Stock Market Liquidity and Bond Risk Premia^{*}

Kees E. Bouwman[†]

Erasmus University

Elvira Sojli

Erasmus University and Duisenberg School of Finance

Wing Wah Tham

Erasmus University

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Abstract

We assess the effect of equity market liquidity on U.S. bond risk premia. We find that stock market liquidity 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 their 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 argue that stock market liquidity contains information about expected future business conditions through the investment, the flight to liquidity, and the macroeconomic channels. Our results support the hypothesis that macroeconomic uncertainty is one of the main determinants of bond risk premia.

Keywords: Market liquidity; Bond risk premia; Flight-to-quality.

JEL Classification: G10; G20; G14.

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[†]Corresponding author. Address: Erasmus School of Economics, H11-15, Erasmus University, PO Box 1738, Rotterdam, 3000DR, the Netherlands. Email: kbouwman@ese.eur.nl, Phone: +31(0)10 4081262. Other authors' email addresses: esojli@rsm.nl (Sojli), tham@ese.eur.nl (Tham).

1 Introduction

Empirical research documents predictability in the excess returns of U.S. sovereign bonds. The earlier literature relates excess bond returns to yield spreads. Excess bond returns can be forecasted by the *n*-year spread of the *n*-year forward rate and the one-year yield (Fama and Bliss, 1987) and by Treasury yield spreads (Campbell and Shiller, 1991). Cochrane and Piazzesi (2005) show that one can also predict excess bond returns using a linear combination of five forward spreads. The more recent literature focuses on factors outside the bond market and related to the macro economy. Ludvigson and Ng (2009) and Cooper and Priestley (2009) show 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. Duffee (2011a) reports that half of the variation in bond risk premia cannot be explained by the cross section of bond yields. He finds a latent component of bond risk premia that contains substantial information about expected future yields and is negatively correlated with aggregated economic activity. However, he finds that macroeconomic variables contain little information about the latent factor. These recent developments in the literature suggest the importance of considering factors outside bond yields and the role of the macro economy in understanding the drivers behind term structure dynamics. In this paper, we focus on examining whether stock market liquidity contains additional information over the existing factors in explaining bond risk premia.¹

The natural question is why should stock market liquidity contain information about bond's expected returns. Chen, Roll, and Ross (1986) and Fama and French (1989) argue that expected macroeconomic and business conditions should be strongly related to expected excess returns. In a frictionless economy, funds are readily liquid and available for investment. Thus, funds can flow into the most profitable projects and to the

¹In addition, Wright and Zhou (2009) find that the realized bond mean jump from the 30-year Treasury futures has additional predictive information over the CP factor. Huang and Shi (2011) support the finding of Ludvigson and Ng (2009) and document higher predictability of bond returns with macroeconomic variables using a statistical method of supervised adaptive group 'least absolute shrinkage and selection operator" approach. Cieslak and Povala (2011) decompose long term yields into a persistent component and maturity-related cycles to study the predictability of bond excess returns.

entrepreneurs who value and need these funds most. In other words, liquidity does not matter in an economy without financial frictions and should not be related to expected excess returns. In an economy with financial frictions, liquidity matters and can be important, because the distribution of wealth across economic agents becomes asymmetric. In an excellent survey, Brunnermeier, Eisenbach, and Sannikov (2011) argues that liquidity risk can amplify a small exogenous shock into a sizable shock in the macroeconomy and liquidity risk can lead to high endogenous risk, due to interactions within the system. Brunnermeier and Pedersen (2009) and Brunnermeier et al. (2011) shows how the mismatch between technological and market liquidity on the asset side of the balance sheet and funding liquidity on the liability side of the balance sheet can interact and create liquidity spirals.² These liquidity spirals can lead to flight to quality and liquidity, because individuals demand more liquid assets for precautionary reasons.

The role of market liquidity on the macroeconomy can be more clearly seen from the monetary model with differential liquidity of Kiyotaki and Moore (2008). In their 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 (equity liquidity) can reduce the amount of entrepreneurs' downpayment which will result in large and persistent reductions in investment, output, and employment. Anticipating lower market liquidity, equity prices fall because entrepreneurs hold more liquid assets in their portfolios as they flee to liquidity. In an analysis of financial markets, Brunnermeier and Pedersen (2009) study the decline of funding liquidity and market liquidity, which are analogous to the borrowing and resaleability constraints in Kiyotaki and Moore (2008), in periods of financial stress. Brunnermeier and Pedersen (2009) show 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. Through these models, one can see how market liquidity affects the macro economy, the cost of raising capital, and investments.

²Brunnermeier et al. (2011) distinguish between three types of liquidity: technological, market, and funding liquidity. The first two are related to how easily a physical asset/investment can be disposed off. Technological liquidity refers to the possibility to reverse an investment, while market liquidity to the ability to sell capital easily.

Thus, equity market liquidity, representing asset resaleability constraints, should be a good indicator of future business and macroeconomic conditions, which can be linked to expected excess returns. Moreover, the availability of market liquidity data at a higher frequency compared to other business and economic expectation variables makes it a more attractive and timely variable to condition on.

There is other supporting evidence that suggests why liquidity might be a useful predictor of bond excess return. Skieltorp and Ødegaard (2011) and Lipson and Mortal (2009) provide empirical evidence of how market liquidity affects the cost of capital, while Lettau and Ludvigson (2002) highlight the importance of the relation between the cost of capital and risk premia through the investment channel. Consistent with Kiyotaki and Moore (2008) and Brunnermeier and Pedersen (2009), Næs, Skjeltorp, and Ødegaard (2011) find that U.S. stock market liquidity contains leading information about the real economy. Using detailed information on ownership for the whole Norwegian stock market, they find evidence of flight to quality, investors exit the stock market to invest in safer assets, and flight to liquidity, portfolio shifts from less liquid to more liquid stocks, before economic recessions. Connolly, Stiversa, and Suna (2005), Underwood (2009), and Beber, Brandt, and Kavajecz (2009) provide other empirical evidence that investors are likely to flee to liquidity within the stock market before fleeing to the safer Treasury market during economic uncertainty. Also, Longstaff (2004) shows that liquidity premia in the Treasury market are higher during periods of flight to quality. The countercyclical and flight-toquality nature of stock liquidity is consistent with Vayanos (2004)'s arguments about the role of flight to quality and flight to liquidity on risk premia. Moreover, Næs, Skjeltorp, and Ødegaard (2011) find that stock liquidity has additional information over various macroeconomic and financial indicators in predicting future states of the real economy. This is especially important because Fama and French (1989) and Cochrane (2007) stress that business cycle related asset risk premia should reflect aggregate macroeconomic risk. An important aspect of such an asset premium predictor is its ability to forecast business cycles and excess returns across various assets.

The role of stock market liquidity as a state variable has been studied by Pastor

and Stambaugh (2003) and Acharya and Pedersen (2005). They show that the time variation in stock market liquidity affects cross sectional equity returns. Amihud (2002) and Jones (2002) document the presence of a time-series relation between equity market liquidity and expected equity market returns and Bekaert, Harvey, and Lundblad (2007) find that liquidity significantly predicts returns in emerging equity markets. In addition, Lee (2011) shows that U.S. stock market liquidity is the main driver of global liquidity risk, and de Jong and Driessen (2006) find that stock market liquidity affects corporate bond returns. The theoretical and empirical links between stock market illiquidity, expected returns, and macroeconomic activity as well as the link between bond excess returns and macroeconomic information suggest that stock market liquidity might contain useful information about U.S. bond risk premia. Despite this evidence, the role of stock market liquidity as a predictive variable for bond excess returns remains unexplored.

We use the Amihud (2002) illiquidity measure to examine whether excess bond returns can be predicted by stock market liquidity. We also use the difference of aggregated liquidity between large and small cap stocks as an alternative variable. The latter variable attempts to capture the flight to liquidity from small to large stocks in the equity market and is quite novel as a flight-to-quality variable. This variable is consistent with Ben-David, Franzoni, and Moussawi (2010) and Næs et al. (2011) who find that market participants shift their portfolios towards larger stocks and out of the equity market during financial crisis. Hence, the difference of aggregated liquidity between large and small cap stocks might capture the time variation in market wide risk aversion.

Our results indicate that equity market liquidity significantly affects bond premia. An increase in illiquidity in the stock market leads to higher bond excess returns. The magnitude of the predictability that we find using aggregate stock market liquidity is not only statistically but also highly economically significant. The difference between the liquidity of the smallest and largest stocks seems to be an especially strong predictor of bond premia. This is not surprising because it is highly likely that investors first pull out from the smallest and least liquid stocks before recessions. Our predictive variables display strong forecasting power for excess returns across bonds of all maturities. They explain 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.

While Cochrane and Piazzesi (2005)'s factor subsumes variables like forward spreads, yield spreads, and yield factors and Ludvigson and Ng (2009)'s factor contains information of 132 measures of economic and financial activities, our single liquidity variable contains additional information about bond's expected returns that are not present in the Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009) factors. Our model with equity liquidity including the Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009) variables explains as much as 45% of next year's equally weighted bond excess return. Our liquidity variables increase the adjusted R^2 by 3-6% across all bond maturities over the Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009) factors. The significance of the predictive power for excess bond returns continues to exist even after accounting for the small-sample properties of the data. In addition, stock market liquidity has strong out-of-sample forecasting power for excess bond returns, above the forecasting ability of the Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009) factors. For robustness, we investigate the impact of equity liquidity on monthly returns of portfolios of Treasury bills and bonds as in Duffee (2011b). The in- and out-of-sample results for monthly portfolios are quantitatively and qualitatively similar as for the yearly portfolios.

To investigate the investment channel through which liquidity affects bond risk premia, we use our liquidity variable to forecast future real investment growth. We find that stock market liquidity can explain real investment growth up to four quarters ahead. In addition, we study the relation between mutual fund flows and stock market liquidity to further investigate the relation between of flight to quality and market liquidity. We find that changes in liquidity are related to shifts of U.S. mutual fund flows, from equity to money market funds indicating its relation to flight to quality. An increase in the gap between small and large stock illiquidity is positively correlated with flows into money market funds and negatively correlated with flows to equity funds. In an alternative exercise, we find that market liquidity explains and predicts changes in the average proportion holding of equity and bonds by balanced funds. This result shows how market liquidity can predict the portfolio shift from equity to bonds of money managers and the potential relation between liquidity and flight to safety. We also find that stock market liquidity can predict changes in implied volatility. All this evidence supports the role of financial frictions in general and the investment channel in particular in affecting bond risk premia through stock market liquidity.

In contrast to the existing literature that focuses on information from macroeconomic activity and the cross-section of yields and forwards, we study the role of liquidity in the equity market on excess bond returns. Our paper contributes to the existing bond risk premia literature by showing that stock market liquidity contains information about future excess bond returns even after controlling for information from bond yields, forward rates, and macro-variables. We join Ludvigson and Ng (2009) and Duffee (2011a) in demonstrating the importance of considering information from sources outside bond yields and forwards and in showing the link of term structure to the macroeconomy. We go a step further by establishing that market liquidity affects bond risk premia via the investment channel. Stock market liquidity appears to contain information about future investment growth, portfolio shifts of individual investors, flight-to-quality, and market expectations of the future state of the economy. Thus, we provide empirical support to the literature of macroeconomics with financial frictions by demonstrating the relevance of market liquidity on the macroeconomy and risk premia.

Furthermore, we contribute to the literature that tries to simultaneously explain prices in aggregated stock and bond markets, see Koijen, Lustig, and Nieuwerburgh (2009) and Lettau and Wachter (2011). Our findings provide empirical evidence that suggests that stock and bond markets are potentially driven by a common aggregate liquidity factor, which could be useful for the future theoretical literature that focuses on the joint modeling of stock and bond returns.

The next section presents the econometric framework. Section 3 discusses our data and preliminary analysis. Section 4 presents the results on the link between bond premia and equity market liquidity and Section 5 tests the robustness of the results. We discuss why equity market liquidity matters in Section 6. Section 7 concludes.

2 Econometric Framework of Bond Return Regressions

Let $p_t^{(n)}$ denote the log-price in year t = 1, ..., 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. Recent empirical evidence however 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, X_t :

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

We run regressions with different sets of predictor variables, including liquidity measures to examine the link between bond risk premia and equity market liquidity. We also consider the predictor variables identified by Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009) to explore whether market liquidity 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 as:

$$\overline{rx}_{t+1} = \gamma' X_t^{CP} + \overline{\varepsilon}_{t+1}, \qquad (2)$$

where $\overline{rx}_{t+1} = \frac{1}{4} \sum_{n=2}^{5} rx_{t+1}^{(n)}$ and $\boldsymbol{X}_{t}^{CP} = [1, y_{t}^{(1)}, f_{t}^{(2)}, \dots, f_{t}^{(5)}]$. The CP-factor combines

the information in all forward rates and is defined as $CP_t = \hat{\gamma}' X_t^{CP}$. We use both the five forward rates and the CP factor as explanatory variables to control for the predictive information in the term structure of interest rates.

Ludvigson and Ng (2009) examine the link between bond risk premia and macroeconomic fundamentals by regressing excess bond returns on several constructed macro factors. Instead of selecting specific macro variables, they use dynamic factor analysis to extract a small set of macroeconomic factors from a panel of 132 measures of economic activity. The macro 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:

$$\overline{rx}_{t+1} = \boldsymbol{\delta}' \boldsymbol{X}_t^{LN} + \overline{\varepsilon}_{t+1}, \qquad (3)$$

where $\mathbf{X}_{t}^{LN} = [1, LNF_{1,t}, \dots, LNF_{9,t}]$ contains the nine macro factors of Ludvigson and Ng (2009). We define the single forecasting factor, the LN-factor, as $LN_{t} = \hat{\boldsymbol{\delta}}' \mathbf{X}_{t}^{LN}$.

Each month we construct one year ahead bond returns, because a purely yearly sample would leave us with 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 corrected using the Newey-West procedure with 18 lags to account for heteroscedasticity and autocorrelation in the residuals.

2.1 Small Sample Performance

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 robustness of our inference in finite samples. In particular, we test for the significance of our variables of interest in the bond return regression:

$$rx_{t+1}^{(n)} = \alpha + \beta' \boldsymbol{X}_t + \varepsilon_{t+1}^{(n)}$$
(4)

by constructing bootstrap samples for both X_t and $rx_{t+1}^{(n)}$. First, we estimate a first-order VAR model for X_t , given by:

$$oldsymbol{X}_{t+1} = oldsymbol{ heta} + oldsymbol{\Phi} oldsymbol{X}_t + oldsymbol{
u}_{t+1},$$

where $\operatorname{var}(\boldsymbol{\nu}_{t+1}) = \boldsymbol{\Sigma}_{\nu}$. Next, we define the standardized residuals by:

$$\boldsymbol{\eta}_t = \boldsymbol{\Sigma}^{-1/2} \boldsymbol{\nu}_t,$$

where $\Sigma^{-1/2}$ is the inverse of the Choleski factorization of Σ_{ν} . We construct bootstrap samples for X_t by resampling from the standardized residuals $\eta_{i,t}$ to generate new sample paths for X_t starting from X_1 . Next, bootstrap samples of $rx_{t+1}^{(n)}$ are constructed from equation (2) by using the bootstrap samples of X_t and by resampling blocks of 12 subsequent residuals $\varepsilon_{t+1}^{(n)}$. The bootstrap procedure is repeated 10,000 times.

2.2 Out-of-sample forecasting exercise

Out-of-sample forecasts are constructed by using a moving window of 15 years (i.e. 180 monthly observations). Using this window of data, first we estimate the Cochrane-Piazzesi and Ludvigson and Ng (CP and LN hereafter) factors, in order to avoid including information not available at the time of the forecast to the econometrician. Next, the regressions are estimated over the sample window of 180 observations. Forecasts of the one-year ahead excess returns are obtained 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 will run from February 1964 to January 1979 and is used to forecast the excess bond return for the period 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) and the Giacomini and White (2006) test for unconditional predictive ability using the quadratic loss function. The null hypothesis is that two forecasting models have equal expected squared prediction errors. The test statistic of the Giacomini-White (GW) test coincides with that of the Diebold and Mariano (1995) test, but the tests use different null hypotheses.

Following the GW approach has some advantages over West (1996) and Clark and McCracken (2001) because it provides test statistics with well-defined distributions and better small-sample properties. In particular, the GW test not only compares forecasting models but also forecasting methods to account for the role of parameter uncertainty, thereby allowing for a stricter and straight forward testing of nested alternatives. For example, Clark and McCracken (2001) assumes that the difference in mean squared error (MSE) is due to poor restricted model performance and not the result of parameter uncertainty. Thus, it sometimes rejects the hypothesis that the restricted model encompasses the unrestricted model even when the MSE of the restricted model is smaller than the MSE of the unrestricted model. GW overcomes this limitation by taking parameter uncertainty into account when evaluating the performance of different forecasting models.

3 Data

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, two, three, four, and five year maturities. The sample contains monthly data for the period spanning from January 1964 up to December 2008. This is a longer sample compared to the one used used by Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009) and includes the current financial crisis.³ We construct annual returns by continuously compounding monthly return observations.

Data on the macro factors of Ludvigson and Ng (2009) are directly obtained from the website of Sydney Ludvigson.⁴ The macro factors are extracted from a balanced panel of 132 monthly macro series related to economic activity using principal components. See Ludvigson and Ng (2009) for details on the underlying macro series and the construction of the factors.

3.1 Equity Liquidity Factor

In the literature, there are many different measures of liquidity, using daily and intraday data. Intraday data is available 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 the low frequency measures of liquidity capture well the spread cost and price impact estimated using intraday data. 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 using only a month of daily data. Thus, we use the Amihud (2002) illiquidity ratio (*ILR*). *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 liquidity is low.

ILR is calculated using stock prices, returns, and trading volume from CRSP. Only common shares listed at the NYSE are included. For each stock the ILR is calculated daily and averaged across the month and then averaged across all the securities to create a market wide measure. Also, we use the difference between the ILR of small and large

³All the results presented remain qualitatively and quantitatively

⁴http://www.econ.nyu.edu/user/ludvigsons/, April 15, 2011.

stocks, *ILR SMB*. A positive change in *ILR* implies a decrease in liquidity. A positive change in *ILR SMB* implies an increasing gap between the liquidity of small and large stocks. The liquidity measures at the monthly level exhibit unit roots. We take the log yearly change in liquidity, to be consistent with the bond risk premia literature.⁵

3.2 Preliminary Analysis

Table 1 presents the sample characteristics for all the variables used and the correlations among the variable for the whole sample. The mean and median yearly log change in illiquidity, $D_{12}ILR$, is highly negative. This implies that stock market liquidity has improved on average over the sample period. The change in the difference between small and large stock liquidity, $D_{12}ILRSMB$, is positive. The liquidity gap between small and large stocks appears to have increased during the sample period, implying that large stocks have benefited more from the 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 return with the illiquidity factors is higher than with many of the other factors. The equity market illiquidity variables are positively correlated with all the Cochrane and Piazzesi factors and most of the Ludvigson and Ng factors. The correlations with these factors are not very large, implying that the equity liquidity variables might have additional information to the ones 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 equity illiquidity factors. The CP and LN factors comove substantially with the average bond excess return, while the liquidity factors exhibit fluctuations of lower magnitudes compared to the excess return and the other factors. $D_{12}ILRSMB$ seems to move more in sync with the average bond excess return than $D_{12}ILR$.

⁵There 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.

4 Results

4.1 In-Sample Predictions

We present the results on the relation between the equally weighted bond premia and stock market liquidity in Table 2. Because we use monthly estimates of yearly bond excess returns our predictive regression is different from Equation (1) and becomes:

$$rx_{t+12} = \boldsymbol{\beta}' \boldsymbol{X}_t + \varepsilon_{t+12}.$$
 (5)

where X_t is a vector of explanatory variables. 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 with serial correlation with 18 lags, because continuously compounded annual returns have an MA(12) error structure. We follow Cochrane and Piazzesi (2005) in using an 18-lag correction lags to capture autocorrelation induced by the overlapping periods, because the Newey-West correction often down-weights high order serial correlation.

Both illiquidity measures have a positive impact on bond excess returns, i.e. increasing illiquidity in the equity market leads to higher bond excess 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. This is not surprising as $D_{12}ILRSMB$ is expected to be a much stronger indicator of flight to liquidity. When $D_{12}ILRSMB$ is large, investors are expected to 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 Ludvigson and Ng factors and the forward rates of Cochrane and Piazzesi, which explain 41% of the monthly variation in future bond excess returns. Nonetheless, the equity illiquidity variables add to the explanatory power of the previously used factors. When adding $D_{12}ILR$ to the LN and CP factors, 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 Table 2, we also report the regressions using the linear combinations of the Ludvigson and Ng and Cochrane and Piazzesi factors, LN and CP respectively. The results remain quantitatively similar when we apply these changes. We will use the combined factors for the rest of the analysis, because there are less parameters to estimate, which improves the precision of the coefficients. The bootstrapped p-value of $D_{12}ILRSMB$ is always 0, while that of $D_{12}ILR$ is always below 0.10.

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 liquidity 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 LNand *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).⁶ More importantly, the stock market liquidity variables are still statistically and economically significant with the inclusion of LN and CP factors across all maturities. The adjusted R^2 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% increase in \mathbb{R}^2 with a *single* return forecasting factor for all maturities suggests that stock market liquidity variables contain additional information not encompassed in the LN and CP factors. We also notice that the estimated coefficients for $D_{12}ILRSMB$ 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.

 $^{^{6}\}mathrm{This}$ alleviates any potential concerns about the use of the combined factors LN and CP and the longer sample.

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 Giacomini and White (2006) test statistic, and its p-value. 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 root mean squared errors than the benchmark model. 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-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 liquidity variables and the benchmark model with the CP and LN factors is statistically significant. 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.

5 Robustness

Ferson, Sarkissian, and Simin (2003) highlight the importance of addressing spurious regression bias in predictive regressions with persistent variables. As strong autocorrelation might be induced from the overlapping scheme we adopt in the bond return regressions using the Fama-Bliss dataset, we investigate the validity and robustness of our results using monthly returns for portfolios of Treasury bills and bonds following Duffee (2011b). We use CRSP maturity 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 substracting 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 (2011b) argues that predicting monthly excess returns of these bond portfolios provides an alternative test to the statistical significance of predictive variables. Moreover, studying the predictability of monthly returns of bond portfolios avoids the use of overlapping data and serve as a robustness test.

We repeat the analysis in the Section 4 using bond portfolio returns as the dependent variable. We first run a regression of the monthly equally weighted bond portfolio returns and the Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009) factors, presented in Table A1 in the Appendix. These factors explain 14% of the variation in average portfolio. As previously, 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 Fama-Bliss excess bond returns. 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 explains almost the same amount of variation in the bond portfolio returns as the individual factors. We will use these two factors for the remaining in sample and out of sample analysis to reduce estimation problems.

5.1 In-Sample Predictions

Table 5 presents the results for the regression of the equally weighted bond portfolio returns equivalent to Table 2:

$$\overline{rx}_{m,t} = \boldsymbol{\beta}' \boldsymbol{X}_t + \varepsilon_t,$$

where $\overline{rx_m}$ is the equally weighted monthly bond portfolio return. Equity liquidity variables are highly statistically significant. In addition, they explain 2% of the monthly variation in bond portfolio excess returns. As before, there is a positive relation between the liquidity variables and bond excess returns. Economically, an increase by one standard deviation in $D_{12}ILRSMB$ increase monthly bond excess returns by 12 basis points.

Table 6 reports results from the in-sample forecasting regression for 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. The statistical significance of the liquidity variables continues is high for each of the six indivial bond portfolio return regressions. The addition of the equity liquidity variables to the *CPBP* and *LNBP* factors increases the adjusted R^2 by 1-3% for all maturities. As noted before with the Fama-Bliss portfolios, the impact of equity liquidity increases with the increase in the maturity of the bonds. In addition, the explanatory power of the factors decreases with the increasing maturity of bonds.

5.2 Out-of-Sample Prediction

Table 7 presents the out-of-sample forecasting results for the equally weighted bond portfolio and for six individual monthly bond portfolio excess returns. The forecasting models that include the stock illiquidity factors $D_{12}ILR$ and $D_{12}ILRSMB$ exhibit lower root mean squared errors than the benchmark model, as can be seen from the RMSE ratio. 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 out-of-sample forecasting power between the models with the liquidity variables and the benchmark model with the CPBP and LNBP factors is mostly statistically significant. Overall these results reflect the robustness of equity market liquidity as a predictive variable for bond excess returns.

5.3 Futures Market

In a recent paper, Hong and Yogo (2012) show that not only future prices but also open interest in the futures market are important indicators of future economic activity. 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). The results in Table A3 in the Appendix show that stock market illiquidity is not associated neither contemporaneously nor with a lag to futures market information. In further robustness 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.

6 Why Does Stock Market Liquidity Matter?

In the introduction, we argue that stock market liquidity could be related to bond excess returns via the investment channel. For the investment channel to be plausible, stock market liquidity should be able to predict future real investment growth. In the following, we assess the link between liquidity and investments. Secondly, individuals and firms should demand more liquid and safer assets if they expect the amplification effect from the interaction of the technological, market and funding liquidity on an exogenous shock. We investigate these flight to quality and liquidity episodes by studying the relation among market liquidity, S&P100 volatility index VXO, mutual fund flows and the equity and bond holdings in balanced funds.

6.1 Illiquidity and Investments

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 10 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 up to four quarters ahead can explain real private fixed investment growth. An decrease in liquidity by 1% cause 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, especially for $D_{12}ILR$, which explains up to 22% of the variation in investment growth. Results from Table 10 shows that liquidity contains leading information about future investment growth which consistent with the investment hypothesis.

6.2 Stock Market Illiquidity and Flight to Safety

A potential reason for the relation between equity market liquidity and bond risk premia could be flight-to-quality, where investors shift their portfolios towards less risky or safe assets in view of a deteriorating future business conditions, i.e. when the stock market liquidity is low or when the spread in liquidity between the small and large stocks is high leading to increasing risk premia in financial markets. Hartmann, Straetmans, and de Vries (2004) study linkages between stock and bond markets in G5 countries and find flight to quality towards U.S. bond market. They find stock market crashes in U.S., Germany, France, U.K., and Japan coincide with U.S. bond market booms. Longstaff (2004) shows that the flight-to-liquidity premium in Refcorp and U.S. Treasury bonds is related to flight to quality measured by the inflow into the money market mutual funds. Beber et al. (2009) emphasizes 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 comovements and suggest that these factors maybe correlated with "flightto-safety" effects.

Illiquidity and mutual fund flows

We investigate the relation between stock market liquidity and investors' shift in their portfolios towards U.S. sovereign bond market in economic downturns using aggregated net mutual equity and money market fund flow as Longstaff (2004). 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. Net equity mutual fund flows capture portfolio shifts of confident investors into equity mutual funds during good economic climate. Consistent with Longstaff (2004), we view the outflow from equity and inflow into money market mutual fund as flight-toquality. We use aggregate mutual fund flows data from the Investment Company Institute (ICI), which collects monthly sales, asset value and redemptions by fund for 98 percent of the U.S. mutual fund industry, from January 1984 to June 2010. We construct the net flows as sales minus redemptions, plus exchange in minus exchange out. 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. The ICI categorizes mutual funds into the following groups: Equity, Bond, Hybrid, and Money Market funds. Following Warther (1995), we standardize the net flow by lagged total market capitalization to control for time series variation in flow magnitude resulting from price appreciations and market growth.⁷

We start our analysis on flight-to-quality by first examining the correlation structure of fund flows. Panel A of Table 8 shows the correlation of net flows among U.S. mutual funds. There is a positive correlation among all the different flows, apart from Taxable money market flows. The largest correlations are between equity and municipal bond flows and hybrid fund flows. This is not surprising, as hybrid portfolios are composed of a mix of stocks and bonds. Money market flows are only positively correlated with Tax exempt money market 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 to short term bonds and are more appropriate to measure flight to quality.

Following Chordia et al. (2005), we investigate fund flows correlation during non-crisis and crisis periods. We identify five crisis periods in our sample: The Black Monday (October 19 1987 - March 31 1988), the Asian financial crisis (October 1 1997 - January 31 1998), Russian Default (July 1 1998 - December 12 1988), Dot-com bubble (February 1 2000 - March 31 2001) and Credit crisis (July 1 2007 - present). Panel A of Table A2 shows summary statistics of various fund flows during normal and crises periods. There is a significant decrease in net flows into equity, hybrid, and bond funds during crises but an

⁷Normalizing fund flows with fund assets rather than total market value does not quantitatively change our results. Results can be produced upon reader's request.

increase in net flows for taxable money market funds. This is consistent with suggestions of flight to quality during the crisis period which causes money to shift from riskier to less risky assets. In addition, Panel A of Table 8 shows that net flows of riskier funds like equity, hybrid, and bond funds become more negatively correlated to money market funds during crises. While the result above is suggestive about the portfolio shift hypothesis of individual investors, the flow variables, we have constructed according to Warther (1995) capture both the actual cash flow entering and exiting a fund family as well as transfers between mutual funds.

In order to study the flows of funds between equity funds and money market funds more carefully, we calculate net exchanges flow variables, exchange in minus exchange out, as suggested by Ben-Rephael, Kandel, and Wohl (2011). Thus, we exclude "sales minus redemptions". Net exchange flow captures portfolio shifts among different categories of funds while net sales and redemptions are likely to be influenced by long-term savings and withdrawals. Figure 3 shows the monthly net exchange equity and money market flows. There is an extremely strong negative relation between them, especially during periods of uncertainty. Panel B of Table 8 shows the correlations among U.S. mutual funds net exchange flows. We observe that net exchange flows into mutual funds are positively correlated with net exchange flows for hybrid and municipal bond funds as before, even though the correlations are slightly smaller. More interestingly, we observe a highly negative correlation between equity and money market net exchange flows. The negative correlation, -0.83, is even higher during crisis periods, -0.89.

Table 9 shows the correlations between mutual fund flows and stock market illiquidity, both monthly changes and yearly changes. Stock market illiquidity is positively correlated up to 30% with flows into money market funds, i.e. an increase in illiquidity in the stock market is related to increased funds flowing into the safer assets. Stock market illiquidity is strongly negatively correlated with flows into equity funds. These results are consistent with the suggestion that stock market liquidity reflects the market expectation about future state of the economy among investors.

6.3 Illiquidity and Balanced Mutual Fund Holdings

mutual funds. In the previous analysis it is not clear whether funds are shifting between equity and money market funds, or it is new funds that are going into money market funds. An alternative way to investigate the relation between market liquidity and flight to safety is to investigate the behavior of balanced 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 calculate the end-of-year proportional holding of equity by balanced funds as the ratio of the total value of their equity portfolio and the net asset value of the fund. 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 Table 11 show that when illiquidity increases managers of balanced funds shift their portfolios out of equities and into bonds. A 1% increase in illiquidity leads to a 3% decrease in equity market exposure.

6.4 Illiquidity and Implied Volatility

To ensure that our results on the relation between illiquidity and flight to safety are robust to non-mutual fund information, we investigate the relation between illiquidity and the S&P100 volatility index VXO, which has been disseminated since 1986. The use of stock index volatility as a proxy for flight to quality is motivated by Bailey and Stulz (1989), where they demonstrate an association between stock index volatility and flight to quality. The results in Table 12 show predictive power of stock market illiquidity for the volatility index, using univariate regressions with one and two lags. Stock market illiquidity is highly statistically significant. An increase in illiquidity by 1% leads to an increase of 3 points in VXO. Nonetheless, stock market illiquidity explains a small proportion of the variation in VXO, much smaller than what it can explain in investments.

7 Conclusions

We assess the effect of market liquidity on U.S. bond risk excess returns. We find that stock market liquidity adds to the well-established Cochrane-Piazzesi and Ludvigson-Ng factors both in in-sample and out-of-sample forecasting performance. The effects are statistically and economically significant. The equity liquidity effect is much stronger for the shorter maturity bonds than for the longer maturity. Our results are robust to using monthly bond portfolio returns.

Our results show that stock market liquidity can explain real investment growth up to four quarters ahead. In addition, we find that changes in stock market liquidity are related to shifts of U.S. mutual fund flows, from equity to money market funds indicating its relation to flight to quality. In an alternative exercise, we find that market liquidity explains and predicts the portfolio shift from equity to bonds of money managers and the potential relation between liquidity and flight to safety. Finally, we also find that stock market liquidity can predict changes in implied volatility. All this evidence supports the role of financial frictions in general and the investment channel in particular in affecting bond risk premia through market liquidity.

HPP HPP ((((((((((((((((($\begin{array}{c} LNF_1\\ 0.000\\ -0.149\\ 5.044\\ -2.308\\ 1.001 \end{array}$	$I_{\circ}NE_{\circ}$				10001			stire							
HP um ev.	$\begin{array}{c} LNF_1 \\ 0.000 \\ -0.149 \\ 5.044 \\ -2.308 \\ 1.001 \end{array}$	LNF				T miner 11.	I airce II. Daniefre Oliai actice isteres		00110							
um ev.	$\begin{array}{c} 0.000\\ -0.149\\ 5.044\\ -2.308\\ 1.001 \end{array}$	2.1.177	LNF_3	LNF_4	LNF_5	LNF_6	LNF_7	LNF_8	LNF_9	F1	F2	F3	F4	F5	$D_{12}ILR$	$D_{12}ILRSMB$
um ev.	-0.149 5.044 -2.308 1.001	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
um ev.	5.044 -2.308 1.001	0.129	0.005	0.068	0.001		-0.029	-0.054	-0.003	0.058	0.064	0.066	0.067	0.068	-0.158	0.044
ev.	-2.308 1.001	2.682	5.104	4.665	4.633		6.670	4.005	128.296	0.158	0.158	0.154	0.167	0.148	1.697	1.413
ev.	1.001	-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
		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
						¢	ر د									
						Pan	Fanel B. Correlations	relations								
	0.00															
	0.00	0.00														
LNF_{4} -0.21	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	0.00									
	0.66	0.01	0.00	0.16	0.09	-0.01	-0.05	0.01								
	0.18	-0.45	-0.13	-0.19	0.24	0.14	0.20	-0.10	0.13							
	0.18	-0.27	-0.09	-0.22	0.19	0.10	0.18	-0.07	0.14	0.96						
	0.21	-0.17	-0.07	-0.22	0.17	0.09	0.18	-0.04	0.15	0.92	0.98					
	0.20	-0.14	-0.07	-0.21	0.15	0.09	0.17	-0.01	0.13	0.88	0.96	0.98				
F5 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			
	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 1 Data Characteristics

1964 to December 2008. HPRXM is the equally weighted bond excess return for one year ahead, LNF₁-LNF₉ are the Ludvigson and Ng factors, F1-F5 are the Cochrane and Piazzesi factors. $D_{12}ILR$ is the log yearly change in the illiquidity ratio and $D_{12}ILRSMB$ is the difference of the log yearly illiquidity ratio This table presents some preliminary statistics. Panel A presents the data characteristics and Panel B presents the correlations. The sample period is January Q

	Premia
Table 2	Liquidity and Bond

factors. LN is the linear combination of the Ludvigson and Ng factors. $D_{12}ILR$ is the log yearly change in the illiquidity ratio and $D_{12}ILRSMB$ is the return, LNF_{1} - LNF_{9} are the Ludvigson and Ng factors, FI-F5 are the Cochrane and Piazzesi factors. CP is the linear combination of the Cochrane Piazzesi difference of the log yearly illiquidity ratio for small and large stocks (small-big). The sample period is January 1964 to December 2008. p-val is the p-value The table presents the monthly in-sample forecasting regression of bond excess returns. $\overline{rx}_{t+12} = \beta' X_t + \varepsilon_{t+12}$. \overline{rx} is the equally weighted yearly bond excess calculated using the Newey-West correction for heteroscedasticity and autocorrelation. The *p*-values based on the bootstrap analysis are presented in round brackets.

Table 3Liquidity and Bond Term Structure

The table presents the monthly in-sample forecasting regression of bond premia and liquidity for individual maturities, $rx_{t+12}^{(n)} = \beta' \mathbf{X}_t + \varepsilon_{t+12}^{(n)}$, 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 log yearly change in the illiquidity ratio and $D_{12}ILRSMB$ is the difference of the log yearly illiquidity ratio for small and large stocks The p-value calculated using the Newey-West correction for autocorrelation and heteroscedasticity is presented in squared brackets. The p-values calculated (small-big). The sample period is January 1964 to December 2008. Excess bond returns regressions are conducted for the 2-, 3-, 4-, and 5-year maturities. using the bootstrap analysis are presented in round brackets.

			2-vear					3-vear					4-vear					5-vear		
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)			(00.0)	(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)			(00.0)	(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)
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

tors. ILR denotes the SMB as an additional sriod January 1979 to k, GW is the statistic tatistic under the null	5 year
Its for bond premia. Benchmark is the model including the CP and LN factors. ILR denotes the or to CP and LN, and ILRSMB denotes the model that includes $D_{12}ILRSMB$ as an additional of 15 years (180 monthly observations) to create the forecasts for the period January 1979 to SE ratio is the ratio of the RMSE of the equity model over the benchmark, GW is the statistic g ability comparison. p-value is the p-value associated with the GW test statistic under the null me.	4 year
remia. Benchmark is the mode LN, and ILRSMB denotes the 180 monthly observations) to a ratio of the RMSE of the eq- parison. p-value is the p-value	3 year
c forecasting results for bond p I forecasting factor to CP and moving window of 15 years (J nared error, RMSE ratio is the model forecasting ability comp models is the same.	2 year
The table presents the monthly out-of-sample forecasting results for bond premia. Benchmark is the model including the CP and LN factors. ILR denotes the model that includes $D_{12}ILRSMB$ 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. We use a moving window of 15 years (180 monthly observations) 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 equity model over the benchmark, GW is the statistic for the Giacomini and White (2006) test for model forecasting ability comparison. p-value is the p-value associated with the GW test statistic under the null hypothesis that the forecasting ability of two models is the same.	Average

Table 4Out of Sample Forecasting of Bond Risk Premia

$5 \mathrm{year}$	ILR ILRSMB	0.065 0.064	0.992 0.975	0.560 1.231	
	Bench.	0.065			
	ILRSMB	0.051	0.973	1.343	0.090
4 year	ILR	0.052	0.990	0.637	0.262
	Bench.	0.053			
	ILRSMB	0.037	0.969	1.482	0.069
3 year	ILR	0.038	0.988	0.683	0.247
	Bench.	0.038			
	ILRSMB	0.020	0.970	1.451	0.073
2 year	ILR	0.020	0.990	0.550	0.291
	Bench.	0.020 0.020			
	ILRSMB	0.043	0.972	1.362	0.087
Average	ILR	0.044 0.043	0.990	0.613	0.270
Ą	Benchmark ILR ILRSMB Bench. ILR	0.044			
		RMSE	RMSE ratio	GW	p-value

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Table 5Liquidity and Monthly Bond Portfolio Returns

LNBP are the linear combinations of the Cochrane-Piazzesi and Ludvigson-Ng factors, respectively, constructed for the monthly bond portfolios. $D_{12}ILR$ is the log yearly change in the illiquidity ratio and $D_{12}ILRSMB$ is the difference of the log yearly illiquidity ratio for small and large stocks (small-big). The The table presents the monthly in-sample forecasting regression of the monthly equally weighted bond portfolio return. $\overline{rx}_{m,t} = \alpha + \beta' X_t + \varepsilon_t$. $\overline{rx_m}$ is the equally weighted monthly bond portfolio return, LNF_1 - LNF_9 are the Ludvigson and Ng factors, F1-F5 are the Cochrane and Piazzesi factors. CPBP and sample period is January 1964 to December 2008. *p-val* is the p-value calculated using the Newey-West correction for heteroscedasticity and autocorrelation. p-val bst is the p-value based on the bootstrap analysis.

	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								
F1					0.232	0.03	0.231	0.03								
F2					-0.229	0.03	-0.225	0.03								
F3					-0.028	0.22	-0.026	0.23								
F4					0.069	0.17	0.068	0.17								
F5					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	
2 L 1 . L 7	0		0000													

The table presents the monthly in-sample forecasting regression of bond portfolios of different maturities, $rx_{t+1}^{(n)} = \beta' \mathbf{X}_t + \varepsilon_{t+1}^{(n)}$, where $rx^{(n)}$ is the bond risk premium of maturity n. *CPBP* and *LNBP* are the linear combination of the Cochrane-Piazzesi and Ludvigson-Ng factors respectively constructed for the monthly bond portfolios. $D_{12}ILR$ is the log yearly change in the illiquidity ratio and $D_{12}ILRSMB$ is the difference of the log yearly illiquidity ratio 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.

		D	Up to 1 Year	ar			1	1 to 2 Years	IS			2	2 to 3 Years	rs	
Constant	0.001	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

		673	3 to 4 Year	ars			4	4 to 5 years	rs			5 C	5 to 10 years	ars	
Constant	0.001	0.001 0.002 -0.001	-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	0.004			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

ILR 3 as 1ary the 1der	I		.		_					1			
² factors. ¹² ILRSM1 period Jam urk, GW is statistic un		ILRSMB	0.011	0.991	1.199	0.12							
and LNBH ncludes <i>D</i> , as for the j benchme GW test	2-3y return	ILR	0.011	0.993	1.428	0.08							
le CPBP del that in del that in he forecast el over the d with the	, ,	Bench.	0.011	1.000									
g results portfolio returns. Benchmark is the model including the CPBP and LNBP factors. ILR al forecasting factor to CP and LN, and ILRSMB denotes the model that includes $D_{12}ILRSMB$ as moving window of 15 years (180 monthly observations) to create the forecasts for the period January d error, RMSE ratio is the ratio of the RMSE of the equity model over the benchmark, GW is the hel forecasting ability comparison. p-value is the p-value associated with the GW test statistic under dels is the same.	urn m n ca ta	ILRSMB Bench. ILR ILRSMB	0.007	0.989	1.410	0.08		urn	ILRSMB	0.020	0.996	0.903	0.18
the mode RSMB de servation ISE of th s the p-vs	1-2y return	ILR	0.007	0.989	1.512	0.07		5-10y return	ILR	0.020	0.997	1.184	0.12
hmark is N, and IL monthly ol of the RM . p-value i	- -	Bench.	0.007	1.000				5	Bench.	0.020	1.000		
eturns. Benc to CP and L 5 years (180) 5 is the ratio y comparison	urn 	ILRSMB Bench.	0.003	0.984	1.406	0.08		ırn	ILRSMB	0.016	0.996	0.930	0.18
ortfolio r ag factor ndow of 1 MSE ratio ing abilit, same.	<1y return		0.003	0.980	1.697	0.04		4-5y return	ILR	0.016	0.997	1.202	0.11
g results p l forecastin moving win l error, RA el forecast dels is the		Bench.	0.003	1.000				4	Bench.	0.016	1.000		
ble forecasting an additiona N. We use a mean squared test for mod ty of two mod		ILRSMB	0.011	0.994	1.112	0.13			ILRSMB	0.014	0.994	1.082	0.14
tt-of-samf 12 <i>LLR</i> as CP and L the root the (2006) thing abili-	Average	ILR	0.011	1.000 0.994	1.386	0.08		3-4y return	ILR	0.014	1.000 0.995	1.281	0.10
the monthly ou hat includes D sting factor to (008. RMSE is 008. RMSE is comini and Wh that the forecas	V .	Benchmark	0.012 0.011	1.000				3-4	Bench.	0.014	1.000		
The table presents the monthly out-of-sample forecasting results portfolio returns. Benchmark is the model including the CPBP and LNBP factors. ILR denotes the model that includes $D_{12}ILRSMB$ as denotes the model that includes $D_{12}ILRSMB$ 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. We use a moving window of 15 years (180 monthly observations) 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 equity model over the benchmark, GW is the statistic for the Giacomini and White (2006) test for model forecasting ability comparison. p-value is the p-value associated with the GW test statistic under the null hypothesis that the forecasting ability of two models is the same.			RMSE	RMSE ratio	GW	p-value				RMSE	RMSE ratio	GW	p-value

Table 7Out of Sample Forecasting of Monthly Bond Portfolio Returns

Table 8Mutual Fund Bond Flows Correlations

The table presents the monthly correlation in mutual fund flows over 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 flows as described in Section 4. Panel B presents the characteristics of net exchange flows as described in Section 4.

	Equity	Hybrid	Municipal	T.E. Money	Taxable
			Bond	Market	Bond
		el A. 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-Cris	sis		
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
		N-+ E			
Hybrid	$\frac{Panel \ B.}{0.19}$	Net Exch	ange Flows		
•	$0.19 \\ 0.24$	0.15			
Municipal Bond		- 0.15	0.96		
T.E. Money Market Taxable Bond	- 0.28		- 0.86	0.59	
	- 0.05	0.01	0.66	- 0.58	0.45
Taxable Money Market	- 0.83	- 0.33	- 0.63	0.56	- 0.45
ТІl:-l	0.10	Non-Cris	515		
Hybrid Municipal Dand	0.19	0.19			
Municipal Bond	0.26	0.18	0.90		
T.E. Money Market	- 0.36	- 0.05	- 0.89	0 50	
Taxable Bond	- 0.01	- 0.03	0.66	- 0.58	0 51
Taxable Money Market	- 0.80	- 0.31	- 0.68	0.65	- 0.51
	0.14	Crisis			
Hybrid Marrieir el Der d	0.14	0.10			
Municipal Bond	0.31	0.19	0.05		
T.E. Money Market	- 0.17	- 0.19	- 0.65	0 50	
Taxable Bond	0.06	0.19	0.72	- 0.52	0.41
Taxable Money Market	- 0.89	- 0.38	- 0.55	0.26	- 0.41

Table 9Mutual Fund Bond Flows and Illiquidity Correlations

The table presents the monthly correlation between mutual fund flows and the illiquidity variables over the period January 1984 to June 2010. *DILRSMB* is the log monthly change in the illiquidity ratio for small-large stock illiquidity, *DILR* is the log monthly change in the market illiquidity ratio, $D_{12}ILR$ is the log yearly change in the illiquidity ratio and $D_{12}ILRSMB$ is the difference of the log yearly illiquidity ratio for small and large stocks (small-big).

	Taxable	Equity
	Money Market	
DILRSMB	0.18	-0.21
	[0.00]	[0.00]
DILR	0.30	-0.32
	[0.00]	[0.00]
$D_{12}ILRSMB$	0.18	-0.24
	[0.00]	[0.00]
$D_{12}ILR$	0.14	-0.21
	[0.00]	[0.00]

Table 10 Investments and Stock Market Illiquidity

The table presents quarterly regressions of real private fixed investment growth and stock market illiquidity. $D_{12}ILR$ is the log yearly change in the illiquidity ratio and $D_{12}ILRSMB$ is the difference of the log yearly illiquidity ratio 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 with up to four quarter lags of inflation.

Variable	Coef.	p-val	Obs	Adj. R^2	Model p-val
Pe	anel A. U	Univario	ate Reg	pressions	
$D_{12}ILRSMB_{t-1}$	-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 11Balanced Funds and Stock Market Illiquidity

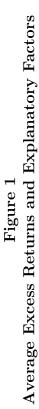
The table presents yearly regression of equity ratio in balanced funds and stock market illiquidity. $D_{12}ILR$ is the log yearly change in the illiquidity ratio and $D_{12}ILRSMB$ is the difference of the log yearly illiquidity ratio for small and large stocks (small-big). The equity ratio for balanced 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 196 to December 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.

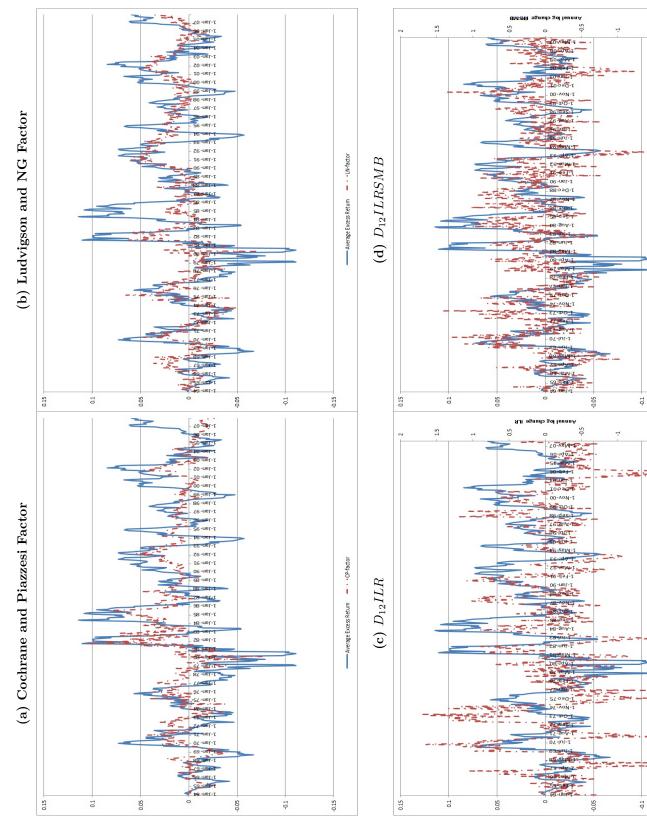
Variable	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
$D_{12}ILRSMB$	-0.028	0.01						
$D_{12}ILRSMB_{t-1}$	-0.035	0.00	-0.020	0.05				
$D_{12}ILRSMB_{t-2}$	-0.025	0.08						
$D_{12}ILR$					-0.019	0.01		
$D_{12}ILR_{t-1}$					-0.017	0.08	-0.018	0.05
$D_{12}ILR_{t-2}$					-0.007	0.48		
R^2	0.22		0.05		0.13		0.06	
Adj. R^2	0.16		0.03		0.06		0.04	

Table 12Volatility Index and Stock Market Illiquidity

The table presents monthly regression of the S&P100 volatility index (VXO) and stock market illiquidity. $D_{12}ILR$ is the log yearly change in the illiquidity ratio and $D_{12}ILRSMB$ is the difference of the log yearly illiquidity ratio for small and large stocks (small-big). 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. *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.	Prob.	Obs	Adj. R^2	Model p-val
$D_{12}ILRSMB_{t-1}$	3.64	0.00	264	0.04	0.00
$D_{12}ILRSMB_{t-2}$	3.15	0.01	264	0.03	0.00
$D_{12}ILR_{t-1}$	4.75	0.00	264	0.09	0.00
$D_{12}ILR_{t-2}$	3.85	0.00	264	0.06	0.00





-15

N

Annual log change ILRSMB

Average Excess Return

-0.15

?

Annual log change ILR

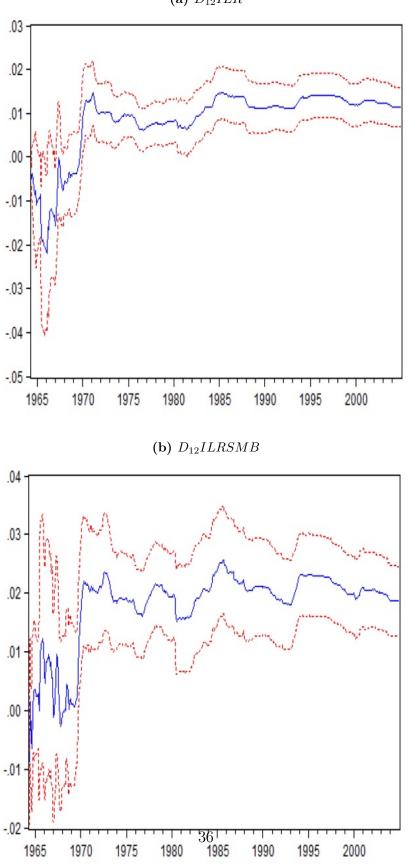
Average Excess Return

-0.15

-15

Figure 2 Parameter Stability of In-Sample Forecasting Illiquidity Variables

The figure presents the recursive estimates of the liquidity coefficients in the regressions in columns (14) and (16) in Table 2.





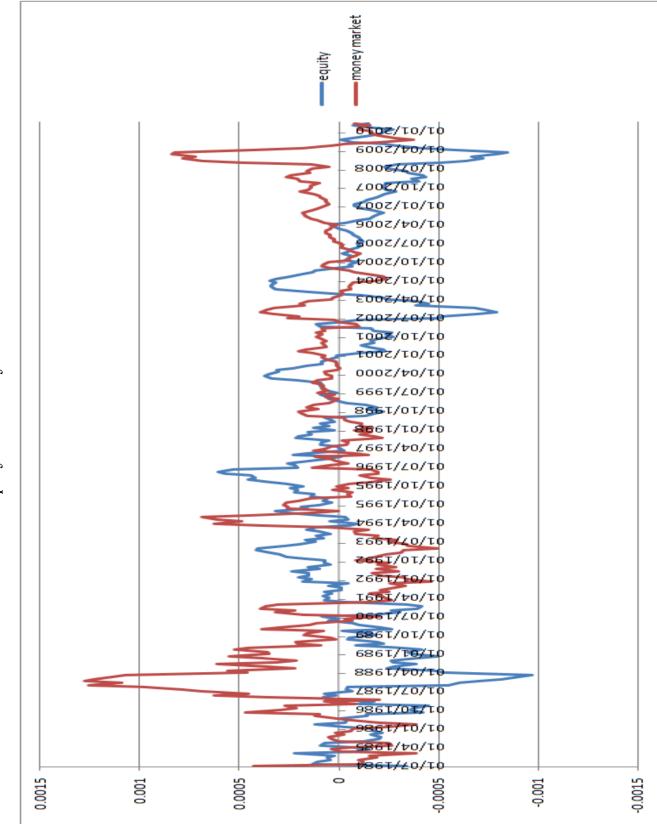


Figure 3 Mutual Fund Equity and Money Market Fund Flows

Table A1Bond Portfolio Return Regressions

The table presents the monthly in-sample forecasting regression the equally weighted bond portfolio returns using the CP and LN factors. $\overline{rx}_{t+1} = \beta' X_t + \varepsilon_{t+1}$. \overline{rx} is the equally weighted monthly bond excess return, LNF_1-LNF_9 are the Ludvigson and Ng factors, F1-F5 are the Cochrane and Piazzesi factors. CP is the linear combination of the Cochrane and Piazzesi factors 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. p-val bst is the p-value based on the bootstrap analysis.

	coeff	p-val	p-val bst	coeff	p-val	p-val bst	coeff	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						
F1	0.213	0.03	0.03						
F2	-0.200	0.04	0.88						
F3	0.013	0.24	0.47						
F4	0.053	0.19	0.30						
F5	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 A2Mutual Fund Bond Flows Characteristics

The table presents the monthly characteristics of mutual fund flows over 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 flows as described in Section 4. Panel B presents the characteristics of net exchange flows as described in Section 4.

	Equity	Hybrid	Municipal	T.E. Money Market	Tax. Bond	Money Market		
				marnet	Donu	11111111111		
		P	Panel A. Net H	Flow				
			Crisis					
Mean	0.00029	0.00001	0.00012	0.00001	0.00063	0.00088		
Median	0.00065	0.00005	0.00010	0.00010	0.00049	0.00123		
St. Dev.	0.00185	0.00029	0.00034	0.00094	0.00123	0.00513		
Minimum	- 0.00577	-0.00116	- 0.00103	-0.00269	- 0.00318	- 0.01171		
Maximum	0.00419	0.00097	0.00091	0.00391	0.00347	0.01199		
Obs.	71	71	71	71	71	71		
			Non Crisis					
	0.00107		0.00005	0.00055	0.0000	0.000.15		
Mean	0.00135	0.00024	0.00032	0.00022	0.00066	0.00042		
Median	0.00123	0.00018	0.00014	0.00020	0.00029	0.00028		
St. Dev.	0.00148	0.00034	0.00061	0.00097	0.00146	0.00357		
Minimum	- 0.00509	-0.00047	- 0.00187	-0.00273	- 0.00323	- 0.00990		
Maximum	0.00591	0.00179	0.00276	0.00529	0.00591	0.01450		
Obs.	245	245	245	245	245	245		
		Par	nel B. Net Exc	change				
			Crisis period	1				
Mean	- 0.00026	- 0.00003	0.00000	- 0.00000	0.00009	0.00019		
Median	- 0.00014	- 0.00002	0.00001	0.00000	0.00008	0.00002		
St. Dev.	0.00054	0.00011	0.00012	0.00010	0.00021	0.00066		
Minimum	- 0.00318	- 0.00029	- 0.00061	- 0.00035	- 0.00088	- 0.00065		
Maximum	0.00070	0.00070	0.00043	0.00036	0.00058	0.00442		
Obs.	70	70	70	70	70	70		
	Non-crisis							
Mean	- 0.00002	- 0.00001	- 0.00003	0.00003	- 0.00006	0.00005		
Median	- 0.00002	- 0.00001	- 0.00003	0.00003	- 0.00003	0.00003 0.00002		
St. Dev.	0.00046	0.00001	0.00021	0.00011	- 0.00003	0.00002 0.00059		
Minimum	- 0.00219	- 0.00024	- 0.00183	- 0.00015	- 0.00175	- 0.00217		
Maximum	0.00219	- 0.00024 0.00019	-0.00183 0.00045	- 0.00025	- 0.00175	-0.00217 0.00273		
Obs.	0.00200 246	0.00019 246	0.00043 246	246	246	0.00213		
000.	240	240	240	240	240			

Table A3Futures Market and Stock Market Illiquidity

The table presents monthly regressions of future market variables from Hong and Yogo (2012) and stock market illiquidity. $D_{12}ILR$ is the log yearly change in the illiquidity ratio and $D_{12}ILRSMB$ is the difference of the log yearly illiquidity ratio for small and large stocks (small-big). *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. In Panel A the dependent variable is the open interest growth in the bond market (*FlowB*) and the sample period is 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 (*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. All regressions include a constant, not reported to conserve space.

	C f	D 1	01		M. 1.1		
Variable	Coef.			v	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		
$D_{12}ILR_{t-1}$	-0.206	0.50	290	0.00	0.26		
$D_{12}ILR$	-0.125	0.68	289	0.00	0.49		
Panel B. He	dgind De	mand Ir	nbalan	ce in Bond	l 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		
$D_{12}ILR_{t-1}$	-0.611	0.64	302	0.00	0.45		
$D_{12}ILR$	-0.906	0.55	301	0.00	0.26		
Panel C. C	Open Ind	ex Grow	th 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		
$D_{12}ILR_{t-1}$	-0.471	0.27	483	0.02	0.00		
$D_{12}ILR$	-0.319	0.49	482	0.01	0.05		
Panel D. Hedge	ing Dem	and Imb	alance	in Commo	odity 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		
$D_{12}ILR_{t-1}$	-3.446	0.22	506	0.02	0.00		
$D_{12}ILR$	-2.701	0.32	505	0.01	0.01		

Panel E. Bond Premia and Futures Information								
Variable	Coef.	Prob.	Coef.	Prob.				
CP	0.780	0.10	0.799	0.00				
LN	0.647	0.04	0.363	0.04				
$D_{12}ILRSMB$	0.016	0.02	0.014	0.02				
FlowInd	-0.002	0.65						
CretInd	0.002	0.72						
FlowB			-0.001	0.71				
ImbalanceB			0.001	0.03				
Obs	482		289					
Adj. R^2	0.43		0.33					

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