU Index	JPETHUMD Index	BUBOR03M Index	
India	JGINULOC Index	JPETINYM Index	JPETINMDT Index	IN003M Index	
China	JGCHULOC Index	JGCHYTOM Index	JGCHMDUR Index	SHIF3M Index	
Russia	JGRUULOC Index	JGRUYTOM Index	JGRUMDUR Index	MOSKP3 Index	
Chile	JGCGPLOC Index	JGCLYTM Index	JGCLDUR Index	CHNI3M Curncy	
Peru	JGENPEUL Index	JGENPEYM Index	JGENPEMD Index	PSNI3M Curncy	
Philippines	JGPHLOC Index	JGENPHYM Index	JGENPHMD Index	PPNI3M Curncy	
Index	JGENVLLG Index	JGENGHYG Index	JGENVHMG Index		
Not diversified	JGENGHUG Index				
Diversified	JGENVHUG Index				
US	JPMTUS Index		JPMDUS Index	US0003M Index	MSDLUS Index
Germany	JPMTWG Index	DM0003M Index	JPMDWG Index		
Japan	JPMTJPN Index		JPMDJPN Index	JY0003M Index	MSDLJN Index
EUR				EUR003M Index	MSDLEMU Index

Appendix B

Additional factor results

Table 24: Grouping - Equal size strategy: overview of DM and EM-like countries

	Carry	Change-in-carry	Value-MR	Value-spread	MOM-YLD	MOM-RET	BAB	AVG
South Korea	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
China	1.00	1.00		1.00	1.00	1.00	1.00	1.00
India	0.99	1.00	1.00	0.99	1.00	1.00	1.00	1.00
Malaysia	0.90	0.89	0.96	0.92	0.94	0.94	0.94	0.93
Chile	0.92	0.75		0.95	0.97	0.97	0.97	0.92
Thailand	0.75	0.79	0.90	0.79	0.92	0.92	0.92	0.85
Poland	0.59	0.59	0.70	0.57	0.59	0.59	0.53	0.59
Philippines					0.55	0.55	0.59	0.56
Russia	0.58	0.59	0.57	0.61	0.43	0.44	0.41	0.52
Mexico	0.21	0.18	0.29	0.24	0.28	0.28	0.28	0.25
South Africa	0.18	0.24	0.11	0.19	0.24	0.24	0.24	0.21
Colombia	0.22	0.28	0.19	0.18	0.06	0.06	0.06	0.15
Peru	0.10	0.03	0.18	0.10	0.02	0.02	0.02	0.07
Hungary	0.28	0.29	0.42	0.32	0.25	0.24	0.30	0.30
Indonesia	0.01	0.01	0.00	0.01	0.03	0.03	0.03	0.01
Brazil	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00
Turkey	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The proportion of DM-like membership per country using the grouping with the equal size is reported. One means that the country has been classified into the DM-like group during the full sample period. The last column is the average value using all seven factors. The sample period runs from 2006-006-09-29 for Value-MR and 2005-02-28 for others, and to 2021-02-26.

Table 25: Grouping - K-means: overview of EM and DM-like countries

	Carry	Change-in-carry	Value-MR	Value-spread	MOM-YLD	MOM-RET	BAB	AVG
South Korea	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
India	0.99	1.00	0.99	0.99	1.00	1.00	1.00	1.00
China	1.00	1.00		1.00	1.00	1.00	1.00	1.00
Chile	1.00	1.00		1.00	1.00	1.00	1.00	1.00
Malaysia	0.97	0.99	1.00	0.98	0.98	0.98	0.98	0.99
Thailand	0.91	0.92	0.94	0.92	1.00	1.00	1.00	0.96
Philippines					0.89	0.89	0.90	0.90
Poland	0.75	0.80	0.84	0.75	0.91	0.91	0.92	0.84
Russia	0.76	0.74	0.67	0.76	0.87	0.87	0.88	0.79
Mexico	0.55	0.62	0.66	0.59	0.79	0.79	0.80	0.68
South Africa	0.54	0.61	0.58	0.55	0.69	0.69	0.69	0.62
Peru	0.50	0.62	0.47	0.50	0.68	0.68	0.70	0.59
Hungary	0.44	0.49	0.49	0.44	0.68	0.68	0.69	0.56
Colombia	0.43	0.63	0.49	0.40	0.64	0.64	0.65	0.55
Brazil	0.25	0.29	0.23	0.26	0.49	0.49	0.50	0.36
Indonesia	0.12	0.16	0.18	0.12	0.41	0.41	0.42	0.26
Turkey	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The proportion of DM-like membership per country using the grouping with K-means clustering is reported. One means that the country has been classified into the DM-like group during the full sample period. The last column is the average value using all seven factors. The sample period runs from 2006-006-09-29 for Value-MR and 2005-02-28 for others, and to 2021-02-26.

Table 26: Grouping strategy: Overview of the size of EM and DM group

	Equal		K-means	
	EM	DM	EM	DM
Carry	0.52	0.48	0.37	0.63
Change-in-carry	0.53	0.47	0.35	0.65
Value-MR	0.53	0.47	0.37	0.63
Value-spread	0.52	0.48	0.37	0.63
MOM-YLD	0.52	0.48	0.24	0.76
MOM-RET	0.52	0.48	0.24	0.76
BAB	0.52	0.48	0.23	0.77

Notes: The overall proportion of each group's size using Equal and K-means grouping is reported. The sample period runs from 2006-006-09-29 for Value-MR and 2005-02-28 for others, and to 2021-02-26.

Table 27: Grouping - Equal size: Beta exposure of EM and DM-like groups

Panel A: EM-like							
	Ex-ante			Ex-post rolling		Ex-post full sample	
Pf strategy	MSE	MAE	beta return	MSE	MAE	beta	$t-$stat
Carry	0.53	0.51	-0.33	0.98	0.75	-0.12	-0.88
Change-in-carry	0.68	0.49	0.38	0.68	0.56	-0.42	-2.92
Value-MR	0.77	0.56	0.50	1.71	0.89	0.92	6.04
Value-spread	0.54	0.49	-0.81	1.05	0.76	0.13	0.88
MOM-YLD	0.93	0.74	0.83	0.96	0.84	-0.82	-5.03
MOM-RET	0.79	0.69	0.55	1.25	0.96	-0.99	-6.67
BAB	0.00	0.00	0.00	0.08	0.25	-0.06	-0.69
Panel B: DM-like							
	Ex-ante			Ex-post rolling		Ex-post full sample	
Pf strategy	MSE	MAE	beta return	MSE	MAE	beta	$t-$stat
Carry	0.03	0.14	-0.07	0.09	0.26	0.09	1.46
Change-in-carry	0.03	0.14	-0.83	0.07	0.19	0.02	0.23
Value-MR	0.04	0.17	0.45	0.11	0.31	-0.23	-3.12
Value-spread	0.04	0.16	-0.04	0.11	0.25	0.13	2.25
MOM-YLD	0.03	0.14	-1.00	0.06	0.22	-0.08	-1.21
MOM-RET	0.03	0.14	4.58	0.08	0.25	-0.06	-0.91
BAB	0.00	0.00	0.00	0.12	0.25	-0.13	-0.88

Notes: The summary statistics of beta exposure for each factor strategy under Group-Equal structure is reported. The ex-ante beta is a one and five-year rolling window FP beta with a shrinkage parameter of 0.8, multiplied by the portfolio weights at each point of time. The ex-post beta is 3-year rolling OLS beta using the factor return series. The beta return is a proxy of how the total cumulative return is separated into the market. The beta return is computed using the cumulative return of the market multiplied by the ex-ante beta divided by the cumulative return of the full sample period. The sample period runs from 2005-02-28 to 2021-02-26.

Table 28: Grouping - K-means: Beta exposure of EM and DM-like groups

Panel A: EM-like							
	Ex-ante			Ex-post rolling		Ex-post whole sample	
Pf strategy	MSE	MAE	beta return	MSE	MAE	beta	$t-$stat
Carry	0.17	0.30	0.01	0.36	0.51	0.27	1.73
Change-in-carry	0.15	0.28	0.03	0.29	0.46	0.21	1.35
Value-MR	0.15	0.28	-0.23	0.32	0.47	0.49	3.25
Value-spread	0.17	0.30	-0.14	0.40	0.52	0.31	2.10
MOM-YLD	0.15	0.24	0.29	0.37	0.54	-0.49	-3.62
MOM-RET	0.18	0.27	0.38	0.41	0.58	-0.51	-3.57
BAB	0.00	0.00	0.00	0.07	0.23	-0.17	-2.85
Panel B: DM-like							
	Ex-ante			Ex-post rolling		Ex-post whole sample	
Pf strategy	MSE	MAE	beta return	MSE	MAE	beta	$t-$stat
Carry	0.06	0.19	0.02	0.10	0.30	-0.03	-0.45
Change-in-carry	0.04	0.15	-0.24	0.04	0.17	-0.07	-1.16
Value-MR	0.04	0.16	0.19	0.10	0.27	-0.06	-0.75
Value-spread	0.07	0.22	0.04	0.08	0.22	0.16	2.83
MOM-YLD	0.08	0.23	1.11	0.20	0.39	-0.28	-3.29
MOM-RET	0.08	0.24	0.75	0.23	0.41	-0.24	-2.90
BAB	0.00	0.00	0.00	0.05	0.19	0.02	0.19

Notes: The summary statistics of beta exposure for each factor strategy under Group-Kmeans structure is reported. The ex-ante beta is a one and five-year rolling window FP beta with a shrinkage parameter of 0.8, multiplied by the portfolio weights at each point of time. The ex-post beta is 3-year rolling OLS beta using the factor return series. The beta return is a proxy of how the total cumulative return is separated into the market. The beta return is computed using the cumulative return of the market multiplied by the ex-ante beta divided by the cumulative return of the full sample period. The sample period runs from 2005-02-28 to 2021-02-26.

Table 29: Residualisation: cross-sectional regression statistics

	Carry	Change-in-carry	Value-MR	Value-spread	MOM-YLD	MOM-RET
$t-$stat	1.07	1.41	1.36	1.34	3.36	2.58
R^2	0.12	0.17	0.23	0.15	0.36	0.29

Notes: The mean of the absolute beta t-statistics and R-squared obtained from the cross-sectional regression in each month are reported. The sample period runs from 2006-006-09-29 for Value-MR and 2005-02-28 for others, and to 2021-02-26.

Table 30: Market beta exposure

Panel A: Carry								
		Ex-ante			Ex-post rolling		Ex-post full sample	
Structure	Methods	MSE	MAE	beta return	MSE	MAE	beta	$t-$stat
Koijen	Basic	0.16	0.30	-0.22	0.20	0.30	-0.02	-0.29
	Div	0.55	0.61	-2.07	0.52	0.62	-0.44	-5.57
	Resid	**0.03**	**0.12**	0.03	0.11	0.24	0.07	0.95
Optimisation	LP	0.00	0.00	0.00	0.06	0.19	0.03	0.37
	LP-limit	0.00	0.00	0.00	**0.01**	**0.07**	-0.07	-1.29
	QP	0.00	0.00	0.00	0.05	0.16	0.03	0.51
Group	Equal	0.12	0.25	-0.21	0.19	0.27	**-0.01**	**-0.15**
	K-means-size	0.04	0.16	**0.01**	0.03	0.14	0.07	1.14
	K-means-risk	0.04	0.16	0.04	0.02	0.10	0.03	0.46
Panel B: Change-in-carry								
		Ex-ante			Ex-post rolling		Ex-post full sample	
Structure	Methods	MSE	MAE	beta return	MSE	MAE	beta	$t-$stat
Koijen	Basic	0.28	0.38	0.36	0.22	0.35	-0.23	-2.56
	Div	0.29	0.40	0.55	0.13	0.31	-0.26	-3.26
	Resid	0.05	0.15	**-0.02**	0.11	0.24	**-0.01**	**-0.14**
Optimisation	LP	0.00	0.00	0.00	0.13	0.28	-0.16	-1.93
	LP-limit	0.00	0.00	0.00	0.06	0.21	-0.12	-1.91
	QP	0.00	0.00	0.00	0.08	0.22	-0.13	-1.98
Group	Equal	0.18	0.27	0.37	0.16	0.31	-0.20	-2.49
	K-means-size	0.04	**0.14**	-0.06	0.04	0.18	-0.08	-1.26
	K-means-risk	**0.03**	**0.14**	-0.04	**0.02**	**0.10**	-0.02	-0.39
Panel C: Value-MR								

		Ex-ante			Ex-post rolling		Ex-post full sample	
Structure	Methods	MSE	MAE	beta return	MSE	MAE	beta	$t-$stat
	Basic	0.46	0.50	0.64	0.98	0.78	0.51	5.03
Koijen	Div	0.38	0.47	1.86	0.81	0.66	0.47	5.15
	Resid	0.06	0.18	**0.16**	0.12	0.29	0.26	3.27
	LP	0.00	0.00	0.00	0.23	0.37	0.38	4.49
Optimisation	LP-limit	0.00	0.00	0.00	0.10	0.24	0.15	2.33
	QP	0.00	0.00	0.00	0.10	0.26	0.25	4.09
	Equal	0.20	0.29	0.51	0.47	0.48	0.34	3.73
Group	K-means-size	0.04	0.15	3.73	**0.05**	**0.17**	**0.04**	**0.56**
	K-means-risk	**0.03**	**0.13**	0.24	0.11	0.29	0.20	2.82

Panel D: Value-spread

		Ex-ante			Ex-post rolling		Ex-post full sample	
Structure	Methods	MSE	MAE	beta return	MSE	MAE	beta	$t-$stat
	Basic	0.23	0.36	-0.32	0.37	0.53	0.25	2.88
Koijen	Div	0.28	0.40	-0.79	0.36	0.46	**0.00**	**-0.01**
	Resid	**0.04**	**0.15**	0.07	0.16	0.31	0.13	1.64
	LP	0.00	0.00	0.00	0.12	0.28	0.20	2.57
Optimisation	LP-limit	0.00	0.00	0.00	**0.04**	**0.15**	0.07	1.05
	QP	0.00	0.00	0.00	0.11	0.28	0.22	3.27
	Equal	0.13	0.24	-0.24	0.30	0.42	0.15	1.90
Group	K-means-size	**0.04**	0.16	-0.03	0.07	0.22	0.23	3.72
	K-means-risk	**0.04**	**0.15**	**0.02**	0.06	0.21	0.21	3.36

Panel E: MOM-YLD

		Ex-ante			Ex-post rolling		Ex-post full sample	
Structure	Methods	MSE	MAE	beta return	MSE	MAE	beta	$t-$stat
	Basic	0.57	0.63	1.30	0.63	0.67	-0.68	-5.80
Koijen	Div	0.33	0.46	0.62	0.68	0.69	-0.72	-7.11
	Resid	**0.07**	**0.20**	**-0.25**	0.30	0.43	-0.45	-5.54
	LP	0.00	0.00	0.00	0.28	0.42	-0.48	-5.43
Optimisation	LP-limit	0.00	0.00	0.00	**0.14**	**0.30**	**-0.31**	**-4.28**
	QP	0.00	0.00	0.00	0.22	0.39	-0.37	-5.83
	Equal	0.27	0.41	2.05	0.31	0.45	-0.48	-5.24
Group	K-means-size	**0.07**	0.22	0.67	0.16	0.32	-0.33	-4.32
	K-means-risk	**0.07**	0.22	0.52	0.26	0.41	-0.44	-5.42

Panel F: MOM-RET

		Ex-ante			Ex-post rolling		Ex-post full sample	
Structure	Methods	MSE	MAE	beta return	MSE	MAE	beta	$t-$stat
	Basic	0.53	0.60	0.90	0.74	0.74	-0.73	-6.88
Koijen	Div	0.33	0.44	-0.16	0.69	0.70	-0.70	-8.41
	Resid	0.35	0.44	**-0.04**	**0.07**	**0.22**	**-0.17**	**-2.02**
	LP	0.00	0.00	0.00	0.25	0.40	-0.40	-4.63
Optimisation	LP-limit	0.00	0.00	0.00	0.12	0.29	-0.25	-3.70
	QP	0.00	0.00	0.00	0.22	0.39	-0.33	-4.76
	Equal	0.23	0.38	1.04	0.39	0.51	-0.55	-6.67
Group	K-means-size	**0.08**	0.23	0.64	0.15	0.29	-0.31	-4.21
	K-means-risk	**0.08**	**0.22**	0.47	0.24	0.40	-0.40	-4.83

Panel G: Average

		Ex-ante			Ex-post rolling		Ex-post full sample	
Structure	Methods	MSE	MAE	beta return	MSE	MAE	beta	$t-$stat
	Basic	0.37	0.46	0.44	0.53	0.56	-0.15	-1.27
Koijen	Div	0.36	0.46	0.00	0.53	0.57	-0.27	-3.20
	Resid	0.10	0.20	**-0.01**	0.15	0.29	**-0.03**	**-0.31**
	LP	0.00	0.00	0.00	0.18	0.33	-0.07	-0.76
Optimisation	LP-limit	0.00	0.00	0.00	**0.08**	**0.21**	-0.09	-1.30
	QP	0.00	0.00	0.00	0.13	0.28	-0.06	-0.78
	Equal	0.19	0.31	0.59	0.30	0.41	-0.13	-1.49
Group	K-means-size	**0.05**	0.18	0.83	**0.08**	0.22	-0.06	-0.73
	K-means-risk	**0.05**	**0.17**	0.21	0.12	0.25	-0.07	-0.67

Panel H: BAB

		Ex-ante			Ex-post rolling		Ex-post full sample	
Structure	Methods	MSE	MAE	beta return	MSE	MAE	beta	$t-$stat
Koijen	Basic	0.00	0.00	0.00	0.06	0.21	-0.19	-2.11
	Equal	0.00	0.00	0.00	0.03	0.13	-0.09	-1.18
Group	K-means-size	0.00	0.00	0.00	**0.02**	**0.12**	**0.05**	**0.53**
	K-means-risk	0.00	0.00	0.00	0.07	0.20	-0.25	-3.03

Notes: The summary statistics of beta exposure for each factor strategy under Koijen, Optimisation and Group structure is reported. The ex-ante beta is a one and five-year rolling window FP beta with a shrinkage parameter of 0.8, multiplied by the portfolio weights at each point of time. The ex-post beta is 3-year rolling OLS beta using the factor return series. The beta return is a proxy of how the total cumulative return is separated into the market. The beta return is computed using the cumulative return of the market multiplied by the ex-ante beta divided by the cumulative return of the full sample period. Panel D is the average value using six factors excluding BAB. The sample period runs from 2006-09-29 for Value-MR and 2005-02-28 for others, and to 2021-02-26.

Table 31: Concentration risk statistics

Panel A: Carry							
		Risk contribution			Return contribution		
Structure	Methods	Min (%)	Max (%)	StDev (%)	Min (%)	Max (%)	StDev (%)
	Basic	-4.24	52.56	15.87	0.25	34.76	10.40
Koijen	Div	-4.32	47.02	14.37	0.24	33.15	10.10
	Resid	-4.24	52.56	15.87	0.25	33.92	10.25
	LP	-3.77	46.10	14.34	0.00	36.66	11.65
Optimisation	LP-limit	-4.16	**40.99**	**13.22**	0.00	32.22	10.63
	QP	-3.40	38.31	12.37	0.18	34.69	10.96
	Equal	-4.33	51.94	15.64	0.15	33.52	10.07
Group	K-means-size	-5.40	47.41	14.79	0.14	32.33	9.83
	K-means-risk	-5.18	48.38	14.97	0.15	**31.54**	**9.72**
Panel B: Change-in-carry							
		Risk contribution			Return contribution		
Structure	Methods	Min (%)	Max (%)	StDev (%)	Min (%)	Max (%)	StDev (%)
	Basic	-5.76	56.76	18.62	0.38	38.27	12.08
Koijen	Div	-4.60	51.54	16.89	0.39	37.00	11.84
	Resid	-5.76	56.76	18.62	0.37	36.24	11.42
	LP	-3.32	47.84	16.05	0.00	39.03	13.23
Optimisation	LP-limit	-3.37	**42.00**	**14.35**	0.03	34.54	11.95
	QP	-3.64	44.83	14.92	0.46	35.45	11.67
	Equal	-4.65	56.11	18.14	0.24	36.91	11.77
Group	K-means-size	-4.91	47.38	15.95	0.35	**34.25**	**11.10**
	K-means-risk	-4.90	49.87	16.34	0.34	34.66	11.24
Panel C: Value-MR							
		Risk contribution			Return contribution		
Structure	Methods	Min (%)	Max (%)	StDev (%)	Min (%)	Max (%)	StDev (%)
	Basic	-7.65	63.52	21.36	0.46	40.10	13.06
Koijen	Div	-5.45	52.71	18.17	0.47	36.77	12.28
	Resid	-7.65	63.52	21.36	0.45	37.98	12.43
	LP	-3.95	55.20	18.34	0.00	40.50	14.22
Optimisation	LP-limit	-3.86	45.72	16.41	0.08	39.41	13.84
	QP	-3.57	43.11	15.03	0.50	35.78	12.11
	Equal	-7.08	62.83	21.12	0.23	38.83	12.97
Group	K-means-size	-4.59	**44.66**	**15.73**	0.39	**35.99**	**12.15**
	K-means-risk	-4.77	45.95	15.92	0.32	36.63	12.42
Panel D: Value-spread							
		Risk contribution			Return contribution		
Structure	Methods	Min (%)	Max (%)	StDev (%)	Min (%)	Max (%)	StDev (%)
	Basic	-6.44	51.96	15.64	0.22	33.37	9.84
Koijen	Div	-4.26	44.44	13.27	0.23	32.02	9.61
	Resid	-6.44	51.96	15.64	0.22	31.99	9.47
	LP	-3.98	**41.56**	12.96	0.00	34.65	10.96
Optimisation	LP-limit	-4.29	41.85	**12.95**	0.00	31.52	10.25
	QP	-4.08	38.49	11.98	0.15	31.94	9.91
	Equal	-5.61	52.75	15.42	0.13	32.57	9.59
Group	K-means-size	-5.99	47.67	14.22	0.15	**30.60**	**9.18**
	K-means-risk	-6.85	49.02	14.67	0.16	30.89	9.34
Panel E: MOM-YLD							
		Risk contribution			Return contribution		
Structure	Methods	Min (%)	Max (%)	StDev (%)	Min (%)	Max (%)	StDev (%)
	Basic	-5.91	49.99	14.53	0.05	32.38	8.89
Koijen	Div	-6.18	45.61	13.31	0.06	30.76	8.50
	Resid	-5.91	49.99	14.53	0.04	30.39	8.37
	LP	-5.33	44.52	13.01	0.00	32.34	9.51
Optimisation	LP-limit	-4.29	**34.85**	**10.91**	0.00	**28.42**	8.65
	QP	-3.59	40.96	11.82	0.15	31.76	9.29
	Equal	-4.90	52.24	14.78	0.03	31.24	8.56
Group	K-means-size	-5.09	41.67	12.50	0.01	28.86	**8.13**
	K-means-risk	-5.34	46.12	13.24	0.01	29.10	8.17
Panel F: MOM-RET							
		Risk contribution			Return contribution		
	Basic	-5.70	50.52	14.38	0.05	31.49	8.70
Koijen	Div	-6.34	50.54	14.42	0.05	30.61	8.52
	Resid	-5.70	50.52	14.38	0.05	29.72	8.18
	LP	-3.38	41.91	12.12	0.00	31.47	9.35
Optimisation	LP-limit	-3.41	**33.02**	**10.46**	0.00	28.91	8.77
	QP	-2.71	35.95	10.63	0.12	30.94	9.11
	Equal	-4.80	52.20	14.57	0.04	31.08	8.55
Group	K-means-size	-5.28	42.02	12.47	0.02	**28.38**	**8.05**
	K-means-risk	-5.74	45.33	13.15	0.02	29.12	8.18
Panel G: Average							
		Risk contribution			Return contribution		
Structure	Methods	Min (%)	Max (%)	StDev (%)	Min (%)	Max (%)	StDev (%)
	Basic	-5.95	54.22	16.74	0.23	35.06	10.50
Koijen	Div	-5.19	48.64	15.07	0.24	33.39	10.14
	Resid	-5.95	54.22	16.74	0.23	33.37	10.02
	LP	-3.95	46.19	14.47	0.00	35.77	11.49

Structure	Methods	Risk contribution Min (%)	Risk contribution Max (%)	Risk contribution StDev (%)	Return contribution Min (%)	Return contribution Max (%)	Return contribution StDev (%)
Optimisation	LP-limit	-3.90	**39.74**	**13.05**	0.02	32.50	10.68
	QP	-3.50	40.28	12.79	0.26	33.43	10.51
Group	Equal	-4.90	37.18	11.61	0.02	25.07	7.21
	K-means-size	-5.21	45.13	14.28	0.18	**31.74**	**9.74**
	K-means-risk	-5.46	47.45	14.72	0.16	31.99	9.85
Panel H: BAB							
		Risk contribution			Return contribution		
Structure	Methods	Min (%)	Max (%)	StDev (%)	Min (%)	Max (%)	StDev (%)
Koijen	Basic	-2.03	32.50	9.28	0.03	26.17	7.36
Group	Equal	-5.23	54.68	16.61	0.14	34.02	10.25
	K-means-size	-4.15	**32.43**	**9.90**	0.00	**24.12**	**6.98**
	K-means-risk	-5.05	37.37	10.96	0.00	25.40	7.30

Notes: The concentration risk statistics for each factor strategy under Koijen, Optimisation and Group structure is reported. The risk contribution is computed by the 3-year rolling estimation of the marginal risk contribution divided by the marginal contribution and subsequently dividing it by the total standard deviation. Afterwards, the minimum, maximum, and standard deviation across the countries are calculated at each time, and the average of them is reported. The return contribution is measured by the absolute return of each country divided by the sum of the absolute returns at each point in time. Subsequently, the minimum, maximum, and standard deviation across the countries are calculated at each time, and the average of them is reported. Panel D is the average value using six factors excluding BAB. The sample period runs from 2006-09-29 for Value-MR and 2005-02-28 for others, and to 2021-02-26.

Table 32: Portfolio performance

Structure	Methods	α (%)	t-stat	β	t-stat	SR	AR	Mean (%)	StDev (%)	Skewness	Kurtosis
Panel A: Carry											
Structure	Methods	α (%)	t-stat	β	t-stat	SR	AR	Mean (%)	StDev (%)	Skewness	Kurtosis
Koijen	Basic	0.62	2.50	-0.02	-0.29	0.62	0.63	0.61	0.98	0.44	2.22
	Div	0.37	1.52	-0.44	-5.57	0.20	0.38	0.21	1.04	0.38	2.66
	Resid	0.55	2.37	0.07	0.95	0.62	0.60	0.57	0.92	0.40	2.56
Optimisation	LP	0.68	2.91	0.03	0.37	0.74	0.73	0.69	0.93	0.56	1.97
	LP-limit	0.59	3.40	-0.07	-1.29	0.82	0.86	0.57	0.70	0.84	2.96
	QP	0.65	3.16	0.03	0.51	0.81	0.8	0.67	0.82	0.59	2.42
Group	Equal	0.57	2.51	-0.02	-0.22	0.63	0.63	0.56	0.9	0.34	2.23
	K-means-size	0.51	2.57	0.07	1.14	0.68	0.65	0.54	0.79	-0.31	3.77
	K-means-risk	0.62	2.97	0.03	0.46	0.76	0.75	0.63	0.82	-0.32	4.08
Panel B: Change-in-carry											
Structure	Methods	α (%)	t-stat	β	t-stat	SR	AR	Mean (%)	StDev (%)	Skewness	Kurtosis
Koijen	Basic	0.76	2.74	-0.23	-2.56	0.61	0.69	0.68	1.12	0.28	2.90
	Div	0.62	2.51	-0.26	-3.26	0.52	0.63	0.52	1.00	0.46	3.83
	Resid	0.60	2.31	-0.01	-0.14	0.58	0.58	0.59	1.02	0.95	3.65
Optimisation	LP	0.60	2.32	-0.16	-1.93	0.52	0.59	0.54	1.04	0.86	3.36
	LP-limit	0.52	2.59	-0.12	-1.91	0.59	0.65	0.48	0.81	0.63	4.73
	QP	0.62	3.03	-0.13	-1.98	0.7	0.76	0.57	0.81	0.65	3.78
Group	Equal	0.46	1.83	-0.2	-2.5	0.38	0.46	0.39	1.01	0.33	3.26
	K-means-size	0.48	2.46	-0.08	-1.26	0.58	0.62	0.45	0.78	0.94	5.94
	K-means-risk	0.57	3.01	-0.02	-0.39	0.75	0.76	0.56	0.75	0.79	3.66
Panel C: Value-MR											
Structure	Methods	α (%)	t-stat	β	t-stat	SR	AR	Mean (%)	StDev (%)	Skewness	Kurtosis
Koijen	Basic	0.09	0.28	0.51	5.03	0.22	0.07	0.28	1.26	0.28	4.65
	Div	-0.03	-0.11	0.47	5.15	0.13	-0.03	0.15	1.14	0.06	4.80
	Resid	-0.29	-1.19	0.26	3.27	-0.20	-0.32	-0.19	0.95	0.13	5.34
Optimisation	LP	-0.47	-1.78	0.38	4.49	-0.31	-0.47	-0.32	1.04	1.00	8.58
	LP-limit	-0.33	-1.65	0.15	2.33	-0.36	-0.44	-0.27	0.76	0.17	2.83
	QP	-0.24	-1.28	0.25	4.09	-0.2	-0.34	-0.15	0.75	0.9	4.67
Group	Equal	0.13	0.45	0.34	3.73	0.23	0.12	0.26	1.1	0.07	4.3
	K-means-size	-0.01	-0.07	0.04	0.56	0.00	-0.02	0.00	0.78	0.99	3.38
	K-means-risk	-0.23	-1.05	0.20	2.82	-0.18	-0.28	-0.15	0.85	1.26	7.06
Panel D: Value-spread											
Structure	Methods	α (%)	t-stat	β	t-stat	SR	AR	Mean (%)	StDev (%)	Skewness	Kurtosis
Koijen	Basic	0.39	1.42	0.25	2.88	0.43	0.36	0.48	1.10	-0.67	5.20
	Div	0.34	1.32	0.00	-0.01	0.33	0.33	0.34	1.02	-0.24	4.46
	Resid	0.39	1.56	0.13	1.64	0.44	0.39	0.44	1.00	-0.95	6.73
Optimisation	LP	0.38	1.60	0.20	2.57	0.47	0.40	0.46	0.96	-0.99	6.18
	LP-limit	0.41	2.05	0.07	1.05	0.55	0.52	0.43	0.79	-0.94	6.04
	QP	0.55	2.67	0.22	3.27	0.75	0.67	0.62	0.83	-1.88	16.45
Group	Equal	0.41	1.7	0.13	1.65	0.48	0.43	0.46	0.97	-0.2	4.02
	K-means-size	0.30	1.58	0.23	3.72	0.49	0.40	0.38	0.77	-0.80	4.81
	K-means-risk	0.45	2.32	0.21	3.36	0.66	0.59	0.53	0.79	-0.65	5.28
Panel E: MOM-YLD											
Structure	Methods	α (%)	t-stat	β	t-stat	SR	AR	Mean (%)	StDev (%)	Skewness	Kurtosis
Koijen	Basic	0.82	2.27	-0.68	-5.80	0.37	0.57	0.57	1.55	0.85	9.32
	Div	0.71	2.27	-0.72	-7.11	0.32	0.57	0.45	1.38	0.85	9.96
	Resid	0.62	2.52	-0.45	-5.54	0.44	0.64	0.46	1.06	0.52	3.26

	LP	0.72	2.66	-0.48	-5.43	0.48	0.67	0.55	1.15	0.81	4.49
Optimisation	LP-limit	0.32	1.45	-0.31	-4.28	0.23	0.37	0.21	0.92	-0.56	5.56
	QP	0.56	2.84	-0.37	-5.83	0.5	0.72	0.43	0.85	1.04	4.65
	Equal	0.53	1.89	-0.45	-4.85	0.31	0.48	0.37	1.19	-0.4	3.51
Group	K-means-size	0.50	2.17	-0.33	-4.32	0.40	0.55	0.39	0.96	0.50	4.57
	K-means-risk	0.67	2.69	-0.44	-5.42	0.48	0.68	0.51	1.06	1.87	13.46
Panel F: MOM-RET											
Structure	Methods	α (%)	t-stat	β	t-stat	SR	AR	Mean (%)	StDev (%)	Skewness	Kurtosis
	Basic	0.95	2.91	-0.73	-6.88	0.48	0.73	0.69	1.45	0.89	11.99
Koijen	Div	0.46	1.81	-0.70	-8.41	0.18	0.46	0.21	1.19	0.03	5.41
	Resid	0.76	2.93	-0.17	-2.02	0.67	0.74	0.70	1.04	0.55	1.88
	LP	0.76	2.85	-0.40	-4.63	0.55	0.72	0.61	1.11	0.88	4.47
Optimisation	LP-limit	0.48	2.34	-0.25	-3.70	0.47	0.59	0.39	0.85	-0.11	4.79
	QP	0.52	2.44	-0.33	-4.76	0.45	0.62	0.40	0.89	1.57	6.89
	Equal	0.65	2.52	-0.52	-6.25	0.41	0.64	0.46	1.11	-0.65	5.33
Group	K-means-size	0.55	2.45	-0.31	-4.21	0.47	0.62	0.44	0.94	0.35	6.32
	K-means-risk	0.75	2.97	-0.40	-4.83	0.57	0.75	0.61	1.06	2.10	17.19
Panel G: BAB											
Structure	Methods	α (%)	t-stat	β	t-stat	SR	AR	Mean (%)	StDev (%)	Skewness	Kurtosis
Koijen	Basic	0.27	0.98	-0.19	-2.11	0.18	0.25	0.20	1.11	1.82	10.83
	Equal	0.13	0.55	-0.1	-1.27	0.1	0.14	0.09	0.93	0.00	4.33
Group	K-means-size	-0.06	-0.23	0.05	0.53	-0.04	-0.06	-0.05	1.10	1.96	13.88
	K-means-risk	0.12	0.49	-0.25	-3.03	0.03	0.12	0.03	1.03	1.08	12.15

Notes: The portfolio performance for each factor strategy under Koijen, Optimisation and Group structure are reported. The alpha, Sharpe Ratio (SR), Appraisal Ratio (AR), Mean and Standard deviations (StDev) are annualised values. The sample period runs from 2006-09-29 for Value-MR and 2005-02-28 for others, and to 2021-02-26.

Appendix C

Predictive ability testing results for ex-ante beta estimators

Table 33: Test statistics of predictive ability testing for ex-ante beta estimators

	$w = 1$		$w = 0.8$	
Beta measure	t-stat cond	t-stat uncond	t-stat cond	t-stat uncond
OLS 1Y	57.71(-)	55.14(-)	35.09(-)	26.63(-)
OLS 3Y	25.74(-)	25.98(-)	32.04(-)	17.54(-)
OLS 5Y	52.70(-)	39.80(-)	36.76(-)	33.44(-)
OLS AVG	31.76(-)	24.99(-)	39.17(-)	36.22(-)
FP 1Y5Y	66.35(-)	51.19(-)	-	-
	$w = 0.6$		$w = 0.4$	
Beta measure	t-stat cond	t-stat uncond	t-stat cond	t-stat uncond
OLS 1Y	28.04(-)	27.13(-)	92.90(-)	79.89(-)
OLS 3Y	101.06(-)	82.11(-)	119.37(-)	101.34(-)
OLS 5Y	85.28(-)	62.19(-)	116.11(-)	84.78(-)
OLS AVG	95.58(-)	76.54(-)	121.39(-)	98.42(-)
FP 1Y5Y	88.20(-)	88.02(-)	123.08(-)	109.35(-)

Notes: The predictive ability testing statistics of the BAB factor strategy using different ex-ante betas with the simple rank-based weighting scheme using different beta estimation methods are reported. Both conditional and unconditional test statistics are given. The sample period is 2007-01-31 to 2021-02-26. A positive test statistc indicates that the estimator outperforms FP 1Y5Y with $w = 0.8$, and vice versa for a negative sign. A critical value for conditional test is 5.99, and 3.84 for unconditional test. The p-values are zero in every case.

Appendix D

Test statistics of robust variance and Sharpe ratio test

Table 34: Robust variance test result

Structure	Methods	Carry	Change-in-carry	Value-MR	Value-spread	MOM-YLD	MOM-RET
Koijen	Div	0.07	0.02	0.04	0.26	0.00	0.19
	Resid	0.30	0.12	0.03	0.02	0.02	0.33
Optimisation	LP	0.36	0.27	0.10	0.08	0.03	0.25
	LP-limit	0.03	0.02	0.01	0.03	0.01	0.05
	QP	0.05	0.00	0.00	0.10	0.01	0.01
Group	Equal	0.02	0.00	0.00	0.01	0.32	0.35
	K-means-size	0.32	0.03	0.13	0.02	0.00	0.02
	K-means-risk	0.16	0.00	0.09	0.01	0.00	0.00

Notes: The p-value of robust variance test for individual factors is reported. The sample period runs from 2006-09-29 for Value-MR and 2005-02-28 for others, and to 2021-02-26.

Table 35: Robust test result of additional results - multi-factor

		Sharpe Ratio	variance	
Structure	Methods	full sample	full sample	Turkish crisis
Koijen	Div	0.98	0.01	0.24
	Resid	0.38	0.35	0.26
Optimisation	LP	0.14	0.17	0.17
	LP-limitW	0.64	0.02	0.01
	QP	0.56	0.08	0.17
Group	Equal	0.89	0.34	0.00
	K-means-size	0.51	0.00	0.34
	K-means-risk	0.32	0.00	0.10

Notes: The p-value of robust variance and Sharpe ratio test of multi-factor model during full sample and Turkish currency and debt crisis is reported. The sample period runs from 2005-02-28 for multi-factor model and 2017-01-31 for Turkish currency and debt crisis, to 2021-02-26.