Noise as Information for Illiquidity

Xing Hu, Jun Pan, and Jiang Wang*

May 31, 2011

Abstract

We propose a measure of liquidity for the overall financial market by exploiting its connection with the amount of arbitrage capital in the market and observed price deviations in US Treasuries. When arbitrage capital is abundant, we expect the arbitrage forces to smooth out the Treasury yield curve and keep the deviations small. During market crises, the shortage of arbitrage capital leaves the yields to move more freely relative to the curve, resulting in more "noise" in prices. As such, noise in the Treasury market can be informative, and we expect this information about liquidity to reflect the broad market conditions given the central importance of the Treasury market and its low intrinsic noise — high liquidity and low credit risk. Indeed, we find that our "noise" measure captures episodes of liquidity crises of different origins and magnitudes and is also related to other known liquidity proxies. Moreover, using it as a priced risk factor we show that it helps explain cross-sectional returns on hedge funds and currency carry trades, both known to be sensitive to the general liquidity conditions of the market.

*Hu (xinghu@princeton.edu) is from University of Hong Kong, Pan (junpan@mit.edu) and Wang (wangj@mit.edu) are from MIT Sloan School of Management, CAFR, and NBER. We are grateful to Darrell Duffie, Mark Krizman, Dimitri Vayanos, Adrien Verdelhan, and Haoxiang Zhu for valuable discussions. We also thank comments from seminar participants from University of Western Australia, University of Michigan, 2011 NBER Asset Pricing Program Spring Meeting, and Moody's 2011 Credit Risk Conference.

1 Introduction

The level of liquidity in the aggregate financial market is closely connected to the amount of arbitrage capital available. During normal times, institutional investors such as investment banks and hedge funds have abundant capital, which they can deploy to supply liquidity. As a result, assets are traded at prices closer to their fundamental values. Price deviations from the fundamental values will be largely eliminated by arbitrage forces. During market crises, however, capital becomes scarce and/or willingness to deploy it diminishes. The liquidity in the overall market dries up. The lack of sufficient arbitrage capital limits the force of arbitrage and assets can be traded at prices significantly away from their fundamental values.[1] Thus, temporary price deviations, or "noise" in prices, being a key symptom of shortage in arbitrage capital, contains important information about the amount of liquidity in the aggregate market. In this paper, we analyze the "noise" in the price of US Treasuries and examine its informativeness as a measure of overall market illiquidity.

Our basic premise is that the abundance of arbitrage capital during normal times helps smooth out the Treasury yield curve and keep the average dispersion low. This is particularly true given the presence of many proprietary trading desks at investment banks and fixed-income hedge funds that are dedicated to relative value trading with the intention to arbitrage across various habitats on the yield curve.[2] During liquidity crises, however, the lack of arbitrage capital forces the proprietary trading desks and hedge funds to limit or even abandon their relative value trades, leaving the yields to move more freely in their own habitats and resulting in more noise in the yield curve. We therefore argue that these abnormal noises in Treasury prices are a symptom of a market in severe shortage of arbitrage capital. More importantly, it is not a symptom specific only to the Treasury market, but more broadly for the financial market overall.

We focus on the U.S. Treasury market for several reasons. First, it is by far the most important asset market in the world. Investors of many types come to the Treasury market to trade and yields on these securities are widely used as benchmarks for pricing. As such, trading in the Treasury market contains information about liquidity needs for the broader financial market. Second, the fundamental values of Treasuries are determined by a small number of interest rate factors, which can be easily captured empirically. Thus, we can have a more reliable measure of price deviations. This aspect of the market is important for our

[1]There is an extensive literature on how the amount of arbitrage capital in a specific market affects the effectiveness of arbitrage forces, or "limits of arbitrage," and possible price deviations. See, for example, Merton (1987), Leland and Rubinstein (1988), Shleifer and Vishny (1997), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009) and Duffie (2010).

[2]Vayanos and Vila (2009), for example, model the interaction between habitat investors and risk-averse arbitrageurs and its impact on bond yields.

purpose because we would like to keep the information content as “pure” as possible. Other markets such as the corporate bond market, the equity market, or the index options market might also be informative, but their information is “contaminated” by the presence of other risk factors. Third, the Treasuries market is one of the most active and liquid markets. A shortage of liquidity in this market provides a strong signal about liquidity in the overall market.

Using CRSP Daily Treasury database, we construct our noise measure by first backing out, day by day, a smooth zero-coupon yield curve. This yield curve is then used to price all available bonds on that day. Associated with each bond is the deviation of its market yield from the model yield. Aggregating the deviations across all bonds by calculating the root mean squared error, we obtain our noise measure. We call it “noise” only to the extent that in the fixed-income literature, deviations from a given pricing model are often referred to as noises. In fact, our results show that these measures are rather informative about the liquidity condition of the overall market. During normal times, the noise is kept at an average level around 3.94 basis points, which is comparable to the average bid/ask yield spread of 2 basis points. In other words, the arbitrage capital on the yield curve is effective in keeping the deviations within a range that is unattractive given the transaction cost. During crises, however, our noise measure spikes up much more prominently than the bid/ask spread, implying a high degree of misalignment in bond yields that would have been attractive for relative value arbitrage during normal times and *are* in fact attractive given the contemporaneous transaction cost. These include the 1987 crash, when the noise was close to 15 basis points; the aftermath of the LTCM crisis, when the noise peaked at 7.36 basis points; the first trading day after the 9/11 terrorist attack, when the noise was at 13.87; the days following the sale of Bear Stearns to JPMorgan, when the noise peaked at 8.38 basis points; and the aftermath of Lehman default, when the noise was above 15 basis points for a sustained period of time. Given the sample standard deviation of 2.36 basis points for the noise measure, these are large standard deviations.

To further understand the information content captured by the noise measure, we examine its relation to other measures of liquidity. One popular measure of liquidity for the Treasury market is the premium enjoyed by on-the-run bonds. Since our noise measure is a daily aggregate of cross-sectional pricing errors, the on-the-run premium is in fact a component of our measure. We find a positive relation between the two, but our noise measure is by far more informative about the overall liquidity condition in the market. In particular, our noise measure spikes up much more prominently than the on-the-run premium during crises. This accentuates the important fact that the information captured by our noise measure is a collective information over the entire yield curve. In other words, our noise measure is sensitive to the commonality of pricing errors, and if such commonality heightens during crises, then it will be captured by our noise measure, but not by a measure that focuses only on a couple of isolated points on the yield curve. Indeed, this is how noise becomes information. Our results also show that factors known to be related to systematic liquidity such at the CBOE VIX index and the Baa-Aaa yield spread have a significant relation with our noise measure. By contrast, term structure variables such as the short- and long-term interest rates and interest-rate volatility do not have strong explanatory power for the time-variation for our noise measure. In other words, the time-variation in our noise measure is not driven by poor yield curve fitting.

The fact that liquidity crises of varying origins and magnitudes can be captured by "noises" measured from the US Treasury bond market reflects the transmission of different liquidity crises through financial markets. Indeed, rather than being a measure specific only to the Treasury market, our noise measure is a reflection of the overall market condition.[3] Given the potential importance of the aggregate liquidity risk, we further explore its asset pricing implications, especially how it can help us to understand the behavior of asset returns. For this purpose, instead of confining ourselves to standard test portfolios such as equity or/and bond portfolios, we look for portfolios or trading strategies that are potentially sensitive to market-wide liquidity risks or crises. Specifically, we consider two sets of returns: hedge fund returns and currency carry-trade returns, both are known to react substantially to market upheavals.

We use TASS hedge fund data from 1994 through 2009 to obtain hedge fund returns. Using a two-factor model that includes monthly changes in noise as one factor and returns on the stock market portfolio as the other, we find that the liquidity risk is indeed priced by hedge fund returns. The estimated risk premium is statistically significant, and is also economically important. For two hedge funds with the same market beta but differing liquidity beta, one unit difference in liquidity beta generates a difference of 0.77% per month in returns.[4] In other words, this liquidity risk premium is a key contributor to the superior performance by hedge funds with very high exposures to market-wide liquidity risk. Interestingly, such highly exposed hedge funds are also found to have a higher death rate in 2008. Using other measures of liquidity such as RefCorp yield spread, on-the-run premiums, Pastor-Stambaugh equity market liquidity measure, CBOE VIX, or default spreads, we do not find such pricing implications in hedge fund returns.

Next, we construct six currency carry portfolios by sorting on the forward discount. The

[3]More specifically, our measure is not a reflection of how constrained the market makers in the Treasury market are. In fact, the bid and ask spreads of Treasury bond prices can be a better measure of such "local" liquidity.

[4]Our results are robust if we add additional risk factors including VIX, default spread, and the slope of term structure.

main driver of the currency carry trade is the average superior performance of currencies with high interest rates, and a typical trade is to be long on such currencies and fund the trading with currencies with low interest rates. Using a two-factor model that includes both stock market returns and monthly changes in noise, we find that the carry portfolio that contains the "target" or "asset" currencies has a negative beta on our noise measure, implying a worsening portfolio performance during liquidity crises. By contrast, the carry portfolio that contains the "funding" currencies has a minimal exposure to our noise measure. The superior average performance of the "asset" currencies can then be explained by a non-trivial amount of liquidity risk premium. Indeed, we test this idea formally and find a risk premium that is significant both statistically and economically. For two carry portfolios with the same stock market beta but differing noise beta, one unit difference in noise beta generates a difference of 0.99% in their monthly performance.[5]

Our paper contributes to the existing literature in several dimensions. It explores the empirical implications of the theoretical theme on the "limits of arbitrage," which emphasizes the link between shortage of capital, market liquidity and price deviations (see, for example, Merton (1987), Shleifer and Vishny (1997) and Gromb and Vayanos (2002)). Recent empirical work, such as Coval and Stafford (2007) on equity fire sales by mutual funds and Mitchell, Pedersen, and Pulvino (2007) on convertible bond arbitrage by hedge funds, provides additional empirical evidence on this link.[6] While these papers focus mostly on the connection between arbitrage capital and liquidity in specific markets, our paper considers the liquidity in the overall market. In particular, our liquidity measure is able to capture episodes of liquidity crises of varying origins and is not limited to one specific market. As such, the fluctuation of arbitrage capital captured by our noise measure is not confined to market makers of certain markets, or hedge funds of certain styles.

A growing body of work explores asset pricing implications of liquidity and liquidity risk. This includes, for example, Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) on equities and Bao, Pan, and Wang (2010) on corporate bonds. These studies follow a common approach, which is to focus on a specific market to both construct and test the liquidity risk measure. We instead focus on the liquidity risk of the overall market by extracting our liquidity measure from the US Treasury market, one of the most liquid markets in the world. We then use test portfolios from other markets, namely hedge fund and currency carry trade strategies, to confirm the importance of this aggregate liquidity risk factor in asset pricing.

[5]We find this result to be robust using a component of our noise measure that is orthogonal to VIX and default spreads.

[6]More recently, Mitchell and Pulvino (2011) provide a detailed and informative account on the financing of hedge funds during the 2008 crisis and its potential implications on asset prices. Nagel (2011) connects the returns of short-term reversal strategies in equity markets with the expected returns from liquidity provision.

Our results also complement studies on hedge fund and carry trade returns. For example, Sadka (2010) extracts a liquidity risk factor from the equity market and finds it to be important in explaining hedge fund returns. His measure of liquidity risk, similar to that of Pastor and Stambaugh (2003), is based on price impact in the equity market, thus is equity specific, while ours is more market-wide. Moreover, we do not find a significant risk premium for the Pastor-Stambaugh equity liquidity risk factor using hedge fund returns as test portfolios.[7] Since Fama (1984), the source of currency carry trade returns has been an object of investigation by many studies.[8] Brunnermeier, Nagel, and Pedersen (2008) focus on interaction of crash risks of currencies and funding conditions of FX speculators. Using CBOE VIX and LIBOR spreads as proxies for funding liquidity, they find that the carry trade tends to incur losses during weeks in which illiquidity increases. Our result is consistent with this observation, but more importantly, we are able to formally test the pricing implication. In particular, our result explicitly links the superior performance of "target" currencies to their high exposures to the noise measure and documents a liquidity risk premium that is statistically significant and economically important.

The paper proceeds as follows. Section 2 describes the construction of our noise measure from Treasury prices. In Section 3, we report the time series properties of the noise measure, focusing in particular on its variation through various crises and its connection with other measures of market liquidity. In Section 4, we provide the cross-sectional tests on our noise measure as a liquidity risk factor using returns on hedge funds and currency carry trades, respectively. Section 5 concludes.

2 Constructing the Noise Measure

2.1 Treasury Data

We use the CRSP Daily Treasury database to construct our noise measure. The main variable we use from the dataset is the daily cross-sections of end-of-day bond prices from 1987 through 2009. The dataset itself starts from January 1962, but we choose to start the sample from 1987 due considerations over both data quality and the sample period of interest. In particular, we will test our noise measure using hedge fund data, which is available only from 1990.

[7]Our paper is also related to the growing literature in hedge fund studies that connects hedge fund activities to market liquidity and market crises such as Cao, Chen, Liang, and Lo (2010) and Billio, Getmansky, and Pelizzon (2010).

[8]It ranges from using consumption-based asset pricing models (e.g., Backus, Gregory, and Telmer (1993) and Verdelhan (2010)), reduced-form term structure models (e.g., Backus, Foresi, and Telmer (2001)), to, more recently, combining carry trade returns with currency options to incorporate tail risks (e.g., Jurek (2009) and Burnside, Eichenbaum, Kleshchelski, and Rebelo (2010)).

Our sample consists of Treasury bills, notes and bonds that are noncallable, non-flower and with no special tax treatment. Observations with obvious pricing errors such as negative prices, negative yields, or negative bid/ask spreads are deleted from the sample. We dropped Treasury securities with remaining maturities less than 1 month because of the potential liquidity problems. We also drop bonds with maturity longer than 10 years to base our noise measure on notes and bonds with maturity between 1 and 10 years. For bonds with maturity long than 10 years, we have fewer observations and the fitted yield curve becomes less reliable.

Table 1 provides the details of our bond sample. On average, we have 159 bonds (including notes) and bills every day to fit the yield curve and 105 bonds with maturity between 1 and 10 years to construct the noise measure. The cross-section varies over time, with a noticeable dip around late 1990s and early 2000s. This coincided with record surpluses of US government and the reduction of gross issuance of Treasury notes and bonds, which fell by 54 percent from 1996 to 2000. Also reported are the key characteristics of the bonds used in constructing the noise measure. For example, the average maturity of the bonds is 3.82 years and the average age of the bonds is 3.94 years. Over time, both variables remain stable, alleviating the concern that the time-series variations in bond characteristics such as maturity and age might cause the time-series variation in our noise measure. Also reported in Table 1 is the average spread between bid and ask yields of the bonds used in our noise construction. The average bid/ask spread is 2.17 basis points, with a decreasing time trend that is caused by both improved liquidity in the market and improved data quality. In particular, after October 16, 1996, the source for price quotations of the CRSP Treasury database changed to GovPX, which receives its data from 5 inter-dealer bond brokers, who broker transactions among 37 primary dealers. For most of the bond characteristics reported in Table 1, the cross-sectional mean and median are close, indicating that the cross-section of bonds is unlikely to be dominated by a few bonds with extremely different characteristics.

2.2 Curve Fitting

Various estimation methods can be employed to back out zero-coupon yield curves from coupon-bearing Treasury securities. These approaches can be broadly classified into spline-based and function-based models. Spline-based methods rely on piecewise polynomial functions that are smoothly joined at selected knots to approximate the yield curve.[9] Function-based models, on the other hand, use a single parsimonious parametric function to describe the entire yield curve. Popular models in this class include Nelson and Siegel (1987) and

[9]This includes McCulloch (1975), Nelson and Siegel (1987), and Svensson (1994). Fisher, Nychka, and Zervos (1995) extend the traditional cubic spline model to smoothed splines with a roughness penalty function that determines the trade-off between the goodness-of-fit and the smoothness of the forward yield curve.

Table 1: **CRSP Treasury Data Summary Statistics**

Sample Period	# bonds (1M-10Y)	# bonds (1Y-10Y)	Coupon (%)	Size ($B)	Bid/Ask (bps)	Maturity (year)	Age (year)	Duration (year)	Price ($)	Yield (%)
					mean					
1987-1990	170	115	9.37	7.64	3.99	3.89	3.43	3.15	103.27	8.06
1991-1995	185	125	7.88	10.35	2.61	3.88	3.68	3.21	106.48	5.85
1996-2000	171	111	7.16	12.72	1.93	3.63	4.57	3.09	104.71	5.74
2001-2005	114	70	5.06	20.00	1.25	3.72	3.95	3.30	104.21	3.49
2006-2009	172	115	4.40	21.58	1.25	4.12	3.94	3.63	106.22	2.87
All	159	105	6.80	14.37	2.17	3.82	3.94	3.25	104.91	5.21
					median					
1987-1990			8.94	7.51	3.59	3.42	2.41	2.95	101.75	8.07
1991-1995			7.68	9.84	2.09	3.32	2.47	2.96	104.36	5.87
1996-2000			6.37	12.98	1.63	3.02	2.81	2.72	101.41	5.74
2001-2005			4.73	20.05	1.01	3.01	2.31	2.80	102.68	3.40
2006-2009			4.28	19.83	1.00	3.47	2.06	3.24	104.16	2.77
All			6.40	14.08	1.83	3.21	2.44	2.90	102.80	5.18
					standard deviation					
1987-1990			2.10	3.76	1.96	2.26	3.26	1.53	6.23	0.24
1991-1995			2.05	5.66	1.53	2.36	3.68	1.63	9.32	0.55
1996-2000			2.31	7.76	1.06	2.25	4.84	1.66	8.93	0.15
2001-2005			2.08	8.89	0.74	2.45	4.69	1.94	6.64	0.51
2006-2009			1.74	8.27	0.81	2.55	5.78	2.00	10.01	0.54
All			2.08	6.97	1.20	2.37	4.40	1.75	8.09	0.40

Bonds with maturity ranging from (1M-10Y) are used for yield curve fitting, while bonds with maturity ranging from (1Y-10Y) are used to construct the noise measure. All other variables are reported for the sample of bonds used to construct the noise measure, and reported are the time-series averages of the cross-sectional mean, median, and standard deviation. The size of a bond is its amount outstanding in billions of dollars. The bid/ask spread is the bid yield minus the ask yield.

Svensson (1994). Compared with function-based models, spline methods usually can fit the data well, but tend to over fit and often generate oscillating yield curves. This is not very attractive for our purpose given that the reason for us to employ a curve-fitting model is not to over fit the yields, but to pass a smooth curve through bond yields of varying maturities. We thus favor the function-based models, and choose the Svensson model because of its improved flexibility over the Nelson-Siegel model.

The Svensson model assumes the following functional form for the instantaneous forward rate f:

$$f(m,b) = \beta_0 + \beta_1 \exp\left(-\frac{m}{\tau_1}\right) + \beta_2 \frac{m}{\tau_1} \exp\left(-\frac{m}{\tau_1}\right) + \beta_3 \frac{m}{\tau_2} \exp\left(-\frac{m}{\tau_2}\right), \tag{1}$$

where m denotes the time to maturity, and $b = (\beta_1\, \beta_2\, \beta_3\, \tau_1\, \tau_2)$ are model parameters to be estimated. Given that $f \to \beta_0$ as $m \to \infty$ and $f \to \beta_0 + \beta_1$ as $m \to 0$, it follows that β_0 represents the forward rate at infinitely long horizon, and $\beta_0 + \beta_1$ represents the forward rate at maturity zero. In addition, (β_2, τ_1) and (β_3, τ_2) control the "humps" of the forward rate curve, while β_2 and β_3 determine the magnitude and direction of the humps, and τ_1 and τ_2 affect the position of the humps. Finally, in order to model nominal interest rates, a proper set of parameters must satisfy the conditions that $\beta_0 > 0$, $\beta_0 + \beta_1 > 0$, $\tau_1 > 0$ and $\tau_2 > 0$.

Using the parameterized forward curve, the zero-coupon yield curve can be derived by,

$$s(m,b) = \frac{1}{m} \int_0^m f(x,b)\, dx\,.$$

Using the zero-coupon yield curve, we can price any coupon-bearing bonds. Conversely, we can use such bonds to back out the model parameters b. Specifically, we use market closing prices, which are mid bid/ask quotes, of all Treasury bills and bonds in our sample with maturity between one month and ten years to do the curve fitting. Let N_t be the number of bonds and bills available on day t for curving fitting and let $P_t^i, i = 1, \ldots, N_t$ be their respective market observed prices. We choose the model parameters b_t by minimizing the sum of the squared deviations between the actual prices and the model-implied prices:

$$b_t = \underset{b}{\operatorname{argmin}} \sum_{i=1}^{N_t} \left[P^i(b) - P_t^i\right]^2,$$

where $P^i(b)$ is the model-implied price for bond i given model parameters b. On each day t, the end product of the curve fitting is therefore the vector of model parameters b_t.

2.3 Noise Measure

We construct our noise measure using the zero-coupon curve backed out from the daily cross-section of bonds and bills. For each date t, let b_t be the vector of model parameters backed out from the data. Suppose that, on date t, there are N_t Treasury bonds with maturity between 1 and 10 years. For each of these N_t bonds, let y_t^i denote its market observed yield, and let $y^i(b_t)$ denote its model-implied yield. As a measure of dispersions in yields around the fitted yield curve, we construct our noise measure by calculating the root mean squared distance between the market yields and the model-implied yields:

$$\text{Noise}_t = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}\left[y_t^i - y^i(b_t)\right]^2}\,. \tag{2}$$

Unlike in curving fitting, where qualified bonds and bills with maturity between 1 month and 10 years are used, we use only bonds with maturity between one and ten years in constructing the noise measure. While short-maturity bonds and bills are needed for fitting the short end of the yield curve, we feel that their information content is limited with respect to the availability of arbitrage capital in the overall market. This is because the short end of the yield curve is known to be noisier than other parts of the yield curve, primarily due to temporary demand/supply fluctuations in that segment of of the market. Moreover, the short end is unlikely to be the object of arbitrage capital, which is the main motivation of our noise measure. While the longer maturity bonds might be useful to further capture the effect of fixed-income relative value trades, the supply of these bonds is not as stable and might introduce unnecessary time-series noise to our measure.[10] For this reason, we exclude bonds with maturity longer than 10 years in constructing the noise measure.

To avoid having the pricing errors of one or two bonds driving the noise measure, we also put in place a filter. Specifically, given the daily cross-section of bonds and their pricing errors, we calculate the cross-sectional dispersion in pricing error in the yield space. Any bond with yield to maturity 4 standard deviations away from the model yield is excluded from the construction of the noise measure. In practice, this is a rather mild filter and affects only one or two bonds when triggered. More specifically, from 1987 through 2009, this filter was triggered on 20% of the days to remove one bond each day, on 7.7% of the days to remove two bonds each day, on 2.7% of the days to remove three bonds each day, and on 0.4% of the days to remove four bonds each day. There was no incident when this filter removed more than four bonds. As reported in Table 1, there are on average 105 bonds contributing to the daily noise measure. Consequently, the noise measure is a collective measure of the entire yield curve and should not be driven by only one or two bonds. This additional filter allows us to take out the few outliers that were missed in our initial sample cleaning process. Indeed, as the data quality improves over time, this filter was triggered even less frequently. For example, from 1994 through 2009, the sample period during which we will later perform our pricing tests

[10]For example, issuance of the 30-year Treasury bonds was suspended for a four and a half year period starting October 31, 2001 and concluding February 2006.

using hedge-fund returns, this filter was triggered only on 14.7% of the days to remove one bond, 0.9% of the days to remove two bonds, and only once to remove three bonds. There was no incident when this filter removed more than three bonds over this sample period.[11]

To further illustrate the construction of our noise measure and the information content it is supposed to capture, we plot in Figure 1 several examples of par-coupon yield curves and the market-observed bond yields. The top left panel in Figure 1 plots three random days in 1994, which represent normal days in terms of curve fitting and as can be seen, our curve fitting method does a reasonable job. The other panels in Figure 1 focus on the days surrounding three events including the 1987 stock market crash, the September 11, 2001 terrorist attack, and the Lehman default in September 2008. For all of these events, we see significant increases in our noise measure. More importantly, as shown in the cross-sectional plots, the sudden increases were not the result of poor curve fitting on these event days. Instead, they were caused by high levels of dispersion in bond yields across the entire yield curve. In fact, a closer examination of this dispersion seems to indicate comovement in dispersion within various bond habitats.

3 Time-Series Properties

3.1 Noise as Information for Liquidity Crises

The daily time-series variation of our noise measure is plotted in Figure 2. The most interesting aspect of this plot is the rich information content embedded in a variable that has been traditionally treated as just noise or pricing errors. During normal times, the noise measure fluctuates around its time-series average of 3.94 basis points with a standard deviation of 2.36 basis points, and it is highly persistent, with a daily autocorrelation of 98.33%. This level of noise and its fluctuation is in fact comparable to the average spread between bid and ask yields of 2 basis points for the same sample of bonds. In other words, the arbitrage capital on the yield curve is effective in keeping the deviations within a range that is unattractive given the transaction cost.

During crises, however, our noise measure spikes up much more prominently than the bid/ask spread, implying a high degree of mis-alignment in the yield curve that would have been attractive for relative value trading during normal times and *are* in fact attractive given the contemporaneous transaction cost. The includes the 1987 crash, when the noise was close to 15 basis points; the aftermath of the LTCM crisis, when the noise peaked at 7.36 basis

[11] To understand the robustness of our hedge-fund pricing results, we also experimented with cutoffs of 3 and 5 standard deviations. Our results stay similar, although in the case of 5 standard deviations, the hedge-fund results are somewhat weaker.

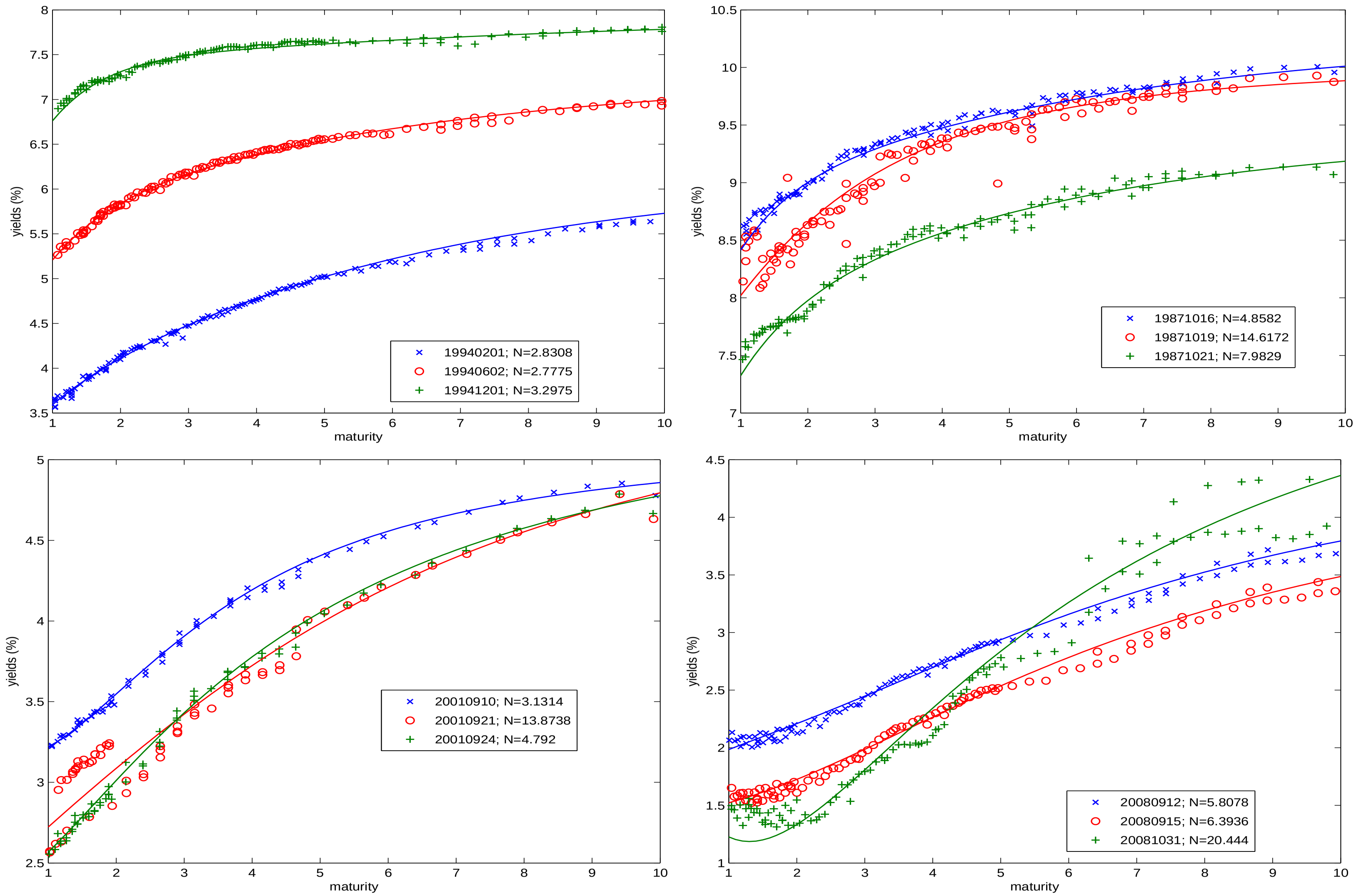

Figure 1: Examples of par-coupon yield curves and the market-observed bond yields, marked by “x”, “o”, or “+”. The top left panel plots three random days in 1994. The other three panels focus on the days surrounding three events: the 1987 stock market crash, the September 11, 2001 terrorist attack, and the Lehman default in September 2008. Marked in the legends are the date of observation and the level of the noise measure for that day.

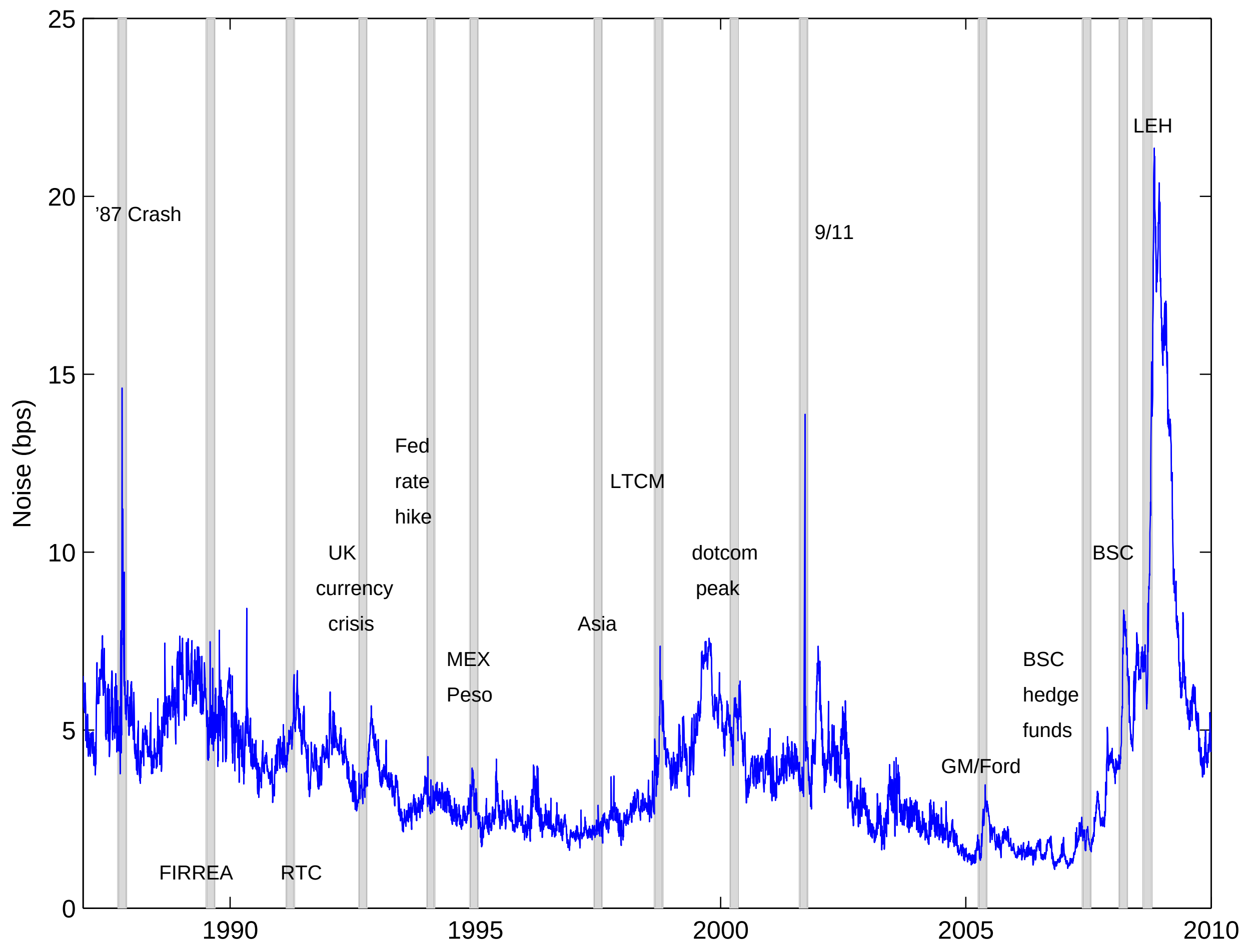

Figure 2: Daily time-series of the noise measure (in basis points).

points; the first trading day after 9/11 terrorist attack, when the noise was at 13.87; the days following the sale of Bear Stearns to JPMorgan, when the noise was peaked at 8.38 basis points; and the aftermath of Lehman default, when the noise was above 15 basis points for a sustained period of time. Given its sample standard deviation of 2.36 basis points, these are large standard deviation moves.

Another interesting aspect captured by our noise measure is that while some liquidity events, such as the 1987 crash or the 9/11 terrorist attack, are short lived, others take much longer to play out. The Savings & Loan crisis in the late 80's and early 90's is one such example, and the aftermath of the Lehman default on September 15, 2008 is another example. Figure 3 provides a closer examination of our noise measure during the period after Lehman default. It shows that when Lehman defaulted on Monday, September 15, 2008, the noise measure was at 6.39, which was about one standard deviation above the historical mean. Compared with the Friday before when the noise measure stood at 5.80, but it was only a mild increase, especially give the severity of the event. But as shown in Figure 3, the Lehman event was the beginning of a cycle of worsening liquidity that lasted until late April and early May of 2009, when Federal Reserve announced and implemented stress tests for large US banks. During this period of liquidity crisis, the noise measure had two noticeable peaks whose magnitudes dwarfed any of the previous crises. The first one was in early November when it peaked at 21.35 on November 4, days after Treasury and Fed injected $125 billion of capital into 9 large US Banks via the Capital Purchase Program (CPP), and the creation of the Commercial Paper Funding Facility (CPFF). The second one was at the middle of December when the noise measure peaked at 20.38 on December 11 as concerns over the financial crisis deepened. Overall, this period was when the crisis was at its worst and this fact was captured by our noise measure.

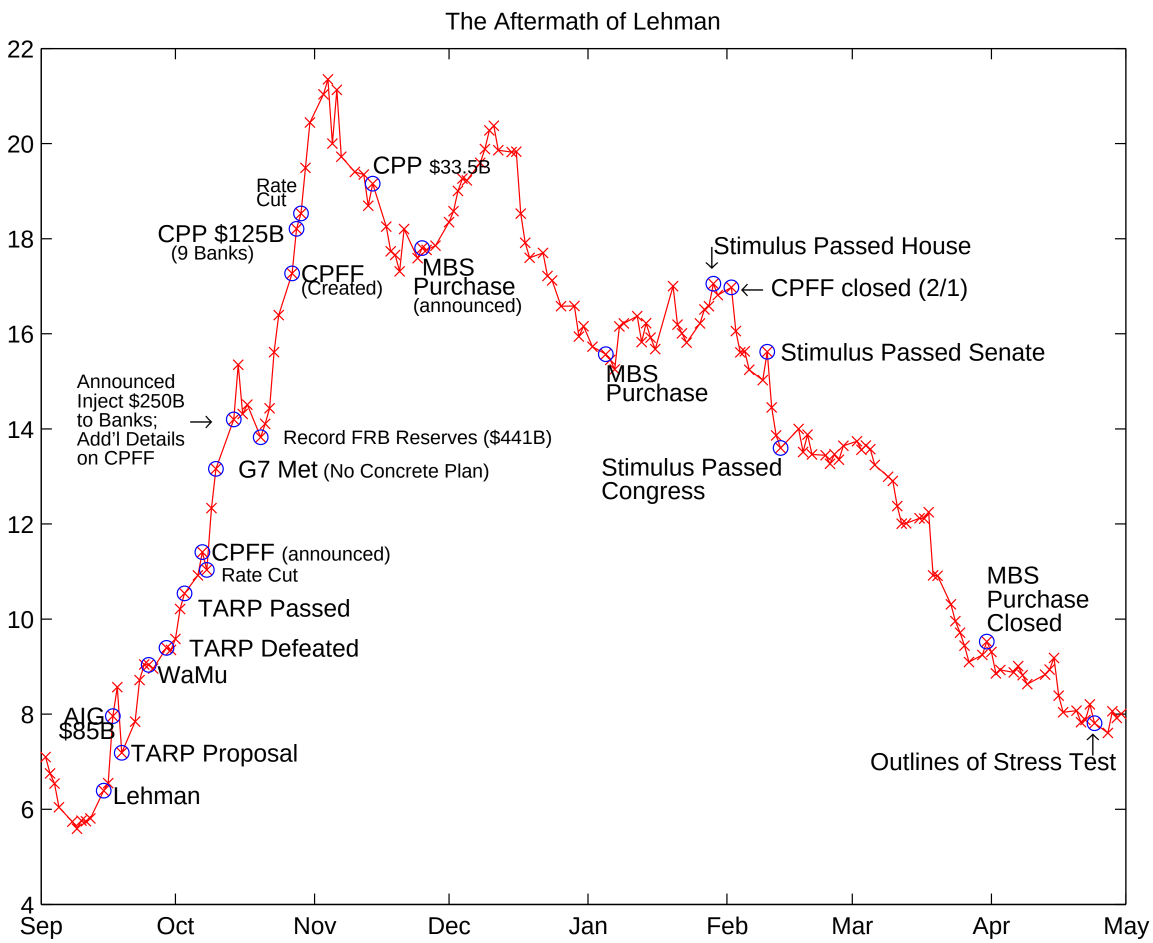

Figure 3: Daily time-series of the noise measure in late 2008 and early 2009. TARP: Troubled Asset Relief Program; CPP: Capital Purchase Program; CPFF: Commercial Paper Funding Facility; and the MBS Program is Fed's $1.25 trillion program to purchase agency mortgage-backed securities.

It is worth emphasizing that our noise measure comes from the US Treasury bond market — the one with the highest credit and liquidity quality and is the number one safe haven during crises, and yet it was able to reflect liquidity crises of varying origins and magnitudes. In this respect, what is captured in our noise measure is not the liquidity concerns specific to the Treasury market, but liquidity conditions across the overall financial market.

3.2 Noise and the On-the-Run Premium

One popular measure of liquidity with respect to the Treasury market is the on-the-run and off-the-run premium: the just issued (on-the-run) Treasury bond enjoys a price premium, therefore lower yield, compared to old bonds with similar maturities. Since our noise measure is a daily aggregate of cross-sectional pricing errors, the on-the-run premium is in fact a component of our measure. Calculating the correlation between daily changes of our noise measure and daily changes of the on-the-run premium, we find that the correlation is 10.74% and 4.34%, respectively, for the five- and ten-year on-the-run premiums. Repeating the same calculation at a month frequency, the correlation increases to 25.39% and 36.26%, respectively. Overall, we see a positive relationship between our noise measure and the on-the-run premium, which is relatively small at the daily frequency but grows larger at the monthly frequency.

Moreover, while the noise measure is on average smaller than the on-the-run premium, it tends to spike up much more significantly during crises. For example, on October 19, 1987, the noise measure was at 4.52 standard deviations away from its sample average, while the five-year on-the-run premium was at 2 standard deviations away from its sample average and the ten-year on-the-run premium was at 0.93 standard deviation below its sample average. On September 21, 2001, the first bond trading day after the terrorist attack, our noise measure was at 4.20 standard deviations away while the five- and ten-year on-the-run premiums were at 1.15 and 2.63 standard deviations away, respectively. On October 15, 2008, when the crisis after Lehman's default deepened, our noise measure was at 4.83 standard deviations away while the ten-year premium was 4.00 standard deviations away and the five-year premium was 0.37 standard deviation below its sample average.

This comparison between our noise measure and the on-the-run premium is instructive as it accentuates the important fact that the information captured by our noise measure is a collective information over the entire yield curve. The fact that our noise measure spikes up during liquidity crises much more prominently than the on-the-run premiums implies that there is commonality in the pricing errors across the entire yield curve. And the heightened commonality during crises is reflected in noisy and mis-aligned yield curves, which are captured by our noise measure. This is how noise could become informative. By contrast, a couple of isolated points on the yield curve as captured by the on-the-run premiums will not be as informative.

3.3 Noise and Other Measures of Liquidity

To further investigate the connection between our noise measure and other measures of market liquidity, we report in Table 2 results of OLS regression of monthly changes in our noise measure on several important market variables. The regressions are done first in univariate form, and then pooled together in the last column to compare their relative contribution. The pairwise correlations of monthly changes of these variables are reported in Table 3.

Treasury Market: Level, Slope and Volatility

First, we examine the connection between our noise measure and the Treasury market variables including the level, slope, and volatility of interest rates. Since our noise measure is computed as pricing errors in yields, it is important to make sure that the time-variation in the noise measure is not caused by time-variations in interest rates. Results are summarized in the top left panel of Table 2. Regressing monthly changes of our noise measure on monthly changes in three-month TBill rates, we find a negative and statistically significant relation. This implies increasing illiquidity during decreasing short rates, which is consistent with the fact that liquidity in the overall market typically worsens during episodes of flight to quality and decreasing interest rates. The explanatory power of the short rate for our noise measure, however, is rather limited. As shown in Table 2, the R-squared of the regression is only 4.62%. Another important factor in the Treasury market is the slope of the term structure, which is labeled as Term in Table 2. We find a positive relation between our noise measure and the term spread, which is consistent with the observation that the slope of the term structure steepens in the depth of economic recessions. This connection, however, is not very strong and the R-squared of the regression is only 7.46%. We also regress changes in our noise measure on monthly Treasury bond returns, and do not find a statistically significant relation.

Overall, although our noise measure is constructed using pricing data in the Treasury market, its connection to the time-variation in bond yields is not very strong. In fact, this is a good indication for the "purity" of our noise measure. Otherwise, high correlations with such term-structure pricing variables might be an indication that our curve fitting is not flexible enough to capture the shapes of the term structure.

Similarly, given that our noise measure captures the cross-sectional dispersion in Treasury bonds, it is natural to ask whether or not it is purely driven by the volatility of this market. To check this, we regress monthly changes of our noise measure on monthly changes in bond volatility, which is calculated as the annualized bond return volatility using a rolling window of 21 business days. We find that a positive relation between our noise measure and bond volatility, but it is not statistically significant. In particular, bond volatility can only explain 1.46% of the monthly variation in our noise measure. In other words, the information contained

Table 2: **Monthly Changes of Noise Measure Regressed on Other Market Variables (1987-2009)**

Treasury: Level, Slope and Volatility	(1)	(2)	(3)	(4)
ΔTB3M	-0.913			-0.377
	[-2.73]			[-1.52]
ΔTerm		0.014		0.011
		[2.04]		[1.42]
ΔBondV			0.086	0.042
			[1.51]	[0.61]
Adj R2 (%)	4.62	7.46	1.46	8.00
# month	275	275	275	275

On-the-Run Premiums and RefCorp	(1)	(2)	(3)	(4)
ΔOn5Y	0.092			0.045
	[3.34]			[1.24]
ΔOn10Y		0.152		0.124
		[2.29]		[1.52]
ΔRefCorp			0.031	0.032
			[2.43]	[2.83]
Adj R2 (%)	6.10	12.83	4.29	15.60
# month	275	275	224	224

Stock Market: Ret, VIX, and Liquidity	(1)	(2)	(3)	(4)
StockRet	-0.078			-0.028
	[-2.39]			[-1.28]
ΔVIX		0.082		0.056
		[2.69]		[2.29]
ΔPSLiq			-4.02	-2.20
			[-3.58]	[-2.88]
Adj R2 (%)	10.57	13.63	5.67	15.88
# month	275	273	275	273

Repo, LIBOR and Default	(1)	(2)	(3)	(4)
ΔRepo	-0.460			-0.299
	[-2.90]			[-2.43]
ΔLIBOR		0.007		0.004
		[3.39]		[1.37]
ΔDefault			0.036	0.039
			[2.15]	[2.21]
Adj R2 (%)	2.73	3.02	16.84	24.34
# month	223	275	275	223

Reported are OLS regression coefficients with Newey-West t-stat's in squared brackets. On5Y and On10Y are the on-the-run premiums for 5-year and 10-year bonds. TB3M is the 3-month Tbill rate. Repo is the overnight general collateral repo rates. LIBOR is the spread of 3-month LIBOR over 3-month Tbill. Default is the yield spread between Baa and Aaa bond indices. VIX is the volatility index from CBOE. RefCorp is the average spread between Treasury and Refcorp zero-coupon bonds. Δ PSLiq is the innovations in the liquidity factor by Pastor and Stambaugh. StockRet is the monthly return on the CRSP value-weighted index. BondV is the annualized return volatility of monthly bond returns calculated from 5-year Treasury yields using a rolling window of 21 business days. Term is spread of 10- over 1-year Treasury yields.

Table 3: **Pairwise Correlations (in %)**

		2	3	4	5	6	7	8	9	10	11	12	13
1	ΔNoise	-22	25	36	13	28	-18	22	18	41	37	-25	-33
2	ΔTB3M		-15	-16	-25	-53	39	-12	-38	-15	-27	27	18
3	ΔOn5Y			33	28	23	-6	-6	12	-12	28	-22	-21
4	ΔOn10Y				-1	2	-3	1	16	15	24	-13	-10
5	ΔBondV					21	-25	21	24	-7	33	-30	-13
6	ΔTerm						-34	4	12	-2	13	-17	-12
7	ΔRepo							-21	-19	-10	-2	10	-1
8	ΔRefCorp								17	23	6	-24	-11
9	ΔLIBOR									7	26	-17	-23
10	ΔDefault										21	-2	-28
11	ΔVIX											-29	-67
12	ΔPSLiq												32
13	StockRet												

Pairwise correlations are computed using monthly changes from 1987 through 2009 and reported in percentage. See Table 2 for definitions of variables.

in our noise measure is driven just by the volatility in the Treasury bond market. In fact, a large component of our noise measure is unrelated to the volatility of the Treasury market.

Treasury Market: Liquidity and Flight-to-Quality Premiums

One important measure of liquidity premium for the Treasury market is proposed by Longstaff (2004), who compares Treasury bonds with bonds issued by RefCorp, a US government agency guaranteed by the Treasury. He finds a large liquidity premium in Treasury bonds, and documents the presence of a flight-to-liquidity premium in Treasury bonds. This measure examines the symptom of illiquidity from a perspective that is very different from ours, but is indeed very much related. It is therefore interesting to see how this measure connects with ours. For this, we construct RefCorp spread by calculating the average spread between RefCorp and Treasury zero-coupon bonds with maturities ranging from 3 months to 30 years. As shown in the top right panel of Table 2, regressing monthly changes of our noise measure on monthly changes in RefCorp spread, we find a positive and statistically significant connection. In other words, when the flight-to-liquidity premium in the Treasury market increases, the illiquidity of the overall market as captured by our noise measure also increases. But this positive relation is not very strong given that RefCorp spread can explain only 4.29% of the monthly changes in our noise measure. In other words, while it is possible that the flight-to-liquidity premium in the Treasury market contributes to our noise measure, it is only a small fraction of the information captured by the noise measure.

The variable with a relatively high explanatory power for our noise measure is the 10-year on-the-run premium, which can explain 12.83% of the monthly variation in our noise measure. The 5-year on-the-run premium is also positively related to our noise measure. This not surprising since the on-the-run premium is a component of our noise measure. In fact, the significance of this result is that a large component of our noise measure is not captured by the on-the-run premium and this uncaptured component is in fact very informative (see the previous subsection for a more extensive discussion). Adding on-the-run premiums together with RefCorp spread in a multivariate regression, we see that together, they explain changes in the noise measure with an adjusted R-squared of 15.60%.

Stock Market: Returns, VIX, and Liquidity

One liquidity factor that has been shown to be important in the US equity market is the one constructed by Pastor and Stambaugh (2003). This liquidity measure is an aggregate of individual-stock liquidity measures proposed by Campbell, Grossman, and Wang (1993), using the idea that order flow induces greater return reversals when liquidity is lower. Given the systematic nature of this liquidity measure and given the importance of the US equity market, it is worth examining how this measure relates to our noise measure, which is designed to capture to overall market liquidity condition including the stock market. As shown in the bottom left panel of Table 2, this measure of liquidity has a statistically significant relation with our noise measure. The coefficient is negative, implying that a negative shock to the systematic liquidity factor in the equity market is likely to be accompanied by an increase in our noise measure and worsening liquidity of the overall market. The R-squared of the regression is 5.67%, implying that the liquidity effect captured by the noise measure cannot be explained by the liquidity of the equity market only. Nevertheless, given that these two measures are constructed using data from two distinctively different markets, this level of comovement indicates the presence and the importance of a systematic liquidity factor.

CBOE VIX index, constructed from S&P 500 index options, is often referred to as the "fear gauge." We find a positive and statistically significant relation between the VIX index and our noise measure. The R-squared of this regression is 13.63%. In other words, an increase in the "fear gauge" is likely to be accompanied by an increase in our noise measure. Given its significant relation with our noise measure, it is important for us to distinguish the relative contribution between the two. We will visit this issue in Section 4, using hedge fund returns as testing portfolios to evaluate their relative importance.

We also find a negative and significant relation between the US stock market returns and our noise measure. In other words, our noise measure spikes up during worsening stock market conditions. The R-squared of this regression is 10.57%, Adding the Pastor-Stambaugh stock market liquidity measure together with the VIX index and stock market returns in a multivariate regression, we find that they can explain the changes in the noise measure with an adjusted R-squared of 15.88%.

Credit Market: Default and LIBOR Spreads

The bottom right panel of Table 2 examines the connection between our noise measure and default spreads, measured as the difference in yield between Baa and Aaa rated bonds. We find a positive and significant relation, and the R-squared of the regression is 16.84%. This result is consistent with the possibility that liquidity risk is an important component of the observed default spreads. We perform a bi-variate OLS regression by including both the default spread and the VIX index — two variables with the highest explanatory power for our noise measure and, interestingly, are often used as proxies for liquidity. We find the slope coefficients for both variables to be positive and statistically significant, and the adjusted R-squared is 23.88%. In other words, these popular proxies of liquidity are both related to our noise measure, but can explain only a very limited amount of the time variation of our noise measure.[12]

Table 2 also reports the connection with overnight general collateral Repo rates and LIBOR spreads. Overall, the results are in the expected direction. For example, our noise measure increases with increasing LIBOR spreads, while our noise measure is negatively related with the repo rates. Including the Repo rates, LIBOR spreads, and default spreads in a multivariate regression, we find that the repo rates and default spreads remain significant and the adjusted R-squared of the regression is 24.34%.

4 Cross-Sectional Pricing Tests

Our noise measure is designed to capture the lack of liquidity in the overall market. The empirical evidences provided so far indicate that this noise measure indeed does a good job in capturing the aggregate liquidity risk. In particular, it is able to capture the drastic variations in liquidity during market crises of various origins and magnitudes. Given the systematic nature of this risk, we now investigate its asset-pricing implications, particularly its impact on asset returns. In order to better identify this impact, we need to consider returns that are potentially sensitive to the market-wide liquidity shocks. For this purpose, we employ two sets of returns for our tests. The first set consists of returns on hedge funds, whose trading activities cover a broad spectrum of asset classes and whose capital adequacy is a

[12] Indeed, as will be shown later in Section 4, our noise measure has important pricing implications and commands a significant risk premium. Moreover, this result remains robust using a component of our noise measure that is orthogonal to VIX and default spreads. By contrast, we do not find strong pricing implications for VIX or default spreads.

good representation of the amount of arbitrage capital available in the market. The second set of returns are those from currency carry trades, which are also known to be connected with the overall arbitrage capital in the market. We conduct separate empirical tests on these two sets of returns.

4.1 Hedge Fund Returns as Test Portfolios

Hedge Fund Data

We obtain hedge fund returns, assets under management (AUM), and other fund characteristics from the Lipper TASS database. The TASS database divides funds into two categories: "Live" and "Graveyard" funds. The "Live" hedge funds are active ones as of the latest update of the TASS database, in our case March 2010. Hedge funds are listed as "Graveyard" funds when they stop reporting information to the database. Fund managers may decide not to reporting their performance for a number of different reasons such as liquidation, merger or closed to new investment. Although TASS has been collecting data since late 1970s, the Graveyard database was created much later in 1994. We thus choose our sample period from 1994 through 2009 to mitigate the impact of survivorship bias.

We only include funds that report returns net of various fees in US dollars on a monthly basis, which covers a majority of the funds in TASS. We also require that each fund has at least \$10 million assets under management, and at least 24 months of return history during our sample period. This ensures that we have a sample of hedge funds of reasonable size and each fund has a long enough time-series for meaningful regression results.[13] The details of our hedge fund sample are summarized in Table 4.

Portfolio Formation by Noise Betas

We follow the standard procedure of Fama and MacBeth (1973) to perform cross-sectional tests on the noise measure. Let R^i_t be the month-t excess return of hedge fund i, and we estimate its exposure to the noise measure by

$$R^i_t = \beta_0 + \beta^N_i \, \Delta\text{Noise}_t + \beta^M_i \, R^M_t + \epsilon^i_t \,, \tag{3}$$

where ΔNoise is the monthly change of our noise measure, R^M is the excess return of CRSP value weighted portfolio, and β^N_i and β^M_i are estimates of fund i's exposures to the noise measure and the stock market risk.

[13] As mentioned in Cao, Chen, Liang, and Lo (2010), smaller funds with AUM less than \$10 million are of less concern from an institutional investor's perspective, and they have less impact on the market as well. But we do experiment with different size criteria such as \$5 million, \$50 million, and \$100 million. Our main result regarding the market price of the liquidity risk factor remains robust.

Table 4: **TASS Hedge Fund Data Summary Statistics**

	Total	Graveyard	ret (%)		stdret(%)		AUM($M)		iAUM($M)		reporting (mn)		age (mn)		auto corr	
	(#)	(#)	mean	med	mean	med	mean	med	mean	med	mean	med	mean	med	mean	med
Panel A: All Hedge Funds																
1994-1999	1698	1201	1.82	1.22	4.49	3.49	60.45	20.64	11.71	2.98	127.81	130.00	29.73	20.75	0.11	0.13
2000-2006	4292	2536	0.89	0.76	3.00	2.04	123.62	45.59	17.52	5.20	88.72	74.00	42.44	28.00	0.12	0.13
2007-2009	3453	1513	0.21	0.20	4.00	3.05	240.16	72.01	20.65	6.21	89.85	74.00	75.16	59.00	0.19	0.20
ALL	4642	2702	0.73	0.65	3.75	2.78	151.40	53.93	18.89	5.50	85.33	70.00	44.09	35.00	0.20	0.20
Panel B: Hedge Funds by Style																
Long/Short Equity	1219	751	0.94	0.86	4.76	3.93	110.14	46.06	13.27	4.52	86.51	72.00	44.90	35.50	0.14	0.14
Global Macro	185	113	0.84	0.71	4.28	3.16	246.34	50.19	30.25	5.06	75.09	63.00	39.54	31.50	0.07	0.07
Fund of Funds	1318	702	0.47	0.44	2.73	2.07	160.10	56.29	25.57	8.92	87.77	74.00	45.10	37.00	0.26	0.26
Fixed Income Arb	152	120	0.55	0.57	2.45	2.04	202.04	87.28	21.32	9.97	82.46	72.00	41.41	37.25	0.22	0.20
Managed Futures	239	104	0.90	0.85	5.20	4.40	164.84	45.65	10.64	2.88	101.89	76.00	55.01	39.00	0.03	0.03
Event Driven	404	277	0.84	0.75	2.63	2.15	195.76	71.35	14.87	3.05	92.12	76.00	48.35	38.00	0.26	0.25
Equity Neutral	208	150	0.54	0.52	2.63	2.13	88.32	39.13	14.15	5.67	72.32	60.50	36.40	30.00	0.11	0.12
Emerging Markets	367	154	1.01	0.92	6.30	5.62	121.93	47.46	20.57	8.00	77.84	64.00	39.22	31.50	0.24	0.24
Convertible Arb	137	102	0.56	0.58	2.65	1.84	142.94	69.41	14.82	4.90	91.47	78.00	47.72	38.50	0.38	0.43
Others	413	229	0.70	0.67	3.25	2.59	193.82	67.04	25.41	7.42	74.64	56.00	38.01	28.00	0.26	0.24

Hedge fund returns ("ret") are monthly net of fees, and "stdret" is the standard deviation of the monthly returns. "AUM" is the asset under management in millions of dollars, and "iAUM" is the initial AUM of the hedge fund. The total number of months a hedge reports returns in the database is recorded by "reporting." For each fund at each month t, we also calculate its "age_t" by counting the number of months from its inception to month t. Also reported are the first-order auto-correlations (auto corr) of hedge funds' monthly returns.

Our specification in Equation (3) implicitly assumes that, other than the liquidity risk factor captured by our noise measure, the stock market risk is the main risk factor for hedge funds. Given the varying styles of hedge funds in our sample, it is perhaps a strong assumption. It is nevertheless a reasonable starting point as long as our noise measure is not a proxy for some well known risk factors other than liquidity risk. Given our earlier analysis in Section 3.3, this does not seem to be the case. We also experimented by adding other well known risk factors such as term spread in the Treasury market and default spread in the corporate bond market, and our results are robust. For this reason and to keep the specification simple, we will perform the cross-sectional test using our simple specification.

For each month t and for each hedge fund i, we first use its previous 24 month returns to estimate the pre-ranking β_i^N using Equation (3). We then sort the month-t cross-section of hedge funds by their pre-ranking beta, β_i^N, into 10 portfolios. The post-ranking beta's of the 10 portfolios are estimated by

$$R_t^p = \beta_0 + \beta_p^N \, \Delta\text{Noise}_t + \beta_p^M \, R_t^M + \epsilon_t^p \,, \quad p = 1, \ldots, 10 \,. \tag{4}$$

where R_t^p is the equal-weighted return for portfolio p in month t and this regression is done over the entire sample period.

Table 5 reports the expected returns of the 10 noise-beta sorted portfolios and their post-ranking beta's. A negative noise beta implies that when the noise measure increases during crises, the hedge fund returns decreases. In other words, a hedge fund with negative noise beta is the one with high exposure to liquidity risk. Among the 10 noise-beta sorted portfolios, portfolio 1 therefore has a much higher exposure to liquidity risk than portfolio 10, and we can loosely characterize the hedge funds in portfolio 1 as more aggressive and those in portfolio 10 as more conservative in taking liquidity risk.

More important for our cross-sectional pricing test, Table 5 also shows that hedge funds in portfolio 1 differ from those in portfolio 10 in average performance. Specifically, the aggressive funds outperform the conservative ones by a large margin. The average excess return for portfolio 1 is 1.08% per month compared with 0.33% for portfolio 10, implying a superior monthly performance of 0.75% with a t-stat of 3.00. In fact, moving from portfolio 10 to 1, there is a general pattern of increasing average returns, indicating improved performances with increasing exposures to the liquidity risk. One direct implication of this pattern of risk and return is that the liquidity risk as captured by our noise measure is priced, and this pricing implication will be formally tested later in this section as we perform cross-sectional tests *a la* Fama and MacBeth (1973).

To further understand these 10 noise-beta sorted portfolios, we report in Table 6 the characteristics of hedge funds within each portfolio. We see that the hedge funds in portfolios 1 and 10 are similar in their characteristics. Also reported in Table 6 is the relative allocation

Table 5: **Noise-Beta Sorted Portfolios, Returns and Beta's**

			Pre Formation			Post Formation					
	exret	ret	ΔNoise	Mkt	Adj-R2	ΔNoise	Mkt	Adj-R2	ΔNoise	Mkt	Adj-R2
rank	(%)	(%)	β^N	β^M	(%)	β^N	β^M	(%)	$\beta^N + \text{lag}$	$\beta^M + \text{lag}$	(%)
1	1.08	1.36	-2.60	0.49	32.4	-0.50	0.42	43.7	-0.97	0.48	49.1
	[4.03]	[5.06]	[-30.07]	[23.02]		[-3.87]	[6.56]		[-7.35]	[8.22]	
2	0.62	0.90	-1.09	0.35	31.3	-0.31	0.30	52.7	-0.50	0.36	57.9
	[3.56]	[5.15]	[-25.41]	[26.84]		[-3.73]	[8.53]		[-4.82]	[9.76]	
3	0.50	0.78	-0.63	0.28	29.7	-0.26	0.27	52.9	-0.45	0.32	58.5
	[3.24]	[5.03]	[-21.07]	[26.96]		[-3.01]	[8.12]		[-3.47]	[9.24]	
4	0.46	0.74	-0.39	0.23	28.0	-0.23	0.21	50.8	-0.35	0.26	56.4
	[3.67]	[5.83]	[-16.28]	[24.29]		[-3.00]	[7.65]		[-2.87]	[8.16]	
5	0.41	0.68	-0.23	0.22	27.7	-0.21	0.20	48.8	-0.31	0.25	54.5
	[3.44]	[5.73]	[-10.70]	[27.25]		[-2.93]	[8.15]		[-2.67]	[8.44]	
6	0.39	0.67	-0.08	0.21	27.2	-0.19	0.19	52.6	-0.25	0.24	57.2
	[3.55]	[6.01]	[-3.69]	[29.78]		[-3.14]	[8.39]		[-2.81]	[8.76]	
7	0.35	0.63	0.09	0.22	26.9	-0.17	0.21	51.6	-0.17	0.25	54.1
	[2.99]	[5.31]	[3.96]	[32.14]		[-2.70]	[7.38]		[-1.65]	[7.1]	
8	0.41	0.69	0.33	0.26	26.7	-0.12	0.24	53.3	-0.05	0.29	54.5
	[3.14]	[5.23]	[11.17]	[37.42]		[-1.84]	[7.32]		[-0.47]	[6.93]	
9	0.44	0.72	0.75	0.34	27.2	-0.00	0.32	57.5	0.20	0.38	59.7
	[2.84]	[4.60]	[17.09]	[34.23]		[-0.04]	[9.74]		[1.48]	[9.72]	
10	0.33	0.61	2.20	0.49	29.2	0.44	0.41	42.5	0.87	0.49	44.8
	[1.48]	[2.73]	[24.18]	[24.44]		[2.27]	[6.63]		[3.16]	[7.31]	

Hedge funds are sorted by their noise-beta's into 10 portfolios. Reported are the pre-ranking beta's as estimated in Equation (3) and the post-ranking portfolio beta's as estimated in Equation (4). Taking into account of persistence in hedge fund returns, the sum of contemporaneous and lagged beta's as estimated in Equation (5) are also reported. The portfolio returns are monthly and equal-weighted, with "ret" as returns and "exret" as returns in excess of riskfree rate.

Table 6: **Noise-Beta Sorted Portfolios, Characteristics**

Portfolio Rank	1	2	3	4	5	6	7	8	9	10
Panel A: Characteristics										
AUM ($M)	149	171	167	191	187	183	184	166	162	131
iAUM ($M)	15.17	14.64	13.49	14.22	14.30	14.49	13.50	12.68	13.82	12.12
reporting (mn)	130	131	132	134	135	134	135	133	132	131
age (mn)	72.7	73.3	73.1	73.3	73.6	72.8	73.8	73.9	74.7	73.8
stdret (%)	3.48	2.25	2.00	1.64	1.55	1.44	1.54	1.71	2.04	2.89
auto corr	0.15	0.19	0.22	0.25	0.26	0.25	0.23	0.20	0.16	0.12
Panel B: Allocation within Hedge Fund Style (%)										
Long/Short Equity	11.44	10.55	8.40	6.32	5.95	6.53	7.87	10.68	14.50	17.76
Global Macro	16.01	12.15	8.60	7.04	5.36	6.20	6.73	10.76	11.79	15.35
Fund of Funds	4.56	8.42	12.24	14.58	14.64	14.12	12.58	9.84	6.11	2.92
Fixed Income Arb	11.56	7.82	9.19	11.75	11.98	11.01	11.05	10.63	8.49	6.52
Managed Futures	18.42	11.38	6.60	4.54	3.95	4.60	5.94	9.35	13.43	21.80
Event Driven	5.29	9.92	11.72	11.93	12.89	12.77	12.90	10.25	8.07	4.26
Equity Neutral	4.42	8.27	9.53	8.25	8.57	9.04	12.33	14.69	15.26	9.63
Emerging Markets	28.38	15.11	8.49	5.83	4.90	4.90	5.35	6.54	8.35	12.15
Convertible Arb	8.68	8.10	10.69	14.07	14.97	14.89	12.22	9.24	4.60	2.55
Others	8.18	9.98	10.59	11.22	11.33	11.44	10.48	9.76	10.19	6.83

The 10 portfolios are ranked, from low to high, by their noise beta's. See Table 4 for variable definitions.

of hedge funds within each style category to the 10 portfolios. One interesting observation is that on average 28% of the hedge funds specializing in Emerging Markets show up in the aggressive portfolio. Other than that, the distribution does not seem to be very informative, although it does point to the fact that it is important to do the cross-sectional test at the hedge fund level. In particular, test the liquidity risk at the style indices level will not be a successful endeavor.

In Figure 4, we compare the liquidity risk of hedge funds in portfolio 1 versus portfolio 10 in a different way. For each year t, we report the one-year "death" rate in the sample calculating how many hedge funds among the live sample in year $t-1$ end up in graveyard by the end of year t. And we report the same exercise within each noise-beta sorted portfolio. From Figure 4, we can see a distinctive increase in death rate in 2008. This is hardly surprising given the severity of the financial crisis in 2008. What's interesting is that the death rate is much higher (close to 43%) for hedge funds in the aggressive category (portfolio 1), while hedge funds in the conservative category have similar death rate of 24.5% as the sample average of 26%.

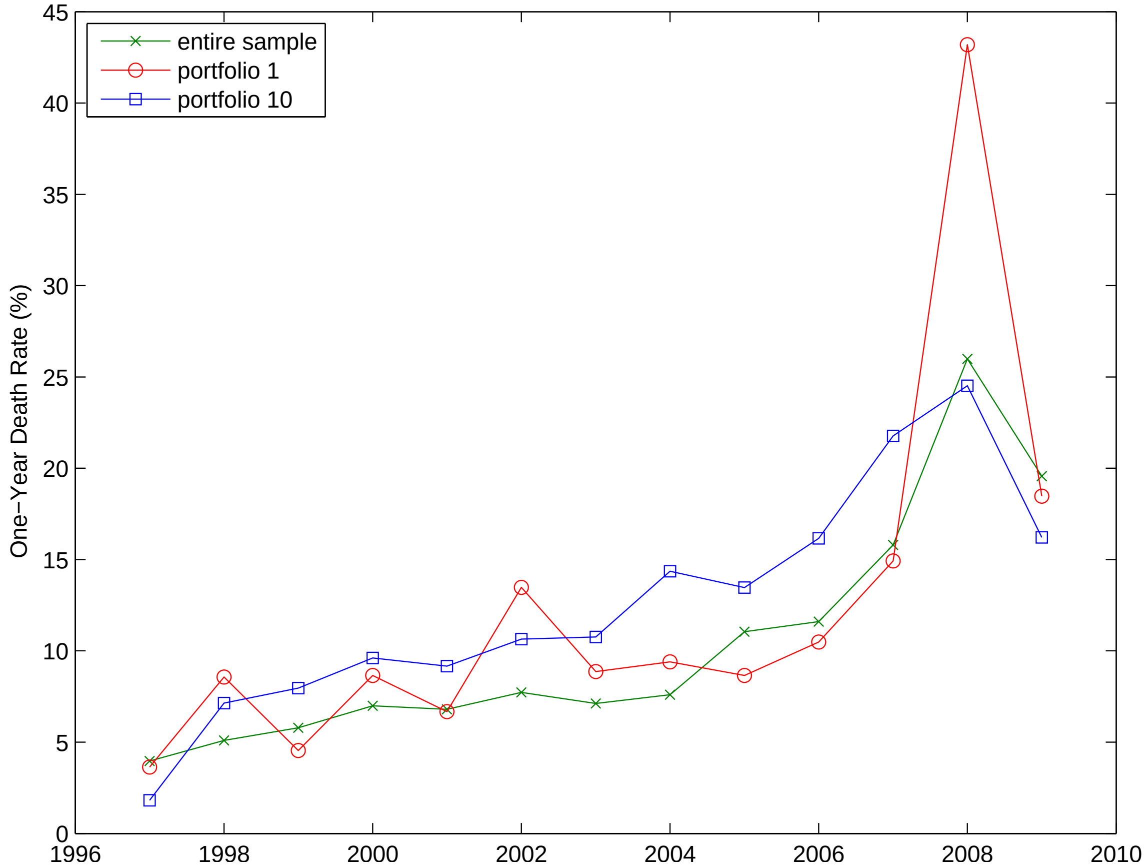

Figure 4: The year-t "death rate" of hedge funds in the top- and bottom-ranked noise-beta sorted portfolios.

Post-Ranking Noise Beta

As shown in Table 5, our post-ranking noise beta's can in fact be estimated with satisfactory precisions and there is a monotonic relation between the portfolio rankings and their post-ranking noise beta's. This is a very encouraging sign for our empirical test, given the importance of having a good measure of risk exposures.[14]

We can in fact further improve the precision of our risk exposure measures. One issue that is unique to the hedge fund data is that their returns are known to be highly serially

[14]Post-ranking beta's for risk factors other than the market portfolio are always difficult to estimate and it is usually difficult to construct portfolios with a strong enough spread in terms of their exposures to the particular risk factor of interest. For example, using cross-sectional stock returns to test the the VIX index, Ang, Hodrick, Xing, and Zhang (2006) have issues in constructing portfolios with strong spread with respect to their post-ranking beta's. Facing a similar issue, Pastor and Stambaugh (2003) use predicted beta's instead. Specifically, they take advantage of stock characteristics that are more stable and postulate that their liquidity beta is an affine function of stock characteristics.

correlated. As shown in Getmansky, Lo, and Makarov (2004), one likely explanation is their illiquidity and the possibility of smoothed returns at the fund level. In this respect, a better way to capture a hedge fund's risk exposure is to regress its returns on the contemporaneous as well as the lagged factor. Using this intuition, we estimate the post-ranking beta by

$$R_t^p = \beta_0 + \beta_p^N \, \Delta\text{Noise}_t + \text{lag}\beta_p^N \, \Delta\text{Noise}_{t-1} + \beta_p^M \, R_t^M + \text{lag}\beta_p^M \, R_{t-1}^M \, . \tag{5}$$

Given the high serial correlation in hedge fund returns, a more accurate estimate of a portfolio's exposure to liquidity risk is $\beta_p^N + \text{lag}\beta_p^N$. As reported in Table 5, there is much improvement in terms of the spread of post-ranking noise beta as well as the statistical significance of the post-ranking noise beta. It is also interesting to note that although the market exposure $\beta_p^M + \text{lag}\beta_p^M$ also has some improvement, the improvement in noise beta is much more significant.

Estimating Liquidity Risk Premiums using Fama-MacBeth Regressions

Following Fama and MacBeth (1973), we perform the cross-sectional regression for each month t:

$$R_t^i = \gamma_{0t} + \gamma_t^N \, \beta_i^N + \gamma_t^M \, \beta_i^M + c_t^{\text{age}} \, \text{age}_t^i + c_t^{\text{AUM}} \, \text{AUM}_t^i + \epsilon_t^i \, . \tag{6}$$

where R_t^i is the month-t return of hedge fund i, β_i^N and β_i^M are the noise and market beta's of hedge fund i. Following Fama and French (1992), we assign the post-ranking portfolio beta's, which are estimated as in Equation (4), to each hedge fund in the portfolio.[15] The fund's age and log of asset under management (AUM) are used as controls. The factor premiums are estimated as the time-series average of γ_t^N and γ_t^M.

Table 7 reports the factor risk premiums for our noise measure as well as the market portfolio. The Fama-MacBeth t-stats are reported in squared brackets. We see that the liquidity risk as captured by our noise measure is indeed priced. The coefficient is negative and statistically significant. Given that our noise measure moves up when the market-wide liquidity deteriorates, this means that the liquidity risk premium is positive and significant. Relating back to the earlier discussions on the relative performance of portfolios sorted by noise beta (β^N), this result provides a formal test in support of the intuition developed there. Specifically, the liquidity risk premium contributes to the higher expected returns provided by hedge funds with high negative noise beta and thus high exposures to liquidity risk.

We also test our noise measure using the sum of contemporaneous and lagged beta $\beta_p^N + \text{lag}\beta_p^N$ to better capture hedge funds exposure to the liquidity risk. The result is also reported in Table7. The statistical significant of the risk premium for our noise measure remains at the

[15]In addition to the 10 noise-beta sorted portfolio used here, we also perform our test using the 5x5 portfolios double-sorted by noise-beta and market-beta. Our results on the liquidity risk premium remains robust.

same magnitude, although the slope coefficient is smaller due to the increased spread in noise beta's. We also use a factor mimicking portfolio and performance our cross-sectional pricing test using beta exposures to the factor mimicking portfolio, and find a similar result. Again, the magnitude of the risk premium decreases because of improved beta estimates and spread.

To take into account of the fact that bid/ask spreads in the Treasury market also have some time-variation, we scale our noise measure by the cross-sectional average of bid minus ask yield for all of the bonds used in the construction of the noise measure. We find that this scaled version is also priced with an estimated risk premium similar to the base case in magnitude and statistical significance.

Table 7: **Estimating Liquidity Risk Premiums using Hedge Fund Returns**

Factor	Intercept	Liquidity	Market	Age	AUM
Panel A: Noise as Proxy of Liquidity					
Noise	1.87	-0.77	1.82	0.00	-0.11
	[4.53]	[-2.45]	[2.62]	[0.05]	[-4.34]
Noise (beta+lag beta)	1.97	-0.38	1.39	0.00	-0.11
	[4.66]	[-2.42]	[2.32]	[0.13]	[-4.38]
Factor Mimicking Portfolio	2.24	-0.45	0.06	0.00	-0.13
	[4.82]	[-1.97]	[0.08]	[0.17]	[-4.86]
Noise/BASpreads	1.92	-0.55	1.43	0.00	-0.11
	[4.51]	[-2.07]	[2.26]	[0.07]	[-4.25]
Noise-VIX-Default	1.77	-1.42	1.87	-0.00	-0.11
	[4.17]	[-2.49]	[2.66]	[-0.03]	[-4.27]
Panel B: Other Proxies of Liquidity					
On5Y	2.26	-2.21	1.00	0.00	-0.11
	[5.27]	[-0.77]	[1.76]	[0.1]	[-4.49]
On10Y	2.24	0.38	2.07	-0.00	-0.11
	[5.09]	[0.59]	[2.25]	[-0.08]	[-4.31]
RefCorp	2.14	-4.60	0.75	0.00	-0.12
	[4.8]	[-1.26]	[1.26]	[0.36]	[-4.32]
PSLiq	2.20	0.93	-0.02	-0.00	-0.11
	[5.11]	[0.88]	[-0.18]	[-0.57]	[-4.36]
VIX	2.17	-0.25	1.04	-0.00	-0.11
	[4.86]	[-0.07]	[1.42]	[-0.04]	[-4.23]
Default	2.31	10.06	1.17	-0.00	-0.11
	[4.88]	[1.54]	[1.80]	[-0.22]	[-4.37]

Each proxy of liquidity is tested together with the equity market portfolio in a two-factor model using hedge fund returns, with age and size (AUM) as additional controls. The Fama-MacBeth t-stat's are reported in squared brackets. Panel A focuses on the noise measure with the base case as described in Equations (4) and (6) and four additional cases. Panel B considers other proxies of liquidity. See Table 2 for variable definitions.

Next, we use the hedge fund returns to perform cross-sectional tests on the other liquidity measures including the on-the-run premiums for 5- and 10-year Treasury bonds, the RefCorp spread, the Pastor-Stambaugh stock market liquidity risk factor, the VIX index, and default spreads. Again, we perform the test by first sorting hedge funds by their exposures to the risk factor into 10 portfolios, and then perform the Fama-MacBeth cross-sectional test. As shown in Table 7, Panel B, we find no evidence that these risk factors help to explain hedge fund returns.

In Section 3, we find CBOE VIX and default spread to have relatively high correlation with our noise measure. Although they have little pricing power for hedge fund returns, we further evaluate the relative importance between the information that is captured in our noise measure versus those in VIX and default spread. We first regress the monthly changes of our noise measure on the monthly changes of VIX and default spreads, and then perform the pricing test using the residual. The result is reported in Table 7, the last row of Panel A, under the case "Noise-VIX-Default." We see that after taking out the information contained in VIX and default spreads, our noise measure maintains its significance and magnitude in pricing the cross-sectional hedge fund returns. Thus, its importance as a liquidity risk factor in pricing hedge funds is independent of the "usual suspects," including VIX, default risk and other existing liquidity measures, which on their own have no pricing power.

4.2 Carry Trade Returns as Test Portfolios

Building Currency Portfolios

We obtain end-of-month spot and forward exchange rates with one-month maturity from Barclays and Reuters via Datastream. The sample period spans from January 1987 to December 2009. Following Lustig, Roussanov, and Verdelhan (2011), we consider 37 currencies from both developed and emerging countries. Currencies are included in the sample only when both spot and forward rates are available. Our sample starts with 19 currencies, and reaches a maximum of 34 currencies. Since the launch of the Euro in January 1999, our sample covers 26 currencies only. For both forward and spot rates, we use mid bid-ask quotes in units of foreign currency per US dollar.

For the rest of this section, we denote the log of the one-month forward rate as f, and the log of the spot rate as s. At the end of each month t, we allocate all currencies into six carry trade portfolios based on their forward discount $f_t - s_t$. Because the covered interest parity holds closely at monthly frequency, our portfolios sorted on forward discounts $f_t - s_t$ are equivalent to portfolios ranked by interest rate differentials $i_t^* - i_t$, where i_t^* and i_t are the foreign and domestic one-month risk-free interest rates, respectively. Portfolio 6 contains the currencies with the smallest forward discounts (or lowest interest rates), and portfolio 1 contains the currencies with the biggest forward discounts (or highest interest rates). From the perspective of a US investor, the log excess return rx of holding a foreign currency in the forward market and then selling it in the spot market one month later at $t+1$ is:

$$rx_{t+1} = f_t - s_{t+1} = i_t^* - i_t + s_t - s_{t+1} = i_t^* - i_t - \triangle s_{t+1}.$$

The log currency excess return for a carry trade portfolio is then calculated as the equally weighted average of the log excess returns of all currencies in the portfolio. We re-balance carry trade portfolios at the end of every month in our sample period.

Cross-sectional Pricing Test

We use the six carry trade portfolios described in the previous section to perform the Fama and MacBeth (1973) cross-sectional pricing test. We first estimate the factor risk exposure by

$$R_t^i = \beta_0 + \beta_i^N \, \Delta\text{Noise}_t + \beta_i^M \, R_t^M + \epsilon_t^i \, , \tag{7}$$

where R_t^i is the month-t excess return of carry portfolio i and R_t^M is the month-t excess return of the aggregate stock market.

For the six carry portfolios, the top panel of Table 8 reports their mean excess returns and their respective exposures, β^N and β^M, to the risk factors implicit in the noise measure and the stock market portfolio. Moving from portfolio 6 to portfolio 1, the mean excess return increases monotonically from negative 20 bps to positive 81 bps per month. Indeed, the difference in their performance is the main driver behind currency carry trades. In particular, currencies in portfolio 6 are those with the lowest interest rate and function as funding currencies, while currencies in portfolio 1 have the highest interest rate and are on the asset side of the carry trade. It is therefore interesting to see that the asset currencies in carry portfolio 1 have a negative beta on our noise measure, implying a worsening portfolio performance during liquidity crises when our noise measure goes up. By contrast, carry portfolio 6 have a small and statistically insignificant beta on our noise measure, implying very low exposure to liquidity risk.

This specific pattern of differing expected returns and liquidity risk exposures β^N across those six carry portfolios implies a potential source of risk premium for the liquidity factor. In particular, the relative high performance of carry portfolio 1 over portfolio 6 could be contributed by the fact that carry portfolio 1 takes on more liquidity risk. Given that carry portfolio 1 also has more market exposure β^M, however, we need to test this idea more formally.

For this, we run monthly cross-sectional regressions:

$$R_t^i = \gamma_{0t} + \gamma_t^N \, \beta_i^N + \gamma_t^M \, \beta_i^M + \epsilon_t^i \, , \tag{8}$$

Table 8: **Liquidity Premiums from Currency Carry Returns**

Panel A: Returns and Beta's

Rank	exret (%)	β^N	β^M	Adj-R2 (%)
1	0.81	-0.75	0.11	12.8
	[4.47]	[-3.83]	[1.84]	
2	0.34	-0.32	0.09	7.23
	[2.41]	[-2.68]	[2.21]	
3	0.31	-0.41	0.04	5.67
	[2.33]	[-2.06]	[0.82]	
4	0.16	-0.17	0.04	1.77
	[1.25]	[-1.06]	[0.83]	
5	-0.06	-0.17	0.03	1.42
	[-0.51]	[-1.09]	[0.68]	
6	-0.20	-0.07	-0.03	0.38
	[-1.5]	[-0.60]	[-0.68]	

Panel B: Estimated Risk Premiums

	constant	Noise	Market	month
estimate	-0.002	-0.99	2.48	276
t-stat	[-1.57]	[-3.15]	[2.01]	

Portfolios are formed by sorting currencies by their forward discount. Currencies in portfolio 6 have the smallest forward discount and the lowest interest rate and are often used as the funding currency in a carry trade, while currencies in portfolio 1 are often used as the asset currency. Returns are monthly in excess of the risk-free rate.

where the time-series average of γ^N is an estimate of the liquidity risk premium, and that for γ^M is an estimate of the stock market risk premium. The results are reported in the bottom panel of Table 8. Our result shows that the market price of "liquidity" risk γ^N is -0.99 with a t-stat of -3.15, while the stock market risk premium γ^M is estimated to be 2.48 with a t-stat of 2.01. Compared with the risk premiums estimated using hedge fund returns reported in Table 7, the results are similar in magnitude and statistical significance.

5 Conclusions

In this paper, we use price deviations from asset fundamentals as a measure of market illiquidity. Instead of focusing the liquidity condition of a specific market, we are interested in the liquidity conditions of the overall market. For this purpose, we consider the US Treasury market, which is arguably the most important and one of the most liquid markets. Presumably, signs of illiquidity in this market reflects a general shortage of arbitrage capital and tightening of liquidity in the overall market, whatever its origins and causes. In particular, we use the average "pricing errors" in US Treasuries as a measure of illiquidity of the aggregate market. Indeed, we found that this measure spikes up during various market crises, ranging from the 1987 stock market crash, the near collapse of LTCM, 9/11, GM credit crisis, to the fall of Bear Stearns and Lehman Brothers. This clearly suggests that this illiquidity measure captures the liquidity condition of the overall market.

The drastic variation of our illiquidity measure over time, especially during crisis, suggests that it represents substantial market-wide liquidity risk. We further explore the pricing implications of this liquidity risk factor by examine its connection with the returns on assets/trading strategies that are generally thought to be sensitive to market liquidity conditions. Two sets of such returns are considered: returns from hedge funds and currency carry trades. We found that the market-wide liquidity risk, as measured by the variation in the price noise of Treasuries, can help to explain both the cross-sectional variation in hedge fund returns and currency carry trade strategies, while various liquidity-related risk factors obtained from other markets such as equity, corporate bonds and equity options show no explanatory power.

References

Acharya, V. V. and L. H. Pedersen (2005). Asset Pricing with Liquidity Risk. *Journal of Financial Economics 77*(2), 375–410.

Ang, A., R. Hodrick, Y. Xing, and X. Zhang (2006). The Cross-Section of Volatility and Expected Returns. *Journal of Finance 61*, 259–299.

Backus, D., S. Foresi, and C. Telmer (2001). Affine Term Structure Models and the Forward Premium Anomaly. *Journal of Finance 56*, 279–304.

Backus, D., A. Gregory, and C. Telmer (1993). Accounting for Forward Rates in Markets for Foreign Currency. *Journal of Finance 48*, 1887–1908.

Bao, J., J. Pan, and J. Wang (2010). The Illiquidity of Corporate Bonds. *Journal of Finance, forthcoming*.

Billio, M., M. Getmansky, and L. Pelizzon (2010). Crises and Hedge Fund Risk. Working Paper, University of Massachusetts, Amherst.

Brunnermeier, M., S. Nagel, and L. H. Pedersen (2008). Carry Trades and Currency Crashes. *NBER Macroeconomics Annual 23*, 313–348.

Brunnermeier, M. K. and L. H. Pedersen (2009). Market Liquidity and Funding Liquidity. *Review of Financial Studies 22*, 2201–2238.

Burnside, C., M. Eichenbaum, I. Kleshchelski, and S. Rebelo (2010). Do Peso Problems Explain the Returns to the Carry Trade? Working Paper, Northwestern University.

Campbell, J., S. Grossman, and J. Wang (1993). Trading Volume and Serial Correlation in Stock Returns. *Quarterly Journal of Economics*, 905–939.

Cao, C., Y. Chen, B. Liang, and A. Lo (2010). Can Hedge Funds Time Market Liquidity? Working Paper, MIT Sloan School of Management.

Coval, J. and E. Stafford (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics 86*, 479–512.

Duffie, D. (2010). Asset Price Dynamics with Slow-Moving Capital. *Journal of Finance 65*, 1238–1268.

Fama, E. (1984). Forward and Spot Exchange Rates. *Journal of Monetary Economics 14*, 319–338.

Fama, E. and K. French (1992). The Cross-Section of Expected Stock Returns. *Journal of Finance 47*, 427–465.

Fama, E. and J. MacBeth (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy 81*, 607–36.

Fisher, M., D. Nychka, and D. Zervos (1995). Fitting the term structure of interest rates with smoothing splines. *Finance and Economics Discussion Series, Board of Governors of the Federal Reserve System 1*.

Getmansky, M., A. Lo, and I. Makarov (2004). An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns. *Journal of Financial Economics 74*, 529–609.

Gromb, D. and D. Vayanos (2002). Equilibrium and Welfare in Markets with Financially Constrained Arbitrageurs. *Journal of Financial Economics 66*, 361–407.

Jurek, J. (2009). Crash-Neutral Currency Carry Trades. Working Paper, Princeton University.

Leland, H. and M. Rubinstein (1988). Comments on the Market Crash: Six Months After. *Journal of Economic Perspectives 2*(3), 45–50.

Longstaff, F. (2004). The Flight-to-Liquidity Premium in U.S. Treasury Bond Prices. *Journal of Business 77*, 511–525.

Lustig, H., N. Roussanov, and A. Verdelhan (2011). Common Risk Factors in Currency Markets. *Review of Financial Studies, forthcoming*.

McCulloch, J. H. (1975). The Tax-Adjusted Yield Curve. *Journal of Finance 30*(3), 811–830.

Merton, R. (1987). A Simple Model of Capital Market Equilibrium with Incomplete Information. *Journal of Finance 42*(3), 483–510.

Mitchell, M., L. H. Pedersen, and T. Pulvino (2007). Slow Moving Capital. *The American Economic Review, P&P 97*, 215–220.

Mitchell, M. and T. Pulvino (2011). Arbitrage Crashes and the Speed of Capital. *Journal of Financial Economics, forthcoming*.

Nagel, S. (2011). Evaporating Liquidity. Working Paper, Stanford University.

Nelson, C. R. and A. F. Siegel (1987, October). Parsimonious Modeling of Yield Curves. *Journal of Business 60*(4), 473–89.

Pastor, L. and R. Stambaugh (2003). Liquidity Risk and Expected Stock Returns. *Journal of Political Economy 111*, 642–685.

Sadka, R. (2010). Liquidity Risk and the Cross-Section of Hedge-Fund Returns. *Journal of Financial Economics 98*, 54–71.

Shleifer, A. and R. Vishny (1997). The Limits of Arbitrage. *Journal of Finance 52*, 35–55.

Svensson, L. (1994). Estimating and Interpreting Forward Interest Rates: Sweden 1992 - 1994. Working Paper 4871, National Bureau of Economic Research.

Vayanos, D. and J.-L. Vila (2009). A Preferred-Habitat Model of the Term Structure of Interest Rates. Working Paper, London School of Economics.

Verdelhan, A. (2010). A Habit-Based Explanation of the Exchange Rate Risk Premium. *Journal of Finance 65*, 123–145.