Stock Market Illiquidity, Funding Liquidity, and Bond Risk Premia*

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Abstract

In this paper, we study the link between government bonds and cross-section of stocks. We provide new evidence that links the stock market liquidity to sovereign bond risk premia. We find that the stock market illiquidity variable adds to the well established Cochrane-Piazzesi and Ludvigson-Ng factors. It explains 10%, 9%, 7%, and 7% of the one-year-ahead variation in the excess return for two-, three-, four-, and five-year bonds respectively and increases the adjusted R^2 by 3-6% across all maturities over Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009) factors. The effects are highly statistically and economically significant both in and out of sample. We find that our result is robust to and is not driven by information from open interest in the futures market, long-run inflation expectations, and dispersion in beliefs. We argue that stock market illiquidity is a timely variable that is associated with the state of funding liquidity.

Keywords: Stock market illiquidity; Bond risk premia; Funding liquidity; Flight-to-quality.

JEL Classification: G10; G20; G14.

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Introduction

Understanding the empirical relation between stock and bond markets is important for asset allocation, information transmission across markets, and studying the stability of financial markets to shocks. Recently, there is increasing interest in understanding the links between government bonds and the cross-section of stocks, see Baker and Wurgler (2012) and Koijen, Lustig, and Nieuwerburgh (2009).[1] In this paper, we provide new evidence that links the aggregate and the cross section of stock market liquidity to sovereign bond risk premia.

Business cycles and macroeconomic information are important determinants of the term structure of interest rates and bond risk premia. In addition, recent papers have shown that aggregate stock market illiquidity is a robust predictor of business cycles and macroeconomic information (e.g. Næs, Skjeltorp, and Ødegaard, 2011). Motivated by this empirical evidence, we examine whether aggregate stock market liquidity can be a factor that links bond and stock markets and explain U.S. Treasury bond risk premia. We use the Amihud (2002) illiquidity measure, the average illiquidity ratio across all stocks, to examine whether stock market illiquidity can predict excess bond returns.[2] We also use the difference between the aggregated illiquidity of large and small cap stocks as an alternative variable, and we find that it is an especially strong predictor of bond excess returns. Stock market illiquidity displays strong forecasting power for excess returns across bonds of *all* maturities. It explains up to 10%, 9%, 7%, and 7% of the one-year-ahead variation in the excess return for two-, three-, four-, and five-year bonds, respectively. The magnitude of the predictability that we find using aggregate stock market illiquidity is not only statistically but also economically significant. One standard deviation increase in the aggregate illiquidity of the stock market leads to an increase of 45 basis points in bond risk premia.

Our paper joins other empirical research documenting predictability in the excess returns of U.S. Treasury bonds. Cochrane and Piazzesi (2005) show that a linear combination of five forward spreads can forecast excess bond returns. Ludvigson and Ng (2009) and Cooper and Priestley (2009) find that macroeconomic variables contain information about future excess bond returns and argue that their findings are related to the premia demanded by investors due to macroeconomic uncertainty. Moreover, Joslin, Priebsch, and Singleton (2010) show

[1] Fama and French (1993) document the relation between yield curve variables and stock portfolios.
[2] This measure is the same used in Næs et al. (2011) and is kindly provided by Johannes Skjeltorp.

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the importance of real economic activity and inflation on market prices of level, slope, and curvature risks in the U.S. Treasury market.

Following the literature, we always condition on the well-established Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009) factors. While the Cochrane and Piazzesi (2005) factor subsumes variables like forward spreads, yield spreads, and yield factors, the Ludvigson and Ng (2009) factor focuses on factors outside the bond market and contains information from 132 measures of economic and financial activities, which include dividend yield, TED spread, credit spread, S&P500 returns. The single illiquidity variable contains additional information about bonds' expected returns that is not present in these factors, and it increases the adjusted R^2 by 3-6% across all bond maturities over the Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009) factors. In addition, stock market illiquidity has strong out-of-sample forecasting power for excess bond returns above the existing factors. Our results are robust to accounting for the small-sample properties of the data and to using different tests of forecasting accuracy. The in- and out-of-sample results remain quantitatively and qualitatively the same when we investigate the impact of stock illiquidity on monthly returns of portfolios of Treasury bills and bonds as in Duffee (2012). Furthermore, we find that our result is robust to and is not driven by information from open interest in the futures market (Hong and Yogo, 2012), long-run inflation expectations (Cieslak and Povala, 2011), and dispersion in beliefs (Buraschi and Whelan, 2012). The additional information of aggregate stock market illiquidity on bond risk premia for all maturities is remarkable and surprising.

There can be two potential explanations for our findings. First is aggregate stock market illiquidity acts as a proxy for bond market illiquidity, see Goyenko and Ukhov (2009). We control for bond market illiquidity in our predictive regressions and find that it does not explain bond risk premia above stock market illiquidity. In addition, the sheer magnitude of stock market illiquidity's economic significance, 45 annual basis points, is related to bond risk premia beyond the price of future bond liquidity and beyond systematic bond liquidity risk in the treasury market. For example, Goldreich, Hanke, and Nath (2005) find that the yield difference between on- and off-the-run securities is less than 2 basis points and show the existence of a price premium for liquidity in the U.S. treasury market. Li, Wang, Wu, and He (2009) focus on the pricing of systematic liquidity in the treasury market and find an annual premium of 9 basis points for a difference of 10 percentage points in systematic liquidity risk.

Second, stock market illiquidity can matter due to the funding illiquidity channel. Stock market illiquidity affects or is affected by the macro economy and investments in the real economy, as shown in the monetary model with liquidity of Kiyotaki and Moore (2008). In the model, investing entrepreneurs need to sell their holdings of liquid assets and equity to finance investments because of borrowing constraints. Thus a negative shock to asset resaleability (stock market liquidity) can reduce the amount of an entrepreneur's down payment, which will result in large and persistent reductions in investment, output, and employment. Anticipating higher market illiquidity, equity prices fall because entrepreneurs hold more liquid assets in their portfolios as they flee to liquidity. Eisfeldt (2005) also attempts to theoretically link endogenous liquidity and returns of risky assets and shows that low productivity leads to lower investment in risky assets and thus decreases liquidity.

We first investigate the plausibility of funding liquidity channel by using our illiquidity variable to forecast real investment growth. We find that stock market illiquidity has a positive relation with investment and can explain real investment growth up to four quarters ahead, consistent with predictions of Kiyotaki and Moore (2008) and Næs et al. (2011).

In a related paper, Brunnermeier and Pedersen (2009) argue that funding conditions are important drivers of market liquidity and that the liquidity spiral effects of funding and market liquidity can have an important impact on the real economy, as observed in the recent financial crisis. Hence, liquidity risk can amplify a small exogenous shock into a sizable shock and into an endogenous risk in the macro economy. They argue that financial institutions reduce liquidity provision from highly volatile securities with higher margins to less volatile stocks with lower margins as funding conditions deteriorates. This suggests that the market liquidity differential between high-volatility and low-volatility securities increases when funding liquidity is low. Brunnermeier and Pedersen (2009) predict that the deterioration of funding conditions and reduction in liquidity provision by speculators can lead to flight to quality episodes.

Consistent with the predictions of Brunnermeier and Pedersen (2009), the strong predictive ability of the difference between the aggregated illiquidity of large (less volatile stocks with lower margin) and small (more volatile stocks with high margin) cap stocks on bond premia supports the funding liquidity hypothesis. In addition, we also find that the liquidity differential between large and small stocks is highly correlated with various measures of funding liquidity such as the changes in aggregate repos (Adrian and Shin, 2010), difference in returns on the three-month commercial paper rate and three-month Treasury bill rate (Krishnamurthy, 2002; Gatev and Strahan, 2006; Hameed, Kang, and Viswanathan, 2010) and funding liquidity factor (Hu, Pan, and Wang, 2012).

To investigate if the liquidity differential is related to flight to quality, we use mutual fund flows as a measure of "flight-to-quality" following Longstaff (2004). We find that changes in stock market illiquidity are related to shifts of U.S. mutual fund flows from equity to money market mutual funds. An increase in illiquidity is positively correlated with flows into money market mutual funds and negatively correlated with flows to equity mutual funds, indicating its connection to flight to quality. In an alternative exercise, we find that stock market illiquidity explains and predicts changes in the average proportional holding of equities and bonds by balanced/hybrid mutual funds. Flight-to-quality episodes are associated with increases in the implied volatility index, and Bekaert, Hoerova, and Duca (2010) suggest that the implied volatility index is a proxy for risk aversion and market uncertainty. We find that stock market illiquidity is contemporaneously associated with and predictive of changes in the implied volatility index (VXO).

Fontaine and Garcia (2012) empirically show that funding liquidity conditions affect the term structure of U.S. sovereign bonds and bond risk premia using a liquidity factor extracted from an extended arbitrage-free Nelson Siegel term structure model. As the flight-to-quality and funding liquidity channel are not mutually exclusive, we study these channels jointly by including flight-to-quality (mutual fund flows and VXO) and funding liquidity (Fontaine and Garcia, 2012) variables into the excess bond return predicting equations. We find that the inclusion of stock market illiquidity and (Fontaine and Garcia, 2012) funding liquidity, subsume the information in all the flight-to-quality variables. The findings provide empirical evidence that supports the theoretical relation between funding and market illiquidity as well as their impact on asset risk premia. However, our results suggest that stock market illiquidity contains information of a different dimension from the existing flight-to-quality and funding liquidity variables, because the stock market illiquidity variable remains significant after controlling for VXO, mutual fund flows, and funding liquidity.

In summary, we document the link and a robust relation between the predictability of excess bond returns and the differential of stock market liquidity across stock portfolios. It appears that credit conditions in financial markets is the economic mechanism that drive the results.

1 Literature Review and Contribution

We contribute to the literature that relates cross sectional information from the equity to the bond market. Koijen et al. (2009) argue that the value premium reflects compensation for macroeconomic risk. They establish empirical and theoretical links among nominal bond risk premium, returns and dividend growth rates on value and growth stocks, and macroeconomic activity. Baker and Wurgler (2012) document that "bond-like" (large, low volatility, firms with mediocre growth opportunities) stocks comove more strongly with bonds than stocks of smaller, highly volatile, and firms with excellent growth opportunities. They find that excess returns on government bonds and on "bond-like" stocks are predictable by the same predictive variables and attribute the results to exposure to common real cash-flow shocks, investor sentiment, and time-varying risk premia. Differently from these papers, we provide new evidence that links aggregate market liquidity of large minus small stock portfolio to business cycle risk via the funding liquidity channel.

One important related paper is Fontaine and Garcia (2012). They argue that funding liquidity conditions affect the prices of U.S. sovereign bonds. Fontaine and Garcia (2012) use the price differentials of treasury securities with similar cash flows but different ages to construct a funding liquidity variable. Their results highlight the importance of the credit conditions for speculators in fixed-income markets. Differently from Fontaine and Garcia (2012) who use the lack of fixed income speculators' ability due to credit constraints to exploit mispricings in the Treasury market, we derive our funding liquidity measure from a different group of speculators who operate in the equity market. Our findings indicate that liquidity differentials across stocks contain a dimension of funding liquidity information not captured by the Fontaine and Garcia (2012) liquidity factor.

There might be other and better measures of funding liquidity, such as the changes in aggregate repos (Adrian and Shin, 2010), difference in returns on the three-month commercial paper rate and three-month Treasury bill rate (Krishnamurthy, 2002; Gatev and Strahan, 2006; Hameed et al., 2010)) and mispricing-based funding liquidity factor of (Fontaine and Garcia, 2012) and Hu et al. (2012). These measures, however, are proprietary data (Adrian and Shin, 2010) that are not available in many non-U.S. financial markets or require estimation of complex term structure models, such as an extended arbitrage-free Nelson Siegel Model, (Fontaine and Garcia, 2012). Even when available, the data do not cover very long periods of time. Our measure of funding liquidity is positively and highly correlated with many of the above measures and it is available for a long time-period, allowing for the construction of a long time series of funding liquidity.

Our paper also contributes to the recent literature on bond return predictability. The earlier literature relates excess bond returns to yield spreads and provides evidence that the n-year spread of the n-year forward rate and the one-year yield (Fama and Bliss, 1987) and the treasury yield spreads (Campbell and Shiller, 1991) can forecast excess bond returns. Extending the findings of Fama and Bliss (1987), Cochrane and Piazzesi (2005) find that a single factor constructed from a linear combination of five forward spreads predicts up to 44% of the variation in excess bond returns.[3]

The more recent literature on bond return predictability focuses on information from macroeconomic variables. Ludvigson and Ng (2009) and Cooper and Priestley (2009) show that macroeconomic variables predict excess bond returns through the cyclical nature of the risk premia. A series of recent papers by Chernov and Mueller (2012), Cieslak and Povala (2011), Joslin et al. (2010), Huang and Shi (2011), and Buraschi and Whelan (2012) support the findings on the relation of macroeconomic variables and business cycles with risk premia. Duffee (2011) also finds a latent component of bond risk premia that contains substantial information about expected future yields and is negatively correlated with aggregate economic activity. Cieslak and Povala (2011) argue that long-run inflation expectations contain important information about bond risk premia. Buraschi and Whelan (2012) study the link between macroeconomic disagreement and the bond market. They show that belief dispersion about the real economy, inflation, and yields predict excess bond returns. Mueller, Vedolin, and Zhou (2011) show that the market variance risk premium has strong predictive power at the one-month horizon, however the predictive power disappears for longer horizons (one year and above). These recent developments in the literature suggest the importance of considering factors outside bond yields in understanding the drivers behind term structure dynamics.

Our paper contributes to the existing bond risk premia literature by showing that stock market illiquidity contains information about future excess bond returns even after controlling

[3]However, Thornton and Valente (2012) find that one-year excess return forecasts using long-term forward rates do not add economic value relative to the expectations hypothesis. Duffee (2011) also reports that half of the variation in bond risk premia cannot be explained by the cross section of bond yields.

for information from bond yields, forward rates, macroeconomic, and dispersion in beliefs variables. Unlike these papers, we consider the role of aggregated stock market illiquidity motivated by the Næs et al. (2011)'s finding that stock market illiquidity is a robust predictor of business cycles. We go a step further by establishing that market illiquidity can affect bond risk premia via credit conditions of financial markets.

2 Econometric Framework of Bond Return Regressions

Let $p_t^{(n)}$ denote the log-price in year $t = 1, \ldots, T$ of an n-year zero-coupon bond. The log yield on this bond is defined as $y_t^{(n)} = -\frac{1}{n} p_t^{(n)}$. The log one-year forward rate at time t of a loan from time $t+n-1$ to $t+n$ is then defined by $f_t^{(n)} = p_t^{(n-1)} - p_t^{(n)}$. The log excess return of holding an n-year zero-coupon bond from time t to $t+1$ is given as $rx_{t+1}^{(n)} = p_{t+1}^{(n-1)} - p_t^{(n)} - y_t^{(1)}$. The predictable component in the excess bond return reflects a bond risk premium. Under the expectations hypothesis, there is no predictability in excess returns and hence the bond risk premium is constant. However, recent empirical evidence shows predictable variation in excess bond returns, which implies a time-varying bond risk premium.

We adopt the standard approach to uncover predictable variation in excess bond returns by regressing excess bond returns on a vector of predictor variables, $\boldsymbol{X}_t$:

$$rx_{t+1}^{(n)} = \beta_0 + \boldsymbol{\beta}_1' \boldsymbol{X}_t + \varepsilon_{t+1}^{(n)}. \tag{1}$$

To examine the link between bond risk premia and stock market illiquidity, we run regressions with different sets of predictor variables, including liquidity measures. We consider the predictor variables identified by Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009) to explore whether stock market illiquidity contains additional information over the existing factors in explaining bond excess returns.

Cochrane and Piazzesi (2005) regress excess returns of two- to five-year maturity bonds on a constant and five forward rates and find that a single tent-shaped linear combination of the five forward rates, the CP-factor, explains between 30% and 35% of the variation in excess bond returns. The CP-factor is constructed by pooling the regressions for the individual maturities:

$$\overline{rx}_{t+1} = \gamma_0^{CP} + \boldsymbol{\gamma}_1^{CP\prime} \boldsymbol{X}_t^{CP} + \bar{\varepsilon}_{t+1}^{CP}, \tag{2}$$

where $\overline{rx}_{t+1} = \frac{1}{4}\sum_{n=2}^{5} rx_{t+1}^{(n)}$ and $\boldsymbol{X}_t^{CP} = [y_t^{(1)}, f_t^{(2)}, \ldots, f_t^{(5)}]$. The CP-factor combines the information in all forward rates and is defined as $CP_t = \widehat{\gamma}_0^{CP} + \widehat{\boldsymbol{\gamma}}_1^{CP\prime}\boldsymbol{X}_t^{CP}$. We use both the five forward rates and the CP factor as predicting variables in the bond risk premia regressions.

Ludvigson and Ng (2009) examine the link between bond risk premia and macroeconomic fundamentals by regressing excess bond returns on several macro factors. Instead of selecting specific macro variables, they use dynamic factor analysis to extract nine macroeconomic factors from a panel of 132 measures of economic activity. These factors are used as predictor variables in bond excess return regressions. We control for the predictive information in macro variables by including the full set of nine macro factors identified Ludvigson and Ng (2009). In addition, we also combine the nine macro factors into a single forecasting factor by using the regression:

$$\overline{rx}_{t+1} = \gamma_0^{LN} + \boldsymbol{\gamma}_1^{LN\prime}\boldsymbol{X}_t^{LN} + \overline{\varepsilon}_{t+1}^{LN}, \tag{3}$$

where $\boldsymbol{X}_t^{LN} = [LNF_{1,t}, \ldots, LNF_{9,t}]$ contains the nine macro factors of Ludvigson and Ng (2009). We define the single forecasting factor, the LN-factor, as $LN_t = \widehat{\gamma}_0^{LN} + \widehat{\boldsymbol{\gamma}}_1^{LN\prime}\boldsymbol{X}_t^{LN}$.

Following the literature, each month we construct one-year-ahead bond excess returns, because a purely yearly sample would have too few observations. Thus, the bond return regressions are estimated over a sample of monthly data, which include overlapping one-year excess return observations. Overlapping data complicate regression inference because they lead to autocorrelated residuals. Following Cochrane and Piazzesi (2005), we compute standard errors using the Newey-West procedure with 18 lags to account for heteroscedasticity and autocorrelation in the residuals.

The Newey-West standard errors are based on asymptotic approximations that might be inadequate in finite samples. We, therefore, use a bootstrap analysis to check for the robustness of our inference in finite samples. In particular, we test for the significance of our variables of interest in the bond return regression (1) by constructing bootstrap samples for both $\boldsymbol{X}_t$ and $rx_{t+1}^{(n)}$. The bootstrap procedure is described in Appendix A.

2.1 Out-of-sample Forecasting

Out-of-sample forecasts are constructed by using a moving window of 15 years (i.e. 180 monthly observations). Using this window, we first estimate the Cochrane-Piazzesi and Ludvigson-Ng

(CP and LN hereafter) factors, in order to avoid including information not available at the time of the forecast to the econometrician. Next, we estimate the regressions over the sample window of 180 observations. We obtain forecasts of the one-year ahead excess returns from the estimated regression. For the next observation, the window is shifted one month ahead. So the first window runs from January 1964 to December 1978 and is used to forecast the excess bond return for the period January to December 1979. The second window runs from February 1964 to January 1979 and is used to forecast the excess bond return for the period February 1979 to January 1980.

Using the forecasts, we compute the one-step-ahead prediction errors that would prevail under two competing models and test which model makes larger errors on average. More specifically, we compare the out-of-sample forecasting ability of the model with liquidity variables as a predictor in addition to the CP and LN factors to the benchmark forecasting model that contains only the CP and LN factors.

We compare the prediction errors of two different forecasting models by the ratio of Root Mean Squared Errors (RMSEs), the Clark and West (2007) and the Giacomini and White (2006) tests for predictive ability. The Clark-West (CW) test considers the null hypothesis of equal predictive ability by comparing mean squared prediction errors of two forecasting methods, applied to nested models. We use the standard normal distribution to obtain approximate p-values for the CW test. The unconditional version of the Giacomini-White (GW) test is also a test of equal predictive ability that compares mean squared prediction errors. The test statistic of the GW test coincides with that of the Diebold and Mariano (1995) test, but the tests use different null hypotheses. The GW test explicitly accounts for parameter uncertainty in the formulation of the null hypothesis.

3 Data

Following the literature, we use end-of-month data on U.S. Treasury bonds from the Fama-Bliss data set available from the Center for Research in Security Prices (CRSP) to construct excess bond returns and forward rates. The data set contains constant-maturity yields for the one to five year maturities. The sample contains monthly data for the period January 1964 to December 2008. This is a longer sample compared to the one used by Cochrane and Piazzesi

(2005) and Ludvigson and Ng (2009) and includes the recent financial crisis. We construct annual returns by continuously compounding monthly return observations. Data on the macro factors of Ludvigson and Ng (2009) are obtained from the website of Sydney Ludvigson.[4]

3.1 Aggregate Stock Market Illiquidity Factor

In the literature, there are many different measures of liquidity constructed from daily and intraday data. Intraday data is only available starting from 1993. Given the need for a long time series in our analysis, we use measures that can be calculated using daily data. Goyenko, Holden, and Trzcinka (2009) show that low frequency measures of liquidity are good approximations for high frequency measures of spreads and price impact. In addition, we need to use variables that yield relatively stable measures of liquidity at the monthly level. The Lesmond, Ogden, and Trzcinka (1999) measure (LOT) and the Roll (1984) implicit spread estimator are very noisy and unreliable, when constructed using only a month of daily data. They are more appropriate for quarterly analysis.[5] Like Næs et al. (2011), we use the Amihud (2002) illiquidity ratio (*ILR*) which is provided by Johannes Skjeltorp. *ILR* is calculated as $\frac{1}{N}\sum_{t=1}^{N}(|r_t|/VOLUME_t)$, where $|r_t|$ is the daily absolute return, $VOLUME_t$ is the daily total dollar volume, and N is the number of trading days in a month. When *ILR* is large, market illiquidity is high.

ILR is calculated using stock prices, returns, and trading volume from CRSP. Only common shares listed on the NYSE are included. For each stock the ILR is calculated daily and averaged across the month for each stocks and then averaged across all securities to create a market-wide measure. Also, we use the difference between the ILR of small and large stocks, represented by the bottom and top quartile respectively, *ILRSMB*. The liquidity measures at the monthly level exhibit unit roots. We take the yearly change in log illiquidity to be consistent with the bond risk premia literature[6], i.e. for time t in months we define:

$D_{12}ILR_t = \log ILR_t - \log ILR_{t-12}$,

$D_{12}ILRSMB_t = (\log ILR_{small,t} - \log ILR_{large,t}) - (\log ILR_{small,t-12} - \log ILR_{large,t-12})$.

[4] `http://www.econ.nyu.edu/user/ludvigsons/`, as of April 15, 2011. See Ludvigson and Ng (2009) for details on the underlying macro series and the construction of the factors.

[5] In addition, Næs et al. (2011) show that the predictive ability of aggregate stock market illiquidity for macroeconomic variables is the same when using different measures of illiquidity using quarterly data.

[6] There are several ways to deal with non-stationarity and the method that we use is only one way to transform the data. We also use a trend and exponential smoothing to transform ILR and find similar results.

A positive change in *ILR* implies a decrease in liquidity. A positive change in *ILRSMB* implies an increasing gap between the liquidity of small and large stocks.

3.2 Preliminary Analysis

Table 1 presents the sample characteristics for all the variables and their correlations. The mean and median $D_{12}ILR$ are highly negative. This implies that stock market liquidity has improved on average over the sample period. The mean and median $D_{12}ILRSMB$ are positive, implying an increase in the liquidity gap between small and large stocks during the sample period. Large stocks have benefited more from overall liquidity improvements than small stocks.

Liquidity deterioration in the stock market is associated with positive bond premia. The correlation of the equally-weighted bond excess returns with stock market illiquidity factors is higher than with many of the other factors. Stock market illiquidity variables are positively correlated with all the forward rates and most of the Ludvigson and Ng factors. The correlations with these factors are not very large, implying that stock market illiquidity might have additional information to these variables already identified in the literature. Also, $D_{12}ILR$ and $D_{12}ILRSMB$ are highly correlated to each other.

Figure 1 presents the fluctuations in the equally-weighted bond excess returns one year ahead, the CP and LN factors, and the stock market illiquidity factors. The CP and LN factors co-move substantially with the average bond excess return. $D_{12}ILRSMB$ seems to move more in sync with the average bond excess return than $D_{12}ILR$.

4 Results

4.1 In-sample Predictions

Table 2 presents the results on the regression of the equally weighted bond premia on stock market illiquidity. For each regression, we report heteroskedasticity and serial-correlation robust p-values, bootstrapped p-values, the R^2, and the adjusted R^2. We use the Newey-West corrected standard errors for serial correlation with 18 lags following Cochrane and Piazzesi (2005). Both stock market illiquidity measures have a positive impact on excess bond returns, i.e., increasing illiquidity in the equity market leads to higher excess bond returns one year ahead. The impact of $D_{12}ILRSMB$ is much stronger than $D_{12}ILR$. $D_{12}ILRSMB$ explains

7% of the variation of yearly excess returns, while $D_{12}ILR$ explains 2% of the variation. When $D_{12}ILRSMB$ is large, investors may pull out of the smallest and least liquid stocks, causing the gap between the two to increase before recessions.

The explanatory power of the illiquidity variables alone is much smaller than that of the nine macro factors of Ludvigson and Ng and the forward rates of Cochrane and Piazzesi, which combined, explain 41% of the monthly variation in future bond excess returns. Nonetheless, stock market illiquidity variables add to the explanatory power of the previously used factors. When adding $D_{12}ILR$ to the macro factors and forward rates, the explanatory power increases by 1%. When adding $D_{12}ILRSMB$, the explanatory power increases by 4%. Both coefficients are highly statistically and economically significant. We find that one standard deviation change in $D_{12}ILRSMB$ increases expected excess returns by about 45 basis points.

In columns (14) and (16) of Table 2, we report regressions using the Ludvigson-Ng (LN) factor and Cochrane-Piazzesi (CP) factor, the linear combinations of the nine macro factors and the forward rates respectively. The results remain quantitatively similar when we apply these changes. We use the LN and CP factors for the rest of the analysis, because it provides a more compact representation of the results. The estimated coefficients for the liquidity variables are stable and always two standard deviations away from zero, as shown in Figure 2. The bootstrapped p-values do not lead to changes in our conclusions.

Table 3 reports results from the in-sample forecasting regression for two-, three-, four-, and five-year log excess bond returns. Here, we ask if stock market illiquidity has predictive power for excess bond returns for individual maturities conditional on previously used factors. As a benchmark, we report the regression specification that includes only the LN and CP factors. The results show that these factors are highly statistically significant, at the 5% level, and the adjusted R^2 for next year's two-, three-, four-, and five-year log excess bond returns are 38%, 39%, 41%, and 38% respectively. Our results are extremely close to those reported in Table 2 of Ludvigson and Ng (2009).[7] More importantly, the stock market illiquidity variables are still statistically and economically significant with the inclusion of LN and CP factors across all maturities. The adjusted R^2s with $D_{12}ILRSMB$, increase to 44%, 44%, 45%, and 42% for two-, three-, four-, and five-year log excess bond returns, respectively. The encouraging 3-6%

[7] This alleviates any potential concerns about the use of the combined factors LN and CP and the longer sample.

increase in R^2 with a ***single*** return forecasting factor for all maturities suggests that stock market illiquidity variables contain additional information not encompassed in the LN and CP factors. We also notice that the estimated coefficients for illiquidity monotonically increase with bond maturity. The estimated coefficient for the five-year log excess bond returns regression is 0.024, more than twice the magnitude of the estimated coefficient for the two-year note. The bootstrapped p-values do not lead to changes in our conclusions.

4.2 Out-of-Sample Prediction

Table 4 presents the forecasting results for the equally-weighted portfolio and for the two-, three-, four-, and five-year excess bond returns. We present the RMSE, the RMSE ratio, the Clark and West (2007) and the Giacomini and White (2006) test statistics, and their p-values. The benchmark model only includes the LN and CP factors. The forecasting models that include the stock illiquidity factors $D_{12}ILR$ and $D_{12}ILRSMB$ exhibit lower RMSEs than the benchmark model, i.e., RMSE Ratios less than 1. The model with $D_{12}ILRSMB$ performs the best. The stock market illiquidity variables appear to add the most to the forecasting power for bonds with shorter maturities, i.e. the two and three-year excess returns. This is in line with the in-sample results, where the liquidity variables lead to larger increases in R^2 for bonds with shorter maturities.

The difference in out-of-sample forecasting power between the models with the illiquidity variables and the benchmark model with the CP and LN factors is statistically significant. The Clark and West (2007) test shows that the model with stock market illiquidity has superior predictive ability compared to the benchmark model. The $D_{12}ILRSMB$ factor appears to have stronger predictive power than $D_{12}ILR$. These results are confirmed by the stricter Giacomini and White (2006) test results. We regard this result as very good, since the CP and LN factors are very strong and encompass a very large variety of information, thus are quite hard to beat out-of-sample. Consistent with Næs et al. (2011) and Amihud (2002), we find that the difference in liquidity between small and large stocks is more informative both in the in- and out-of-sample analysis. Thus, we use mainly $D_{12}ILRSMB$ for the rest of our analysis and exhibit results for both measures where space permits.

4.3 Yield Curve Analysis

The focus on bond risk premia only provides a partial perspective on the behavior of the yield curve. In this section we take a more comprehensive perspective on the yield curve and investigate how aggregate stock market illiquidity affects the yield curve. We follow Cochrane and Piazzesi (2005) and construct a simple arbitrage-free yield curve model that reproduces the basic annual bond return regressions.

We model the yearly dynamics of the joint vector $\boldsymbol{x}_t = (y_t^{(1)}, f_t^{(2)}, f_t^{(3)}, f_t^{(4)}, f_t^{(5)}, LN_t, D_{12}ILRSMB_t)'$ of forward rates, the LN factor, and stock market illiquidity by a first-order VAR model:

$$\boldsymbol{x}_{t+1} = \boldsymbol{a}_x + \boldsymbol{B}_x \boldsymbol{x}_t + \boldsymbol{\nu}_{x,t+1}, \qquad \text{where } \boldsymbol{\nu}_{x,t} \sim IIDN(\boldsymbol{0}, \boldsymbol{\Sigma}_x). \tag{4}$$

The log excess bond return on a n-year zero-coupon bond is given by:

$$rx_{t+1}^{(n)} = -\sum_{i=1}^{n-1} f_{t+1}^{(i)} + \sum_{i=2}^{n} f_t^{(i)}$$

and is a linear function of forward rates and lagged forward rates. Hence, we apply a non-singular linear transformation to the VAR model in equation (4) to obtain an equivalent system of regression equations expressed in terms of excess bond returns:

$$\boldsymbol{z}_{t+1} = \boldsymbol{a}_z + \boldsymbol{B}_z \boldsymbol{x}_t + \boldsymbol{\nu}_{z,t+1}, \qquad \text{where } \boldsymbol{\nu}_{z,t} \sim IIDN(\boldsymbol{0}, \boldsymbol{\Sigma}_z), \tag{5}$$

where $\boldsymbol{z}_t = (rx_t^{(2)}, rx_t^{(3)}, rx_t^{(4)}, rx_t^{(5)}, f_t^{(5)}, LN_t, D_{12}ILRSMB_t)'$. The VAR and the system of equations are equivalent with a unique mapping between the parameters $\boldsymbol{a}_x$, $\boldsymbol{B}_x$, $\boldsymbol{\Sigma}_x$ and $\boldsymbol{a}_z$, $\boldsymbol{B}_z$, $\boldsymbol{\Sigma}_z$ as described in Appendix B. The first four regression equations of this system are the bond return regressions, hence the VAR model can exactly reproduce them. The full yield model complements these bond return regressions with a dynamic regression equation for the longest forward rate, the LN factor, and stock market illiquidity.

The VAR model provides a statistical representation of the joint dynamics of the yield curve, the LN factor, and stock market illiquidity. An important question is whether there is an economic model that rationalizes these dynamics. Following Cochrane and Piazzesi (2005), the model is consistent with a discrete-time Gaussian affine asset pricing model with state variables $\boldsymbol{x}_t$. We start by directly specifying the nominal stochastic discount factor as:

$$M_{t+1} = \exp\{-y_t^{(1)} - \tfrac{1}{2}\boldsymbol{\lambda}_t{}'\boldsymbol{\Sigma}_\nu\boldsymbol{\lambda}_t - \boldsymbol{\lambda}_t{}'\boldsymbol{\nu}_{t+1}\} \tag{6}$$

where the one-period yield $y_t^{(1)}$ and the market prices of risk $\boldsymbol{\lambda}_t$ are linear in the state variables:

$$y_t^{(1)} = \delta_0 + \boldsymbol{\delta}_1{}'\boldsymbol{x}_t \tag{7}$$

$$\boldsymbol{\lambda}_t = \boldsymbol{\lambda}_0 + \boldsymbol{\Lambda}_1\boldsymbol{x}_t. \tag{8}$$

Bonds are priced according to:

$$p_t^{(n)} = \log \mathrm{E}_t(M_{t+1}\cdots M_{t+n}). \tag{9}$$

The objective is to find a specification of the stochastic discount factor that reproduces the yield curve dynamics implied by the VAR model. Since the state vector $\boldsymbol{x}_t$ contains forward rates, it is important that the model is self-consistent in that it reproduces these forward rates exactly. Self-consistency imposes conditions on the parameters $\delta_0, \boldsymbol{\delta}_1, \lambda_0, \boldsymbol{\Lambda}_1$ of the stochastic discount factor as described in Appendix B. However, the stochastic discount factor is not uniquely defined and in fact multiple different stochastic discount factors are consistent with the VAR model. Fortunately, this indeterminacy does not affect our analysis since we restrict our analysis only to forward rates contained in $\boldsymbol{x}_t$, which are exactly reproduced by all consistent stochastic discount factors.

Results

The VAR model is estimated equation by equation using OLS. The model describes yearly dynamics, which are estimated from monthly data with overlapping observations, using Newey-West standard errors. Table 5 shows the estimation results of the VAR model in equation (4) and the implied estimates for the bond return regressions in equation (5). The implied estimates of the bond return regression in columns (9)-(12) in Panel A of Table 5 closely match the bond return regressions in Table 3. Differences are mainly due to directly including individual forward rates instead of the CP factor. Results in Panel B show that innovations in illiquidity exhibit a weak negative correlation with innovations in forward rates.

The VAR can be used to derive impulse response functions to examine the impact of a shock to aggregate stock market illiquidity on the yield curve. The innovations in Equation (4) are correlated and have to be orthogonalized to define meaningful shocks. We orthogonalize the innovations by using a Choleski decomposition of $\boldsymbol{\Sigma}_\nu$ based on a causal ordering from the LN factor to aggregate stock market illiquidity to the yield curve. Hence, a shock to aggregate stock market illiquidity is defined as orthogonal to a macro shock to the LN factor. The illiquidity shock can be contemporaneously correlated with the yield curve, which allows the illiquidity variable to explain part of the cross section of forward rates.

Figure 3 shows the response of the yield curve to a positive one-standard-deviation shock in aggregate stock market illiquidity. The yield curve is contemporaneously not affected by the shock. The one-year yield drops by about 5 basis points and longer rates drop even less. The illiquidity variable only has a marginal effect in explaining the current yield curve and may act as a “hidden factor” to the yield curve (Duffee, 2011). However, the shock has a strong negative effect on the yield curve after one year. The one-year yield declines by over 40 basis points while longer yields drop by more than 25 basis points. This decrease in yields implies an appreciation in bond prices generating a positive excess bond return. For subsequent years the effect gradually dies out.

The yield on a long-term bond equals the average expected short-term yields over the life of the bond plus a risk premium. Hence, we can decompose the yield on a long-term bond in two parts: expectations and risk premium:

$$y_t^{(n)} = \underbrace{\frac{1}{n} E_t(y_t^{(1)} + \ldots + y_{t+n-1}^{(1)})}_{\text{expectations part}} + \underbrace{tp_t^{(n)}}_{\text{risk premium}} .$$

The expectations part can be obtained directly from the VAR model and hence the impulse response function for a yield can be decomposed as well. Figure 4 plots the impulse response function to a shock in illiquidity for the five-year yield and its decomposition. As before, the yield is marginally affected contemporaneously by the shock. However, in the decomposition, the expectations part shows a strong negative effect, which is compensated by a strong positive effect on the risk premium. The effect on the risk premium disappears in subsequent periods, while the effect on expectations slowly decays, such that the net effect on the yield is negative.

5 Robustness

5.1 Monthly Bond Portfolio Returns

Ferson, Sarkissian, and Simin (2003) highlight the importance of addressing spurious regression bias in predictive regressions with persistent variables. Because the overlapping scheme we adopt in the bond return regressions in Section 4 might induce strong autocorrelation, we investigate the validity and robustness of our results using monthly returns for portfolios of Treasury bills and bonds, following Duffee (2012). We use CRSP bond portfolio returns with maturities up to one year, between one and two years, two and three years, three and four years, four and five years, and five and ten years. Excess returns are obtained by subtracting the 1-month T-bill rate from the portfolio returns. While this is different from Cochrane and Piazzesi (2005) and our earlier exercise in studying annual returns, Duffee (2012) argues that predicting monthly excess returns of these bond portfolios provides an alternative test to the statistical significance of predictive variables.

We repeat the analysis in Section 4 using monthly bond portfolio returns as the dependent variable.[8] We re-estimate the CP and LN factors using the same methodology as in equations 2 and 3 using the equally-weighted monthly bond portfolio return as the dependent variable and create two new variables: *CPBP* and *LNBP*. These two factors explain almost the same amount of variation in the bond portfolio returns as the individual macro factors and forward rates. We use the *CPBP* and *LNBP* factors for the remaining in-sample and out-of-sample analysis.

Table 6 presents the results for the regression of the equally-weighted bond portfolio returns equivalent to Table 2, i.e. for time t in months:

$$\overline{rx}_{m,t} = \theta_0 + \boldsymbol{\theta}_1' \boldsymbol{X}_t + \overline{\varepsilon}_{m,t}, \tag{10}$$

where $\overline{rx}_m$ is the equally-weighted monthly bond portfolio return. As before, there is a positive relation between the illiquidity variables and bond excess returns. Stock market illiquidity

[8] We first run a regression of the monthly equally-weighted bond portfolio returns on the nine macro factors of Ludvigson and Ng and the forward rates of Cochrane and Piazzesi, presented in Table A1 in the Appendix. These variables explain 14% of the variation in average portfolio returns. As in previous analysis, we also use the combined CP and LN factors described in Section 2. The combined factors perform poorly compared to the individual factors. This is not surprising because they were constructed using the annual excess bond returns.

variables are highly statistically significant, and they explain 2% of the monthly variation in bond portfolio excess returns. Economically, an increase by one standard deviation in $D_{12}ILRSMB$ increases monthly bond excess returns by 12 basis points. The results are equally strong for bond portfolio returns for all maturities, see Table 7.

Table 8 presents the out-of-sample forecasting results for the monthly equally weighted bond portfolio and for six individual monthly bond portfolio excess returns. The RMSE ratio shows that the forecasting models that include the stock market illiquidity factors $D_{12}ILR$ and $D_{12}ILRSMB$ exhibit lower root mean squared errors than the benchmark model. The stock market illiquidity variables appear to add the most to the forecasting power for bonds with shorter maturities, i.e. the <1 year to 2-3 year excess returns. This is in line with the in-sample results, where the liquidity variables lead to larger increases in R^2 for bonds with shorter maturities, and the out-of-sample results for the annual returns in Section 4.2. The difference in the out-of-sample forecasting power between the models with the liquidity variables and the benchmark model with the CPBP and LNBP factors is statistically significant using both the Clark and West (2007) and the Giacomini and White (2006) tests. Overall, these results reflect the robustness of stock market illiquidity as a predictive variable for excess bond returns.

5.2 Long-run Inflation Expectations and Macroeconomic Disagreement

Cieslak and Povala (2011) argue the importance of accounting for long-run inflation expectations when considering excess bond return predictability. They decompose yields into long-horizon expected inflation and maturity-related cycles and use the cycles to construct a return forecasting factor similar to Cochrane and Piazzesi (2005). Following their work, we construct the Cieslak-Povala factor. Buraschi and Whelan (2012) show that belief dispersion regarding the real economy, inflation, and yields predict excess bond returns. To investigate if the stock market illiquidity variable is capturing belief dispersion, we construct expectation dispersion measures for one-quarter and one-year ahead expectations for: real GDP (*RGDP 1Q, RGDP 1Y*), industrial production growth (*INDPROD 1Q, INDPROD 1Y*), GDP deflator (*GDP Deflator 1Q, GDP Deflator 1Y*), CPI (*CPI 1Q, CPI 1Y*), and the difference in forecasts for the 3-month Treasury bill and 10-year note rates (*Tbill-Notes 1Q, Tbill-Notes 1Y*). These dispersion measures are collected from the widely-used and publicly available Survey of Professional

Forecasters (SPF) data provided by the Philadelphia Fed.[9]

We include the dispersion in beliefs variables and the Cieslak-Povala factor in the bond premia regression together with CP, LN, and $D_{12}ILRSMB$. Table A2 shows that the illiquidity variable remains highly statistically and economically significant, and it increases the adjusted R^2 by 4-5% over other variables. The results suggest that the illiquidity variable is not capturing information about long-run inflation expectations and dispersion in beliefs.

5.3 Futures Market

In a recent paper, Hong and Yogo (2012) show that not only futures prices but also open interest in the futures market are important indicators of future economic activity and can predict equity, bond, and currency returns. In order to understand whether stock market illiquidity is capturing information already in the futures market, we estimate contemporaneous and lagged regressions of illiquidity and futures returns and futures open interest, as in Hong and Yogo (2012).[10] The results in Table A3 in the Appendix show that stock market illiquidity is not associated either contemporaneously or with a lag to futures market information. In most specifications the model p-value is higher than 10%, suggesting that these are inadequate variables for explaining stock market illiquidity. In further robustness analysis in Panel E, we include the Hong and Yogo (2012) variables in the bond premia regression together with CN, LN, and $D_{12}ILRSMB$. The illiquidity variable remains highly statistically and economically significant.

5.4 Market-wide Private Information

Albuquerque et al. (2008) build a model where they separate firm specific and market-wide private information and liquidity trades. This leads to a generalized version of the Easley et al. (1996) model, which allows for trading in multiple stocks and for two reasons: firm-specific and market-wide information. They construct market-wide private information (MPI) from the order flow for five industries which have substantial exports and imports: Primary Smelting and Refining of Nonferrous Metal (MPI1), Oil and Gas Field Machinery and Equipment

[9]The data is available at http://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/. The SPF survey is conducted quarterly. To obtain monthly data, we linearly interpolate between quarterly observations following Cieslak and Povala (2011) and Kiley (2008).

[10]The data is available from https://sites.google.com/site/motohiroyogo/home/publications.

Manufacturing (MPI2), Aircraft Manufacturing (MPI3), Aircraft Engine and Engine Parts Manufacturing (MPI4), and Other Aircraft Parts and Auxiliary Equipment Manufacturing (MPI5). All series start in January 1993, but their ending dates vary. Series MPI1 ends in December 2002, series MPI2 ends in June 2002, the series for MPI3 and MPI4 end in December 1999 and December 2000 respectively, and MPI5 ends in February 2003. The series for MPI3 and MPI4 are too short to estimate the model with Newey-West standard errors with 18 lags, therefore we only analyze MPI1, MPI2, and MPI5.

The results in Table A4 show that market-wide private information variables predict future excess bond returns, consistent with the story in Albuquerque et al. (2008). Nonetheless, the addition of this variable does not affect the predictive power of stock market illiquidity. If anything, the magnitude of the impact of stock market illiquidity increases with the addition of the market-wide private information variable. Thus, we conclude that our variables are not capturing market-wide private information.

6 Why Does Market Liquidity Matter?

In the introduction, we argue that stock market illiquidity could be related to bond excess returns via bond liquidity and funding liquidity. In this section we investigate each of these explanations.

6.1 Bond Market Liquidity

One important determinant of bond risk premia is the liquidity of the Treasury market itself. Following Fleming (2003), Goyenko and Ukhov (2009), and Goyenko, Subrahmanyam, and Ukhov (2011), we use the standard measures of liquidity of the treasury market: relative quoted bid-ask spread. The quoted bid and ask prices are from the daily Treasury Quotes file in CRSP from January 1964 to December 2007. The file includes Treasury fixed income securities of 3 and 6 months and 1, 2, 3, 5, 7, 10, 20, and 30 years to maturity. Once issued, the security is considered as on-the-run and the older issues are off-the-run. We use the daily data for on-the-run treasuries to calculate monthly average bid-ask spreads for bonds with two to five year maturity. Then construct the equally-weighted spread from the 2 to 5 year bonds to match the equally-weighted risk premium.

The bond liquidity series exhibits a unit root, therefore we take the yearly log difference in the same way as for the stock market illiquidity. The results in Table 9 show that bond market illiquidity is not significant at the conventional 10% significance level. The statistical and economic significance of stock market illiquidity is not affected by the introduction of bond market illiquidity.[11]

6.2 Funding Liquidity Hypothesis

To test the funding liquidity hypothesis, we first document the correlation between cross sectional differential of market illiquidity and various measures of funding liquidity. then, motivated by Kiyotaki and Moore (2008)'s prediction, we study the predictive ability of market liquidity on real investment growth. Given Brunnermeier and Pedersen (2009)'s prediction that the deterioration of funding condition and reduction in liquidity provision by speculators can lead to flight-to-quality episodes, we study how changes in stock market liquidity are related to U.S. mutual fund flows and implied volatility as a measure of "flight-to-quality". Finally, we include the price-based measure of Fontaine and Garcia (2012) and all "flight-to-quality" measures into our predictive regression to investigate if cross-sectional liquidity differentials contain information about a different dimension of funding liquidity.

Stock Illiquidity and Other Funding Liquidity Measures

We use four funding liquidity measures to capture the tightness of capital in financial markets. Adrian and Shin (2009) suggest that market-based liabilities such as repos and commercial papers are good indicators of credit conditions that influence the economy. In particular, Adrian and Shin (2010) show that changes in aggregate intermediary balance sheets are related to funding liquidity as financial intermediaries adjust their leverage through repos. Therefore, we use the level of aggregate repos as the first measure of funding constraints.[12] A decline in aggregated primary dealer repos position is associated with an increase in funding constraints.

[11]Unfortunately, the CRSP Treasury bid-ask spread data is of poor quality for more recent years. For the period after 1994, there is almost no variation in the bid-ask spread of any of these securities. Michael Fleming at the New York Fed has collected information on the bid-ask spread of 3 and 6-month bills from GovPX, an electronic platform where treasuries were heavily traded in the period 1994-2004. We use his measure of bid-ask spreads to amend the liquidity measure from CRSP, by replacing the CRSP Treasury bills bid-ask spreads with the GovPX bid-ask spread for the period August 1994-December 2004. The results remain unchanged.

[12]We are thankful to Tobias Adrian for sharing the data on the primary dealer repo positions from July 1994 to June 2012 compiled by the Federal Reserve Bank of New York.

Krishnamurthy (2002), Gatev and Strahan (2006), and Hameed et al. (2010) argue that changes in the difference between commercial paper and Treasury bill rates capture intermediaries willingness to provide liquidity. Following Hameed et al. (2010), we use the monthly spread in commercial paper (CP spread), measured as the difference of the three-month commercial paper rate and three-month Treasury bill rate as the second measure of funding liquidity. An increase in the CP spread is associated with an increase in funding constraint.[13]

We use Fontaine and Garcia (2012)'s liquidity factor as the third measure.[14] Fontaine and Garcia (2012) measure the value of funding liquidity based on the mispricing of bonds with similar characteristics but different ages. They argue that funding constraints of intermediaries hinder speculators' ability to exploit such arbitrage opportunities. Fontaine and Garcia (2012) suggest that the value of their liquidity factor is low when there is ample supply of funds to intermediaries.

Finally, we also use the illiquidity measure of Hu et al. (2012) which exploits the connection between the amount of arbitrage capital in the market and observed price deviations in U.S. Treasury bonds. The measure is constructed using yield errors or differences between observed market yields and the model-implied yields based on Svensson (1994).[15] Thus, the value of Hu et al. (2012)'s illiquidity measure is high when funding constraints are high.

Table 10 shows that aggregate illiquidity and cross sectional illiquidity differential are strongly correlated to various measures of funding liquidity. The correlation with the aggregate primary dealer repo positions is negative and highly significant. When the stock market is illiquid or when there is a large illiquidity differential between large and small stocks, the level of aggregate repo position is low, which suggests the presence of high funding constraints. The relation between stock illiquidity and funding liquidity is further supported by the positive correlation of of 0.38 and 0.61 between stock illiquidity and the CP spread and Hu et al. (2012) illiquidity measures, respectively. When there is large capital constraints in the funding market, which results in an increase of CP spread and larger mispricing in the treasury market, the aggregate stock market illiquidity and the cross-sectional illiquidity difference are also

[13]The data from April 1971 to June 2012 is downloaded from the Federal Reserve website at `www.federalreserve.gov`.

[14]The Fontaine and Garcia (2012) liquidity data from December 1985 to June 2012 is downloaded from Jean-Sébastien Fontaine's website at `http://jean-sebastienfontaine.com/wp-content`.

[15]The Hu et al. (2012) liquidity data from January 1987 to December 2011 is downloaded from Jun Pan website at `http://www.mit.edu/~junpan/`.

high. These results provide further support to the funding liquidity hypothesis. Interestingly, we do not find any statistically significant relation with Fontaine and Garcia (2012)'s value of funding liquidity. Fontaine and Garcia (2012) may be capturing a different dimension of funding liquidity.

Illiquidity and Investments

Given that the monetary model with credit constraints and market liquidity of Kiyotaki and Moore (2008) predicts that more illiquidity will lead to lower investments, an alternative way to test the funding liquidity hypothesis is to investigate the relation between market liquidity and real investments. For our results to be driven by the funding liquidity channel, we expect stock market liquidity to be able to predict real investment growth. Our proxy for investment is real private fixed investment, a component of GDP, provided by the Bureau of Economic Analysis, as in Næs et al. (2011). Table 11 presents the quarterly regressions of real private fixed investment growth on lags of stock market illiquidity. From the univariate regressions in Panel A, it is noticeable that stock market illiquidity can explain real private fixed investment growth up to four quarters ahead. A decrease in liquidity by 1% causes a decrease in investment by 0.02% in the next quarter, which means roughly $1 billion for our sample period. The explanatory power of illiquidity is very high in the univariate regressions and even higher in the multivariate regressions, explaining between 16-21% of the variation in investment growth. Consistent with Kiyotaki and Moore (2008), results from Table 11 show that aggregate and cross-sectional differential of liquidity contain leading information about future investment growth and provides empirical support of the funding liquidity hypothesis.

Stock Market Illiquidity and Flight to Quality

Brunnermeier and Pedersen (2009) argue that a deterioration of credit conditions and a reduction in liquidity provision by speculators will lead to flight-to-quality episodes. Under these conditions, financial institutions will reduce liquidity provision from highly volatile securities with higher margins to less volatile stocks with lower margins. Thus, the funding liquidity hypothesis suggests that bigger cross-sectional liquidity differential should be positively related to flight to quality.[16]

Following Longstaff (2004), we first investigate the relation between stock market illiquidity and investors' shift in portfolios towards the U.S. sovereign bond market using aggregated net equity and money market mutual fund flows. Longstaff (2004) argues that money market mutual funds are short-term nearly riskless investments where investors allocate their funds during heightened market uncertainty, because their value is less likely to be affected by market turbulence, while net equity mutual fund flows capture portfolio shifts of confident investors into equity mutual funds during good economic conditions. Consistent with Longstaff (2004), we view the outflow from equity and inflow into money market mutual funds as flight-to-quality.

We use aggregate mutual fund flow data from the Investment Company Institute (ICI) from January 1984 to June 2010, which is the standard data set in this literature. ICI collects monthly sales, asset values, and redemptions by fund for 98 percent of the U.S. mutual fund industry. Sales and redemptions are actual cash flows that enter or exit a fund family, while "exchanges in" and "exchanges out" are transfers between different funds in the same fund family. We construct net exchanges flow variables as (exchange in) - (exchange out), see Ben-Rephael, Kandel, and Wohl (2012).[17] Net exchange flows capture portfolio shifts among different categories of funds, thus are more appropriate to capture flight to quality, while net sales and redemptions are likely to be influenced by long-term savings and withdrawals. The ICI categorizes mutual funds into the following groups: equity, bond (municipal and taxable), hybrid, and money market (tax exempt and taxable) funds. Following Warther (1995), we standardize net exchange flows by lagged total market capitalization to control for time series variation in flow magnitude resulting from price appreciations and market growth.[18]

We start our analysis of flight-to-quality by examining the correlation structure of fund flows. Bond funds consist of corporate and sovereign bonds, thus using these flows makes it difficult to investigate the flight-to-quality hypothesis, which relates equities and treasury bonds. Money market flows include only funds into short term bonds and are more appropriate

[16]Beber et al. (2009) emphasize the importance of flight-to-liquidity and flight-to-quality as avenues to better understand sources of risk premia in sovereign bond markets. Baele et al. (2010) find stock and bond illiquidity factors to be useful in explaining stock and bond return co-movements and suggest that these factors maybe correlated with "flight-to-safety" effects.

[17]An alternative way to calculate flows is: (sales-redemptions+(exchange in - exchange out)). The results using both methods are qualitatively similar.

[18]Normalizing fund flows with fund assets rather than total market value does not quantitatively change our results. Results are available from the authors upon request.

to measure flight-to-quality. Figure 5 shows the monthly net exchange equity and taxable money market flows. There is an extremely strong negative relation between them, especially during periods of uncertainty. Panel A of Table A5 in the Appendix shows the correlations among U.S. mutual funds net exchange flows. Flows into equity mutual funds are positively correlated with flows to hybrid and municipal bond funds. This is not surprising, as hybrid portfolios are composed of a mix of stocks and bonds. More interestingly, there is a highly negative correlation between equity and money market net exchange flows.

Following Chordia et al. (2005), we investigate fund flows correlation during non-crisis and crisis periods. We identify five crisis periods in the sample: Black Monday (October 19, 1987 - March 31, 1988), Asian financial crisis (October 1, 1997 - January 31, 1998), Russian Default (July 1, 1998 - December 12, 1998), Dot-com bubble (February 1, 2000 - March 31, 2001), and Credit crisis (July 1, 2007 - present). Panel A of Table A5 shows that net flows of riskier funds like equity, hybrid, and bond funds become more negatively correlated to money market funds during crises. The negative correlation between equity and money market net exchange flows -0.83, is even higher during crisis periods, -0.89.

Panel A of Table 12 shows the correlations between mutual fund net exchange flows and the cross-sectional differential of stock market illiquidity, both monthly and yearly changes. The stock market illiquidity differential is positively correlated up to 30% with flows into money market funds, i.e., a reduction in liquidity provision from highly volatile securities with higher margins to increased liquidity provision in less volatile stocks with lower margins in the stock market is related to increased funds flowing into the safer assets. Consistent with the above results, the illiquidity differential has a strong negative correlation with flows into equity funds.

Illiquidity and Balanced Mutual Fund Holdings

An alternative way to investigate the relation between liquidity differential and flight to safety is to investigate the behavior of balanced (hybrid) mutual funds. Balanced mutual funds invest both in equity and bonds. Thus, one could proxy the flight-to-quality behavior of managers by looking at the change in the equity holdings relative to bond holdings in balanced funds. We use the CRSP Mutual Fund Database to calculate the end-of-year proportional holdings of equity by balanced funds as the ratio of the total value of their equity portfolio and the net asset value of the fund for the period 1964 to 2007. If asset managers perceive equities as more risky than bonds, then they will tend to shift funds from equities towards bonds in periods of economic uncertainty. The results in Panel B of Table 12 show that when illiquidity differential increases, managers of balanced funds shift their portfolios out of equities and into bonds. A 1% increase in illiquidity differential leads to a 3% decrease in stock market exposure.

Illiquidity and S&P Volatility Index

To ensure that our results on the relation between illiquidity differential and flight to safety is robust to other measures of flight to quality, we investigate the relation between illiquidity differential and the S&P100 volatility index, VXO. We use VXO instead of the more popular VIX because it is available for a longer period, from 1986 instead of 1990. The use of stock index volatility as a proxy for flight to quality is motivated by Bailey and Stulz (1989), where they show an association between stock index volatility and flight to quality. The data is obtained from CBOE Indexes in WRDS. The results in Panel C of Table 12 show predictive power of cross sectional stock market illiquidity differential for the volatility index, using univariate regressions with one and two lags. Stock market illiquidity differential is highly statistically significant. An increase in cross-sectional illiquidity differential by 1% leads to an increase of 3 points in VXO.

Market Liquidity, Funding Liquidity, and Flight to Quality

The flight-to-quality and funding liquidity channels are not mutually exclusive. Thus we study these channels jointly by including mutual fund flows, VXO, and funding liquidity variables into the equally-weighted yearly excess bond return forecasting equation. We use the funding liquidity measure from Fontaine and Garcia (2012) (FG), which is constructed from a cross-section of bonds by adding a liquidity factor correlated with bond age to an arbitrage-free term structure model. Table 13 presents the results. In Column (1) of Table 13, the FG funding liquidity coefficient is negative and statistically significant. Consistent with the sign found in Fontaine and Garcia (2012), we find that risk premia in Treasury securities decrease when the value of FG funding liquidity increases. The estimated coefficient of the cross sectional stock market illiquidity differential variable remains positive and statistically significant. The magnitude of the estimated coefficient remains very close to that reported in Table 2.

We study the role of flight-to-quality on bond risk premia using the net exchange mutual fund flow data. Column (3) of Table 13 presents the estimated coefficients of equity, taxable money market, and taxable bond mutual fund flows. Consistent with a flight-to-quality effect, we find positive and statistically significant coefficients for the taxable money market and bond flows. We find that bond risk premia increase when flows into money market and bond mutual funds increase. Results in column (3) show that stock market illiquidity is related to flight-to-quality as we observe that the inclusion of cross sections of stock market illiquidity subsumed the effect of money market flows. Column (7) shows that the inclusion of market illiquidity and FG funding liquidity completely subsume all mutual fund flows variables. The result is robust to the inclusion of VXO, an alternative proxy for flight to quality in columns (11) and (13).[19] The predictive power of cross-sectional liquidity differential remains even after controlling for alternative price-based funding liquidity measure of Hu et al. (2012). While the finding supports the flight to quality and funding liquidity channel, stock market illiquidity appears to contain information of a different dimension, because it remains significant after controlling for VXO, mutual fund flows, and different funding liquidity measures.

7 Conclusions

We assess the effect of stock market illiquidity on U.S. excess bond returns. We use the Amihud (2002) illiquidity measure, the average illiquidity ratio across all stocks, to examine whether excess bond returns can be predicted by stock market liquidity. We find that stock market liquidity adds to the well-established Cochrane-Piazzesi and Ludvigson-Ng factors for both in-sample and out-of-sample forecasting performance. Stock illiquidity has strong forecasting power for excess returns across bonds of all maturities. The effects are statistically and economically significant and stronger for shorter maturity than for longer maturity bonds. Our results are robust to using monthly bond portfolio returns.

We investigate two potential reasons why stock illiquidity contains information about bond excess returns. First, we study whether bond market liquidity can account for this effect. Second, we study the funding illiquidity channel. Consistent with the predictions of Brunnermeier and Pedersen (2009), we find strong predictive ability of the difference between the aggregated illiquidity of large (less volatile stocks with lower margin) and small (more volatile stocks with

[19] Results for individual maturity produce qualitatively similar results. See Table A6 in the Appendix.

high margin) cap stocks on bond excess returns supports the funding liquidity hypothesis. We find this cross-sectional liquidity differential is highly correlated various measures of funding liquidity, such as the changes in aggregate repos (Adrian and Shin, 2010), difference in returns on the three-month commercial paper rate and three-month Treasury bill rate (Krishnamurthy, 2002; Gatev and Strahan, 2006; Hameed et al., 2010)) and mispricing-based funding liquidity factor of Fontaine and Garcia (2012) and Hu et al. (2012). More importantly it enables one to construct long time series of funding liquidity measure which is difficult with other measures.

Consistent with predictions of Kiyotaki and Moore (2008), we also find that stock illiquidity variables are able to forecast real investment growth up to four quarters ahead. Consistent with Brunnermeier and Pedersen (2009), we find that changes in stock market illiquidity are related to flight to quality through shifts of U.S. mutual fund flows from equity to money market mutual funds. In an alternative exercise, we find that stock market illiquidity explains and predicts changes in the average proportional holding of equities and bonds by balanced/hybrid mutual funds. Stock market illiquidity is also contemporaneously associated with and predictive of changes in the implied volatility index (VXO). However, our results suggest that stock market illiquidity contains information of a different dimension from the existing flight-to-quality and funding liquidity variables.

Table 1
Data Characteristics

The table presents preliminary statistics. Panel A presents the data characteristics, and Panel B presents the correlations. The sample period is January 1964 to December 2008. *HPRXM* is the equally weighted bond excess return for one year ahead, LNF_1 to LNF_9 are the Ludvigson and Ng factors, $f^{(1)}$-$f^{(5)}$ are the one- to five-year forward rates. $D_{12}ILR$ is the yearly change in log illiquidity, and $D_{12}ILRSMB$ is the yearly change in the difference of log illiquidity for small and large stocks (small-big).

Panel A. Sample Characteristics

	HPRXM	LNF_1	LNF_2	LNF_3	LNF_4	LNF_5	LNF_6	LNF_7	LNF_8	LNF_9	$f^{(1)}$	$f^{(2)}$	$f^{(3)}$	$f^{(4)}$	$f^{(5)}$	$D_{12}ILR$	$D_{12}ILRSMB$
Mean	0.008	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.247	0.063	0.067	0.070	0.072	0.072	-0.107	0.047
Median	0.004	-0.149	0.129	0.005	0.068	0.001	0.028	-0.029	-0.054	-0.003	0.058	0.064	0.066	0.067	0.068	-0.158	0.044
Maximum	0.114	5.044	2.682	5.104	4.665	4.633	8.267	6.670	4.005	128.296	0.158	0.158	0.154	0.167	0.148	1.697	1.413
Minimum	-0.111	-2.308	-4.676	-5.321	-4.790	-3.296	-3.465	-12.167	-2.988	-12.299	0.010	0.015	0.022	0.031	0.037	-1.644	-1.396
Std. Dev.	0.039	1.001	1.001	1.001	1.001	1.001	1.001	1.001	1.001	9.854	0.027	0.026	0.025	0.025	0.024	0.572	0.429

Panel B. Correlations

	HPRXM	LNF_1	LNF_2	LNF_3	LNF_4	LNF_5	LNF_6	LNF_7	LNF_8	LNF_9	$f^{(1)}$	$f^{(2)}$	$f^{(3)}$	$f^{(4)}$	$f^{(5)}$	$D_{12}ILR$	$D_{12}ILRSMB$
LNF_1	0.25																
LNF_2	0.21	0.00															
LNF_3	0.01	0.00	0.00														
LNF_4	-0.21	0.00	0.00	0.00													
LNF_5	-0.09	0.00	0.00	0.00	0.00												
LNF_6	-0.18	0.00	0.00	0.00	0.00	0.00											
LNF_7	-0.10	0.00	0.00	0.00	0.00	0.00	0.00										
LNF_8	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00									
LNF_9	-0.03	0.66	0.01	0.00	0.16	0.09	-0.01	-0.05	0.01								
$f^{(1)}$	0.08	0.18	-0.45	-0.13	-0.19	0.24	0.14	0.20	-0.10	0.13							
$f^{(2)}$	0.19	0.18	-0.27	-0.09	-0.22	0.19	0.10	0.18	-0.07	0.14	0.96						
$f^{(3)}$	0.25	0.21	-0.17	-0.07	-0.22	0.17	0.09	0.18	-0.04	0.15	0.92	0.98					
$f^{(4)}$	0.27	0.20	-0.14	-0.07	-0.21	0.15	0.09	0.17	-0.01	0.13	0.88	0.96	0.98				
$f^{(5)}$	0.22	0.18	-0.11	-0.06	-0.22	0.14	0.12	0.18	-0.02	0.15	0.86	0.95	0.97	0.96			
$D_{12}ILR$	0.14	0.31	-0.35	-0.05	0.08	0.11	-0.01	-0.06	0.15	0.20	0.26	0.20	0.18	0.15	0.11		
$D_{12}ILRSMB$	0.28	0.26	-0.17	0.01	-0.02	-0.02	0.13	0.03	0.10	0.13	0.28	0.27	0.27	0.25	0.22	0.58	

Table 2
Liquidity and Bond Premia

The table presents the monthly in-sample forecasting regression of excess bond returns: $\overline{rx}_{t+12} = \boldsymbol{\beta}' \boldsymbol{X}_t + \bar{\varepsilon}_{t+12}$. $\overline{rx}$ is the equally weighted yearly excess bond return, LNF_1-LNF_9 are the Ludvigson and Ng factors, $f^{(1)}$-$f^{(5)}$ are the one- to five-year forward rates. CP is the Cochrane-Piazzesi factor, a linear combination of the forward rates, LN is the linear combination of the Ludvigson and Ng factors. $D_{12}ILR$ is the yearly change in log illiquidity and $D_{12}ILRSMB$ is the yearly change in the difference of log illiquidity for small and large stocks (small-big). The sample period is January 1964 to December 2008. *p-val* is the p-value calculated using the Newey-West correction for heteroscedasticity and autocorrelation with 18 lags. The p-values based on the bootstrap analysis are presented in round brackets.

Variable	Coef. (2)	p-val (3)	Coef. (4)	p-val (5)	Coef. (6)	p-val (7)	Coef. (8)	p-val (9)	Coef. (10)	p-val (11)	Coef. (12)	p-val (13)	Coef. (14)	p-val (15)	Coef. (16)	p-val (17)
Constant	0.007	0.04	0.009	0.03	-0.018	0.05	- 0.017	0.05	- 0.018	0.05	-0.004	0.08	-0.004	0.06	-0.003	0.12
LNF_1					0.015	0.00	0.013	0.00	0.013	0.00						
LNF_2					0.002	0.12	0.004	0.07	0.004	0.06						
LNF_3					-0.001	0.12	- 0.001	0.10	- 0.001	0.15						
LNF_4					-0.004	0.03	- 0.004	0.02	- 0.005	0.01						
LNF_5					-0.002	0.06	- 0.002	0.08	- 0.003	0.04						
LNF_6					-0.005	0.01	- 0.006	0.00	- 0.005	0.00						
LNF_7					-0.005	0.00	- 0.005	0.00	- 0.005	0.00						
LNF_8					0.006	0.00	0.005	0.00	0.005	0.00						
LNF_9					-0.001	0.00	- 0.001	0.00	- 0.001	0.00						
$f^{(1)}$					-1.400	0.00	- 1.253	0.00	- 1.336	0.00						
$f^{(2)}$					0.604	0.08	0.375	0.13	0.511	0.09						
$f^{(3)}$					2.106	0.00	1.780	0.00	1.962	0.00						
$f^{(4)}$					0.521	0.06	0.647	0.03	0.576	0.05						
$f^{(5)}$					-1.515	0.00	- 1.272	0.00	- 1.399	0.00						
CP											0.725	0.00	0.672	0.00	0.730	0.00
												(0.00)		(0.00)		(0.00)
LN											0.718	0.00	0.713	0.00	0.708	0.00
												(0.00)		(0.00)		(0.00)
$D_{12}ILRSMB$	0.025	0.00					0.018	0.00					0.019	0.00		
		(0.00)						(0.00)						(0.00)		
$D_{12}ILR$			0.010	0.04					0.007	0.05					0.009	0.02
				(0.06)						(0.05)						(0.02)
R^2	0.08		0.02		0.42		0.45		0.43		0.40		0.44		0.42	
Adj. R^2	0.07		0.02		0.41		0.44		0.41		0.40		0.44		0.41	

Table 3
Liquidity and Bond Term Structure

The table presents the monthly in-sample forecasting regression of bond premia and liquidity for individual maturities, $rx_{t+12}^{(n)} = \boldsymbol{\beta}' \boldsymbol{X}_t + \varepsilon_{t+12}^{(n)}$, where $rx^{(n)}$ is the bond risk premium of maturity n. CP denotes the Cochrane-Piazzesi factor. LN is the linear combination of the nine macro factors of Ludvigson and Ng. $D_{12}ILR$ is the yearly change in log illiquidity and $D_{12}ILRSMB$ is the yearly change in the difference of log illiquidity for small and large stocks (small-big). The sample period is January 1964 to December 2008. Excess bond return regressions are for the 2-, 3-, 4-, and 5-year maturities. The p-values calculated using the Newey-West correction for autocorrelation and heteroscedasticity with 18 lags are presented in square brackets. The p-values calculated using the bootstrap analysis are presented in round brackets.

	2-year					3-year					4-year					5-year				
Constant	0.005	0.004	-0.001	0.000	-0.001	0.009	0.007	-0.002	-0.001	-0.003	0.012	0.009	-0.004	-0.003	-0.005	0.012	0.009	-0.007	-0.006	-0.007
	[0.02]	[0.03]	[0.15]	[0.21]	[0.12]	[0.02]	[0.03]	[0.12]	[0.17]	[0.09]	[0.02]	[0.04]	[0.08]	[0.12]	[0.06]	[0.04]	[0.06]	[0.05]	[0.07]	[0.04]
CP			0.315	0.318	0.286			0.610	0.615	0.560			0.917	0.923	0.856			1.058	1.064	0.988
			[0.00]	[0.00]	[0.00]			[0.00]	[0.00]	[0.00]			[0.00]	[0.00]	[0.00]			[0.00]	[0.00]	[0.00]
			(0.00)	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)
LN			0.359	0.353	0.357			0.639	0.630	0.635			0.847	0.835	0.842			1.026	1.014	1.020
			[0.00]	[0.00]	[0.00]			[0.00]	[0.00]	[0.00]			[0.00]	[0.00]	[0.00]			[0.00]	[0.00]	[0.00]
			(0.00)	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)			(0.00)	(0.00)	(0.00)
$D_{12}ILR$	0.006			0.005		0.010			0.009		0.012			0.011		0.012			0.011	
	[0.02]			[0.01]		[0.03]			[0.01]		[0.04]			[0.02]		[0.06]			[0.03]	
	(0.03)			(0.01)		(0.04)			(0.00)		(0.06)			(0.02)		(0.10)			(0.05)	
$D_{12}ILRSMB$		0.013			0.010		0.023			0.018		0.030			0.022		0.034			0.024
		[0.00]			[0.00]		[0.00]			[0.00]		[0.00]			[0.01]		[0.00]			[0.00]
		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)		(0.00)			(0.00)
R^2	0.03	0.10	0.39	0.41	0.44	0.03	0.09	0.40	0.42	0.44	0.02	0.07	0.41	0.43	0.45	0.01	0.07	0.38	0.40	0.42
Adj. R^2	0.03	0.09	0.38	0.41	0.44	0.02	0.09	0.39	0.41	0.44	0.02	0.07	0.41	0.43	0.45	0.01	0.06	0.38	0.39	0.41

Table 4
Out of Sample Forecasting of Bond Risk Premia

The table presents the monthly out-of-sample forecasting results for excess bond returns. *Bench.* denotes the benchmark model with the CP and LN factors. *ILR* denotes the model that includes $D_{12}ILR$ as an additional forecasting factor to CP and LN, and *ILRSMB* denotes the model that includes $D_{12}ILRSMB$ as an additional forecasting factor to CP and LN. Forecasts are generated using a moving window of 15 years (180 monthly observations). *RMSE* is the root mean squared error, *RMSE ratio* is the ratio of the RMSE of the respective model over the benchmark, *CW* is the Clark and West (2007) test for equal predictive ability, with corresponding approximate *p-value* based on the standard normal distribution. *GW* is the statistic for the Giacomini and White (2006) test for equal predictive ability with corresponding asymptotic *p-value*.

	Average			2 year			3 year			4 year			5 year		
	Bench.	ILR	ILRSMB	Bench.	ILR	ILRSMB	Bench.	ILR	ILRSMB	Bench.	ILR	ILRSMB	Bench.	ILR	ILRSMB
RMSE	0.044	0.043	0.043	0.020	0.020	0.020	0.038	0.038	0.037	0.053	0.052	0.051	0.065	0.065	0.064
RMSE ratio		0.990	0.972		0.990	0.970		0.988	0.969		0.990	0.973		0.992	0.975
CW		1.342	2.100		1.283	2.378		1.443	2.313		1.365	2.062		1.247	1.880
p-value		0.09	0.02		0.10	0.01		0.08	0.01		0.09	0.02		0.11	0.03
GW		0.613	1.362		0.550	1.451		0.683	1.482		0.637	1.343		0.560	1.231
p-value		0.27	0.09		0.29	0.08		0.25	0.07		0.26	0.09		0.29	0.10

Table 5
Estimation Results for VAR model

The table presents the estimation results for the VAR model. Panel A presents the estimated regressions comprising the VAR system. Columns (9)-(12), $rx^{(2)}$-$rx^{(5)}$, present the bond return regressions implied by the VAR model. $f^{(1)}$ to $f^{(5)}$ denote the forward rates, LN is the linear combination of the nine macro factors of Ludvigson and Ng, $D_{12}ILRSMB$ is the yearly change in the difference of log illiquidity for small and large stocks (small-big), and σ_ν is the standard error of the regression. The sample period is January 1964 to December 2007. p-values calculated using the Newey-West correction for autocorrelation and heteroscedasticity with 18 lags are presented in square brackets. Panel B shows the correlation matrix of the regression residuals.

	$f^{(1)}$	$f^{(2)}$	$f^{(3)}$	$f^{(4)}$	$f^{(5)}$	LN	$D_{12}ILRSMB$	$rx^{(2)}$	$rx^{(3)}$	$rx^{(4)}$	$rx^{(5)}$
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Regressions											
Constant	0.015	0.008	0.009	0.009	0.010	-0.001	-0.133	-0.015	-0.023	-0.032	-0.040
	[0.00]	[0.06]	[0.02]	[0.01]	[0.01]	[0.83]	[0.27]	[0.00]	[0.01]	[0.01]	[0.01]
$f^{(1)}$	0.558	0.502	0.581	0.480	0.552	0.906	0.049	-0.558	-1.060	-1.641	-2.122
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.99]	[0.00]	[0.00]	[0.00]	[0.00]
$f^{(2)}$	0.502	0.127	-0.296	-0.323	-0.387	-1.228	9.636	0.498	0.371	0.667	0.990
	[0.13]	[0.59]	[0.15]	[0.15]	[0.16]	[0.01]	[0.26]	[0.13]	[0.50]	[0.36]	[0.28]
$f^{(3)}$	-0.588	-0.412	-0.205	-0.227	-0.345	-0.207	-2.226	0.588	2.000	2.205	2.432
	[0.05]	[0.06]	[0.23]	[0.24]	[0.14]	[0.73]	[0.75]	[0.05]	[0.00]	[0.00]	[0.00]
$f^{(4)}$	-0.208	-0.030	0.147	0.064	0.307	0.554	2.591	0.208	0.238	1.091	1.027
	[0.28]	[0.87]	[0.34]	[0.69]	[0.07]	[0.05]	[0.61]	[0.28]	[0.52]	[0.03]	[0.12]
$f^{(5)}$	0.547	0.727	0.694	0.939	0.780	0.091	-6.161	-0.547	-1.274	-1.968	-1.906
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.69]	[0.22]	[0.00]	[0.00]	[0.00]	[0.00]
LN	-0.378	-0.253	-0.177	-0.137	-0.093	0.404	-5.289	0.378	0.631	0.809	0.946
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
$D_{12}ILRSMB$	-0.009	-0.007	-0.005	-0.004	-0.004	0.003	-0.246	0.009	0.015	0.020	0.023
	[0.00]	[0.01]	[0.04]	[0.09]	[0.11]	[0.36]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]
σ_ν	0.01	0.01	0.01	0.01	0.01	0.02	0.38				
R^2	0.77	0.80	0.84	0.83	0.81	0.18	0.20	0.50	0.48	0.49	0.45
Adj. R^2	0.76	0.80	0.83	0.83	0.81	0.17	0.19	0.49	0.48	0.48	0.44
Panel B: Correlation matrix of residuals											
$f^{(1)}$	1.00										
$f^{(2)}$	0.90	1.00									
$f^{(3)}$	0.80	0.93	1.00								
$f^{(4)}$	0.73	0.88	0.90	1.00							
$f^{(5)}$	0.66	0.82	0.85	0.81	1.00						
LN	-0.35	-0.23	-0.14	-0.07	-0.17	1.00					
$D_{12}ILRSMB$	-0.11	-0.06	-0.01	-0.01	-0.08	0.19	1.00				

Table 6
Liquidity and Monthly Bond Portfolio Returns

The table presents the monthly in-sample forecasting regression of the monthly equally-weighted bond portfolio returns: $\overline{rx}_{m,t+1} = \alpha + \boldsymbol{\beta}'\boldsymbol{X}_t + \bar{\varepsilon}_{m,t+1}$. $\overline{rx}_m$ is the equally-weighted monthly bond portfolio return, LNF_1-LNF_9 are the Ludvigson and Ng factors, $f^{(1)}$-$f^{(5)}$ are the one- to five-year forward rates. *CPBP* and *LNBP* are the Cochrane-Piazzesi and Ludvigson-Ng factors, respectively, constructed for the monthly bond portfolios. $D_{12}ILR$ is the yearly change in log illiquidity and $D_{12}ILRSMB$ is the yearly change in the difference of log illiquidity for small and large stocks (small-big). The sample period is January, 1964 to December, 2008. *p-val* is the p-value calculated using the Newey-West correction for heteroscedasticity and autocorrelation with 18 lags.

	coeff	p-val	coeff	p-val	coeff	p-val	coeff	p-val	coeff	p-val	coeff	p-val	coeff	p-val	coeff	p-val
Constant	0.001	0.01	0.001	0.00	-0.004	0.01	-0.004	0.01	0.000	0.18	0.000	0.16	-0.001	0.04	0.000	0.10
LNF_1					0.001	0.01	0.001	0.01								
LNF_2					0.002	0.03	0.002	0.02								
LNF_3					-0.001	0.07	0.000	0.09								
LNF_4					0.000	0.12	0.000	0.10								
LNF_5					-0.002	0.00	-0.002	0.00								
LNF_6					-0.002	0.00	-0.002	0.00								
LNF_7					-0.001	0.00	-0.001	0.00								
LNF_9					0.002	0.00	0.002	0.00								
LNF_9					0.000	0.18	0.000	0.18								
$f^{(1)}$					0.232	0.03	0.231	0.03								
$f^{(2)}$					-0.229	0.03	-0.225	0.03								
$f^{(3)}$					-0.028	0.22	-0.026	0.23								
$f^{(4)}$					0.069	0.17	0.068	0.17								
$f^{(5)}$					0.034	0.19	0.035	0.18								
CPBP													0.441	0.09	0.530	0.06
LNBP													0.935	0.00	0.911	0.00
$D_{12}ILRSMB$	0.003	0.00			0.002	0.02			0.003	0.00			0.002	0.01		
$D_{12}ILR$			0.003	0.00			0.002	0.01			0.002	0.00			0.002	0.00
R^2	0.02		0.02		0.15		0.15		0.09		0.09		0.13		0.13	
Adj. R^2	0.01		0.02		0.12		0.12		0.08		0.09		0.13		0.13	

Table 7

Liquidity and Monthly Bond Portfolio Returns for Individual Maturities

The table presents the monthly in-sample forecasting regression of bond portfolios of different maturities, $rx_{t+1}^{(n)} = \boldsymbol{\beta}' \boldsymbol{X}_t + \varepsilon_{t+1}^{(n)}$, where $rx^{(n)}$ is the bond risk premium of maturity n. *CPBP* and *LNBP* are the linear combination of the forward rates and Ludvigson-Ng factors, respectively, constructed for the monthly bond portfolios. $D_{12}ILR$ is the yearly change in log illiquidity and $D_{12}ILRSMB$ is the yearly change in the difference of log illiquidity for small and large stocks (small-big). The sample period is January 1964 to December 2008. The p-value calculated using the Newey-West correction for autocorrelation and heteroscedasticity is presented in square brackets.

	Up to 1 Year					1 to 2 Years					2 to 3 Years				
Constant	0.001	0.001	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.000	0.001	0.002	0.000	0.000	0.000
	[0.00]	[0.00]	[0.02]	[0.01]	[0.00]	[0.00]	[0.00]	[0.20]	[0.21]	[0.18]	[0.01]	[0.00]	[0.11]	[0.11]	[0.20]
CPBP			0.090	0.056	0.095			0.244	0.178	0.253			0.404	0.311	0.416
			[0.13]	[0.17]	[0.12]			[0.11]	[0.15]	[0.11]			[0.10]	[0.13]	[0.09]
LNBP			0.251	0.245	0.233			0.645	0.633	0.612			0.913	0.896	0.871
			[0.00]	[0.00]	[0.00]			[0.00]	[0.00]	[0.00]			[0.00]	[0.00]	[0.00]
$D_{12}ILRSMB$	0.001			0.001		0.002			0.002		0.003			0.002	
	[0.00]			[0.00]		[0.00]			[0.00]		[0.00]			[0.00]	
$D_{12}ILR$		0.001			0.001		0.002			0.001		0.003			0.002
		[0.00]			[0.00]		[0.00]			[0.00]		[0.00]			[0.00]
R^2	0.03	0.04	0.13	0.15	0.15	0.02	0.03	0.14	0.15	0.15	0.02	0.02	0.12	0.13	0.13
Adj. R^2	0.03	0.04	0.13	0.14	0.15	0.02	0.03	0.13	0.14	0.14	0.02	0.02	0.12	0.13	0.13

	3 to 4 Years					4 to 5 years					5 to 10 years				
Constant	0.001	0.002	-0.001	-0.001	-0.001	0.001	0.002	-0.001	-0.001	-0.001	0.001	0.002	-0.001	-0.001	-0.001
	[0.01]	[0.00]	[0.03]	[0.03]	[0.07]	[0.02]	[0.01]	[0.01]	[0.01]	[0.04]	[0.03]	[0.01]	[0.01]	[0.01]	[0.03]
CPBP			0.707	0.618	0.719			0.782	0.691	0.794			0.889	0.788	0.902
			[0.05]	[0.06]	[0.04]			[0.05]	[0.06]	[0.05]			[0.06]	[0.07]	[0.05]
LNBP			1.116	1.099	1.073			1.271	1.254	1.227			1.500	1.481	1.450
			[0.00]	[0.00]	[0.00]			[0.00]	[0.00]	[0.00]			[0.00]	[0.00]	[0.00]
$D_{12}ILRSMB$	0.004			0.002		0.004			0.002		0.004			0.003	
	[0.00]			[0.01]		[0.00]			[0.02]		[0.01]			[0.03]	
$D_{12}ILR$		0.003			0.002		0.003			0.002		0.004			0.002
		[0.00]			[0.00]		[0.01]			[0.01]		[0.01]			[0.01]
R^2	0.01	0.02	0.12	0.13	0.13	0.01	0.01	0.12	0.12	0.12	0.01	0.01	0.11	0.11	0.12
Adj. R^2	0.01	0.01	0.12	0.13	0.13	0.01	0.01	0.11	0.12	0.12	0.01	0.01	0.11	0.11	0.11

Table 8
Out-of-sample Forecasting of Monthly Bond Portfolio Returns

The table presents the monthly out-of-sample forecasting results for the Fama-Bliss monthly portfolio returns. *Bench.* denotes the benchmark model with the CPBP and LNBP factors. *ILR* denotes the model that includes $D_{12}ILR$ as an additional forecasting factor to CPBP and LNBP, and *ILRSMB* denotes the model that includes $D_{12}ILRSMB$ as an additional forecasting factor to CPBP and LNBP. $D_{12}ILR$ is the yearly change in log illiquidity and $D_{12}ILRSMB$ is the yearly change in the difference of log illiquidity for small and large stocks (small-big). A moving window of 15 years (180 monthly observations) is used to create the forecasts for the period January 1979 to December 2008. *RMSE* is the root mean squared error, *RMSE ratio* is the ratio of the RMSE of the respective model over the benchmark, *CW* is the Clark and West (2007) test for equal predictive ability, with corresponding approximate *p-value* based on the standard normal distribution, and *GW* is the statistic for the Giacomini and White (2006) test for model forecasting ability with corresponding asymptotic *p-value*.

	Average			<1 Year			1-2 Years			2-3 Years		
	Bench.	ILR	ILRSMB	Bench.	ILR	ILRSMB	Bench.	ILR	ILRSMB	Bench.	ILR	ILRSMB
RSME	0.012	0.011	0.011	0.003	0.003	0.003	0.007	0.007	0.007	0.011	0.011	0.011
RMSE ratio		0.994	0.994		0.980	0.984		0.989	0.989		0.993	0.991
CW		1.999	1.874		2.445	2.367		2.143	2.281		2.053	2.089
p-value		0.02	0.03		0.01	0.01		0.02	0.01		0.02	0.02
GW		1.386	1.112		1.697	1.406		1.512	1.410		1.428	1.199
p-value		0.08	0.13		0.05	0.08		0.07	0.08		0.08	0.12

	3-4 Years			4-5 Years			5-10 Years		
	Bench.	ILR	ILRSMB	Bench.	ILR	ILRSMB	Bench.	ILR	ILRSMB
RSME	0.014	0.014	0.014	0.016	0.016	0.016	0.020	0.020	0.020
RMSE ratio		0.995	0.994		0.997	0.996		0.997	0.996
CW		1.903	1.846		1.809	1.646		1.726	1.496
p-value		0.03	0.03		0.04	0.05		0.04	0.08
GW		1.281	1.082		1.202	0.930		1.184	0.903
p-value		0.10	0.14		0.12	0.18		0.12	0.18

Table 9
Bond Risk Premia and Stock and Bond Iliquidity

The table presents the monthly in-sample forecasting regression of excess bond returns and stock and bond market illiquidity: $\overline{rx}_{t+12} = \boldsymbol{\beta}'\boldsymbol{X}_t + \bar{\varepsilon}_{t+12}$. $\overline{rx}$ is the equally-weighted yearly excess bond return, *Bond Illiquidity* is the Treasury market illiquidity measured as the log yearly change in the average monthly relative bid-ask spread for 2 to 5 year bonds, *CP* is the Cochrane Piazzesi factor, *LN* is the linear combination of the Ludvigson and Ng factors, $D_{12}ILR$ is the yearly change in log illiquidity, and $D_{12}ILRSMB$ is the yearly change the difference of log illiquidity for small and large stocks (small-big). The sample period is January 1964 to December 2007. *p-val* is the *p*-value calculated using the Newey-West correction for heteroscedasticity and autocorrelation with 18 lags. All regressions include a constant, not reported to conserve space.

	Coef.	Prob.	Coef.	Prob.
Constant	-0.005	0.42	-0.003	0.63
Bond Iliquidity	-0.010	0.10	-0.010	0.10
CP	0.652	0.00	0.709	0.02
LN	0.741	0.00	0.736	0.00
$D_{12}ILRSMB$	0.018	0.00		
$D_{12}ILR$			0.009	0.09
R^2	0.45		0.43	
Adj. R^2	0.45		0.43	

Table 10
Correlation of Illiquidity and Other Funding Liquidity Measures

The table presents the correlations among various measures of funding liquidity levels. ILR is the level of log aggregated stock market illiquidity, and $ILRSMB$ is the difference of log illiquidity for small and large stocks (small-big). *AggRepo* is the aggregate primary dealer repo positions compiled by the Federal Reserve Bank of New York from July 1994. $CPTBSpread$ the difference between the 3-month commercial paper rate and 3-month T-bill rate from April 1971. $FGLiq.$ is the value of funding liquidity of Fontaine and Garcia (2012) based on the mispricing of bonds with similar characteristics but different ages from December 1985. $HPWLiq.$ is a funding measure constructed by Hu et al. (2012) using yield errors or differences between observed market yields and the model-implied yields based on Svensson (1994), from January 1987.

	ILRSMB	ILR	AggRepo	CPTBSpread	FG Liq.	HPW Liq.
ILR	0.971	1.00				
	(0.00)					
AggRepo	-0.81	-0.85	1.00			
	(0.00)	(0.00)				
CPTBSpread	0.36	0.38	-0.03	1.00		
	(0.00)	(0.00)	(0.73)			
FG Liq.	-0.08	-0.03	-0.11	0.62	1.00	
	(0.20)	(0.59)	(0.18)	(0.00)		
HPW Liq.	0.61	0.63	-0.35	0.54	0.20	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

Table 11
Investments and Stock Market Illiquidity

The table presents quarterly regressions of real private fixed investment growth and stock market illiquidity. Quarterly data on real private fixed investment is obtained from the Bureau of Economic Analysis. $D_{12}ILR$ is the yearly change in log illiquidity and $D_{12}ILRSMB$ is the yearly change in the difference of log illiquidity for small and large stocks (small-big). The sample period is Quarter 1 in 1964 to Quarter 4 in 2007. *p-val* is the *p*-value calculated using the Newey-West correction for heteroscedasticity and autocorrelation. *Model p-val* is the *p*-value for the model specification F-statistic. All regressions include a constant, not reported to conserve space. Panel A presents the univariate regressions and Panel B presents two multivariate regressions.

Variable	Coef.	p-val	Obs	Adj. R^2	Model p-val
Panel A. Univariate Regressions					
$D_{12}ILRSMB_{t-1}$	-0.021	0.00	175	0.15	0.00
$D_{12}ILRSMB_{t-2}$	-0.015	0.00	174	0.08	0.00
$D_{12}ILRSMB_{t-3}$	-0.011	0.00	173	0.03	0.01
$D_{12}ILRSMB_{t-4}$	-0.007	0.12	172	0.01	0.10
$D_{12}ILR_{t-1}$	-0.019	0.00	175	0.19	0.00
$D_{12}ILR_{t-2}$	-0.016	0.00	174	0.14	0.00
$D_{12}ILR_{t-3}$	-0.013	0.00	173	0.09	0.00
$D_{12}ILR_{t-4}$	-0.009	0.04	172	0.04	0.01
Panel B. Multivariate Regression					
$D_{12}ILRSMB_{t-1}$	-0.018	0.01	173	0.16	0.00
$D_{12}ILRSMB_{t-2}$	-0.004	0.21			
$D_{12}ILRSMB_{t-3}$	-0.003	0.38			
$D_{12}ILR_{t-1}$	-0.014	0.00	173	0.21	0.00
$D_{12}ILR_{t-2}$	-0.005	0.05			
$D_{12}ILR_{t-3}$	-0.004	0.09			

Table 12
Stock Market Illiquidity and Flight-to-quality Measures

The table presents the relation between stock market illiquidity and flight-to-quality measures. $D_{12}ILRSMB$ is the yearly change in the difference of log illiquidity for small and large stocks (small-big). *p-val* is the p-value calculated using the Newey-West correction for heteroscedasticity and autocorrelation. All regressions include a constant, not reported to conserve space. Panel A presents the monthly correlation between net exchange mutual fund flows and illiquidity over the period January 1984 to June 2010. *DILRSMB* is the monthly log change in the difference for small-large stock illiquidity. Panel B presents the yearly regression of equity ratio in balanced funds and stock market illiquidity. The equity ratio for balanced funds is calculated as the ratio of the total value of the equity portfolio and the net asset value of the fund. The sample period is 1964 to 2007. Panel C presents the monthly regressions of the S&P100 volatility index (VXO) and stock market illiquidity. The sample period is January 1986 to December 2007, 269 observations.

Panel A. Correlations with Mutual Fund Flows

	Taxable Money		Equity Market	
Variable	Coef.	p-val	Coef.	p-val
$DILRSMB$	0.18	0.00	-0.21	0.00
$D_{12}ILRSMB$	0.18	0.00	-0.24	0.00

Panel B. Balanced Funds

Variable	Coef.	p-val	Coef.	p-val
$D_{12}ILRSMB$	-0.028	0.01		
$D_{12}ILRSMB_{t-1}$	-0.035	0.00	-0.020	0.05
$D_{12}ILRSMB_{t-2}$	-0.025	0.08		
R^2	0.22		0.05	
Adj. R^2	0.16		0.03	

Panel C. Volatility Index

Variable	Coef.	p-val	Adj. R^2
$D_{12}ILRSMB_{t-1}$	3.64	0.00	0.04
$D_{12}ILRSMB_{t-2}$	3.15	0.01	0.03

Table 13
Bond Risk Premia and Funding Liquidity

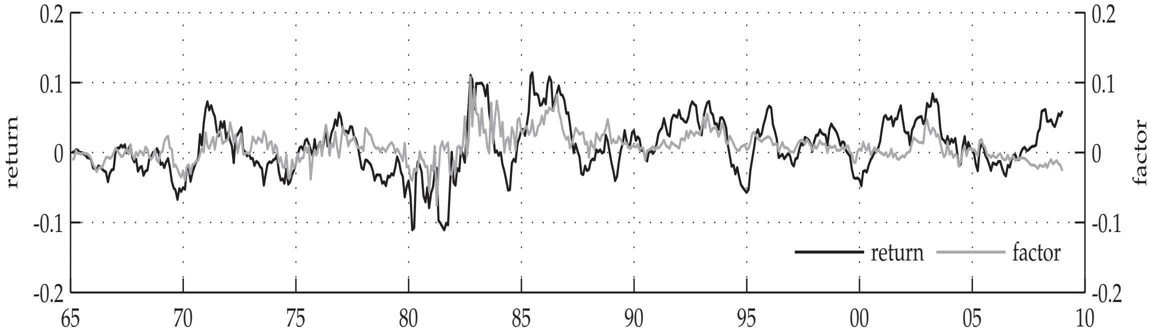
The table presents the relation between bond risk premia, stock market illiquidity, and flight to quality measures. $D_{12}ILRSMB$ is the yearly change in the difference of log illiquidity for small and large stocks (small-big), *FG Liq.* is the funding liquidity variable of Fontaine and Garcia (2012), *HPW Liq.* is the liquidity measure of Hu et al. (2012), *Tax Bond* are taxable bond flows, *T.E. Money Market* are Tax Exempt Money Market flows, *Equity* are equity flows, and *VXO* is the S&P100 volatility index. All mutual fund flows are calculated as net exchange flows, Ben-Rephael et al. (2012). The sample period is January 1984 to December 2007. *p-val* is the p-value calculated using the Newey-West correction for heteroscedasticity and autocorrelation with 18 lags.

	Coef. (1)	Prob. (2)	Coef. (3)	Prob. (4)	Coef. (5)	Prob. (6)	Coef. (7)	Prob. (8)	Coef. (9)	Prob. (10)	Coef. (11)	Prob. (12)	Coef. (13)	Prob. (14)	Coef. (15)	Prob. (16)
C	0.036	0.00	0.023	0.00	0.01	0.58	0.022	0.00	0.035	0.00	0.028	0.05	0.029	0.08	0.011	0.42
$D_{12}ILRSMB$	0.016	0.05					0.018	0.01	0.015	0.04	0.015	0.08	0.014	0.06	0.011	0.04
FG Liq.	-0.021	0.00							-0.019	0.00	-0.021	0.00	-0.019	0.01		
HPW Liq.															0.001	0.72
Taxable Bond			46.190	0.00			42.431	0.00	22.786	0.20			19.666	0.15	31.987	0.01
TE Money Market			28.725	0.07			24.565	0.12	1.900	0.93			-3.574	0.82	6.329	0.57
Equity Flow			0.157	0.96			1.179	0.64	-1.659	0.69			0.024	1.00	-0.803	0.84
VXO					0.00	0.29					0.00	0.43	0.000	0.64	0.000	0.77
R^2	0.18		0.09		0.02		0.15		0.22		0.19		0.22		0.12	
Adj. R^2	0.18		0.09		0.01		0.13		0.21		0.18		0.20		0.10	
Obs	265		288		263		288		265		263		263		251	

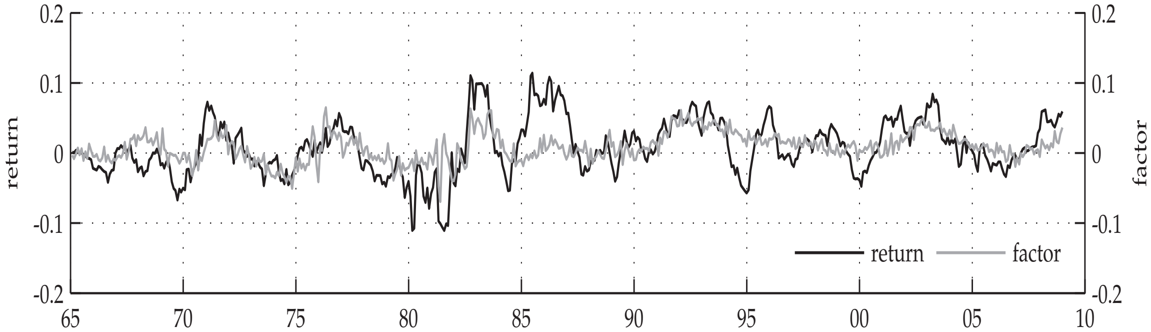
Figure 1
Average Annual Excess Bond Returns and Explanatory Factors

The figure presents the average annual excess bond return, $\overline{rx}_t$ *return* and forecasts from explanatory factors, *factors*. The explanatory factors are: the Cochrane-Piazzesi factor CP_t in Panel (a), the Ludvigson-Ng factor LN_t in Panel (b), the stock market illiquidity factor $D_{12}ILR$ in Panel (c), and the stock market illiquidity factor $D_{12}ILRSMB$ in Panel (d).

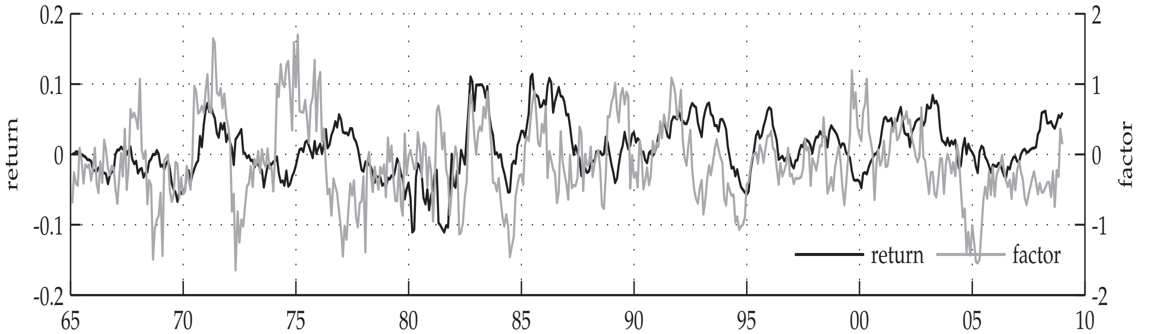
(a) Cochrane-Piazzesi factor



(b) Ludvigson-Ng factor



(c) $D_{12}ILR$ liquidity factor



(d) $D_{12}ILRSMB$ liquidity factor

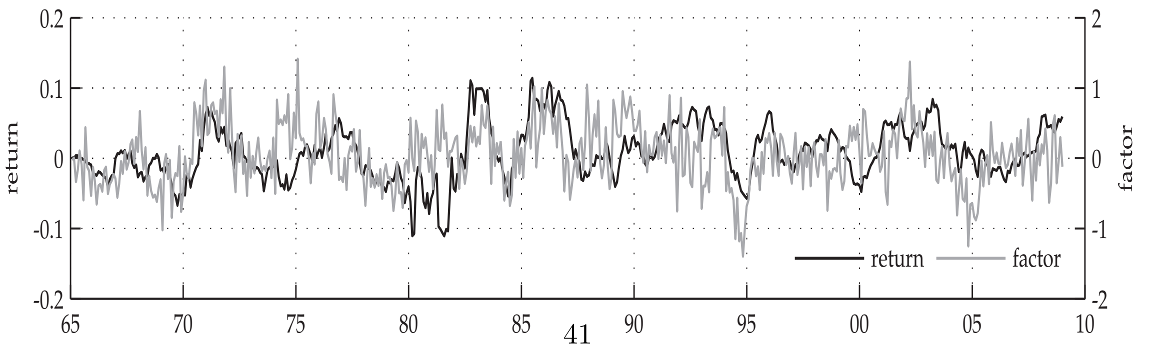
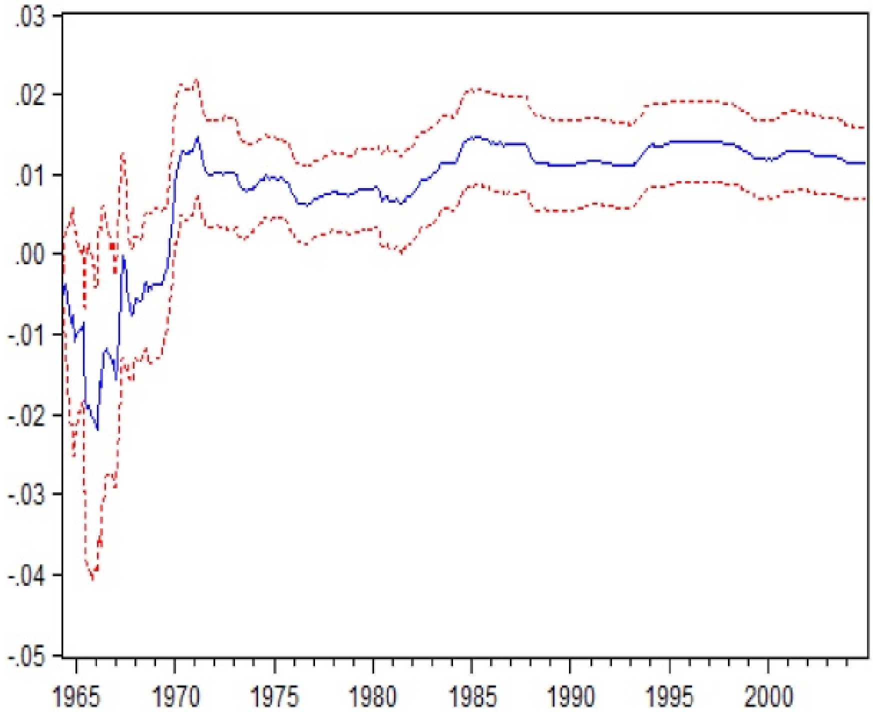


Figure 2
Parameter Stability of Illiquidity Variables

The figure presents the recursive estimates of the liquidity coefficients in the in-sample forecasting regressions in columns (14) and (16), in Table 2, in Panels A and B respectively. The dotted lines show the 95% confidence intervals.

(a) $D_{12}ILR$



(b) $D_{12}ILRSMB$

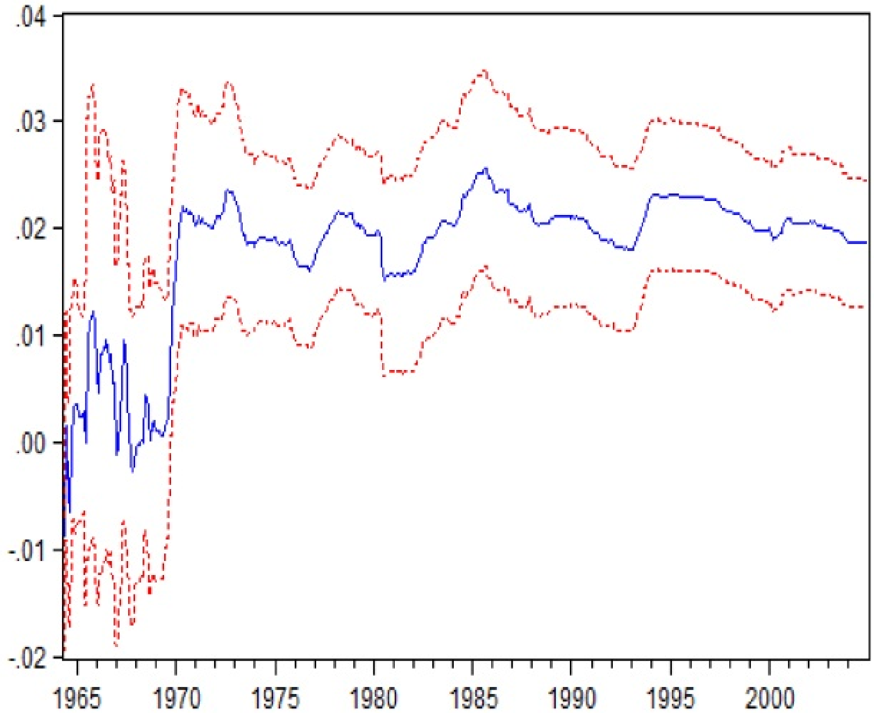


Figure 3
Impulse Response of Yield Curve

The figure presents the response of the yield curve to a shock in aggregate stock market illiquidity $D_{12}ILRSMB$.

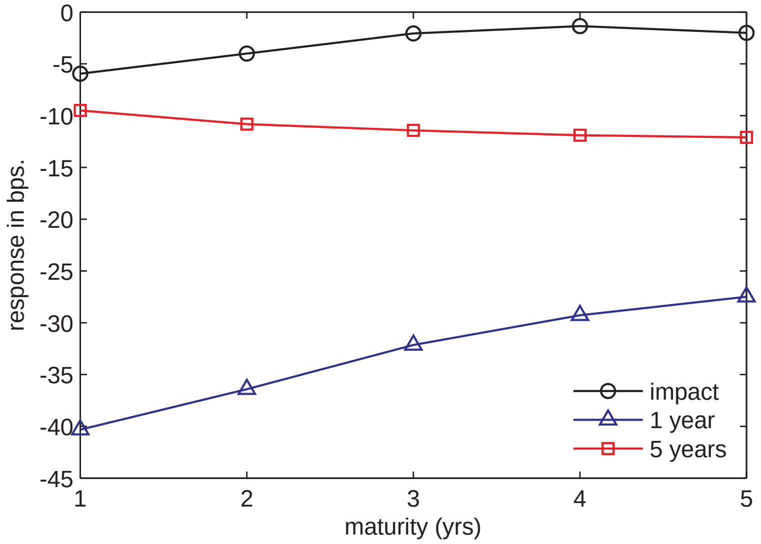


Figure 4
Decomposition of Impulse Response Function of 5-Year Yield

The figure presents the impulse response function of the 5-year yield to a shock in aggregate stock market illiquidity $D_{12}ILRSMB$. The impulse response function of the 5-year yield is decomposed into an expectations part and a risk premium.

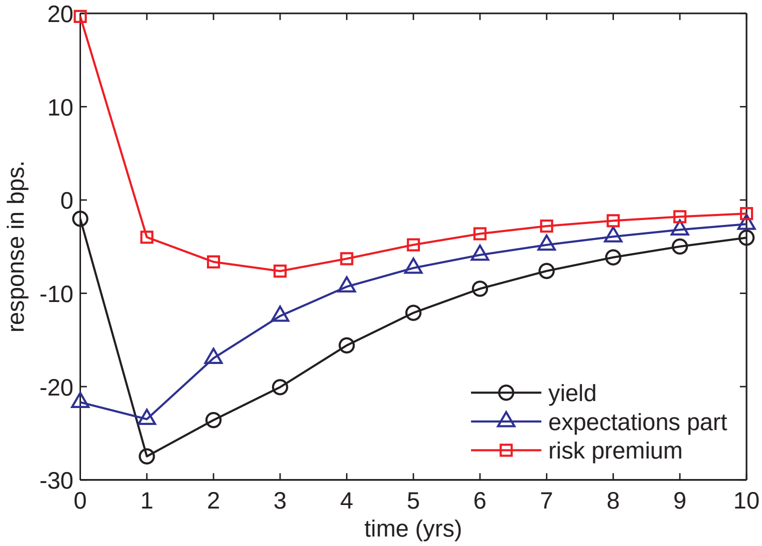
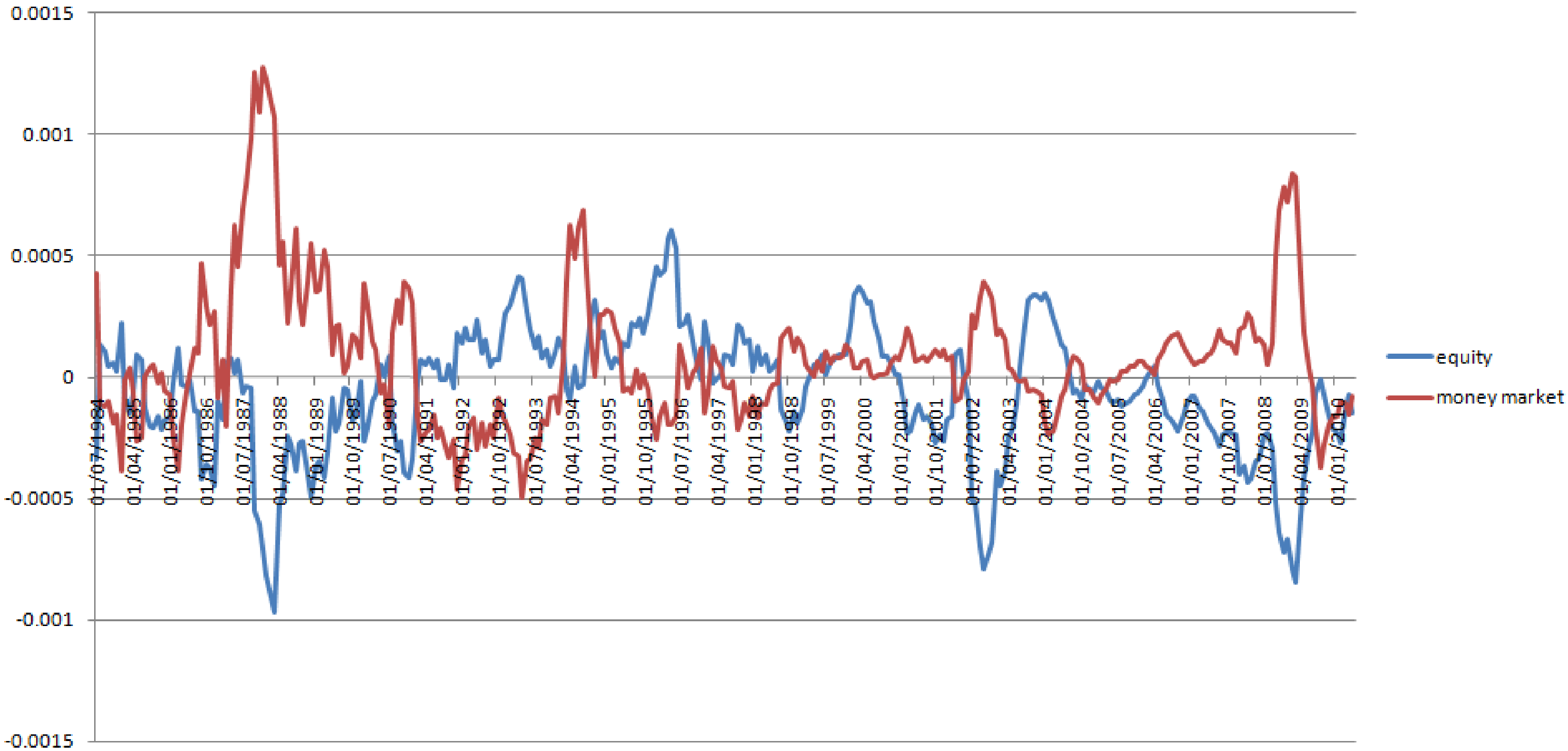


Figure 5
Equity and Money Market Mutual Fund Flows

The figure presents the monthly flows into equity and money market mutual funds calculated as net exchange flows. The sample period is January 1984 to January 2010.



Appendix

A Bootstrap Procedure

We use a bootstrap procedure to conduct small sample inference on the stock market illiquidity variables in the bond return regressions. In particular, we test the significance of variables of interest in the regression:

$$y_t = \alpha_0 + \boldsymbol{\alpha}_1' \boldsymbol{X}_t + \eta_t \tag{11}$$

by constructing bootstrap samples of $(y_t^*, \boldsymbol{X}_t^*)$ generated under the null hypothesis that the variable of interest has a regression coefficient equal to zero. To assess its significance, the actual regression coefficient is compared to the distribution of regression coefficients obtained for the bootstrap samples.

Our bootstrap procedure has two important features. First, we sample blocks of 12 subsequent regression residuals n_t to accommodate the autocorrelation in the residuals. Second, our procedure accounts for the endogeneity of the regressors $\boldsymbol{X}_t$ by sampling new sample paths based on a VAR process. The procedure uses the following steps:

1. Estimate a first-order VAR by OLS on the regressors $\boldsymbol{X}_t$ in:

   $$\boldsymbol{X}_{t+1} = \boldsymbol{\phi}_0 + \boldsymbol{\Phi}_1 \boldsymbol{X}_t + \boldsymbol{\zeta}_{t+1}, \qquad \boldsymbol{\eta}_t \sim IIDN(0, \boldsymbol{\Sigma}_\zeta).$$

   Store the estimates $\widehat{\boldsymbol{\phi}}_0$, $\widehat{\boldsymbol{\Phi}}_1$, $\widehat{\boldsymbol{\Sigma}}_\zeta$ and calculate the time series of the residuals $\boldsymbol{v}_t$. Let $\boldsymbol{L}$ denote the Choleski factorization of $\widehat{\boldsymbol{\Sigma}}_\zeta$ such that $\widehat{\boldsymbol{\Sigma}}_\zeta = \boldsymbol{L}\boldsymbol{L}'$. Store the orthogonalized residuals calculated by:

   $$\boldsymbol{w}_t = \boldsymbol{L}^{-1} \boldsymbol{v}_t.$$

2. Run the restricted regression in (11) under the null-hypothesis. Store the estimates $\widehat{\alpha}_0^o$, $\widehat{\boldsymbol{\alpha}}_1^o$ and the residuals n_t.

3. Generate an artificial sample $\boldsymbol{w}_t^*$ by randomly sampling individual elements $w_{i,t}$ with replacement. Subsequently simulate a new sample path $\boldsymbol{X}_t^*$ of the same length as $\boldsymbol{X}_t$ by

starting with $\boldsymbol{X}_1^* = \boldsymbol{X}_1$ and generating subsequent values by:

$$\boldsymbol{X}_{t+1}^* = \widehat{\boldsymbol{\phi}}_0 + \widehat{\boldsymbol{\Phi}}_1 \boldsymbol{X}_t^* + \boldsymbol{L}\boldsymbol{w}_t^*.$$

4. Generate an artificial sample of regression residuals n_t^* by randomly drawing with replacement blocks of 12 subsequent residuals of n_t. Construct an artificial sample of the dependent variable under the null hypothesis via:

$$y_t^* = \widehat{\alpha}_0^o + \widehat{\boldsymbol{\alpha}}_1^{o\prime} \boldsymbol{X}_t^* + n_t^*.$$

5. Run the full regression (11) on the artificial sample $(y_t^*, \boldsymbol{X}_t^*)$ and store the coefficient of interest $\widehat{\alpha}_{1,i}^*$.

6. Repeat steps 3-5 10,000 times.

7. Calculate the one-sided bootstrapped p-value of $\widehat{\alpha}_{1,i}$ by comparing it to the distribution of the $\widehat{\alpha}_{1,i}^*$ for the artificial samples. The p-value is calculated as the fraction of $\widehat{\alpha}_{1,i}^*$'s that exceeds $\widehat{\alpha}_{1,i}$.

B Yield Curve Analysis

B.1 Relation between VAR Model and Bond Return Regressions

In this section, we establish the link between the VAR model (4) and the system of regression equations (5). Similar to Cochrane and Piazessi (2005), excess bond returns $\boldsymbol{rx}_{t+1} = (rx_{t+1}^{(2)}, rx_{t+1}^{(3)}, rx_{t+1}^{(4)}, rx_{t+1}^{(5)})'$ are by definition given by:

$$\begin{pmatrix} rx_{t+1}^{(2)} \\ rx_{t+1}^{(3)} \\ rx_{t+1}^{(4)} \\ rx_{t+1}^{(5)} \end{pmatrix} = -\begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 \end{pmatrix} \begin{pmatrix} y_{t+1}^{(1)} \\ f_{t+1}^{(2)} \\ f_{t+1}^{(3)} \\ f_{t+1}^{(4)} \\ f_{t+1}^{(5)} \end{pmatrix} + \begin{pmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 & 1 \end{pmatrix} \begin{pmatrix} y_t^{(1)} \\ f_t^{(2)} \\ f_t^{(3)} \\ f_t^{(4)} \\ f_t^{(5)} \end{pmatrix}$$

or compactly in:

$$\boldsymbol{rx}_{t+1} = -\boldsymbol{V}\boldsymbol{f}_{t+1} + \boldsymbol{W}\boldsymbol{f}_t.$$

Hence $\boldsymbol{z}_t = (rx_t^{(2)}, rx_t^{(3)}, rx_t^{(4)}, rx_t^{(5)}, f_t^{(5)}, LN_t, D_{12}ILRSMB_t)'$ is given by:

$$\boldsymbol{z}_{t+1} = \begin{bmatrix} -\boldsymbol{V} & \mathbf{O}_{3\times 3} \\ \mathbf{O}_{3\times 3} & \boldsymbol{I}_3 \end{bmatrix} \boldsymbol{x}_{t+1} + \begin{bmatrix} \boldsymbol{W} & \mathbf{O}_{3\times 3} \\ \mathbf{O}_{3\times 3} & \boldsymbol{I}_3 \end{bmatrix} \boldsymbol{x}_t \equiv \boldsymbol{M}\boldsymbol{x}_{t+1} + \boldsymbol{N}\boldsymbol{x}_t.$$

Substituting the VAR equations in (4) for $\boldsymbol{x}_{t+1}$ and rearranging gives:

$$\boldsymbol{z}_{t+1} = \boldsymbol{M}\boldsymbol{a}_x + \{\boldsymbol{M}\boldsymbol{B}_x + \boldsymbol{N}\}\, \boldsymbol{x}_t \begin{bmatrix} -\boldsymbol{V} & \mathbf{O}_{3\times 3} \\ \mathbf{O}_{3\times 3} & \boldsymbol{I}_3 \end{bmatrix} \boldsymbol{\nu}_{t+1}$$

and hence the parameters of the system of regression equations in (5) are linked to the VAR parameters according to:

$$\begin{aligned} \boldsymbol{a}_z &= \boldsymbol{M}\boldsymbol{a}_x \\ \boldsymbol{B}_z &= \boldsymbol{M}\boldsymbol{B}_x + \boldsymbol{N} \\ \boldsymbol{\Sigma}_z &= \boldsymbol{M}\boldsymbol{\Sigma}_x\boldsymbol{M}'. \end{aligned}$$

B.2 The VAR model as a Self-consistent Gaussian Affine Model

The nominal stochastic discount factor defined in (6) defines a Gaussian affine model. Solving (9) implies that log bond prices are affine functions of the state variables $\boldsymbol{x}_t$. Expressed in terms of forward rates, the solution is given by: $f_t^{(n)} = a_f(n) + \boldsymbol{b}_f(n)'\boldsymbol{x}_t$, where,

$$\begin{aligned} \boldsymbol{b}_f(n)' &= \boldsymbol{\delta}_1'(\boldsymbol{B}_x - \boldsymbol{\Lambda}_1)^{n-1}, \\ a_f(n) &= \delta_0 + \left(\sum_{i=1}^{n-1} \boldsymbol{b}_f(i)\right)' (\boldsymbol{a}_x - \boldsymbol{\lambda}_0) - \frac{1}{2}\left(\sum_{i=1}^{n-1} \boldsymbol{b}_f(i)\right)' \boldsymbol{\Sigma}_\nu \left(\sum_{i=1}^{n-1} \boldsymbol{b}_f(i)\right). \end{aligned}$$

The first five elements of the state vector $\boldsymbol{x}_t$ are forward rates and hence a self-consistent model must exactly replicate these, which for all $m = 1, \ldots, 5$ implies that

$$a_f(m) = 0, \qquad \text{and} \qquad \boldsymbol{b}_f(m) = \boldsymbol{e}_m,$$

where $\boldsymbol{e}_m$ is a 7-dimensional unit vector with the m-th element equal to one and all other elements equal to zero. These conditions imply the following restrictions on the parameters of the stochastic discount factor:

$$\delta_0 = 0, \qquad \boldsymbol{\delta}_1 = \boldsymbol{e}_1,$$

$$\boldsymbol{e}_j'\boldsymbol{\Lambda}_1 = \boldsymbol{e}_j'\boldsymbol{B}_x - \boldsymbol{e}_{j+1}, \qquad \boldsymbol{e}_j'\boldsymbol{\lambda}_0 = \boldsymbol{e}_j'\boldsymbol{a}_x - \frac{1}{2}\boldsymbol{e}_j'\boldsymbol{\Sigma}_\nu\left(\sum_{i=1}^{j}\boldsymbol{e}_i\right), \qquad \text{for all } j = 1, \ldots, 4.$$

The restrictions fix δ_0, $\boldsymbol{\delta}_1$ and the first four rows of $\boldsymbol{\lambda}_0$ and $\boldsymbol{\Lambda}_1$. The three remaining rows of $\boldsymbol{\lambda}_0$ and $\boldsymbol{\Lambda}_1$ are unrestricted and hence the stochastic discount factor is not uniquely pinned down. This stochastic discount factor however exactly reproduces the forward rates in $\boldsymbol{x}_t$ and hence there is no indeterminacy for these maturities.

Table A1
Monthly Bond Portfolio Return Regressions

The table presents the monthly in-sample forecasting regression of the equally-weighted bond portfolio returns using the CP and LN factors. $\overline{rx}_{m,t+1} = \alpha + \boldsymbol{\beta}' \boldsymbol{X}_t + \bar{\varepsilon}_{m,t+1}$. $\overline{rx}_m$ is the equally weighted monthly bond excess return, LNF_1-LNF_9 are the Ludvigson and Ng factors, $f^{(1)}$-$f^{(5)}$ are the one- to five-year forward rates. *CP* is the Cochrane-Piazzesi factor, a linear combination of the forward rates, and *LN* is the linear combination of the Ludvigson and Ng factors. *CPBP* and *LNBP* are the linear combination of the Cochrane-Piazzesi and Ludvigson-Ng factors, respectively, constructed for the monthly bond portfolios. The sample period is January 1964 to December 2008. *p-val* is the *p*-value calculated using the Newey-West correction for heteroscedasticity and autocorrelation with 18 lags. *p-val bst* is the bootstrapped *p*-value.

	Coef.	p-val	p-val bst	Coef.	p-val	p-val bst	Coef.	p-val	p-val bst
Constant	-0.004	0.01	0.98	0.000	0.21	0.64	-0.001	0.04	0.89
LNF_1	0.002	0.00	0.01						
LNF_2	0.002	0.04	0.01						
LNF_3	-0.001	0.07	0.87						
LNF_4	0.000	0.14	0.72						
LNF_5	-0.002	0.00	1.00						
LNF_6	-0.002	0.00	1.00						
LNF_7	-0.001	0.01	0.99						
LNF_8	0.002	0.00	0.00						
LNF_9	0.000	0.17	0.70						
$f^{(1)}$	0.213	0.03	0.03						
$f^{(2)}$	-0.200	0.04	0.88						
$f^{(3)}$	0.013	0.24	0.47						
$f^{(4)}$	0.053	0.19	0.30						
$f^{(5)}$	0.004	0.24	0.48						
CP				0.020	0.15	0.19			
LN				0.136	0.00	0.00			
CPBP							0.519	0.07	0.03
LNBP							0.949	0.00	0.00
R^2		0.14			0.08			0.13	
Adj. R^2		0.12			0.07			0.12	

Table A2
Expectations, Bond Risk Premia, and Stock Market Illiquidity

The table presents the in-sample forecasting regression for the equally-weighted bond portfolio returns using macroeconomic expectations and dispersion of expectations in addition to stock market illiquidity. Panel A presents the regressions without stock market illiquidity, Panel B presents the regressions including $D_{12}ILRSMB$. The factors included are the Cieslak and Povala (2011) factor (*Cieslak-Povala*) and the dispersions for one quarter and one year expectations for: real GDP (*RGDP 1Q, RGDP 1Y*), industrial production growth (*INDPROD 1Q, INDPROD 1Y*), GDP deflator (*GDP Deflator 1Q, GDP Deflator 1Y*), CPI (*CPI 1Q, CPI 1Y*), and the difference in the forecast for the 3-month T-bill and 10-year note rates (*Tbill-Notes 1Q, Tbill-Notes 1Y*) from the Survey of Professional Forecasters provided by the Philadelphia Fed. $D_{12}ILRSMB$ is the yearly change in the difference of log illiquidity for small and large stocks (small-big). *p-val* is the p-value calculated using the Newey-West correction for heteroscedasticity and autocorrelation with 18 lags. All regressions include a constant, not reported to conserve space.

	Coef.	p-val	Coef.	p-val	Coef.	p-val	Coef.	p-val
Panel A. Expectations and Dispersion of Expectations								
CP	0.305	0.43	0.659	0.00	0.549	0.01	0.620	0.03
LN	0.553	0.00	0.732	0.00	0.705	0.00	0.499	0.03
Cieslak-Povala	0.659	0.00						
RGDP 1Q			-0.027	0.02				
RGDP 1Y			0.012	0.30				
INDPROD 1Q			0.000	0.88				
INDPROD 1Y			-0.002	0.11				
CPI 1Q					-0.010	0.36		
CPI 1Y					0.050	0.00		
GDP Deflator 1Q					0.004	0.66		
GDP Deflator 1Y					-0.038	0.01		
Tbill-Notes 1Q							0.032	0.00
Tbill-Notes 1Y							0.004	0.76
R^2	0.50		0.42		0.34		0.31	
Adj. R^2	0.50		0.41		0.33		0.30	
Obs	528		471		319		319	
Panel B. Expectations and Dispersion of Expectations with Stock Market Liquidity								
CP	0.268	0.38	0.619	0.00	0.537	0.00	0.548	0.00
LN	0.554	0.20	0.703	0.00	0.673	0.00	0.515	0.00
$D_{12}ILRSMB$	0.017	0.01	0.023	0.00	0.019	0.02	0.020	0.03
Cieslack-Povala	0.641	0.11						
RGDP 1Q			-0.029	0.01				
RGDP 1Y			0.011	0.18				
INDPROD 1Q			0.000	0.77				
INDPROD 1Y			-0.003	0.04				
CPI 1Q					-0.006	0.64		
CPI 1Y					0.040	0.00		
GDP Deflator 1Q					0.006	0.39		
GDP Deflator 1Y					-0.038	0.02		
Tbill-Notes 1Q							0.029	0.01
Tbill-Notes 1Y							0.005	0.73
R^2	0.54		0.48		0.39		0.37	
Adj. R^2	0.54		0.47		0.38		0.36	
Obs	528		471		319		319	

Table A3
Futures Market and Stock Market Illiquidity

The table presents monthly regressions of future market variables from Hong and Yogo (2012) and stock market illiquidity. In Panel A the dependent variable is the open interest growth in the bond market (*FlowB*) and the sample period starts in December 1983. In Panel B the dependent variable is hedging demand imbalance in bond market (*ImbalanceB*) and the sample period starts in December 1983. In Panel C the dependent variable is open index growth in commodity index (*FlowInd*) and the sample period starts in December 1965. In Panel D the dependent variable is hedging demand imbalance in commodity index (*ImbalanceInd*) and the sample period starts in January 1965. In Panel E the dependent variable bond risk premia at t+1. CP denotes the Cochrane-Piazzesi factor. LN is the linear combination of the nine macro factors of Ludvigson and Ng. $D_{12}ILRSMB$ is the yearly change in the log illiquidity difference for small and large stocks (small-big). *p-val* is the p-value calculated using the Newey-West correction for heteroscedasticity and autocorrelation with 18 lags. *Model p-val* is the p-value for the model specification F-statistic. All regressions include a constant, not reported to conserve space.

Variable	Coef.	p-val	Obs	Adj. R^2	Model p-val
Panel A. Open Interest Growth in Bond Market					
$D_{12}ILRSMB_{t-1}$	0.348	0.33	290	0.01	0.09
$D_{12}ILRSMB$	0.326	0.23	289	0.01	0.11
Panel B. Hedgind Demand Imbalance in Bond Market					
$D_{12}ILRSMB_{t-1}$	1.314	0.58	302	0.00	0.16
$D_{12}ILRSMB$	0.957	0.69	301	0.00	0.30
Panel C. Open Index Growth in Commodity Index					
$D_{12}ILRSMB_{t-1}$	-0.428	0.42	483	0.01	0.04
$D_{12}ILRSMB$	-0.288	0.61	482	0.00	0.18
Panel D. Hedging Demand Imbalance in Commodity Index					
$D_{12}ILRSMB_{t-1}$	-5.803	0.05	506	0.03	0.00
$D_{12}ILRSMB$	-4.968	0.12	505	0.02	0.00

Panel E. Bond Premia and Futures Information

Variable	Coef.	p-val	Coef.	p-val
CP	0.680	0.00	0.799	0.00
LN	0.512	0.01	0.363	0.04
$D_{12}ILRSMB$	0.013	0.06	0.014	0.02
FlowInd	-0.001	0.77		
ImbalanceInd	-0.001	0.00		
FlowB			-0.001	0.71
ImbalanceB			0.001	0.03
Obs	482		289	
Adj. R^2	0.48		0.33	

Table A4
Bond Risk Premia and Market-Wide Private Information

The table presents the monthly in-sample forecasting regression of excess bond returns and market-wide private information as calculated in Albuquerque et al. (2008), $\overline{rx}_{t+12} = \boldsymbol{\beta}'\boldsymbol{X}_t + \bar{\varepsilon}_{t+12}$. $\overline{rx}$ is the equally-weighted yearly excess bond return, *MPI1* is the market-wide private information in the Primary Smelting and Refining of Nonferrous Metal industry, *MPI2* is the market-wide private information in the Oil and Gas Field Machinery and Equipment Manufacturing industry, and *MPI5* is the market-wide private information in the Other Aircraft Parts and Auxiliary Equipment Manufacturing industry. *CP* is the Cochrane Piazzesi factor and *LN* is the linear combination of the Ludvigson and Ng factors. $D_{12}ILR$ is the yearly change in log illiquidity and $D_{12}ILRSMB$ is the yearly change in the difference of log illiquidity for small and large stocks (small-big). Coefficients on MPI have been multiplied by 1,000. The sample period is January 1993 to February 2003. *p-val* is the p-value calculated using the Newey-West correction for heteroscedasticity and autocorrelation with 18 lags.

	MPI1				MPI2				MPI5			
	Coef.	p-val	Coef.	p-val	Coef.	p-val	Coef.	p-val	Coef.	p-val	Coef.	p-val
Constant	0.001	0.76	0.002	0.51	0.000	0.79	0.002	0.11	0.001	0.57	0.002	0.33
MPI	0.178	0.00	0.136	0.13	-0.113	0.00	-0.102	0.00	-0.037	0.06	-0.046	0.11
CP	1.034	0.00	0.956	0.00	1.176	0.00	1.085	0.00	1.071	0.00	0.974	0.00
LN	0.389	0.00	0.275	0.00	0.322	0.00	0.210	0.00	0.343	0.00	0.258	0.00
$D_{12}ILR$	0.019	0.06			0.020	0.01			0.018	0.11		
$D_{12}ILRSMB$			0.027	0.06			0.027	0.00			0.025	0.00
R^2	0.19		0.261		0.22		0.29		0.19		0.26	
Adj. R^2	0.16		0.235		0.19		0.26		0.17		0.23	
Obs	120				114				121			

Table A5
Mutual Fund Bond Flows Correlations

The table presents the monthly correlation in mutual fund flows for the period January 1984 to June 2010. *T.E. Money Market* are Tax Exempt Money Market flow, *Tax. Bond* are taxable bond flows. Panel A presents the characteristics of net exchange flows as described in Section 6.4. Panel B presents the characteristics of net flows as described in Section 6.4.

	Equity	Hybrid	Municipal Bond	T.E. Money Market	Taxable Bond
			Panel A. Net Exchange Flows		
Hybrid	0.19				
Municipal Bond	0.24	0.15			
T.E. Money Market	- 0.28	- 0.07	- 0.86		
Taxable Bond	- 0.05	0.01	0.66	- 0.58	
Taxable Money Market	- 0.83	- 0.33	- 0.63	0.56	- 0.45
			Non-Crisis		
Hybrid	0.19				
Municipal Bond	0.26	0.18			
T.E. Money Market	- 0.36	- 0.05	- 0.89		
Taxable Bond	- 0.01	- 0.03	0.66	- 0.58	
Taxable Money Market	- 0.80	- 0.31	- 0.68	0.65	- 0.51
			Crisis		
Hybrid	0.14				
Municipal Bond	0.31	0.19			
T.E. Money Market	- 0.17	- 0.19	- 0.65		
Taxable Bond	0.06	0.19	0.72	- 0.52	
Taxable Money Market	- 0.89	- 0.38	- 0.55	0.26	- 0.41
			Panel B. Net Flows		
Hybrid	0.57				
Municipal Bond	0.08	0.41			
T.E. Money Market	0.02	0.07	0.28		
Taxable Bond	0.01	0.29	0.75	0.20	
Taxable Money Market	- 0.13	- 0.19	- 0.08	0.44	- 0.16
			Non-Crisis		
Hybrid	0.58				
Municipal Bond	0.02	0.37			
T.E. Money Market	- 0.02	0.11	0.32		
Taxable Bond	- 0.04	0.22	0.75	0.31	
Taxable Money Market	- 0.08	- 0.12	- 0.01	0.41	- 0.02
			Crisis		
Hybrid	0.42				
Municipal Bond	0.16	0.58			
T.E. Money Market	0.04	- 0.18	- 0.05		
Taxable Bond	0.19	0.69	0.87	- 0.29	
Taxable Money Market	- 0.19	- 0.38	- 0.37	0.57	- 0.59

Table A6
Bond Term Structure and Flight to Liquidity

The table presents the relation between bond premia for individual maturities, stock market illiquidity, and flight to quality measures. $D_{12}ILRSMB$ is the yearly change in the difference of log illiquidity for small and large stocks (small-big), *FG Liq.* is the funding liquidity variable of Fontaine and Garcia (2012), *Tax Bond* are taxable bond flows, *T.E. Money Market* are Tax Exempt Money Market flows, *Equity* are equity flows, and *VXO* is the S&P100 volatility index. All mutual fund flows are calculated as net exchange flows, Ben-Rephael et al. (2012). The sample period is January 1986 to December 2007. *p-val* is the p-value calculated using the Newey-West correction for heteroscedasticity and autocorrelation with 18 lags.

	2-year		3-year		4-year		5-year	
	Coef.	p-val	Coef.	p-val	Coef.	p-val	Coef.	p-val
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
C	0.013	0.08	0.025	0.11	0.036	0.12	0.042	0.01
$D_{12}ILRSMB$	0.007	0.01	0.013	0.02	0.017	0.06	0.018	0.08
FG Liq.	-0.009	0.00	-0.017	0.00	-0.024	0.00	-0.028	0.00
Taxable Bond	9.785	0.28	18.619	0.34	24.662	0.40	25.599	0.11
TE Money Market	0.930	0.92	-0.559	0.98	-3.401	0.91	-11.266	0.60
Equity Flow	0.680	0.77	0.536	0.91	-0.277	0.97	-0.843	0.91
VXO	0.000	0.50	0.000	0.56	0.000	0.67	0.000	0.59
R^2	0.24		0.24		0.23		0.20	
Adj. R^2	0.22		0.23		0.21		0.18	
Obs	263		263		263		263	

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