Aggregate Stock Market Illiquidity and Bond Risk Premia*

Kees E. Bouwman †
Erasmus University

Elvira Sojli
Erasmus University and Duisenberg School of Finance

Wing Wah Tham
Erasmus University

June 11, 2012

Preliminary Draft

Abstract

We assess the effect of aggregate stock market illiquidity on U.S. Treasury 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 the open interest in the futures market (Hong and Yogo, 2012), long-run inflation expectations (Cieslak and Povala, 2011), dispersion in beliefs (Buraschi and Whelan, 2012), and funding liquidity (Fontaine and Garcia, 2011). We argue that stock market illiquidity is a more timely variable that is related to "flight to quality" episodes and might contain information about expected future business conditions through the funding liquidity and investment channels.

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

JEL Classification: G10; G20; G14.

*We thank Ekkehart Boehmer, Mikhail Chernov, Greg Duffee, Wayne Ferson, Nicolae Garleanu, Harald Hau, Wolfgang Lemke, Martin Lettau, Sydney Ludvigson, Paolo Pasquariello, Johannes Skjeltorp, Clara Vega, Kumar Venkataraman, Annette Vissing-Jorgensen, Motohiro Yogo, Avi Wohl and participants at the 7^{th} Annual Central Bank Workshop on the Microstructure of Financial Markets, 5^{th} Financial Risk International Forum in Institut Louis Bachelier and Europlace Institute of Finance, 7^{th} ECB Workshop on Forecasting Techniques and American University for very useful comments. We are grateful to Johannes Skjeltorp for providing the data on aggregate stock market liquidity, Rui Albuquerque for providing the data on market-wide private information, Jean-Sébastien Fontaine for providing the data on funding liquidity, and Michael Fleming for providing the data on Treasury market liquidity. Sojli gratefully acknowledges the financial support of the European Commission Grant PIEF-GA-2008-236948. Tham gratefully acknowledges the financial support of the European Commission Grant PIEF-GA-2009-255330.

†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

We examine whether aggregate stock market liquidity can 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. We also use the difference of aggregated illiquidity between large and small cap stocks as an alternative variable, and we find that it is an especially strong predictor of bond premia. 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. The magnitude of the predictability that we find using aggregate stock market illiquidity is not only statistically but also economically significant. We find that one standard deviation increase in the aggregate illiquidity of the stock market leads to an increase of 45 basis point in bond risk premia.

Our paper joins other empirical research documenting predictability in the excess returns of U.S. sovereign bonds. Cochrane and Piazzesi (2005) show that excess bond returns can be forecasted using a linear combination of five forward spreads. 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. 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 of 132 measures of economic and financial activities, which include dividend yield, TED spread, credit spread, S&P500 returns. Consistent with Cooper and Priestley (2009) and Ludvigson and Ng (2009), Joslin, Priebsch, and Singleton (2010) show the importance of real economic activity and inflation on market prices of level, slope, and curvature risks in the U.S. Treasury markets. In a more recent paper, Duffee (2011a) finds a latent component of bond risk premia that contains substantial information about expected future yields and is negatively correlated with aggregated economic activity.

Following the literature, we always condition on the well-established Cochrane and Piazzesi (2005) and Ludvigson and Ng (2009) factors in our analysis. Our single illiquidity variable contains additional information about bond's 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 equity illiquidity on monthly returns of portfolios of Treasury bills and bonds as in Duffee (2011b). Furthermore, we find that our result is robust to and is not driven by information from bond market liquidity, the open interest in the futures market (Hong and Yogo, 2012), long-run inflation expectations (Cieslak and Povala, 2011), dispersion in beliefs (Buraschi and Whelan, 2012), and funding liquidity factor (Fontaine and Garcia, 2011).

The magnitude of illiquidity's economic significance, 45 annual basis points, on bond risk premia is especially interesting as it suggests that aggregate stock market illiquidity is related to bond risk premia beyond the price of future bond liquidity and systematic bond liquidity risk in the treasury market. For example, Goldreich, Hanke, and Nath (2005) find that the yield difference between on-the-run 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. The additional information of aggregate equity market illiquidity on bond risk premia for all maturities is remarkable but surprising.

There can be three potential explanations for our findings. First, the equity market illiquidity variables can be related to bond risk premia through the channel of asymmetric information. Albuquerque, De Francisco, and Marques (2008) presents a model of market-wide information that is useful for trading across a variety of assets and argues that this private information is informative about discount rates and future cash flows that fluctuate with economy-wide business conditions. They show that this information from the U.S. equity market forecasts industry stock returns and currency returns. Brennan, Huh, and Subrahmanyam (2011) consider the Amihud (2002) illiquidity measure as a noisier version of Kyle (1985)'s measure of price impact. They argue that the Amihud illiquidity measure increases when trading on private information increases. Thus, U.S. stock market aggregate illiquidity might contain this market-wide private information. To investigate the asymmetric information hypothesis, we include the market-wide information variables from Albuquerque et al. (2008) into our predictive regression.[1] Consistent with Albuquerque et al. (2008), we find that market-wide private information variables predict future bond excess returns but do not affect the predictive power of our variable. As a result, we rule out the suggestion that our stock market illiquidity predicts future bond excess returns because of market-wide private information.

Second, stock market illiquidity can be related to flight to quality and can contain information about the uncertainty of investors' preferences. Gallmeyer, Hollifield, and Seppi (2005) theoretically show that investors' information asymmetry about each-other's preferences can explain the empirical relation between stock market illiquidity and future returns. In their model learning through trading, demand discovery, leads to market liquidity becoming a forward looking proxy for risk preferences in future prices. The model can generate "flight to quality"-like volume and price characteristics under some model parameters. From an alternative perspective, Baker and Stein (2004) theoretically relates the predictability of returns by market liquidity and flight to quality through the information asymmetry about future cash flows, short sale constraints, and irrational investors.

We assess the relation between "flight to quality" and stock market illiquidity by studying the relation between mutual fund flows and equity illiquidity. We find that changes in illiquidity are related to shifts of U.S. mutual fund flows from equity to money market mutual funds, indicating its relation to flight to quality. An increase in illiquidity is positively correlated with flows into money market mutual funds and negatively correlated with flows to equity mutual funds. In an alternative exercise, we find that stock market illiquidity explains and predicts changes in the average proportion holding of equity and bonds by balanced mutual funds. Flight-to-quality episodes are associated with increases in VIX and Bekaert, Hoerova, and Duca (2010) suggest that VIX is a proxy for risk aversion and market uncertainty. As an alternative exercise to investigate the relation between aggregate stock market illiquidity and "flight to quality", we explore the relation between stock market illiquidity and VXO. We find that stock market illiquidity is contemporaneously associated and can predict changes to VXO.

Third, stock market illiquidity can matter through the funding illiquidity channel. Stock market illiquidity affects or is affected by the macro economy and investments in the real economy. The role of stock market illiquidity on the macro economy can be seen from the monetary

[1] The data, from 1993 to 2003, on market-wide private information is kindly provided by Rui Albuquerque.

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 illiquidity) 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. 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.

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. In an excellent survey, Brunnermeier, Eisenbach, and Sannikov (2011) argues that liquidity risk can amplify a small exogenous shock into a sizable shock and endogenous risk in the macroeconomy. To investigate the relation of equity illiquidity and investments, we use our illiquidity variable to forecast future 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 Næs, Skjeltorp, and Ødegaard (2011), we cannot rule out the investment hypothesis.

As the flight to quality and funding liquidity channel are not mutually exclusive, we study these channels jointly by including flight to quality variables, like mutual fund flows, VXO, and funding liquidity variables into the bond excess return forecasting equations. We find that the inclusion of stock market illiquidity, funding liquidity, and an interaction term of the two subsume all 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 additional information beyond the investment and funding liquidity channel as the stock market illiquidity variable remains significant after controlling for VXO, mutual fund flows, and funding liquidity. We argue that this result might come from the timely availability of the market illiquidity variable relative to other bond excess return predictors.

The paper proceeds as follows. Section 2 positions our paper with respect to the existing literature. In the next section, we present the econometric framework. Then, we discuss our data and preliminary analysis in Section 4. Section 5 presents our results on the link between bond premia and equity market illiquidity. Section 6 presents results from further robustness analysis. Section 7 discusses the potential channels that relate aggregate stock market illiquidity to bond excess returns. Section 8 concludes.

2 Literature Review and Contribution

Our paper contributes to the recent literature on bond return predictability in the debate about the validity of the expectation hypothesis. The earlier literature relates excess bond returns to yield spreads and provides evidence that 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). Extending the findings of Fama and Bliss (1987), Cochrane and Piazzesi (2005) find a R^2 up to 44% for bond excess returns prediction using a single factor constructed from a linear combination of five forward spreads.[2]

The more recent literature focuses on information from macroeconomic variables. Ludvigson and Ng (2009) and Cooper and Priestley (2009) show that macroeconomic variables predicts excess bond returns through the cyclical nature of the risk premia. A series of recent papers Chernov and Mueller (2011); Cieslak and Povala (2011); Joslin et al. (2010); Huang and Shi (2011), and Buraschi and Whelan (2012) support their findings on the relation of macroeconomic variables and business cycle with the risk premia. Duffee (2011a) also finds a latent component of bond risk premia that contains substantial information about expected future yields and is negatively correlated with aggregated economic activity.

Several papers focus on inflation and GDP expectations and the dispersion of expectations. Cieslak and Povala (2011) argues that long-run inflation expectations contain important information about bond risk premia. Buraschi and Whelan (2012) study the link of macroeconomic disagreement and the bond market. They show that belief dispersion about the real economy, inflation, and signals predict excess bond returns. Mueller, Vedolin, and Zhou (2011) shows that 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 devel-

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

opments 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 for information from bond yields, forward rates, macroeconomic, and dispersion in beliefs variables. Differently from these papers, we consider the role of aggregated equity market illiquidity motivated by the Næs et al. (2011)'s finding that equity market illiquidity is a robust and good predictor of business cycles. We go a step further by establishing that market illiquidity can affect bond risk premia via either the investment channel or it is a more timely variable that better captures time-varying investors' risk aversion and the uncertainty of investor preferences. Thus, we provide empirical support for the asset pricing literature of macroeconomics with financial frictions and market microstructure models with endogenous liquidity.

One important related paper is Fontaine and Garcia (2011). They argue that funding liquidity conditions affect prices of U.S. sovereign bonds. Fontaine and Garcia (2011) use the price differentials of treasury securities with similar cash flows but different maturities to construct a funding liquidity variable. They use the funding liquidity factor in predictive regressions of *off-the-run* bond excess returns. Their results highlight the importance of the funding market for fixed-income markets. Although we consider the information content of stock market illiquidity for *on-the-run* bond excess returns, our result is consistent with Fontaine and Garcia (2011) if one considers the endogenous relation between market and funding liquidity in the spirit of Brunnermeier and Pedersen (2009). Thus our findings provide empirical support for the interaction between securities' market liquidity and funding conditions of financial intermediaries.

Furthermore, we contribute to the literature that theoretically relates stock and bond markets, see Koijen, Lustig, and Nieuwerburgh (2009) and Lettau and Wachter (2011). Our findings provide empirical evidence that suggests that stock market variables are important in understanding asset prices in bond markets, which could be useful for the future theoretical literature that focuses on the joint modeling of stock and bond returns.

3 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. 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, $\boldsymbol{X}_t$:

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

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 also 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 as:

$$\overline{rx}_{t+1} = \boldsymbol{\gamma}'\boldsymbol{X}_t^{CP} + \overline{\varepsilon}_{t+1}, \tag{2}$$

where $\overline{rx}_{t+1} = \frac{1}{4}\sum_{n=2}^{5} rx_{t+1}^{(n)}$ and $\boldsymbol{X}_t^{CP} = [1, y_t^{(1)}, f_t^{(2)}, \ldots, f_t^{(5)}]$. The CP-factor combines the information in all forward rates and is defined as $CP_t = \hat{\boldsymbol{\gamma}}'\boldsymbol{X}_t^{CP}$. 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:

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

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

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.

3.1 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:

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

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

$$\boldsymbol{X}_{t+1} = \boldsymbol{\theta} + \boldsymbol{\Phi} \boldsymbol{X}_t + \boldsymbol{\nu}_{t+1},$$

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

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

where $\boldsymbol{\Sigma}^{-1/2}$ is the inverse of the Choleski factorizaiton of $\boldsymbol{\Sigma}_\nu$. We construct bootstrap samples for $\boldsymbol{X}_t$ by resampling from the standardized residuals $\eta_{i,t}$ to generate new sample paths for $\boldsymbol{X}_t$ starting from $\boldsymbol{X}_1$. Next, bootstrap samples of $rx_{t+1}^{(n)}$ are constructed from equation (2) by using the bootstrap samples of $\boldsymbol{X}_t$ and by resampling blocks of 12 subsequent residuals $\varepsilon_{t+1}^{(n)}$. The bootstrap procedure is repeated 10,000 times.

3.2 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 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 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) and the Clark and West (2007) and the Giacomini and White (2006) tests for predictive ability. The Clark-West test considers the null hypothesis of equal predictive ability by comparing mean squared prediction errors of two forecasting methods, applied to nested models. It explicitly accounts for parameter uncertainty by adjusting the mean squared prediction errors. We use the standard normal distribution to obtain approximate p-values for the CW test Clark and West (2007). 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 Giacomini-White (GW) test coincides with that of the Diebold and Mariano (1995) test, but the tests use different null hypotheses as the GW test explicitly accounts for parameter uncertainty.

4 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, 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. 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.[3] 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.

4.1 Stock Market Liquidity 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 only 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, when constructed using only a month of daily data. They are more appropriate for quarterly analysis. 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.

[3] `http://www.econ.nyu.edu/user/ludvigsons/`, as of April 15, 2011.

Also, we use the difference between the ILR of small and large stocks, represented by the bottom and top quartile respectively, *ILRSMB*. 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. 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.[4]

4.2 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 $D_{12}ILR$.

[4] 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.

5 Results

5.1 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:

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

where $\boldsymbol{X}_t$ 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 stock market 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 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).[5] 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 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.

5.2 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 root mean squared errors than the benchmark model, i.e. RMSE Ratios less than 1. The model with $D_{12}ILRSMB$ performs

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

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. The Clark and West (2007) test results show that the model with stock market liquidity 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 liquidity of the small stocks is most informative. Thus, we will focus on using $D_{12}ILRSMB$ for the rest of our analysis.

6 Robustness

6.1 Monthly Bond Portfolio Returns

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.

6.2 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 indiviual 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.

6.3 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 highly statistically significant using both the Clark and West (2007) and the Giacomini and White (2006) tests. Overall these results reflect the robustness of equity market liquidity as a predictive variable for bond excess returns.

6.4 Macroeconomic Disagreement and Long-run Inflation Expectation

Cieslak and Povala (2011) argue the importance of accounting for long-run inflation expectations when considering excess bond return predictability. Buraschi and Whelan (2012) show that belief dispersion regarding the real economy, inflation, and signals predict excess bond returns. Following Cieslak and Povala (2011), we construct long-run inflation expectations. To investigate if the stock market illiquidity variable is capturing dispersion in beliefs, 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 the forecasts for the 3-month Treasury bill and 10-year note rates (*Tbill-Notes 1Q, Tbill-Notes 1Y*), consistent with Buraschi and Whelan (2012). These dispersion measures are collected from the widely-used and publicly available Survey of Professional Forecasters (SPF) data provided by the Fed Philadelphia.[6] We include the dispersion in beliefs and long-run inflation expectation variables in the bond premia regression together with CP, LN, and $D_{12}ILRSMB$. In Table A2, we show that the illiquidity variable remains highly statistically and economically significant. The

[6] 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).

illiquidity variable increases the adjusted R^2 by 4-5% over these variables and suggest that the illiquidity variable is not capturing information about dispersion in beliefs and long-run inflation expectations.

6.5 Bond Market Liquidity

One important determinant of the bond risk premia is the liquidity of the Treasury market itself. One way to measure Treasury market liquidity is to use the CRSP Treasury bid-ask spreads. Unfortunately this data is aggregated only in four categories: notes, bonds, bills, and ten-year bond and is of poor quality for more recent years. For the period after 1994 there is no variation in the bid-ask spread of any of these securities. Michael Fleming at the Fed of New York 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.[7] We use his measure of bid-ask spreads to amend the Treasury bill's liquidity measure from CRSP.

In Table A3 in the Appendix, we condition on both bond and stock market liquidity. We use the CRSP bid-ask spread for the Treasury bills as a proxy for bond market liquidity, and two additional measures, which replace the CRSP bid-ask spread with the GovPX bid-ask spread for the period August 1994-December 2004. The results show that the addition of the bond market liquidity measure does not affect the predictive power of the other variables.

6.6 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 most specifications the model p-value is higher than 10%, suggesting that these are inadequate variables for explaining stock market illiquidity. 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

[7] We are grateful to Michael Fleming for providing us with the data.

and economically significant.

7 Why Does Market Liquidity Matter?

In the introduction, we argue that stock market liquidity could be related to bond excess returns via the market-wide private information, "flight to quality" episodes, funding liquidity and the investment channel. To investigate the market-wide private information channel, we include the orderflow variable of Albuquerque et al. (2008) into our predictive regressions.

Individuals and firms should demand for more liquid and safer assets if they expect the amplification effect from the interaction the technological, market, and funding liquidity on an exogenous shock. For the investment channel to be plausible, stock market liquidity should be able to predict future real investment growth and should be related to funding liquidity. In the following, we assess the link between liquidity and real private investments. In addition, we also investigate 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. We also investigate role of market liquidity, funding liquidity variable suggested by Fontaine and Garcia (2011) and the interaction of market and funding liquidity on excess bond returns.[8]

7.1 Market-wide Private Information

Albuquerque et al. (2008) construct market wide private information (MPI) for five industries which have substantial exports and imports: Primary Smelting and Refining of Nonferrous Metal (MPI1), Oil and Gas Field Machinery and Equipment 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 HAC with 18 lags, thus we only focus on MPI1, MPI2 and MPI5.

The results in Table 8 show that market-wide private information variables predict future bond excess returns, consistent with the story in Albuquerque et al. (2008). Nonetheless, the

[8] We are grateful to Jean-Sébastien Fontaine for providing us with his funding liquidity data.

addition of this variable does not affect the predictive power of the stock market liquidity variable. If anything, the magnitude of the impact of stock market liquidity increases with the addition of the market-wide private information variable. Thus, we conclude that our variables are not capturing market-wide private information.

7.2 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 Skjeltorp and Ødegaard (2011). Table 9 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, explaining between 16-22% of the variation in investment growth. Results from Table 9 shows that liquidity contains leading information about future investment growth which consistent with the investment hypothesis.

7.3 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 via the investment channel, where investors shift their portfolios towards less risky or safe assets in view of a deteriorating future business conditions, 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 US bond market. They find stock market crashes in U.S., Germany, France, U.K., and Japan coincide with U.S. bond market booms. Baur and Lucey (2006) finds strong negative correlations between stock and bond markets during crises. Longstaff (2004) shows that the flight-to-liquidity premium in the 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) 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 comovements and suggest that these factors maybe correlated with the "flight-to-safety" effects.

Næs et al. (2011) show that U.S. stock market liquidity contains information, not captured in stock returns, on changes of individuals' expectation of the real economy and flight to quality before economic recessions. They find that stock market liquidity is a useful and robust variable in predicting real GDP growth, unemployment, and investment growth after controlling for other asset price predictors. They argue that time variation of liquidity is related to flight-to-quality and contains leading information about the current and the future state of the real economy.

Illiquidity and Mutual Fund Flows

Therefore, we first 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-to-quality.

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.[9]

We start our analysis on flight-to-quality by first examining the correlation structure of fund flows. Panel A of Table A6 in the Appendix shows the correlation of net flows among U.S.

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

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 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 A6 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 A6 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.

Panel A of Table 10 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.

Illiquidity and Balanced Mutual Fund Holdings

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 Panel B of Table 10 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.

Illiquidity and S&P Volatility Index

To ensure that our results on the relation between illiquidity and flight to safety is robust to non-mutual fund studies, we investigate the relation between illiquidity and the S&P100 volatility index VXO, which has been disseminated since 1986. The use of stock index volatity 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 Panel C of Table 10 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.

7.4 Market liquidity, Funding liquidity and Flight to Quality

The investment, 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 bond excess return forecasting equation.[10] We use the funding variable from Fontaine and Garcia (2011), which is constructed from the cross-section of bonds by adding a liquidity factor correlated with age to an arbitrage-free term structure model. Table 11 presents the results. In Column (1) of Table 11, the funding liquidity coefficient is negative and statistically significant. Consistent with sign found in Fontaine and Garcia (2011), we find that the risk premia of the Treasury securities decreases when the value of funding liquidity increases. The estimated coefficient of the stock market illiquidity variable remains positive and statistically significant. The magnitude of the estimated coefficient remains very close those reported in Table 2. To investigate the interacting relation between market and funding liquidity in Kiyotaki and Moore (2008) and Brunnermeier and Pedersen (2009), we include the interaction term of the market illiquidity and funding liquidity variable. From column (3) of Table 11, we find that the interaction term is negative and statistically significant. The finding supports Brunnermeier and Pedersen (2009) and Kiyotaki and Moore (2008)'s suggestions of relation between binding credit (funding) and resaleability (market liquidity) constraint in the market.

We study the role the flight to quality on bond risk premia using mutual fund flow data. Column (5) of Table 11 presents the estimated coefficients of equity, taxable money market and taxable bond flows. Consistent with 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 increases when flows into money market and bond funds increase. Results in column (9) show that stock market illiquidity is related to flight to quality as we observe that the inclusion of the stock market illiquidity variable subsuming the effect of money market flow variable. Column (11) shows that the inclusion of the market illiquidity, funding liquidity and their interaction

[10] Results for individual maturity produce qualitatively similar results. See Table ABC in appendix

term completely subsume all mutual fund flows variables. The result is robust to the inclusion of VXO, an alternative proxy for flight to quality. These results are very important as it shows the role of funding and market liquidity and its interaction on bond risk premia. While the finding supports the investment and funding liquidity channel, stock market illiquidity appears to contain additional information beyond the investment and funding liquidity channel as the stock market illiquidity variable remains significant after controlling for VXO, mutual fund flows and funding liquidity. We argue that this result might come from the timely availability of the market illiquidity variable relative to other bond excess return predictors.

8 Conclusions

We assess the effect of market liquidity on U.S. bond risk excess 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 both in-sample and out-of-sample forecasting performance. Stock liquidity has strong forecasting power for excess returns across bonds of all maturities. The effects are statistically and economically significant and its effect is stronger for the shorter maturity bonds than for the longer maturity. Our results are robust to using monthly bond portfolio returns. Our results are also robust to information from the open interest in the futures market (Hong and Yogo (2012)), long-run inflation expectation (Cieslak and Povala (2011)), dispersion in beliefs (Buraschi and Whelan (2012)), bond market liquidity and on-the-run liquidity factor (Fontaine and Garcia (2011)).

We investigate three potential reasons for reasons why stock liquidity contain information about bond excess returns. First, we study if stock liquidity contains market-wide private information motivated by Albuquerque et al. (2008). Using the market wide private information data provided by Albuquerque et al. (2008), we find that it is unlikely that stock market liquidity contains market wide private information. Secondly, we investigate the flight-to-quality channel of the relation between stock market liquidity and bond risk premia. We find that changes in illiquidity 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 stock market illiquidity explains and predicts changes in the average proportion holding of equity and bonds by balanced funds. We also explore the relation between stock market illiquidity and VIX and find that stock market illiquidity is contemporaneously associated and can predict changes to VIX.

Third, we study the funding illiquidity channel which stock market liquidity can matter. As the flight to quality and funding liquidity channel are not mutually exclusive, we study these channels jointly by including flight to quality variables, like mutual fund flows, VXO, and funding liquidity variables (see Fontaine and Garcia (2011)) into the bond excess return forecasting equations. We find that the inclusion of stock market illiquidity, funding liquidity, and an interaction term of the two subsume all 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. Our results also suggest that stock market illiquidity is a more timely predictive variable relative to other bond excess return predictors and it contains additional information beyond the investment and funding liquidity channel as the stock market illiquidity variable remains significant after controlling for VXO, mutual fund flows, and funding liquidity.

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 for information from bond yields, forward rates, macroeconomic, and dispersion in beliefs variables. Our findings provide empirical support for the interaction between securities' market liquidity and funding conditions of financial intermediaries. Furthermore, our results have important implications to the theoretical and empirical literature relating stock and bond markets as it provides empirical evidence that suggests that stock market variables are important in understanding asset prices in bond markets.

Table 1
Data Characteristics

This table presents some 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-LNF_9 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 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	F1	F2	F3	F4	F5	$D_{12}ILR$	$D_{12}ILRSMB$
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

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							
F1	0.08	0.18	-0.45	-0.13	-0.19	0.24	0.14	0.20	-0.10	0.13						
F2	0.19	0.18	-0.27	-0.09	-0.22	0.19	0.10	0.18	-0.07	0.14	0.96					
F3	0.25	0.21	-0.17	-0.07	-0.22	0.17	0.09	0.18	-0.04	0.15	0.92	0.98				
F4	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			
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		
$D_{12}ILR$	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 bond excess returns. $\overline{rx}_{t+12} = \boldsymbol{\beta}' \boldsymbol{X}_t + \varepsilon_{t+12}$. $\overline{rx}$ is the equally weighted yearly 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 Piazzesi 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 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. 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	- 0.017	0.05	- 0.018	0.05	-0.018	0.05	-0.004	0.08	-0.004	0.06	-0.003	0.12
LNF_1					0.013	0.00	0.013	0.00	0.015	0.00						
LNF_2					0.004	0.07	0.004	0.06	0.002	0.12						
LNF_3					- 0.001	0.10	- 0.001	0.15	-0.001	0.12						
LNF_4					- 0.004	0.02	- 0.005	0.01	-0.004	0.03						
LNF_5					- 0.002	0.08	- 0.003	0.04	-0.002	0.06						
LNF_6					- 0.006	0.00	- 0.005	0.00	-0.005	0.01						
LNF_7					- 0.005	0.00	- 0.005	0.00	-0.005	0.00						
LNF_8					0.005	0.00	0.005	0.00	0.006	0.00						
LNF_9					- 0.001	0.00	- 0.001	0.00	-0.001	0.00						
F1					- 1.253	0.00	- 1.336	0.00	-1.400	0.00						
F2					0.375	0.13	0.511	0.09	0.604	0.08						
F3					1.780	0.00	1.962	0.00	2.106	0.00						
F4					0.647	0.03	0.576	0.05	0.521	0.06						
F5					- 1.272	0.00	- 1.399	0.00	-1.515	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		0.45		0.43		0.42		0.40		0.44		0.42	
Adj. R^2	0.07		0.02		0.44		0.41		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, $rx^{(n)}_{t+12} = \boldsymbol{\beta}' \boldsymbol{X}_t + \varepsilon^{(n)}_{t+12}$, 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 (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. The p-value calculated using the Newey-West correction for autocorrelation and heteroscedasticity is presented in squared 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)
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 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. 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 respective model over the benchmark, *CW* is the **?** test for equal predictive ability, with corresponding approximate *p-value* based on the standard normal distribution. *GW* is the statistic for the **?** 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
Liquidity and Monthly Bond Portfolio Returns

The table presents the monthly in-sample forecasting regression of the monthly equally weighted bond portfolio return. $\overline{rx}_{m,t} = \alpha + \boldsymbol{\beta}'\boldsymbol{X}_t + \varepsilon_t$. $\overline{rx_m}$ 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 *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 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	
Adj. R^2	0.01		0.02		0.12		0.12		0.08		0.09		0.13		0.13	

Table 6
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 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.

	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 7
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. 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 respective model over the benchmark, *GW* is the statistic for the Giacomini and White (2006) test for model forecasting ability comparison with corresponding asymptotic *p-value*. *CW* is the Clark and West (2007) test for equal predictive ability, with corresponding approximate *p-value* based on the standard normal distribution.

		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 8
Bond Risk Premia and Market-Wide Private Information

The table presents the monthly in-sample forecasting regression of bond excess returns and market-wide private information as calculated in Albuquerque et al. (2008). $\overline{rx}_{t+12} = \boldsymbol{\beta}'\boldsymbol{X}_t + \varepsilon_{t+12}$. $\overline{rx}$ is the equally weighted yearly bond excess return, *MPI1* is the market-wide private information in the Primary Smelting and Refining of Nonferrous Metal industry, emphMPI1 is the market-wide private information in the Oil and Gas Field Machinery and Equipment Manufacturing industry, and emphMPI5 is the market-wide private information in the Other Aircraft Parts and Auxiliary Equipment Manufacturing industry. *CP* is the linear combination of the Cochrane Piazzesi 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 difference of the log yearly illiquidity ratio for small and large stocks (small-big). 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. The *p*-values based on the bootstrap analysis are presented in round brackets.

	MPI1				MPI2				MPI5			
	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
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	0.000	0.00	0.000	0.13	0.000	0.00	0.000	0.00	0.000	0.06	0.000	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 9
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
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 10
Stock Market Illiquidity and Flight to Quality Measures

The table presents the relation between stock market illiquidity and different flight to quality measures. $D_{12}ILRSMB$ 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. All regressions include a constant, not reported to conserve space. Panel A 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. Panel B presents yearly regression of equity ratio in balanced funds and stock market illiquidity. The equity ration 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 monthly regression 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	Coefficient	Prob.	Coefficient	Prob.
$DILRSMB$	0.18	0.00	-0.21	0.00
$D_{12}ILRSMB$	0.18	0.00	-0.24	0.00

Panel B. Balanced Funds

Variable	Coefficient	Prob.	Coefficient	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		
R^2	0.22		0.05	
Adj. R^2	0.16		0.03	

Panel C. Volatility Index

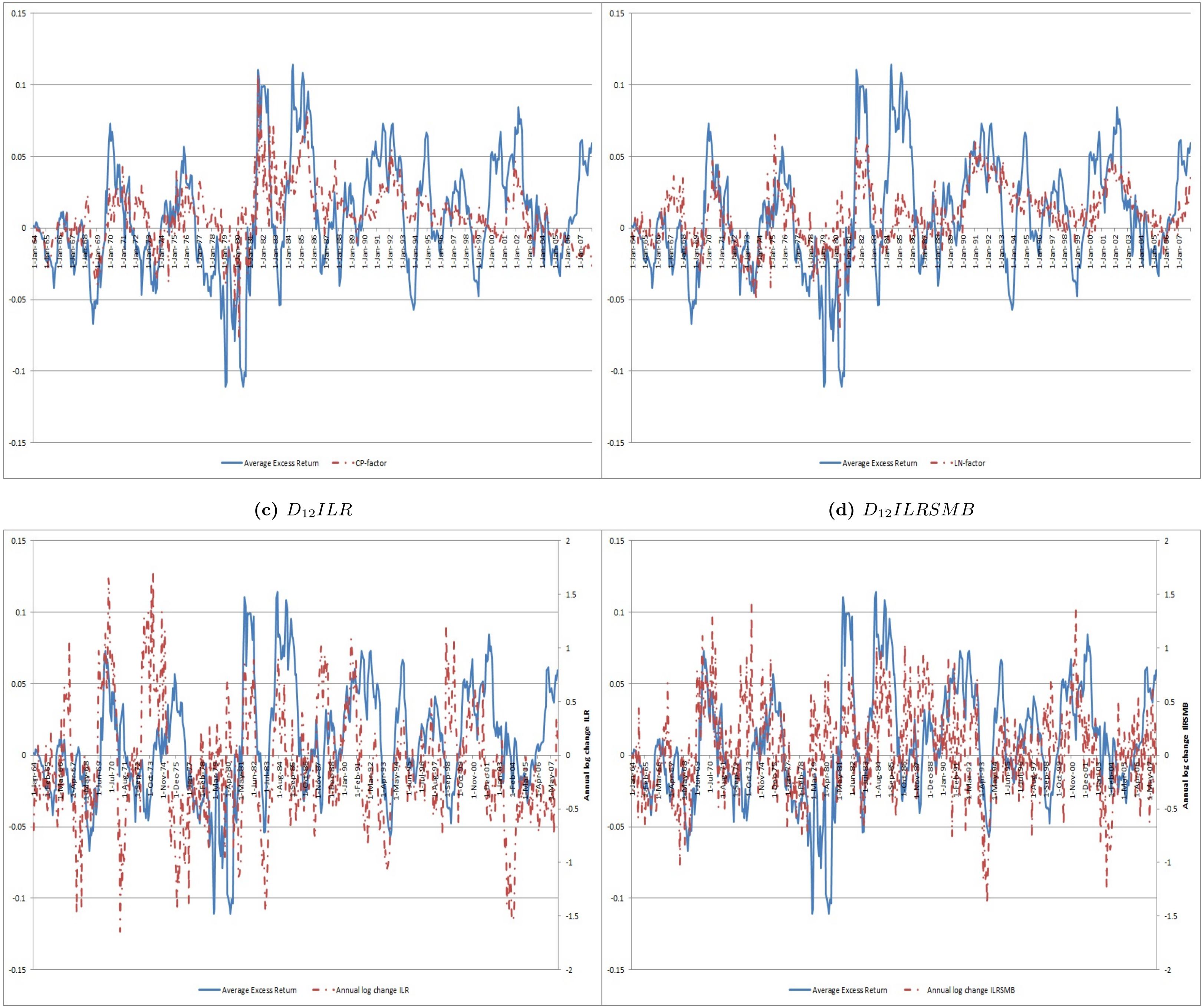
Variable	Coef.	Prob.	Adj. R^2
$D_{12}ILRSMB_{t-1}$	3.64	0.00	0.04
$D_{12}ILRSMB_{t-2}$	3.15	0.01	0.03

Table 11
Bond Risk Premia and Flight to Liquidity

The table presents the relation between bond risk premia, stock market illiquidity, and different flight to quality measures. $D_{12}ILRSMB$ is the difference of the log yearly illiquidity ratio for small and large stocks (small-big), *Funding Liq.* is the funding liquidity variable of Fontaine and Garcia (2011), *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. 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.

	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
C	0.036	0.00	0.034	0.00	0.023	0.00	0.022	0.00	0.034	0.00	0.01	0.58	0.027	0.00	0.029	0.00
$D_{12}ILRSMB$	0.016	0.05	0.028	0.00			0.018	0.01	0.027	0.00			0.025	0.00	0.024	0.01
Funding Liq.	-0.021	0.00	-0.019	0.00					-0.017	0.00			-0.019	0.00	-0.018	0.00
$D_{12}ILRSMB$*Funding Liq.			-0.013	0.08					-0.013	0.05			-0.011	0.06	-0.011	0.04
Taxable Bond					46.190	0.00	42.431	0.00	22.948	0.12					20.141	0.04
TE Money Market					28.725	0.07	24.565	0.12	2.452	0.87					-2.627	0.78
Equity Flow					0.157	0.96	1.179	0.64	-2.112	0.58					-0.693	0.91
VXO											0.00	0.29	0.00	0.22	0.000	0.47
R^2	0.18		0.19		0.09		0.15		0.23		0.02		0.20		0.23	
Adj. R^2	0.18		0.18		0.09		0.13		0.21		0.01		0.18		0.21	
Obs	265		265		288		288		265		263		263		263	

Figure 1
Average Excess Returns and Explanatory Factors



(a) Cochrane and Piazzesi Factor

(b) Ludvigson and NG Factor

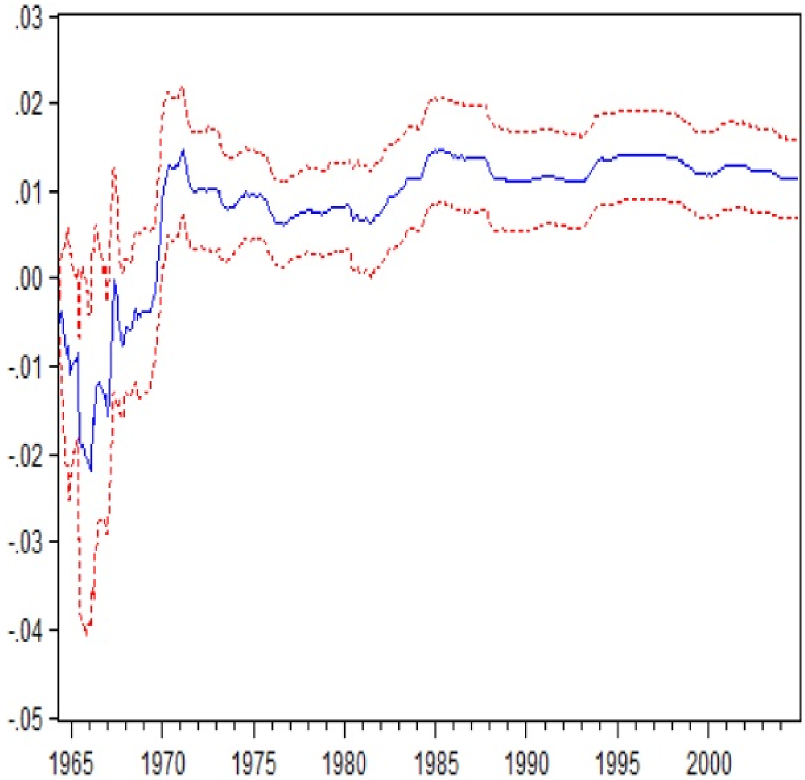
(c) $D_{12}ILR$

(d) $D_{12}ILRSMB$

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.

(a) $D_{12}ILR$



(b) $D_{12}ILRSMB$

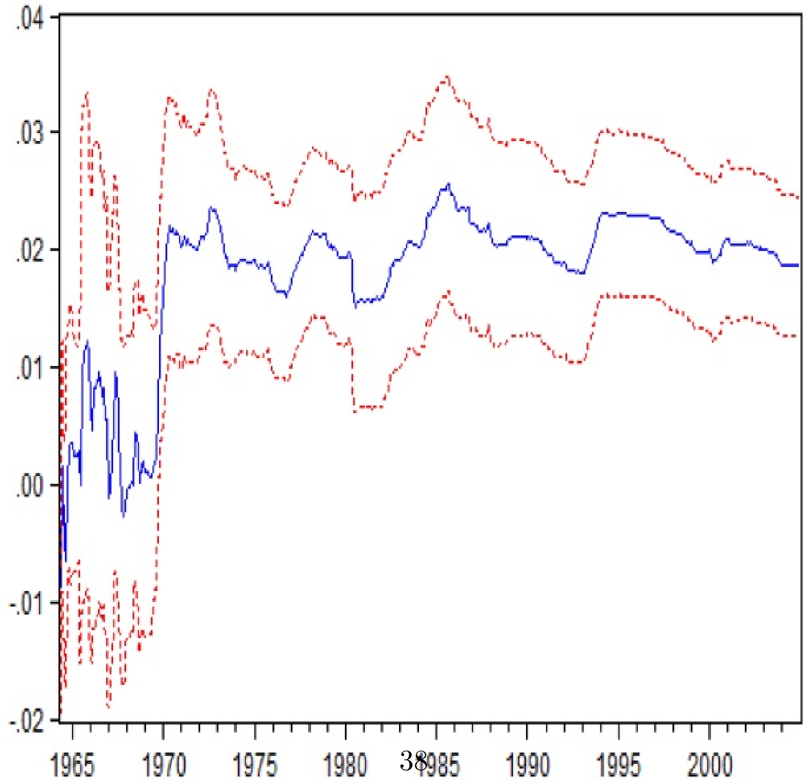


Figure 3
Mutual Fund Equity and Money Market Fund Flows

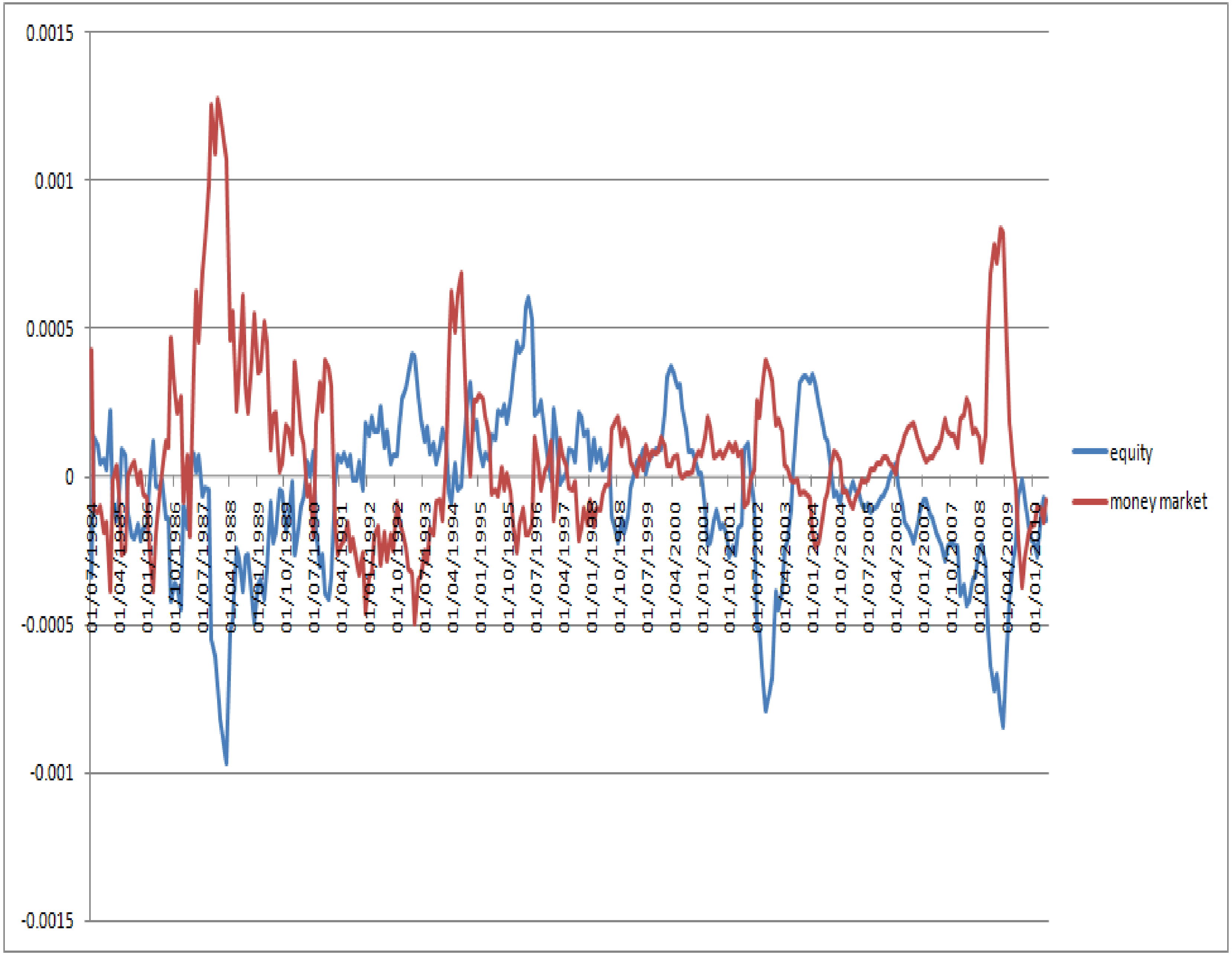


Table A1
Bond Portfolio Return Regressions

The table presents the monthly in-sample forecasting regression the equally weighted bond portfolio returns using the CP and LN factors. $\overline{rx}_{t+1} = \boldsymbol{\beta}'\boldsymbol{X}_t + \varepsilon_{t+1}$. $\overline{rx}$ 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 A2
Expectations, Bond Risk Premia, and Stock Market Illiquidity

The table presents the monthly in-sample forecasting regression for the equally weighted bond portfolio returns using macroeconomic expectations and dispersion of expectations in addition to the stock market liquidity. Panel A presents the regressions without the stock market illiquidity, while 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 Treasury bill and 10-year note rates (*Tbill-Notes 1Q, Tbill-Notes 1Y*) from the Survey of Professional Forecasters provided by the Philadelphia Fed. *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.

	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
Panel A. Expectations and Dispersion of Expectations								
CP			0.659	0.00	0.549	0.01	0.620	0.03
LN			0.732	0.00	0.705	0.00	0.499	0.03
Cieslack-Povala								
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			0.42		0.34		0.31	
Adj. R^2			0.41		0.33		0.30	
Obs			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
Bond Risk Premia and Stock and Bond Liquidity

The table presents the monthly in-sample forecasting regression of bond excess returns and bond market liquidity. $\overline{rx}_{t+12} = \boldsymbol{\beta}'\boldsymbol{X}_t + \varepsilon_{t+12}$. $\overline{rx}$ is the equally weighted yearly bond excess return, *Bond Liquidity* is the liquidity of Treasury Bills measured as the bid-ask spread difference, *Treasury Bills Amended by 3m* replaces the Treasury Bill bid-ask spread from CRSP with the 3-month bills spread in GovPX for the period August 1994-December 2004, *Treasury Bills Amended by 6m* replaces the Treasury Bill bid-ask spread from CRSP with 6-month bills spread in GovPX for the period August 1994-December 2004. *CP* is the linear combination of the Cochrane Piazzesi 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 difference of the log yearly illiquidity ratio 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. The *p*-values based on the bootstrap analysis are presented in round brackets. All regressions include a constant, not reported to conserve space.

	Treasury Bills				Treasury Bills Amended by 3m				Treasury Bills Amended by 6m			
	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
Bond Liquidity	-10.165	0.51	-12.800	0.37	-10.187	0.47	-13.161	0.31	-10.496	0.46	-13.852	0.30
CP	0.744	0.01	0.686	0.00	0.744	0.01	0.686	0.00	0.744	0.01	0.687	0.00
LN	0.677	0.00	0.675	0.00	0.676	0.00	0.673	0.00	0.676	0.00	0.673	0.00
$D_{12}ILR$	0.010	0.06			0.010	0.06			0.010	0.06		
$D_{12}ILRSMB$			0.020	0.00			0.020	0.00			0.020	0.00
R^2	0.42		0.44		0.42		0.44		0.42		0.45	
Adj. R^2	0.42		0.44		0.42		0.44		0.42		0.44	
Obs			528				528				528	

Table A4
Futures Market and Stock Market Illiquidity

The table presents monthly regressions of future market variables from Hong and Yogo (2012) and stock market illiquidity. $D_{12}ILRSMB$ 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 (*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. All regressions include a constant, not reported to conserve space.

Variable	Coef.	Prob.	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.	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	

Table A5
Mutual 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 flows, *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*
			Panel A. Net 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			
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
			Panel B. Net Exchange			
			Crisis period			
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	- 0.00000	- 0.00001	- 0.00000	0.00001	- 0.00003	0.00002
St. Dev.	0.00046	0.00006	0.00021	0.00013	0.00027	0.00059
Minimum	- 0.00219	- 0.00024	- 0.00183	- 0.00025	- 0.00175	- 0.00217
Maximum	0.00200	0.00019	0.00045	0.00114	0.00101	0.00273
Obs.	246	246	246	246	246	

Table A6
Mutual 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 Bond	T.E. Money Market	Taxable Bond
			Panel 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-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
			Panel B. 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

References

R. Albuquerque, E. De Francisco, and L. B. Marques. Marketwide private information in stocks: Forecasting currency returns. *Journal of Finance*, 63:2297–2343, 2008.

Y. Amihud. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1):31 – 56, 2002.

L. Baele, G. Bekaert, and K. Inghelbrecht. The determinants of stock and bond return comovements. *Review of Financial Studies*, 23:2374–2428, 2010.

W. Bailey and R. M. Stulz. The pricing of stock index options in a general equilibrium model. *Journal of Financial and Quantitative Analysis*, 24:1–12, 1989.

M. Baker and J. C. Stein. Market liquidity as a sentiment indicator. *Journal of Financial Markets*, 3: 271–299, 2004.

D. Baur and B. Lucey. Flight to quality or contagion? An empirical analysis of stock bond correlation. Institute of Integration Studies, 2006.

A. Beber, M. Brandt, and K. Kavajecz. Flight-to-quality or flight-to-liquidity? Evidence from the Euro-area bond market. *Review of Financial Studies*, 22:925–957, 2009.

G. Bekaert, M. Hoerova, and M. L. Duca. Risk, uncertainty and monetary policy. NBER Working Paper 16397, 2010.

A. Ben-Rephael, S. Kandel, and A. Wohl. Measuring investorsentiment with mutual fund flows. *Journal of Financial Economics*, Forthcoming, 2011.

M. Brennan, S.-W. Huh, and A. Subrahmanyam. The anatomy of the illiquidity premium in stock prices. Working paper, 2011.

M. K. Brunnermeier and L. H. Pedersen. Market liquidity and funding liquidity. *Review of Financial Studies*, 22(6):2201–2238, 2009.

M. K. Brunnermeier, T. M. Eisenbach, and Y. Sannikov. Macroeconomics with financial frictions: A survey. Working paper, 2011.

A. Buraschi and P. Whelan. Term structure models with differences in beliefs. Imperial College Business School Working Paper, 2012.

J. Campbell and R. Shiller. Yield spreads and interest rates: A bird's eye view. *Review of Economic Studies*, 58:495–514, 1991.

M. Chernov and P. Mueller. The term structure of inflation expectations. *Journal of Financial Economics*, forthcoming, 2011.

T. Chordia, A. Sarkar, and A. Subrahmanyam. An empirical analysis of stock and bond market liquidity. *Review of Financial Studies*, 18(1):85 – 129, 2005.

A. Cieslak and P. Povala. Understanding bond risk premia. Working paper, 2011.

T. E. Clark and K. D. West. Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, 138:291–311, 2007.

J. Cochrane and M. Piazzesi. Bond risk premia. *American Economic Review*, 95:138–160, 2005.

I. Cooper and R. Priestley. Time-varying risk premiums and the output gap. *Review of Financial Studies*, 22: 2801–2833, 2009.

F. X. Diebold and R. S. Mariano. Comparing predictive accuracy. *Journal of Business and Economic Statistics*, 13:253–263, 1995.

G. Duffee. Information in (and not in) the term structure. *Review of Financial Studies*, Forthcoming, 2011a.

G. Duffee. The term structure and the macroeconomy. Johns Hopkins Working Paper, 2011b.

A. L. Eisfeldt. Endogenous liquidity in asset markets. *Journal of Finance*, 59:1–30, 2005.

E. Fama and R. Bliss. The information in long-maturity forward rates. *American Economic Review*, 77:680–692, 1987.

W. Ferson, S. Sarkissian, and T. Simin. Spurious regressions in financial economics. *Journal of Finance*, 58:1393–1413, 2003.

J.-S. Fontaine and R. Garcia. Bond liquidity premia. *Review of Financial Studies*, forthcoming, 2011.

M. Gallmeyer, B. Hollifield, and D. J. Seppi. Demand discovery and asset pricing. Carnegie Mellon University Working Paper, 2005.

R. Giacomini and H. White. Tests of conditional predictive ability. *Econometrica*, 74:1545–1578, 2006.

D. Goldreich, B. Hanke, and P. Nath. The price of future liquidity: Time-varying liquidity in the U.S. treasury market. *Review of Finance*, 9:1–32, 2005.

R. Y. Goyenko, C. W. Holden, and C. A. Trzcinka. Do liquidity measures measure liquidity? *Journal of Financial Economics*, 92(2):153–181, 2009.

P. Hartmann, S. Straetmans, and C. G. de Vries. Asset market linkages in crisis periods. *Review of Economics and Statistics*, 86:313–326, 2004.

H. Hong and M. Yogo. What futures market interest tell us about the macroeconomy and asset prices? *Journal of Financial Economics*, forthcoming, 2012.

J. Z. Huang and Z. Shi. Determinants of bond risk premia. Penn state working paper, 2011.

S. Joslin, M. Priebsch, and K. J. Singleton. Risk premiums in dynamic term structure models with unspanned macro risk. Stanford University Working Paper, 2010.

M. T. Kiley. Monetary policy actions and long-run inflation expectations. Federal reserve board finance and economics discussion series, 2008.

N. Kiyotaki and J. Moore. Liquidity, business cycles, and monetary policy. Princeton University Working Paper, 2008.

R. Koijen, H. Lustig, and S. V. Nieuwerburgh. The cross-section and time series of stock and bond returns. Working Paper, 2009.

A. Kyle. Continuous auctions and insider trading. *Econometrica*, 53:1315–1335, 1985.

D. Lesmond, J. P. Ogden, and C. A. Trzcinka. A new estimate of transaction costs. *Review of Financial Studies*, 12(5):1113–1141, 1999.

M. Lettau and J. Wachter. The term structures of equity and interest rates. *Journal of Financial Economics*, Forthcoming, 2011.

H. Li, J. Wang, C. Wu, and Y. He. Are liquidity and information risks priced in the treasury bond market? *Journal of Finance*, 64:467–503, 2009.

F. A. Longstaff. The flight-to-liquidity premium in US treasury bond prices. *Journal of Business*, 77:511–526, 2004.

S. Ludvigson and S. Ng. Macro factors in bond risk premia. *Review of Financial Studies*, 22:5027–5067, 2009.

P. Mueller, A. Vedolin, and H. Zhou. Short run bond risk premia. Financial markets group discussion paper, 2011.

R. Næs, J. A. Skjeltorp, and B. A. Ødegaard. Stock market liquidity and the business cycle. *Journal of Finance*, 66:139–176, 2011.

R. Roll. A simple implicit measure of the effective bid-ask spread in an efficient market. *The Journal of Finance*, 39(4):1127–1139, 1984.

J. A. Skjeltorp and B. A. Ødegaard. Why do firms pay for liquidity provision in limit order markets? Working paper, University of Stavanger, 2011.

D. L. Thornton and G. Valente. Out-of-sample predictions of bond excess returns and forward rates: An asset allocation perspective. *Review of Financial Studies*, forthcoming, 2011.

V. A. Warther. Aggregate mutual fund flows and security returns. *Journal of Financial Economics*, 39: 209–235, 1995.