Local Currency Bond Returns, Foreign Investors and Portfolio Flows in Emerging Markets *

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Abstract

This study, building upon theoretical frameworks incorporating portfolio decisions of institutional investors and fund flows, proposes a conditional asset pricing model to explain the cross-section local currency bond returns in emerging markets. We find that bonds whose returns covary positively (negatively) with the returns on foreign investors' portfolios exhibit higher (lower) average returns. The price of this type of risk increases with capital outflows, and bonds whose returns are higher on average exhibit a higher exposure when the price of risk is high. These results have important implications for the development of the local currency bond market.

JEL classification: **F31, F34, G15**

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1 Introduction

Local currency sovereign debt instruments issued by emerging economies ("EMEs" henceforth) have increased dramatically during the past two decades. By 2017, the amount of local currency sovereign debt has reached almost US dollar 10 trillion, a sizeable amount by any metric. Foreign investors have been a major driver in the growth of such bonds: they now own, for the average EME, about 20 percent of outstanding local currency sovereign debt, with some EMEs experiencing shares as high as 40 percent (G20 IFA WG, 2018). Among foreign investors, institutional participants play a substantial role, facilitated by the inclusion of EMEs debt securities in major tradable benchmarks and improved secondary market liquidity (Arslanalp and Tsuda, 2014; Agur et al., 2018).[1]

One natural question is how this foreign participation relates to the cross-section of returns in these sovereign bond markets. This is an important question as the participation of active foreign investors has often been associated with surges and sudden stops in asset prices experienced by EMEs (Kaminsky et al., 2004). Therefore, they represent a channel through which changes in the risk appetite or monetary policy of advanced economies are transmitted to EME's local currency bond markets, in the spirit of the global financial cycle proposed by Rey (2013).[2]

In this paper we present a framework to quantify the risk premia that arise from covariances with returns and fund flows originating from foreign investors actively managing their portfolio holdings. Taking the view that returns to active funds may represent a source of risk ("active fund risk" henceforth) for EME sovereign debt, we estimate a conditional asset pricing model based on key predictions of theoretical models incorporating portfolio decision,

[1]Foreign participation is highly heterogeneous across EMEs. While most exhibit a large share of debt owned by non-resident investors, a few countries continue to have a limited participation. We discuss the implications of this heterogeneity in Section 6.

[2]Several studies have attempted to quantify the occurrence of a global financial cycle: see Shin (2012), Bruno and Shin (2014), Blanchard et al. (2016). Others, such as Cerutti et al. (2017), are more skeptical. Miranda-Agrippino and Rey (2015) document a variety of patterns that suggest that shocks in globally integrated markets are transmitted via risk premia.

and the resulting fund flows, of institutional investors.[3] With the help of these estimations we uncover that bonds exposed more to active fund risk exhibit higher expected returns and this exposure increases when the price of risk is high—that is, when active funds face outflow pressure. Together these two results can explain why spikes in the required returns on EME sovereign debt are especially large when outflows occur.

Our empirical framework is based on Vayanos and Woolley (2013), who show that in an economy where competitive risk-averse investors have access to risky assets via both passive and active investment funds, expected returns on risky assets are due not only to compensation for bearing market risk, but also to the additional compensation required when active investment funds face large redemption and liquidate their positions. Intuitively, bonds whose returns positively covary with the returns of active funds will see their price drop in bad times, as active funds are forced to liquidate their holdings exerting price pressures in these markets. An appealing feature contained in the model is that the price of active fund risk increases as fund outflows becomes larger. This is described by Vayanos and Woolley (2013) as an amplification effect.[4] As fund outflows gather pace and as the price of active fund risk increases, the model predicts that the covariation between bond returns and fund returns increases even further, magnifying its effect on bond expected returns.

We document this double covariation in our empirical work, uncovering an important source of risk which links active fund returns and portfolio flows to EME sovereign bond returns. The model we estimate covers local currency bonds for a panel of 16 EMEs at five maturities, spanning the sample period July 2007 - March 2018. Our findings display a large heterogeneity of exposures to active fund risk in the panel of local currency bond. A

[3]See, among others, Vayanos and Woolley (2013), Basak and Pavlova (2013), He and Krishnamurthy (2013) and Koijen and Yogo (2018). See also Lou (2012) for an empirical investigation of flow-driven returns and their impact on asset return predictability.

[4]Shifts in risk sentiments, as in Goldstein et al. (2017), may represent an alternative rationalization of the same stylized fact. The Currency risk-taking channel, as in Hofmann et al. (2017), is also another possible explanation as currency risk premia represent non-negligible components of local-currency bond returns in US dollar.

portfolio comprising bonds with the largest exposure exhibits higher average excess returns, adjusted for market risk, than the ones recorded for another portfolio comprising bonds with the smallest exposure. The difference is statistically and economically significant, ranging between to 73 and 119 basis points per month, depending on bond maturity. The bonds contained in the portfolio with the largest exposure to active fund risk are issued by countries that exhibit weaker economic fundamentals, such as a smaller current account, since active funds tend to invest in these countries in a pro-cyclical manner.

In line with theory, we also find a strong and statistically significant positive relationship between the time-varying price of active fund risk and aggregate portfolio net outflows from EMEs. Our estimations suggest that US dollar 1 billion portfolio net outflows from EMEs funds generate an increment in the price of risk about 25 basis points per month (or 3 percent p.a.). In addition, we also find that the portfolio containing bonds with the highest exposure to active fund risk exhibit a positive and statistically significant *beta-premium sensitivity*: when the price of active fund risk increases by one percentage point per month, the exposure to this risk will rise by 1 to 1.6 percent for the portfolio containing bonds with the largest exposure relative to the portfolio of least exposed bonds.

Our study contributes to several strands of literature: the growing set of contributions exploring theoretically and empirically the role of institutional investors in financial markets and their impact on asset prices (Vayanos and Woolley, 2013; Basak and Pavlova, 2013; He and Krishnamurthy, 2013; Koijen and Yogo, 2018) and the studies that proposed a flow-based rationalization of asset return patterns (Lou, 2012; Feroli et al., 2017). We also refer to works that link bond yield dynamics to institutional holdings (D'Amico and King, 2013; Gagnon et al., 2011; Krishnamurthy and Vissing-Jorgensen, 2011, 2012; Neely, 2011; Goldstein et al., 2017; Morris et al., 2017); and the literature on the estimation and assessment of conditional asset pricing models (Fama and French, 1996; Jagannathan and Wang, 1996; Lettau and Ludvigson, 2001; Santos and Veronesi, 2004; Nagel and Singleton, 2011).

The structure of this paper is as follows: Section 2 discusses the main features of the theoretical asset pricing framework while Section 3 defines the empirical setup. In Section 4 we describe the details of the data sources and data construction and discuss some preliminary statistics. Section 5 reports the main empirical results. In Section 6 we discuss the implication of the empirical results in light of the development occurring in EMEs local currency bond market. Section 7 presents a battery of robustness checks and a final Section 8 concludes.

2 Bond Returns and Institutional Investors Portfolio Flows: An Asset Pricing Framework

In this section we introduce the asset pricing framework that we use to model the impact of institutional investors' portfolio returns and flows onto local currency bond returns in EMEs. A growing theoretical literature has studied the impact of institutional investor portfolio decisions on asset prices (see Koijen and Yogo, 2018 and the references therein). Among those studies, Vayanos and Woolley (2013) explore an infinite economy environment where competitive risk-averse investors access risky assets via two investment funds: a market index and an active fund. In a partial equilibrium setup[5], the authors show that expected returns on risky assets are determined by the following two-factor model (equations 3.17 and 4.13 in the study):

$$E_t\left(r_{t+1}\right) = \lambda_1 cov_t\left(r_{t+1}, r_{t+1}^M\right) + \lambda_{2,t} cov_t\left(r_{t+1}, r_{t+1}^A\right), \tag{1}$$

where r_{t+1}, r_{t+1}^M, r_{t+1}^A denote the excess return on a risky asset, the market index, and the active fund at time $t+1$, respectively. The operators E_t and cov_t denote the expected value and covariance conditional upon the information set at time t, respectively. The price of

[5]Vayanos and Woolley (2013) assume that i) the portfolio composition of the active fund is defined by a competitive manager that maximizes her expected utility of intertemporal consumption, ii) she allocates her wealth between the risk-free rate and the active fund, to ensure that the manager acts as a trading counterparty to the investor's flows, and iii) the holding of the active fund is subject to time-varying costs.

risk associated with the market index, λ_1 is constant while the one of the active fund, $\lambda_{2,t}$ is time-varying and depends on the fund flows. Equation (1) suggests that excess returns on risky asset are due not only to exposure to market risk but also to variations in returns from the active fund. In bad times, negative returns on the active fund generate fund outflows, which then increases $\lambda_{2,t}$ and hence raising expected returns of assets that covary positively with r^A_{t+1}. This time-varying covariation represents an alternative source of risk which links the dynamic of fund returns and flows to asset prices.

In our study, we apply the framework in equation (1) to EMEs' long-term local currency bonds. In doing so, we assume that the active fund invests exclusively EMEs local currency bonds and it is managed by foreign investors. Hence, the flows that generate the time variation in the price of active fund risk are proportional to the overall net capital outflows from EMEs.[6] We also assume that all returns are expressed in the US dollar, reflecting the perspective of a global financial intermediary that obtain short-term funds in US dollar (Adrian et al., 2017). This latter choice is also motivated by the findings in Hofmann et al. (2017) suggesting that US dollar returns are more representative of actual returns accruing to foreign investors holding local currency bonds.[7] [8]

We highlight the role played by active fund returns in affecting expected bond returns and rewrite, as in Pástor and Stambaugh (2003), the asset pricing equation (1) in terms of individual bond returns adjusted for market risk. More specifically, we define excess returns adjusted for market risk as $e^{(n)}_{h,t+1} = r^{(n)}_{h,t+1} - \gamma^{(n)}_h r^M_{t+1}$, where $r^{(n)}_{h,t+1}$ denote US dollar excess returns from the long-term bond with maturity n from country h. We then rewrite equation

[6] We implicitly assume that active funds invest in various EMEs at once. When there are shocks to these economies (or because of withdrawal from the active fund), investments in EMEs are liquidated jointly and their proceeds are repatriated. This joint liquidation causes co-movements across capital flows from EMEs.

[7] Important local currency bonds benchmarks associated with the Asian Bond Fund 2 (ABF2) initiative, for example the ABF Pan Asia Bond Index Fund, are also expressed in US dollar to reflect both local currency capital appreciation and exchange rate changes. See https://www.abf-paif.com/hk/eng/fund.aspx for further information. See also Chan et al. (2012) for the institutional details of ABF2.

[8] The investigation of the separate dynamics of local currency returns and exchange rate returns in EMEs is left as a major and important avenue for future research.

(1) in terms of a conventional expected returns-beta representation (Cochrane, 2005):

$$\begin{aligned} E_t\left(e_{h,t+1}^{(n)}\right) &= \lambda_t \beta_{h,t}^{A,(n)}, \\ \lambda_t &= \left[var_t\left(r_{t+1}^A\right)\lambda_{2,t}\right] \\ \beta_{h,t}^{A,(n)} &= \left[\frac{cov_t\left(e_{h,t+1}^{(n)}, r_{t+1}^A\right)}{var_t\left(r_{t+1}^A\right)}\right]. \end{aligned} \tag{2}$$

where the variables and parameters of interest carry the same interpretation as the ones reported in equation (1). This reparametrization allows us to reduce the asset pricing equation (1) to a one-factor conditional asset pricing model where the conditional US dollar expected returns of local currency bonds, adjusted for market risk, move only because of the active fund risk premium. This risk premium is simply the product of each bond's exposure to active fund risk (or active fund beta) times the price of this risk. Both price and quantity of active fund risk change over time.[9]

In order to measure the effect of this time-varying risk premium on local currency bond returns we use equation (2) and take, as in Jagannathan and Wang (1996), the unconditional expectations of both side of the equation. This leads to

$$E\left(e_{h,t+1}^{(n)}\right) = \overline{\lambda}_t \overline{\beta}_{h,t}^{A,(n)} + \phi_h^{(n)} var\left(\lambda_t\right), \tag{3}$$

where $\overline{\lambda}_t = E\left(\lambda_t\right), \overline{\beta}_{h,t}^{A,(n)} = E\left(\beta_{h,t}^{A,(n)}\right)$ and $\phi_h^{(n)} = cov\left(\lambda_t, \beta_{h,t}^{A,(n)}\right)/var\left(\lambda_t\right)$. Equation (3) indicates that unconditonal US dollar expected bond returns, adjusted for market risk, are due to two components: the first is linked to the average exposure to active fund risk and the average price of active fund risk. The second component captures the time-varying effect on bond returns and it is due to the beta-premium sensitivity ϕ_h and the volatility of the price of active fund risk. The beta-premium sensitivity, common in the context of the conditional

[9]Note that although equation (2) is derived directly from the theoretical findings of Vayanos and Woolley (2013), similar conditional asset pricing equations can be obtained from alternative specifications (for example, from dynamic models with institutional agents subject to multiple constraints, as in Adrian et al., 2017). However, these other specifications, unlike Vayanos and Woolley (2013), do not include explicitly fund flows as a determinant of the price of risk.

CAPM, denotes in this case the instability of individual bond's active risk exposure to the changes in aggregate EMEs net portfolio outflows. Intuitively, local currency bonds with positive beta-premium sensitivities have high risk precisely when the active fund experiences negative returns and large outflows. This is the time when investors dislike risk and the price of risk is high. Hence, these bonds earn higher average returns than bonds with low or negative beta-premium sensitivity. We test this hypothesis directly using the framework discussed in the following section.

3 The Empirical Setup

We bring the asset pricing equation (3) to the data by using the empirical procedures proposed by Pástor and Stambaugh (2003) and Petkova and Zhang (2005). More specifically, we use a simple sorting procedure that assigns bonds to portfolios according to the value of the estimated conditional active fund betas. Because the conditional betas are unobservable, we estimate them, in the spirit of Shanken (1990), using the following auxiliary regression:

$$\begin{aligned} e_{h,t+1}^{(n)} &= \psi_{h,0}^{(n)} + \beta_{h,t}^{A,(n)} r_{t+1}^{A} + \upsilon_{h,t+1}^{(n)} \\ &= \psi_{h,0}^{(n)} + (\psi_{h,1}^{(n)} + \psi_{h,2}^{(n)} \mathbf{Z}_{h,t}) r_{t+1}^{A} + \upsilon_{h,t+1}^{(n)} \\ &= \psi_{h,0}^{(n)} + \psi_{h,1}^{(n)} r_{t+1}^{A} + \psi_{h,2}^{(n)} \mathbf{Z}_{h,t} r_{t+1}^{A} + \upsilon_{h,t+1}^{(n)}, \end{aligned} \tag{4}$$

where $\mathbf{Z}_{h,t}$ denotes a vector of bond-specific characteristics. To increase precision in the face of the substantial variance in individual bond returns across countries, we restrict, as in Pástor and Stambaugh (2003, p. 665), the coefficients $\psi_{h,1}^{(n)}$ and $\psi_{h,2}^{(n)}$ to be identical across countries h and estimate them per maturity. The estimated active fund beta for each bond is then given by:

$$\widehat{\beta}_{h,t}^{A,(n)} = \widehat{\psi}_{1}^{(n)} + \widehat{\psi}_{2}^{(n)} \mathbf{Z}_{h,t}. \tag{5}$$

At the end of each month the bonds in the top tercile of the active fund beta estimates are assigned to the high (H) portfolio while the ones in the bottom tercile are assigned to the low (L) portfolio. Portfolio betas are then computed as the equal-weighted average of the beta of the constituent bonds while portfolio returns are computed keeping the composition of the two portfolio constant over the following month, after which the formation procedure is repeated.

We estimate the time-varying price of active fund risk λ_t following the procedure proposed in Petkova and Zhang (2005). More specifically, we carry out the auxiliary regression

$$r^A_{t+1} = \delta_0 + \delta_1 \overline{FL}_t + \delta_2 \mathbf{X}_t + \varepsilon_{t+1}, \tag{6}$$

where $\overline{FL}_t$ is the aggregate net capital outflow for bond investments from EMEs, $\mathbf{X}_t$ denotes a set of control variables and the estimated expected risk premium on the active fund is the fitted component from equation (6), i.e. $\widehat{\lambda}_t = \widehat{\delta}_0 + \widehat{\delta}_1 \overline{FL}_t$. [10]

We finally estimate the beta-premium sensitivities for both H and L portfolios using the following regression:

$$\widehat{\beta}^{A,(n)}_{i,t} = c_i + \phi^{(n)}_i \widehat{\lambda}_t + \eta^{(n)}_{i,t}, \tag{7}$$

where $\widehat{\beta}^{A,(n)}_{i,t}$ denote portfolio's conditional active fund beta with $i = \{H, L\}$. In our empirical exercise, we test for the one-sided null hypothesis that $\phi^{(n)}_i > 0$ suggesting that bonds with high conditional beta exhibit larger exposure to active fund risk when the price of risk is high. We also test whether H-L portfolio strategies have positive beta-premium sensitivities.

4 Data and Preliminary Statistics

The empirical analysis is carried out using data from multiple sources. Zero-coupon yield curves are computed using a standard Nelson and Siegel (1987) methodology applied to Bloomberg Fair Value (BFV) par yield curves.[11]. For consistency across countries, where

[10] The specification of equation (6) follows closely the theoretical implications of Vayanos and Woolley (2013, equation 3.17 and 4.13) where the price of risk associated with the active portfolio is a function of the active fund outflows.

[11] The BFV curves are estimated by Bloomberg on actively traded local currency bonds using a piecewise linear methodology (Du and Schreger, 2016)

not all maturities are available, we limit the analysis to five maturity tenors ranging from 1 to 5 years. Monthly bond log-holding period returns are computed as follows:

$$\rho^{(n)}_{h,t+1} = -(n-1)y^{(n-1)}_{h,t+1} + ny^{(n)}_{h,t}, \tag{8}$$

where $y^{(n)}_t$ denotes the log-zero coupon yield on a bond with maturity n, expressed in months, at time t. Bond log-excess returns in US dollar are then computed as

$$r^{(n)}_{h,t+1} = \rho^{(n)}_{h,t+1} + \Delta s_{h,t+1} - y^{(1)}_{US,t}, \tag{9}$$

where $\Delta s_{h,t+1}$ are log-exchange rate returns between country h and the US and $y^{(1)}_{US,t}$ is the US dollar 1-month interest rate used as proxy for the risk-free rate. US dollar exchange rates are expressed as local currency unit per 1 US dollar and they are obtained, together with the US interest rate, from Bloomberg. We proxy the returns of the market portfolio with the log-returns of a broad index comprising local currency bonds in both advanced and emerging economies. The selected index is the JP Morgan GBI Global Traded Index. We use the log-returns of the JP Morgan GBI-EM Broad Index to proxy for the returns from the active fund investing in emerging market local currency bonds.[12] Returns from both indices are expressed in US dollar in excess of the US dollar 1-month interest rate.

We use the EPFR sovereign bond fund flows to/from EMEs to proxy for the aggregate net outflows from the active fund. Because of data availability, the dataset is compiled over the sample period between June 2007 and March 2018.[13] In the empirical analysis we use the classification reported in BIS (2018) and explore the following sample of 16 emerging

[12]It would have been ideal to use an index of returns on portfolios of institutional investors. However, to the best of our knowledge, these indices are not readily available and their construction from individual fund sources is beyond the scope of this study. Nonetheless, it is important to note that returns from an index with a very specific focus, such as the one we employ in our estimations, are still valuable since the performance of the majority of active funds generally align with the one exhibited by more passive benchmarks (Fama and French, 2010). Furthermore, the potential statistical bias induced by the use of our selected benchmark is minimal, as long as institutional investor fund betas and alphas are relatively persistent over time.

[13]Although bond return data are available from an earlier period, reliable data on fund flows are available only from mid-2000s.

economies: China, Colombia, Czech Republic, Hong Kong, Hungary, Indonesia, Malaysia, Mexico, Peru, Poland, Russia, Singapore, South Africa, South Korea, Thailand, Turkey.

Table 1 reports preliminary statistics for the variables of interest used in the empirical investigation. All statistics for individual bond variables are computed per maturity across all countries in the sample. The figures reported in the table suggest that local currency bond yields over the sample period are higher than 4 percent, on average, and the slope of the term structure is positive. However, the yield spread between 5-year and 1-year bond is less than one percent across countries in the sample. US dollar excess returns, $r_t^{(n)}$, range between 49 and 74 basis points per month exhibiting an inverse u-shape pattern with extreme maturities recording similar average excess returns.[14] Individual bond US dollar excess returns are higher than US dollar excess returns exhibited by both the bond world market portfolio and the active portfolio, at about 25 - 30 basis points per month, suggesting the presence of large idiosyncratic components associated with individual countries' bond returns. After adjusting for market risk, the resulting US dollar excess returns, $e_t^{(n)}$, do not change much, confirming the inverse u-shape pattern recorded for overall bond excess returns. The aggregate net bond portfolio outflows from EMEs are on average negative, at US dollar 1.6 billion, suggesting that, in line with the existing anecdotal evidence, over the sample period EMEs have experienced consistent sovereign bond portfolio inflows.

5 Main Results

In this section, we discuss the results of the main estimations. We first report the results of the estimation related to time-varying betas and their use in forming bond portfolios. We then discuss the estimation of the time-varying price of risk and conclude this section by validating the empirical asset pricing model and its ability to explain actual average bond

[14] There is no obvious reason to rationalize this pattern. Although it may be due to a short sample period, it is also consistent with the evidence reported in Hördahl et al. (2018) who find that changes in bond yields around macroeconomic announcement news also exhibit a hump shape, with the larger response recorded for 2-3 year bond maturities.

returns.

5.1 Time-varying Betas and Portfolio Formation

The first step of the empirical analysis requires the estimation of time-varying betas in line with the framework proposed in Section 3. When estimating equation (4), we use individual country's level and slope of the yield curve as characteristics, $\mathbf{Z}_{h,t}$. We compute the level characteristic as the average yield across the five maturities used in this study. We compute the slope characteristic as the spread between the 5-year and the 1-year yields. The choice of these characteristics is necessarily arbitrary, although the variables possess some appeal ex ante. In fact, both characteristics are chosen on the basis of the large literature documenting that yield-curve based factors are important in explaining and forecasting bond yields and bond excess returns (see, among others, Joslin et al., 2014 and the references therein). To increase precision in the face of the substantial variance in individual bond returns, we restrict, as in Pástor and Stambaugh (2003, p. 665), the coefficients associated with the time-variation of beta, i.e. $\psi_{h,1}^{(n)}$ and $\psi_{h,2}^{(n)}$, to be identical for all bonds with the same maturity across countries h. Table 2 Panel A reports the estimated coefficients from equation (4) in Section 3. The slope of the yield curve is the most important determinant of the predicted beta over the sample period. It is consistently significant across all bond maturities at conventional confidence level. The coefficients associated with the slope characteristic range between 0.63 and -0.57 and exhibit an inverted u-shape with the largest value occurring for the 3-year maturity.[15]

At the end of each month we sort bonds according to the estimated betas into three portfolios, each comprising one third of the existing sample. We label the portfolio containing the one third of bonds exhibiting the highest beta as high (H) portfolio and the one containing the lowest beta as low (L) portfolio. The average value of the H and L portfolio betas are

[15]These results are based on conditional betas estimated using data over the full sample period. We have also computed parameter estimates using characteristics available up to the time of estimation in a rolling-window fashion and the baseline results are quantitatively and qualitatively similar.

reported in Table 2 Panel B. Average betas for the H portfolio are all statistically significantly different from zero at the 1 percent level and range between 2 and 3.7 across bond maturities while the ones for the L portfolio range between 0.2 and 1. For both portfolios, betas generally increase with maturity. The H-L beta spreads are all large and positive, and statistically significant. These findings suggest that, across countries, there is a substantial heterogeneity of exposures to active fund risk.

The theory highlighted in Section 2 indicates that bonds with large and positive betas should command a large risk premium and a higher expected return. This is because those are the assets that experience the largest losses in bad times, i.e. the active funds that experience negative returns and large outflows. Conversely, bonds exhibiting small positive or negative betas will act as a hedge in bad times, resulting in lower expected returns. We check these predictions in Table 3 where portfolio average returns, adjusted for market risk, are reported. We compute returns by keeping the composition of portfolio determined on month t constant for the subsequent month. The average excess returns exhibited by the H portfolio are positive and significantly higher than the ones recorded for the L portfolio. Excess returns from the H portfolio are all statistically significant at the 1 percent level and range between 0.95 and 1.4 percent per month (11 and 16 percent p.a., respectively) across maturities. The same excess returns computed for the L portfolio are overall insignificantly different from zero. Hence, the resulting H-L return differentials are large and significant. Taken together, these results confirm the main predictions of the theory and suggest that bonds whose returns positively co-move with the ones of the active fund command a substantial premium which can be quantified in about 11 percent p.a. across bond maturities.[16]

Given the results reported in Tables 2 and 3, it is important to explore the features of the two extreme portfolios. For all maturities and both portfolios, the constituents are not always

[16]Given that the excess returns used in the exercise are expressed as residuals from a market regression, the average excess returns reported in Table 3 can be also interpreted as World CAPM alphas. See Pástor and Stambaugh (2003, p. 668-669).

the same over time. Indeed, the first-order serial correlation of a binary indicator recording the presence of a country in a given portfolio is on average close to 0.64. This number suggests a moderate persistence and it rules out a random composition of two portfolios. On average, across maturities and portfolios, countries tend to remain in a given portfolio for about 5 months (with a maximum of 36 months and a minimum of 1 month).

Table 4 reports some key macroeconomic indicators relative to the countries that are included the two extreme portfolios.[17] More specifically, we first identify the countries that have been most included in the H and L portfolios over the sample period and then we compute the time-series average of each indicator across those countries. The results reported in Table 4 suggest the set of countries which are regularly included in the H portfolio tend to have weaker macroeconomic indicators than those in L portfolio. In fact, countries most frequently included in the H portfolio record current account deficits, hold less foreign reserve and their exchange rates against US dollar depreciate significantly over the sample period. Meanwhile, countries mostly included in the L portfolio run large current account surpluses, possess larger foreign exchange reserve, and their currencies remain relatively stable over the sample period. This evidence suggests that the H portfolio comprises bonds issued by countries that exhibit a larger fragility than the one recorded for the L portfolio, and this fragility affects the reaction of bond returns to active fund risk and, ultimately, impact bond risk premia.

5.2 Time-Varying Price of Risk

The asset pricing equation (3) in Section 2 requires the price of active fund risk to be time-varying. We compute it by estimating equation (6) in Section 3. We use the aggregate net bond portfolio outflows from EMEs as key dependent variables as suggested by the theory. However, we also use additional control variables that are routinely employed to explain

[17] The data for each country used to carry out the computations are obtained from the IMF International Financial Statistics database.

the variation in risk aversion and therefore affect the price of risk in international markets, namely changes in the VIX index and changes in the Federal Fund effective rate. Both variables have been found to be significant in related empirical works and linked to the presence of a global financial cycle that could potentially affect risk premia and capital flows in internationally integrated markets (see, Miranda-Agrippino and Rey, 2015; Chari et al., 2017 and the references therein).[18]

The estimation of equation (6) highlights a positive and statistically significant parameter on the net outflows from EMEs, even after controlling for the effect of potentially relevant variables. A US dollar 1 billion capital net outflows from EMEs induces an increase in the price of active fund risk by 25 basis points per month (or 3 percent p.a.).[19]

We report the time-series estimate of the price of risk, together with the level of the VIX index, in Figure 1. In Vayanos and Woolley (2013)'s framework the price of risk associated with the active fund is positively correlated with fund outflows as the price of risk increases in bad times when the active fund experiences losses and large outflows. Over the sample period, we find that the price of risk was relatively flat at around 20 basis points per month (per unit of beta) until mid-2013. Then a large portfolio net outflows from EMEs shifted the price of risk from a value close to zero to 80 basis points. After this episode, the price of active fund risk remained higher on average at around 40 basis points per month until 2016 and it decreased afterwards. This pattern is indicative of a potential risk attitude shift around 2013 which led a more cautious behavior of market participants over the subsequent three years.

The inclusion of the VIX index in level in the figure allows us to compare the two time-series over the same period of time. We carry out this simple comparison as a vast literature routinely employs shocks to the VIX index as proxy for variation in aggregate risk aversion

[18]In order to control for the potential contamination due to common sources of variation for capital flows and the control variables we orthogonalize the shocks of the control variables against the net capital outflows and use the orthogonalized shocks in the empirical estimation.

[19]This translates into a reduction of the price of the 3-year bond, for example, by 5 percent.

or a reflection of the effect of the global financial cycle on asset returns. Our time-varying price of risk directly reflects changes in aggregate risk aversion, therefore it provides a useful benchmark to evaluate changes in the VIX index against. The comparison in Figure 1 suggests that there are little commonalities between our estimate of the price of active fund risk and changes in the VIX index. More specifically the two measures move in tandem, even quantitatively, until 2011-2012. After the 'taper tantrum' in mid-2013, the VIX index has been relatively flat while our measure of price of risk experienced large variations. Although it would be unwise to draw any definitive conclusion, certainly the patterns recorded in Figure 1 suggest that it may not always be appropriate to use the VIX index to proxy for changes in the aggregate risk aversion, especially in the context of EMEs. In addition, the comparison also suggests that shocks recorded in leading economies, such as the US for the VIX index, may not necessarily correlate with risk premia in EMEs.

5.3 Beta-Premium Sensitivities and Model Validation

We use the time series of both time-varying betas, i.e. the quantities of active fund risk, and the price of active fund risk to calculate a term structure of time-varying active fund risk premia over the five bond maturities. Individual maturity's risk premia are computed as $(\widehat{\beta}_{H,t}^{A,(n)} - \widehat{\beta}_{L,t}^{A,(n)})\widehat{\lambda}_t$ and reported for all maturities in Figure 2. Although the average values of the risk premia are consistent with the H-L return differentials reported in Table 3, the time series plotted in Figure 2 exhibit a substantial variability over the sample period. The highest values of the risk premia were recorded in 2008, but they receded very quickly to low levels. Similar high values of the risk premia are also recorded after mid-2013 but at this time risk premia did not dissipate quickly and remained high on average with considerable variability until the beginning of 2017.

We complement the evidence reported in Figure 2 by estimating the beta-premium sensitivities using equation (7) in Section 3. More specifically we assess the co-movement between the prices and quantities of active fund risk to explore whether, in line with the theory discussed in Section 2, bonds in the H portfolio have high returns not only because of the average positive exposure active fund risk but also because of the price of this risk increases in bad times. The results of the estimations are reported in Table 5.[20] In all cases, with the exception of the 5-year maturity, the H-L beta-premium sensitivity difference is positive and statistically significant. This corroborates the theory and confirms that the time-variation of both price and quantity of active fund risk are important in characterizing the expected returns of local currency bonds. More specifically, the results also suggest that local currency bonds with positive beta-premium sensitivities have high risk precisely when the active fund experiences negative returns and large outflows. This is the time when investors dislike risk and the price of this risk is high. Hence, these bonds are indeed the ones to earn higher average returns than the bonds with low or negative beta-premium sensitivity.

We complete the assessment of the empirical model by comparing the expected returns of the H and L portfolios computed according to equation (4) of the main text with the actual average returns for the same portfolios computed over the sample period. The result of this exercise are reported in Figure 3. For the comparison, we report portfolio returns for H and L portfolios in different colors (blue for L and black for H). If the proposed model were the perfect representation of the bond returns' data generating process, the squares in the figure should align along a 45 degree line. Overall, despite the intrinsic simplicity of the theoretical framework and the lack of any general equilibrium features, the fit reported in Figure 3 is very satisfactory. The predicted returns align comfortably closer to the actual average portfolio returns and this is true for both L and H portfolios. However, the fit is not perfect as the model always provide smaller expected returns than the actual average. This

[20]It is instructive to note that equation (7) estimated using conventional least square estimators may be subject to biases since both regressor and regressand are obtained from prior estimations, and are therefore measured with sampling error. Although several methods have been proposed in the literature to take into account these type of biases (Pagan, 1984; Murphy and Topel, 2002; Lewis and Linzer, 2005), none of these is able to deal with the joint presence of generated regressands and regressors. See also the discussion in Hördahl et al., 2018.

is not surprising given that various important aspects, such as bond market liquidity, have not explicitly taken into account.

6 Discussion

The results reported in Section 5 highlight the existence of a risk-return relationship between local currency bond returns and the returns from actively managed funds from institutional investors. Bonds that exhibit higher and positive exposures to returns of actively managed funds tend to experience higher expected returns. These bonds are generally issued by countries that are considered more fragile in that they record current account deficits, hold less foreign reserve and their exchange rates against US dollar depreciate significantly. We also show that changes in risk premia due to changes in the price of this specific type of risk are associated with capital outflows from EMEs. Hence, fragile countries experience high expected returns on their local currency bonds not only because their exposure to active fund risk is high on average, but also because in bad times (i.e. when the risk aversion in international markets increases) large portfolio outflows affect the pricing of this risk causing a larger effect on bond returns. This mechanism offers an alternative reading of the current debate on the occurrence of a global financial cycle. In fact, our model suggests a prominent role played by the time-variation of the price of active fund risk in generating higher returns because of large capital outflows in bad times.

Another important pattern highlighted in the empirical results is that the term structure of expected returns across countries is not monotonically increasing. In fact, it exhibits an inverse u-shape pattern where the largest expected returns are recorded for the intermediate maturities while the extreme maturities experience similar returns.

Recent developments in local currency bond markets also suggest that more bonds are being included in relevant traded benchmarks (see, for example, ABF2 initiative and the details in Chan et al., 2012). This, in turn, increases commonalities among bond returns and fund flows. In light of our framework, this development may lead to unintended consequences, as the larger and positive exposures of bond returns to active fund returns (and the associated active fund risk) will generate higher beta and therefore larger risk premia. If outflows from local currency bond markets are also subject to such commonalities, then the impact of risk premia will be even higher as the price of active fund risk will also be affected.

The internationalization of local currency bond markets means that the quantity of active fund risk is bound to increase over time. Against this backdrop, countries have various options at hand to reduce the emergence of active fund risks and reduce the size of the associated risk premia. As it is in the interest of EMEs to continue to develop and expand their local currency bond markets, the reduction of risk premia will have to occur via policies that strengthen the underlying macroeconomic fundamentals, or "getting one's house in order". Countries may also promote a robust domestic investor base as a way to diversify their debt holders, and affect the time-varying price of active fund risk by, for example, fostering the development of derivative instruments aimed at helping foreign investors hedge currency and credit risks. In fact, partially or fully hedged institutional investors may not experience heavy losses which in turn will not trigger large outflows and a heightened price of risk. An alternative route is represented by policies that aim to minimize the negative externalities associated with first-mover advantages (Goldstein et al. (2017)). These, in turn, will affect the price of risk and therefore lower risk premia.[21]

7 Robustness (ongoing)

In this section we carry out a set of checks to assess the robustness of the baseline results reported in Section 5. More specifically, we initially test whether the estimates of the time-varying betas and the price of risk change if 1) different proxies for the active portfolio

[21]It is worthwhile noting that FX intervention may also represent an additional route to prevent spikes in the price of active fund risk. For example, Hofmann et al. (2018) focus the analysis on episodes of capital inflows and their effect on domestic credit.

returns are used 2) different control variables are used in the estimation of the price of risk and 3) a direct proxy for active capital net outflows is used in the estimation of the price of active fund risk. Overall, the results of the exercises carried out suggest that changes in the baseline specification do not affect quantitatively and qualitatively the results reported in Section 5.[22]

8 Conclusions

The growth of local currency bond markets in EMEs is an important institutional development that has accelerated after the 2008 global financial crisis. Although several studies have emphasized the benefits and potential risks associated with this development, little has been written to provide academics and central bankers with a manageable framework to use for policy and investment purposes. This study builds upon the empirical implications of theoretical models incorporating portfolio decisions of institutional investors and fund flows, and proposes a conditional asset pricing model to explain the cross-section of emerging market local currency bond returns.

We estimate the empirical model over the sample period July 2007 - March 2018 using local currency bond data across 5 maturities for a panel of 16 EMEs. We find a host of interesting results: First, there is a large heterogeneity of exposures to active fund risk in the panel of local currency bond. The portfolio comprising bonds with the largest exposure exhibits average excess returns, adjusted for market risk, that are higher than the ones recorded for the portfolio comprising bonds with the smallest exposure. The difference is statistically and economically significant ranging between to 76 and 118 basis points per month across bond maturities. We also show that bonds contained in the portfolio with the largest exposure to active fund risk are issued by countries exhibit weaker fundamentals over the sample period. Such evidence is not present for the countries issuing bonds included in

[22]The tables for the full set of robustness exercises will be added to the draft at a later date.

the portfolio with the lowest exposure. Second, we find a strong and statistically significant positive relationship between the time-varying price of active fund risk and aggregate net portfolio outflows from EMEs. Our estimations suggest that US dollar 1 billion net portfolio outflows from EMEs generate an increment in the price of risk of about 25 basis points per month (or 3 percent p.a.). Third, we also find that the portfolio containing bonds with the highest exposure to active fund risk exhibit a positive and statistically significant beta-premium sensitivity. Put differently, these bonds exhibit higher exposures precisely when the active fund experiences negative returns and large outflows. This is the time when investors dislike risk and the price of risk is high. Hence, these bonds earn higher average returns than bonds with low or negative beta-premium sensitivity.

Our baseline results are robust to a variety of checks. They also potentially hold important policy suggestions for the further development of local currency bond markets in EMEs: Countries experiencing high exposure to active fund risk may consider to provide institutional investors with derivative instruments to hedge such risks in bad times. Policies aiming at minimize the negative externalities first-mover advantages also be considered to reduce price of risk thereby lowering active fund risk premia accruing to local currency bonds.

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Table 1: This Table reports the summary statistics of the main variables of interest used in the empirical investigation. $y_t^{(n)}$ denote average bond yield with maturity n computed across the 16 countries in the sample. $r_t^{(n)}$ and $e_t^{(n)}$ denote US dollar excess returns and excess returns adjusted for market risk (computed as in Section 3 of the main text), respectively. The maturity n are expressed in months. r_t^W and r_t^A denote the US dollar excess returns exhibited by the bond world portfolio and the active fund proxies, respectively. $\overline{FL}_t$ is the aggregate capital outflow from EMEs relative to sovereign bond portfolio investments. Flows are expressed in US dollar millions. Average, Std Dev and AR(1) denote sample average, standard deviation and first-order serial correlation coefficient calculated over the period June 2007 - March 2018.

	Average	Std Dev	AR(1)
$y_t^{(12)}$	4.247	3.198	0.979
$y_t^{(24)}$	4.511	3.240	0.980
$y_t^{(36)}$	4.748	3.243	0.981
$y_t^{(48)}$	4.934	3.199	0.981
$y_t^{(60)}$	5.085	3.139	0.981
$r_t^{(12)}$	0.496	3.316	0.098
$r_t^{(24)}$	0.608	3.227	0.108
$r_t^{(36)}$	0.745	3.200	0.125
$r_t^{(48)}$	0.744	3.163	0.127
$r_t^{(60)}$	0.533	3.225	0.130
r_t^W	0.252	1.797	0.114
r_t^A	0.299	2.693	-0.020
$e_t^{(12)}$	0.493	3.311	0.101
$e_t^{(24)}$	0.725	3.197	0.136
$e_t^{(36)}$	0.719	3.161	0.138
$e_t^{(48)}$	0.508	3.221	0.139
$e_t^{(60)}$	0.508	3.221	0.139
$\overline{FL}_t$	-1699	5874	0.583

Table 2: This table reports the determinants and the estimated portfolio betas according to the empirical framework discussed in Section 3 of the text. Panel A shows the parameter estimates of equation (4) where the country's level and slope of the yield curve are used as individual characteristics. Level is computed as the average yield across the five maturities ranging from 1 to 5 year while Slope is the yield spread between the 5-year and 1-year bond. Parameter estimates are computed for all countries per maturity using a nonlinear system estimation. Panel B reports the portfolio betas comprising bonds in the top and bottom tercile of beta estimates, respectively. Portfolio are formed monthly on the basis of the estimated betas and kept constant for a month following the procedure detailed in Section 3. The values reported are the time-series average of the portfolio betas. Values in parentheses are serial correlation- and heteroskedasticity-adjusted standard errors.***,**,* denote statistically significant at 1, 5 and 10 percent levels respectively.

Panel A: Determinants of Predicted Betas

n=	**12**	**24**	**36**	**48**	**60**
Intercept	-0.268*	-0.582*	-0.622	-0.259	1.068
	(0.15)	(0.30)	(0.39)	0.21	(1.85)
Level	0.051	0.071	0.089	0.080	0.055
	(0.03)	(0.06)	(0.10)	(0.11)	(0.08)
Slope	0.129***	0.401***	0.637***	0.412***	-0.570***
	(0.03)	(0.04)	(0.17)	(0.13)	(0.10)

Panel B: Portfolio betas

n=	**12**	**24**	**36**	**48**	**60**
$\widehat{\beta}_{H,t}^{(n)}$	2.056***	2.816***	3.745***	3.515***	3.061***
	(0.18)	(0.26)	(0.34)	(0.29)	(0.23)
$\widehat{\beta}_{L,t}^{(n)}$	0.268***	0.323***	0.603***	0.728***	1.007***
	(0.06)	(0.10)	(0.14)	(0.11)	(0.08)
$\widehat{\beta}_{H,t}^{(n)} - \widehat{\beta}_{L,t}^{(n)}$	1.778***	2.493***	3.141***	2.786***	2.053***
	(0.14)	(0.19)	(0.24)	(0.21)	(0.20)

Table 3: This table reports returns, in excess of market returns, for the High and Low portfolios, respectively. Portfolio returns are reported as percentage points per month and recorded for each month subsequent to the construction of the portfolio. All returns are expressed in US dollar. Values in parentheses are serial correlation- and heteroskedasticity-adjusted standard errors. ***,**,* denote statistically significant at 1, 5 and 10 percent levels respectively. See also notes to Table 2.

n=	**12**	**24**	**36**	**48**	**60**
$e_{H,t}^{(n)}$	1.008***	1.181***	1.406***	1.256***	0.951***
	(0.29)	(0.28)	(0.26)	(0.26)	(0.21)
$e_{L,t}^{(n)}$	0.112	0.148	0.218	0.297*	0.225
	(0.16)	(0.15)	(0.14)	(0.16)	(0.19)
$e_{H,t}^{(n)} - e_{L,t}^{(n)}$	0.895***	1.032***	1.187***	0.959***	0.725***
	(0.19)	(0.15)	(0.15)	(0.11)	(0.09)

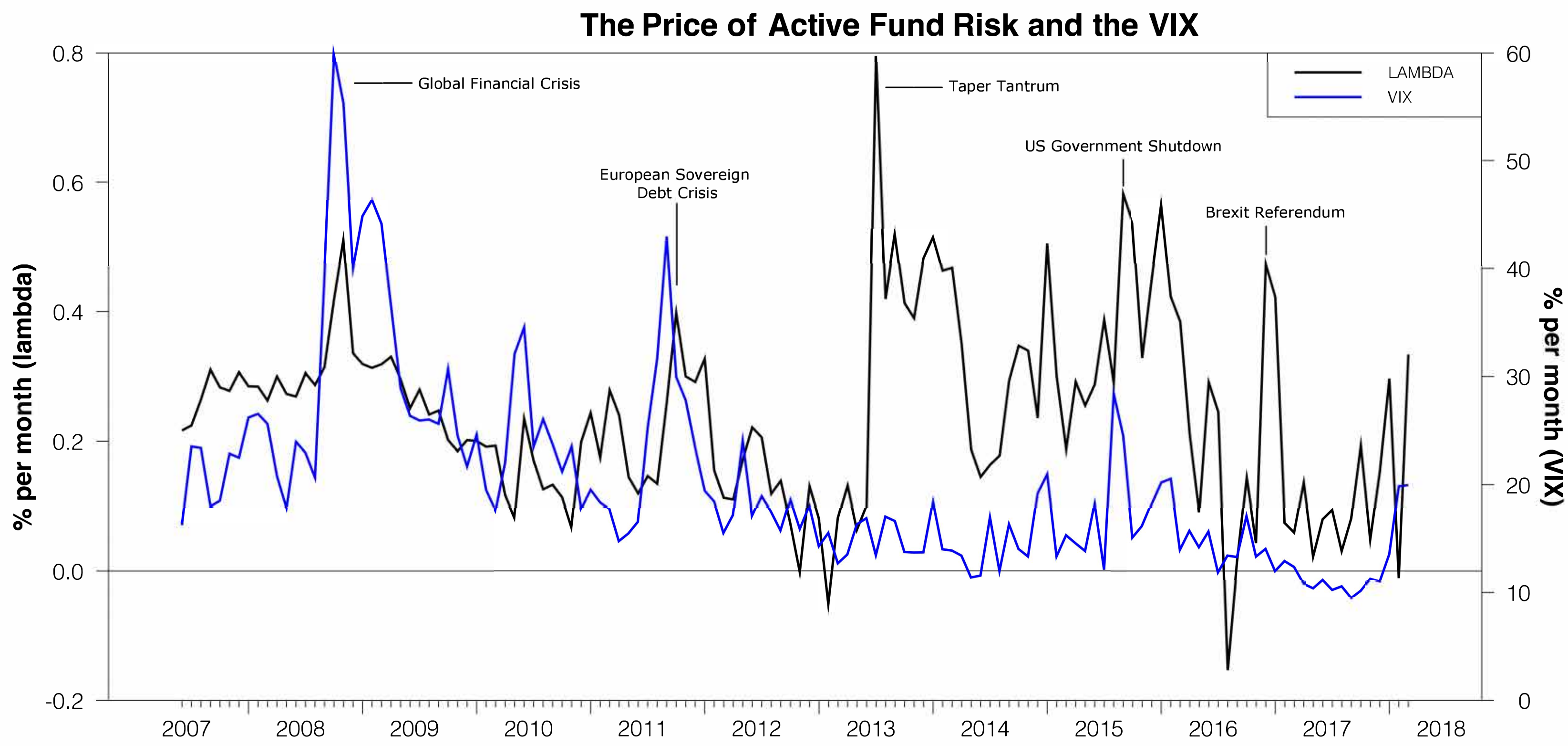
Table 4: This table reports the equally-weighted averages of selected macroeconomic and financial variables for countries included the most in the H and L portfolios over the sample period. Values for current account and foreign reserve are expressed as a percentage of GDP. FX rates are nominal bilateral exchange rates expressed as local currency for one US dollar (July 2007 = 100). Values in parentheses are serial correlation- and heteroskedasticity-adjusted standard errors. ***,**,* denote statistically significant at 1, 5 and 10 percent levels respectively.

	Current Account	Foreign Reserve	FX rate
Portfolio H	-1.98***	2.69***	140.29***
	(0.28)	(0.11)	(3.45)
Portfolio L	7.07***	7.59***	98.67***
	(0.52)	(0.22)	(0.96)
Portfolio H - Portfolio L	-9.04***	-4.90***	41.63***
	(0.45)	(0.23)	(6.80)

Table 5: This table reports the beta-premium sensitivities obtained from estimating equation (7) of the main text. Values in parentheses are serial correlation- and heteroskedasticity-adjusted standard errors.***,**,* denote statistically significant at 1, 5 and 10 percent levels respectively. See also notes to Tables 2 and 3.

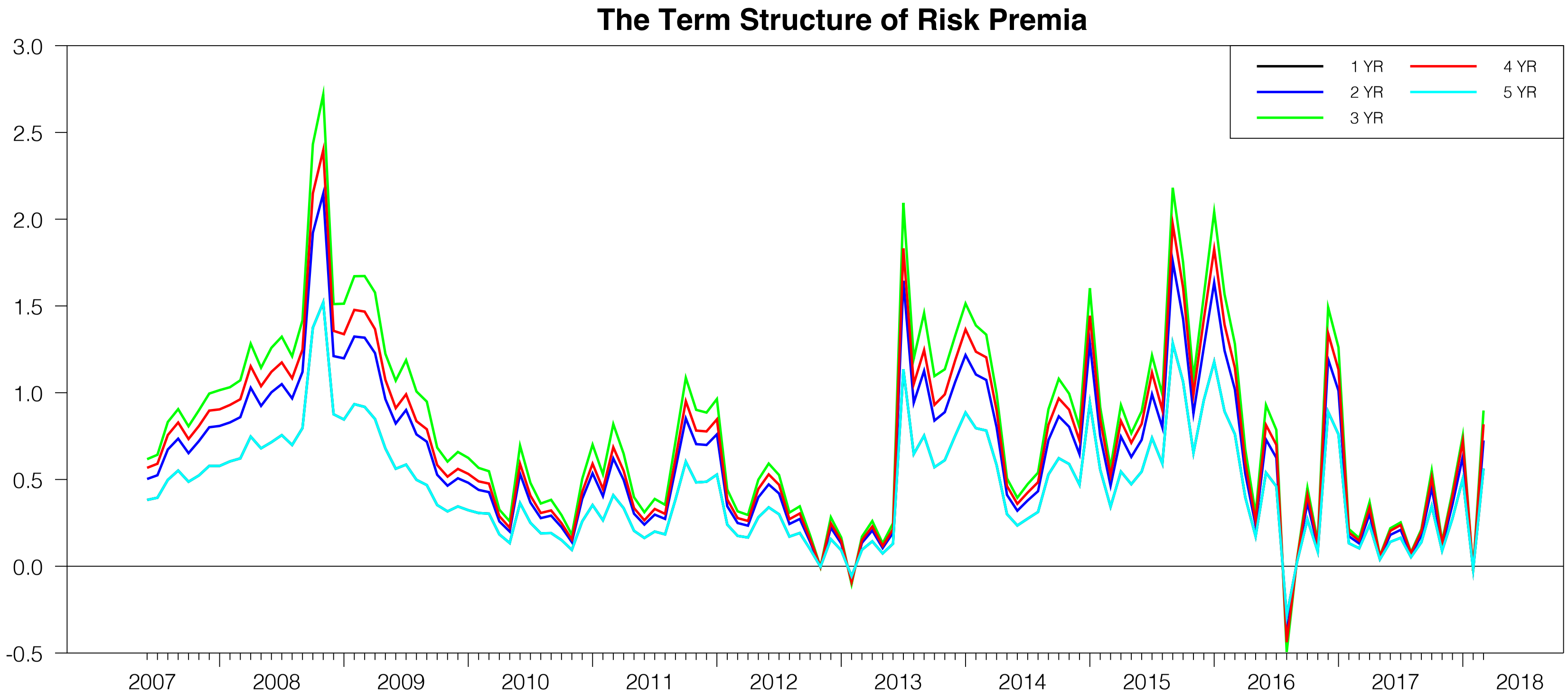
n=	**12**	**24**	**36**	**48**	**60**
$\widehat{\phi}_H^{(n)}$	1.170*	1.708**	2.156**	1.905**	1.033
	(0.62)	(0.87)	(1.11)	(0.97)	(0.87)
$\widehat{\phi}_L^{(n)}$	0.164	0.253	0.340	0.278	0.045
	(0.20)	(0.32)	(0.42)	(0.35)	(0.29)
$\widehat{\phi}_H^{(n)} - \widehat{\phi}_L^{(n)}$	1.007*	1.454**	1.816**	1.627**	0.988
	(0.55)	(0.73)	(0.91)	(0.82)	(0.79)

Figure 1



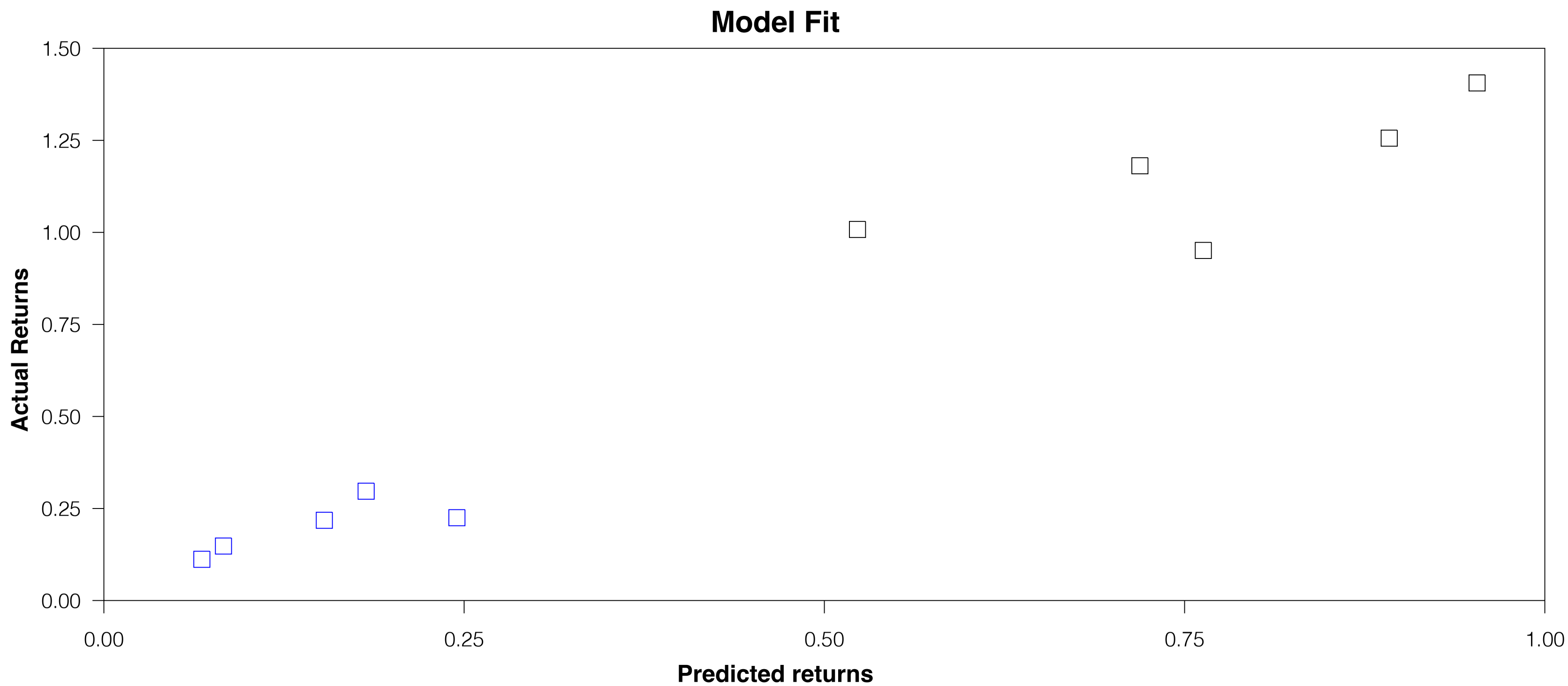
Note: The price of active fund risk is the estimate of λ_t as in equation (6) of the main text.

Figure 2



Note: Risk premia are computed as $(\widehat{\beta}_{H,t}^{A,(n)} - \widehat{\beta}_{L,t}^{A,(n)})\widehat{\lambda}_t$ for all maturities.

Figure 3



Note: Blue squares are for L portfolio and black squares are for H portfolio. If the model perfectly represent the data generating process of bond expected returns, the squares should align along a 45 degree line.