Noise as Information for Illiquidity

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Abstract

We propose a broad measure of liquidity for the overall financial market by exploiting its connection with the amount of arbitrage capital in the market and the potential impact on price deviations in US Treasurys. When arbitrage capital is abundant, we expect the arbitrage forces to smooth out the Treasury yield curve and keep the dispersion low. During market crises, the shortage of arbitrage capital leaves the yields to move more freely relative to the curve, resulting in more "noise." As such, noise in the Treasury market can be informative and we expect this information about liquidity to reflect the broad market conditions because of 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 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.

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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 capital diminishes. The illiquidity in the overall market spikes 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. During liquidity crises, however, the lack of arbitrage capital forces the prop 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 U.S. Treasury market is one of the safest markets in the world, essentially free of credit risk. More importantly, the fundamental values of Treasuries are determined by a small number of 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

[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) and Brunnermeier and Pedersen (2008).

for our 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. This measure of noise is "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 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 14 basis points; the aftermath of the LTCM crisis, when the noise peaked at 7 basis points; the first trading day after the 9/11 terrorist attack, when the noise was at 14.5; the sale of Bear Stearns to JPMorgan, when the noise was close to 8 basis points; and the aftermath of Lehman default, when the noise was above 10 basis points for a sustained period of time. Given its sample standard deviation of 1.6 basis points, these are 4 to 9 standard deviations moves.

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 have a significant relation with our noise measure. This includes the RefCorp spread used as a flight-to-liquidity premium by Longstaff (2004), the systematic liquidity factor in the US equity market by Pastor and Stambaugh (2003), and the CBOE VIX index. 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.[2] 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 that are potentially sensitive to market-wide illiquidity 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.[3] In particular, this liquidity risk premium is a main contributor to the superior performance by hedge funds with very high exposures to liquidity risk. Moreover, such highly exposed hedge funds have a higher death rate in 2008 than those hedge funds with minimal exposures to liquidity risk. By contrast, we do not find such pricing implications using other measures of liquidity such as RefCorp spread, on-the-run premiums, Pastor-Stambaugh equity liquidity risk factor, and VIX.

Next, we construct six currency carry portfolios by sorting on the forward discount. The main driver of the currency carry trade is the average superior performance of currencies with high interest rate, and a typical trade is to be long on such currencies and fund the trading with currencies with low interest rate. We find that the carry portfolio that contains

[2]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.

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

the "target" or "asset" currencies have 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 have a positive beta on our noise measure, implying relative good performance during crises. 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 significant risk premium for our noise measure using currency carry portfolios.

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), Leland and Rubinstein (1988), Shleifer and Vishny (1997), Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2008)). Recent empirical work, such as Coval and Stafford (2007) on equity fire sales by mutual funds and Mitchell, Pedersen, and Pulvino (2007) and Getmansky, Lo, and Makarov (2004) on convertible bond arbitrage by hedge funds, provides additional empirical evidence on this link. 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. Our liquidity measure is able to capture episodes of liquidity crises of varying origins and is not limited to a specific market. As such, the lack and abundance of arbitrage capital we would like to attribute our measure to are 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 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 whole market. By using the liquidity condition of the US Treasury market, one of the most liquid markets in the world, we are capturing the liquidity risk of the overall market. In addition, we 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.

Our results also complement studies specifically 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.[4] Since Fama (1984), the source of currency carry trade returns has been an

[4]Our paper is also related to the growing literature in hedge fund studies that connects hedge fund activities

object of investigation by many studies, ranging 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 analysis shows that exposures to market-wide liquidity crises and the associated liquidity risk premium might be an important component of the risk and return tradeoff associated with this trading strategy.

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, in particular, how it varies through various crises and correlates 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. 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 or yields are deleted from the sample. We also 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 bonds with maturity between 1 and 10 years. For bonds with maturity long than 10 years, we have fewer observations, the fitted yield curve becomes less reliable and their prices are less subject to arbitrage forces.

Table 1 provides details of our bond sample. On average, we have 145 bonds and bills every day to fit the yield curve and 92 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

to market liquidity and market crises, such as Cao, Chen, Liang, and Lo (2010) and Billio, Getmansky, and Pelizzon (2010).

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	157	102	9.38	8.39	3.84	3.74	2.58	3.03	103.09	8.05
1991-1995	169	112	7.44	11.18	2.54	3.64	2.64	3.09	104.13	5.83
1996-2000	155	95	6.33	13.94	2.05	3.42	2.80	2.97	101.43	5.72
2001-2005	107	64	4.57	20.99	1.25	3.75	2.74	3.34	102.86	3.51
2006-2009	149	98	3.96	22.46	1.33	3.76	2.29	3.41	103.39	2.79
All	145	92	6.33	15.32	2.17	3.65	2.65	3.16	102.93	5.19
						median				
1987-1990			8.96	7.80	3.56	3.14	2.00	2.72	101.70	8.05
1991-1995			7.47	10.20	2.11	3.21	2.09	2.87	103.88	5.85
1996-2000			6.21	13.41	1.79	2.73	2.32	2.51	100.94	5.72
2001-2005			4.57	21.12	1.00	3.07	2.00	2.87	102.07	3.44
2006-2009			4.18	20.86	1.09	3.16	1.79	2.96	103.67	2.70
All			6.27	14.71	1.87	3.05	2.06	2.78	102.36	5.16
						standard deviation				
1987-1990			2.14	3.27	1.67	2.29	2.17	1.55	6.08	0.24
1991-1995			1.51	5.09	1.35	2.13	2.20	1.55	4.24	0.53
1996-2000			0.98	7.32	1.08	2.23	2.25	1.69	2.86	0.14
2001-2005			1.29	8.23	0.75	2.45	2.53	1.96	3.77	0.52
2006-2009			0.93	6.87	0.80	2.33	2.02	1.92	3.00	0.49
All			1.37	6.31	1.12	2.29	2.27	1.74	3.98	0.39

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.

reported are the key characteristics of the bonds used in constructing the noise measure. For example, the average maturity of the bonds is 3.65 years and the average age of the bonds is 2.65 years. Over time, both variables remain stable, alleviating the concern that 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 all 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.[5] 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 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

[5] 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.

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,

$$s\left(m, b\right) = \frac{1}{m} \int_0^m f\left(m, b\right)\, dm\,.$$

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:

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

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 next 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:

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

It should be mentioned that for curving fitting, we use qualified bonds and bills with maturity between 1 month and 10 years, while in constructing the noise measure, we use only bonds with maturity between one and ten years. While the short-maturity bonds and bills are informative for the purpose of fitting the short end of the yield curve, we feel that their information content might be 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. This aspect of noise is not what we are interested in. More over, the short end is unlikely to be the object of arbitrage capital, which is the main motivation of our noise measure. It should also be mentioned that we do not use bonds with maturity longer than 10 years in our construction. The longer maturity bonds might be useful to further capture the effect of fixed-income relative value trades. But the supply of these bonds is not as stable, and might introduce unnecessary time-series noise to our measure.[6]

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. 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 3.32 basis points with a standard deviation of 1.65 basis points, and it is highly persistent, with a daily autocorrelation of 94.82%. 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

[6]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.

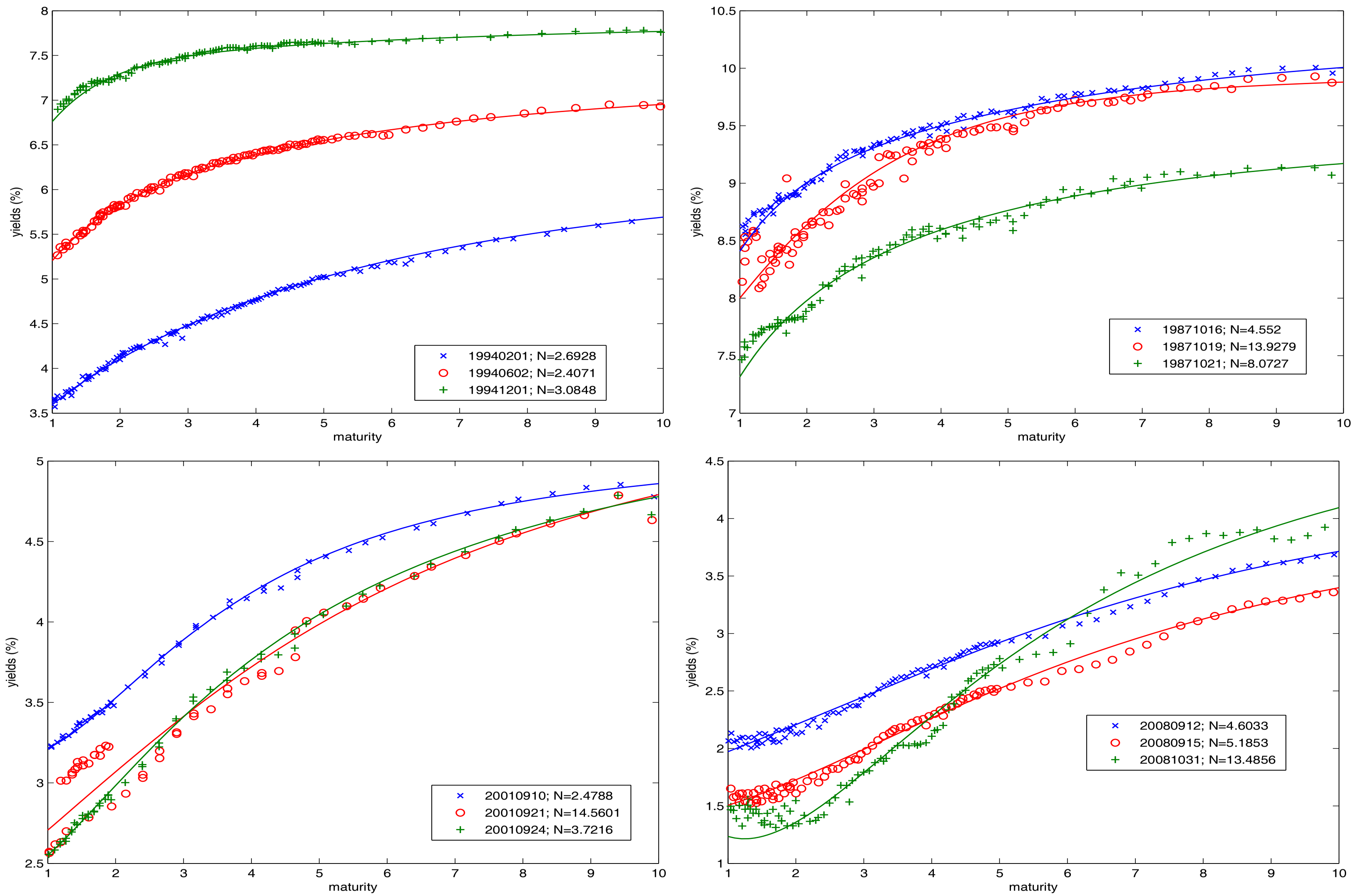

Figure 1: Examples of par-coupon yield curves and the market-observed bond yields, marked by “x”, “o”, or “+”. The top left panel plots three random days in 1994. The other three panels focus on the days surrounding three events: the 1987 stock market crash, the September 11, 2001 terrorist attack, and 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.

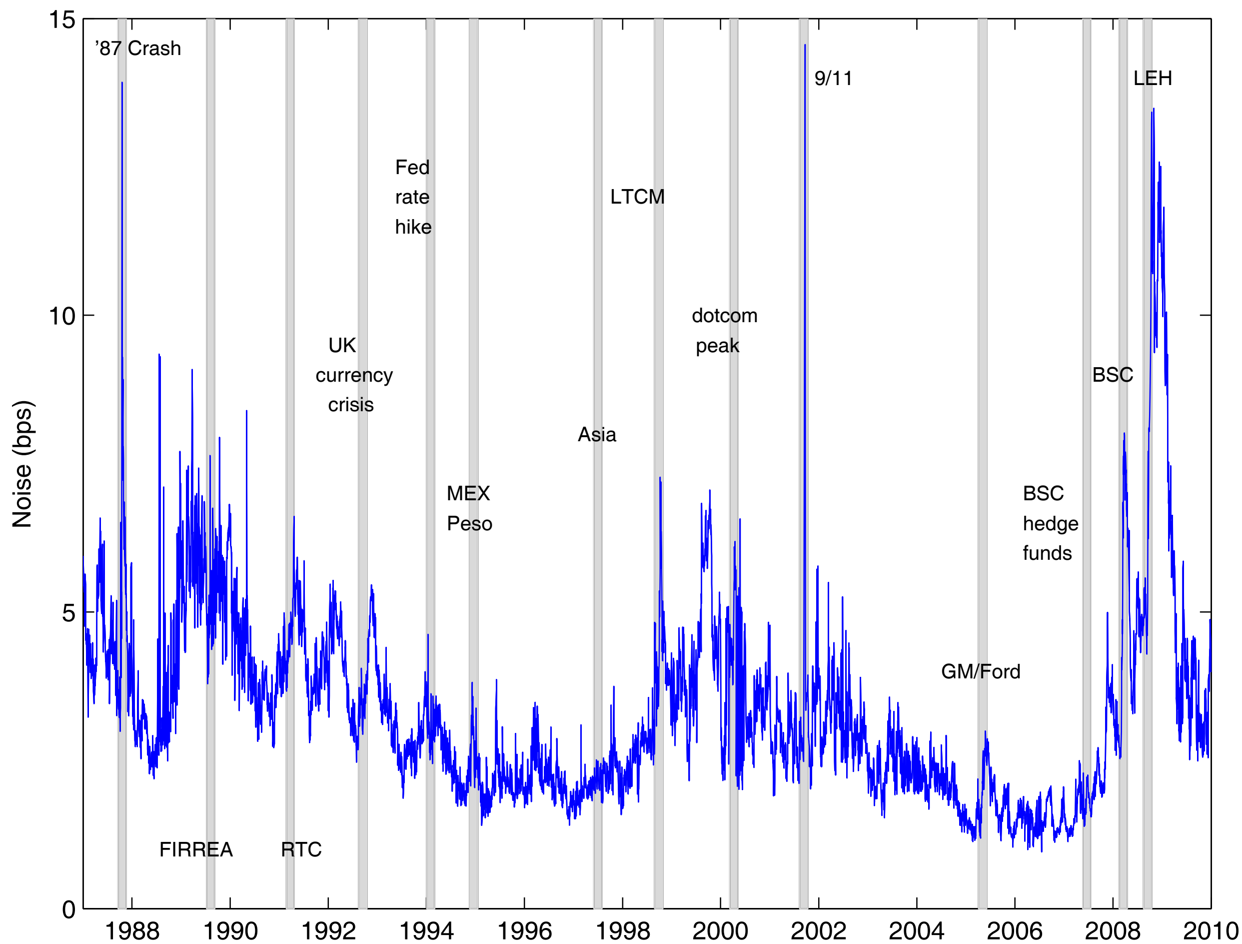

Figure 2: Daily time-series of the noise measure (in basis points).

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 14 basis points; the aftermath of the LTCM crisis, when the noise peaked at 7 basis points; the first trading day after 9/11 terrorist attack, when the noise was at 14.5; the sale of Bear Stearns to JPMorgan, when the noise was close to 8 basis points; and the aftermath of Lehman default, when the noise was above 10 basis points for a sustained period of time. Given its sample standard deviation of 1.65 basis points, these are 4 to 9 standard deviations 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 and 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 5.18, which was about one standard deviation above the historical mean. Compared with the Friday before when the noise measure stood at 4.60, 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 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 were comparable to the 87 crash and the 9/11 attack. The first one was in mid-October when it peaked at 13.42 on October 15, one day after Treasury and Fed announced to inject $250 billion of capital into large US Banks via the Capital Purchase Program (CPP), and additional details on the Commercial Paper Funding Facility (CPFF). The second one was at the end of October when the noise measure peaked at 13.49 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.

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 numerous episodes of "flight to quality," and yet it was able to capture liquidity crises of varying origins and magnitudes. In this respect, what captured in our noise measure is not credit or liquidity concerns that are specific only to the Treasury market. Instead, it is a reflection of the overall market condition, and the absence of arbitrage capital coupled with flight to quality could be one channel through which "noise" can become "information." Given how well our noise measure picks up the past events, the evidence seems to be in support of such a hypothesis.

3.2 Noise and 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 the rest of the yield curve. Since our noise measure is a daily aggregate of cross-sectional pricing errors, this 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 3.95% and 8.85%, respectively, for the five- and ten-year on-the-run premiums. Repeating the same calculation at a month frequency, the correlation increases to 27.73% and 37.49%, respectively. Overall, we see a positive relationship between our noise measure and the on-the-run premium, which is not significant at the daily frequency but becomes more significant 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 6.45 standard deviations away from its sample average, while the

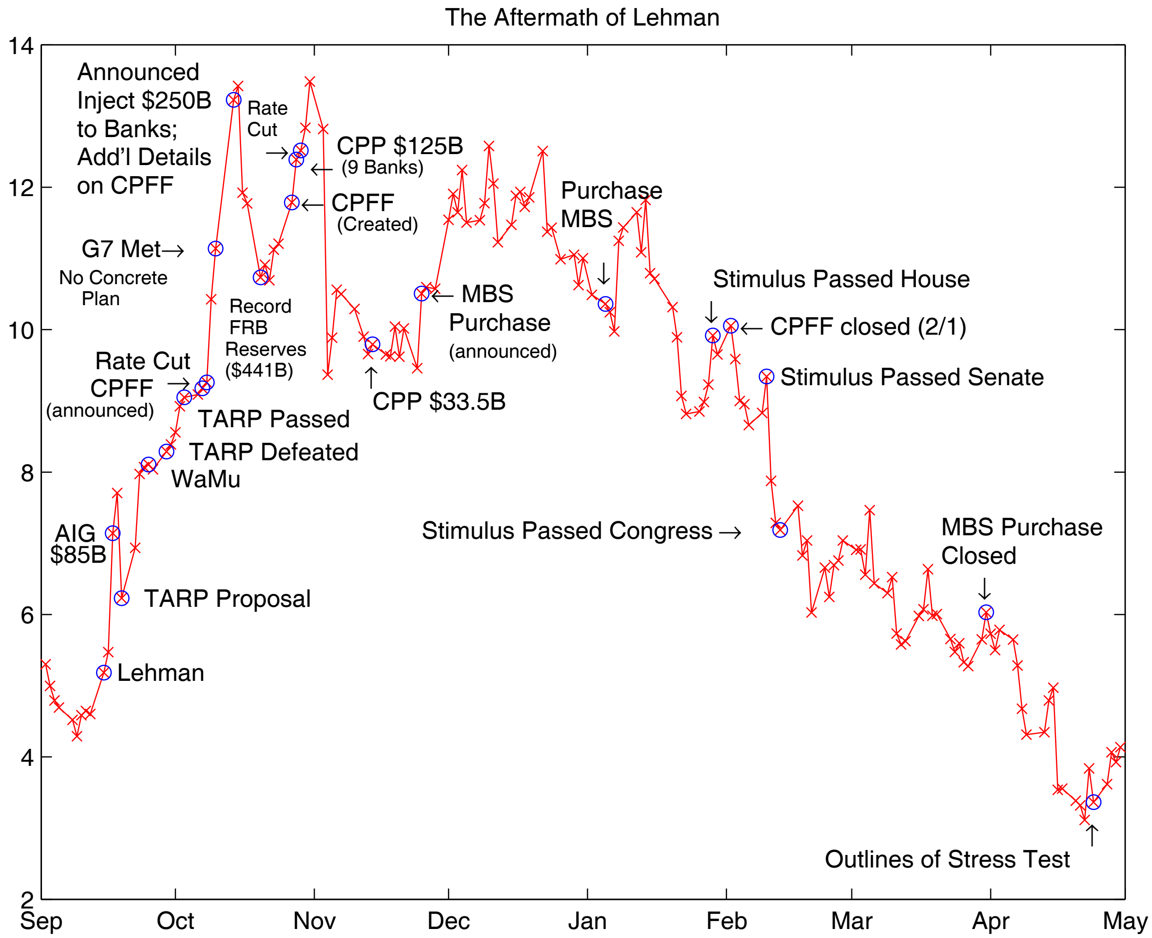

Figure 3: Daily time-series of the noise measure in late 2008 and early 2009. TARP: Troubled Asset Relief Program; CPP: Capital Purchase Program; CPFF: Commercial Paper Funding Facility; and the MBS Program is Fed's \$1.25 trillion program to purchase agency mortgage-backed securities.

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 6.83 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 was at one of its worst moments, our noise measure was at 6.14 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.

First, we examine the connection of our noise measure with Treasury market variables including the level, slope, and volatility of interest rates. Since our noise measure is computed as pricing errors in yield, 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 3.15%. Another important factor in the Treasury market is the slope of the term structure, which is labeled as Term in Table 2. We do not find a strong connection between our noise measure and the term spread. 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 since term structure pricing is not something we would like to capture in our noise measure. By contrast, a high correlation with the term-structure pricing variables might be an indication that our curve fitting is not flexible enough to capture the shapes of the term structure.

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

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

Treasury: Level, Slope and Volatility	(1)	(2)	(3)	(4)
ΔTB3M	-0.678			-0.323
	[-2.21]			[-1.25]
ΔTerm		0.008		0.005
		[1.79]		[0.92]
ΔBondV			0.122	0.097
			[2.42]	[2.01]
Adj R2 (%)	3.15	3.13	4.31	6.28
# month	275	275	275	275

On-the-Run Premiums and RefCorp	(1)	(2)	(3)	(4)
ΔOn5Y	0.089			0.040
	[2.35]			[1.14]
ΔOn10Y		0.139		0.101
		[3.83]		[2.61]
ΔRefCorp			0.045	0.045
			[4.81]	[5.15]
Adj R2 (%)	7.35	13.74	13.56	24.89
# month	275	275	224	224

Stock Market: Ret, VIX, and Liquidity	(1)	(2)	(3)	(4)
StockRet	-0.048			0.001
	[-2.59]			[0.04]
ΔVIX		0.066		0.055
		[3.89]		[3.12]
ΔPSLiq			-4.99	-3.85
			[-4.28]	[-3.86]
Adj R2 (%)	5.05	11.15	11.83	18.74
# month	275	273	263	261

Repo, LIBOR and Default	(1)	(2)	(3)	(4)
ΔRepo	-0.461			-0.346
	[-2.43]			[-2.33]
ΔLIBOR		0.008		0.005
		[4.41]		[3.20]
ΔDefault			0.018	0.019
			[2.25]	[2.24]
Adj R2 (%)	4.19	4.70	5.33	13.06
# 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**

		2	3	4	5	6	7	8	9	10	11	12	13
1	ΔNoise	-19	28	37	22	19	-21	37	22	24	34	-35	-23
2	ΔTB3M	-15	-16	-25	-53	39	-12	-38	-15	-27	28	18	
3	ΔOn5Y	33	28	23	-6	-6	12	-12	28	-19	-21		
4	ΔOn10Y	-1	2	-3	1	16	15	24	-12	-10			
5	ΔBondV	21	-25	21	24	-7	33	-32	-13				
6	ΔTerm	-34	4	12	-2	13	-15	-12					
7	ΔRepo	-21	-19	-10	-2	11	-1						
8	ΔRefCorp	17	23	6	-32	-11							
9	ΔLIBOR	7	26	-19	-23								
10	ΔDefault	21	-3	-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.

volatility, which is calculated as the annualized bond return volatility using a rolling window of 21 business days. We find that indeed there is a statistically significant relation between our noise measure and bond volatility, but bond volatility can only explain 4.31% of the monthly variation in our noise measure. In other words, the information contained in our noise measure is not driven just by the volatility in the Treasury bond market. By contrast, a large component of our noise measure is unrelated to the volatility of the Treasury market.

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. In fact, the RefCorp spread can explain 13.56% of the monthly changes in our noise measure, which makes it one of the most important variables considered in Table 2 in explaining the time-series variation of our noise measure.

The variable with the highest explanatory power for our noise measure is the 10-year on-the-run premium, which can explain 13.74% 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 24.89%.

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, 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 interesting to see 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 pretty strong connection with our noise measure. The coefficient is negative and significant, 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 11.83%, making it one of the most important variables in explaining the time-variation of our noise measure. Given that these two measures are constructed using data from two distinctively different markets, this level of comovement reflects the presence and the importance of a systematic liquidity factor.

Similarly, if we use the CBOE VIX index, which is constructed from S&P 500 index options and is often referred to as the "fear gauge," we find a positive and statistically significant relation, and the R-squared of this regression 11.15%. In other words, an increase in the "fear gauge" is likely to be accompanied by an increase in our noise measure. 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 18.74%.

The bottom right panel of Table 2 also examines the connection between our noise measure and default spread, measured as the difference in yield between Baa and Aaa rated bonds. We find a positive and significant relation, although the R-squared of the regression is only 5.33%. This result is consistent with the possibility that default risk and liquidity risk are correlated. 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.

Finally, we add all of the variables considered in Table 2 in a multi-variate regression.[7] Overall, these variables can explain the monthly variation of our noise measure with an adjusted R-squared of 35.38%, and the 10-year on-the-run premium, the RefCorp spread, the default spread, the VIX index, and the Pastor-Stambaugh equity liquidity factor remain significant.

Overall, it is encouraging that factors known to be related to liquidity have a significant relation with our noise measure. In the next Section, we bring our hypothesis on the information content of our noise measure to the next step by testing its pricing implications directly using, among other, hedge fund returns. And we will be sure to perform the same test on other liquidity measures such as the on-the-run premium, the RefCorp spread, the Pastor-Stambaugh liquidity factor, and the VIX index.

4 Cross-Sectional Pricing Tests

Since our noise measure reflects the lack of liquidity in the overall market, its variation, which is drastic during market crises of various origins, captures the aggregate liquidity risk. Given the systematic nature of this risk, we now investigate its asset-pricing implications, in particular, 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 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 returns.

4.1 Hedge Fund Returns as Test Portfolios

Hedge Fund Data

We obtain hedge fund returns, assets under management (AUM), and other fund-specific 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

[7] Given the level of comovement among these variables, collinearity might be a concern. This concern, however, does not turn out to be too pressing since the pairwise correlations of these variables as reported in Table 3 are not very high.

"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.[8] 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_t^i be the month-t excess return of hedge fund i, and we estimate its Beta exposure to the noise measure by

$$R_t^i = \beta_0 + \beta_i^N \, \Delta\text{Noise}_t + \beta_i^M \, R_t^M + \epsilon_t^i \,, \tag{3}$$

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

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 our cross-sectional test using this model.

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

[8] 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.

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.

Figure 4 shows an interesting pattern in how hedge funds in portfolio 1 might be different from those in portfolio 10. 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 40%) for hedge funds in the aggressive category (portfolio 1), while hedge funds in the conservative category have similar death rate of 27% as the sample average of 26%.

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 monthly return for portfolio 1 is 1.45% compared with 0.49% for portfolio 10, implying a superior monthly performance of 0.96% with a t-stat of 3.45. In fact, moving from portfolio 10 to 1, there is a general pattern of increasing average returns, implying improved performance with increasing exposure 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 of hedge funds within each style category to the 10 portfolios. One interesting observation is that on average 25% of the hedge funds specializing in Emerging Markets show up in the

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

			Pre Formation						Post Formation		
rank	exret (%)	ret (%)	ΔNoise β^N	Mkt β^M	Adj-R2 (%)	ΔNoise β^N	Mkt β^M	Adj-R2 (%)	ΔNoise $\beta^N + \text{lag}\beta^N$	Mkt $\beta^M + \text{lag}\beta^M$	Adj-R2 (%)
1	1.17	1.45	-2.55	0.50	31.8	-0.40	0.45	41.1	-1.41	0.50	48.4
	[4.29]	[5.30]	[-27.19]	[28.07]		[-1.32]	[5.97]		[-4.36]	[8.29]	
2	0.69	0.96	-0.99	0.33	30.7	-0.31	0.32	49.7	-0.87	0.38	57.9
	[3.83]	[5.35]	[-23.84]	[26.77]		[-1.62]	[6.82]		[-3.55]	[9.07]	
3	0.55	0.83	-0.55	0.26	29.3	-0.22	0.25	48.6	-0.65	0.30	56.6
	[3.90]	[5.83]	[-20.55]	[25.93]		[-1.59]	[7.30]		[-4.14]	[9.31]	
4	0.45	0.73	-0.32	0.22	27.6	-0.22	0.19	44.5	-0.58	0.24	53.5
	[3.88]	[6.19]	[-15.58]	[24.00]		[-1.69]	[6.61]		[-3.82]	[9.43]	
5	0.41	0.69	-0.16	0.20	27.1	-0.26	0.20	50.1	-0.57	0.24	57.4
	[3.59]	[5.97]	[-8.97]	[25.12]		[-2.45]	[7.75]		[-4.38]	[9.39]	
6	0.38	0.65	-0.02	0.21	26.9	-0.25	0.19	51.3	-0.50	0.22	56.2
	[3.52]	[6.03]	[-0.91]	[29.19]		[-2.38]	[7.93]		[-3.57]	[10.05]	
7	0.38	0.65	0.16	0.24	27.7	-0.23	0.23	51.0	-0.39	0.26	53.8
	[2.98]	[5.13]	[6.87]	[33.91]		[-2.06]	[7.48]		[-2.91]	[7.52]	
8	0.37	0.65	0.42	0.27	27.7	-0.10	0.27	54.7	-0.16	0.30	55.7
	[2.70]	[4.71]	[12.87]	[30.35]		[-0.87]	[8.49]		[-1.00]	[8.13]	
9	0.38	0.66	0.84	0.36	28.7	0.02	0.32	54.6	0.03	0.35	55.1
	[2.40]	[4.12]	[17.03]	[27.49]		[0.12]	[8.39]		[0.12]	[9.06]	
10	0.22	0.49	2.29	0.50	30.3	0.18	0.42	39.8	0.54	0.48	40.3
	[0.88]	[2.01]	[21.78]	[21.11]		[0.64]	[5.68]		[1.02]	[6.45]	

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.

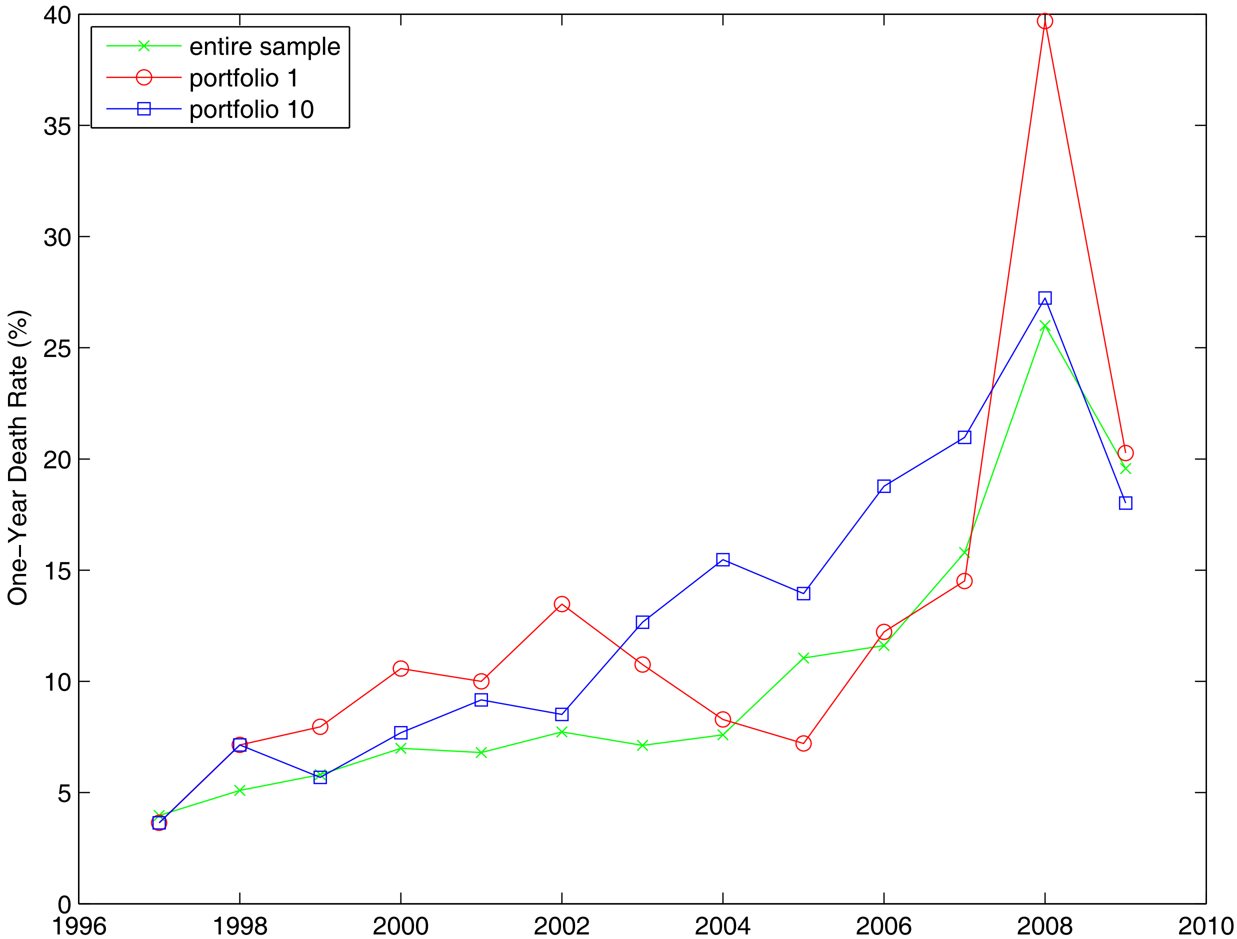

Figure 4: The year-t "death rate" of hedge funds in the top- and bottom-ranked noise-beta sorted portfolios.

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.

Post-Ranking Noise Beta

One remaining concern over our results in Table 5 is the fact that while the post-ranking noise-beta in large part preserves the monotonicity in the pre-ranking noise-beta, it is not perfect. Moreover, the spread is much smaller, and the statistical significance of the post-ranking noise-beta is weak. Indeed, this issue of weak spread in post-ranking beta is not specific only to the risk factor tested in this paper. Using cross-sectional stock returns to test the the VIX index, Ang, Hodrick, Xing, and Zhang (2006) have the same issue in constructing

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

Portfolio Rank	1	2	3	4	5	6	7	8	9	10
Panel A: Characteristics										
AUM ($M)	151.44	170.62	166.80	184.45	188.59	189.40	185.61	164.48	157.29	132.59
iAUM ($M)	14.12	13.91	12.13	14.19	14.68	13.63	12.65	12.54	12.86	11.47
reporting (mn)	130	132	133	134	135	135	134	133	133	131
age (mn)	72.7	73.2	72.6	73.2	73.8	73.8	73.2	73.8	74.7	73.9
stdret (%)	3.55	2.34	1.85	1.52	1.49	1.41	1.65	1.78	2.08	3.18
auto corr	0.14	0.18	0.22	0.25	0.26	0.25	0.23	0.20	0.17	0.13
Panel B: Allocation within Hedge Fund Style (%)										
Long/Short Equity	11.88	10.64	8.38	6.09	5.55	6.18	7.94	10.97	14.63	17.73
Global Macro	17.05	13.23	7.71	7.19	5.67	6.10	6.86	10.68	12.30	13.20
Fund of Funds	4.40	7.87	11.60	14.00	14.38	14.13	13.36	10.25	6.80	3.21
Fixed Income Arb	8.93	7.70	9.90	14.74	12.04	12.03	10.83	9.39	8.13	6.31
Managed Futures	22.71	13.64	6.98	4.60	3.73	5.33	5.94	7.20	10.01	19.86
Event Driven	4.51	9.94	12.58	13.04	14.22	12.43	11.59	10.02	7.55	4.11
Equity Neutral	5.72	10.70	9.38	8.29	8.94	9.70	11.51	12.61	13.61	9.56
Emerging Markets	25.77	13.32	8.64	5.45	5.02	5.05	6.45	7.91	9.17	13.22
Convertible Arb	7.30	8.95	10.32	14.50	15.25	13.98	10.59	9.95	6.10	3.07
Others	6.87	9.79	11.17	11.06	11.76	12.18	10.05	9.63	10.20	7.28

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

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.

For our hedge fund sample, however, this parametric approach is not feasible given the limited characteristics available in the data for hedge funds. But one issue that is unique to the hedge fund data is that their returns are known to be highly serially correlated. As shown in Getmansky, Lo, and Makarov (2004), one likely explanation is their illiquidity exposure 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

$$R^p_t = \beta_0 + \beta^N_p \, \Delta\text{Noise}_t + \text{lag}\beta^N_p \, \Delta\text{Noise}_{t-1} + \beta^M_p \, R^M_t + \text{lag}\beta^M_p \, R^M_{t-1} \, . \tag{5}$$

Given the high serial correlation in hedge fund returns, a more accurate estimate of a portfolio's exposure to liquidity risk is $\beta^N_p + \text{lag}\beta^N_p$. 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 $\beta^M_p + \text{lag}\beta^M_p$

also has some improvement, the improvement in noise beta is much more significant.

Following Ang, Hodrick, Xing, and Zhang (2006), we also construct a factor mimicking portfolio using hedge fund returns and perform the cross-sectional test using this factor mimicking portfolio. Similar to Ang, Hodrick, Xing, and Zhang (2006), we find that portfolio exposures to this factor mimicking portfolio has a much wider spread and the statistical significant of the noise beta's is also greatly improved.[9]

Estimating Liquidity Risk Premiums using Fama-MacBeth Regressions

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

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

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.[10] 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 risk premium. 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 high exposures to illiquidity risk.

Relating to the issue with respect to post-ranking beta discussed earlier in the section, 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 same magnitude, although the slope coefficient is smaller due increased 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

[9]We do not report the details here in the paper to save space, but they are available upon request.

[10]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.

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

Factor	Intercept	Liquidity	Market	Age	AUM
Panel A: Noise as Proxy of Liquidity					
Noise	1.65	-1.43	1.76	0.0001	-0.11
	[3.99]	[-2.86]	[2.60]	[0.19]	[-4.18]
Noise (beta+lag beta)	1.90	-0.44	1.00	0.0002	-0.11
	[4.46]	[-2.81]	[1.79]	[0.25]	[-4.24]
Factor Mimicking Portfolio	1.74	-0.29	1.47	0.0001	-0.12
	[3.75]	[-3.15]	[2.05]	[0.54]	[-4.26]
Noise/BASpreads	1.63	-0.98	1.56	0.0001	-0.10
	[4.00]	[-2.64]	[2.45]	[0.17]	[-4.11]
Panel B: Other Proxies of Liquidity					
On5Y	2.26	-2.21	1.00	0.0001	-0.11
	[5.27]	[-0.77]	[1.76]	[0.1]	[-4.49]
On10Y	2.24	0.38	2.07	0.0001	-0.11
	[5.09]	[0.59]	[2.25]	[-0.08]	[-4.31]
RefCorp	2.14	-4.60	0.75	0.0001	-0.12
	[4.8]	[-1.26]	[1.26]	[0.36]	[-4.32]
PSLiq	2.20	0.93	-0.02	0.0001	-0.11
	[5.11]	[0.88]	[-0.18]	[-0.57]	[-4.36]
VIX	2.17	-0.25	1.04	0.0001	-0.11
	[4.86]	[-0.07]	[1.42]	[-0.04]	[-4.23]

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 three additional cases. Panel B considers other proxies of liquidity: "On5Y" and "On10Y" are the on-the-run premiums for 5- and 10-year Treasury bonds, "RefCorp" is the RefCorp Treasury spread, "PSLiq" is the Pastor-Stambaugh equity liquidity measure, and "VIX" is the CBOE VIX index.

the risk premium decreases because the increased and improved beta estimates. 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.

Finally, 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, and the VIX index. 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, we do not find strong evidence that these risk factors are priced by hedge fund returns.

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 (2009), 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 1 contains the currencies with the smallest forward discounts (or lowest interest rates), and portfolio 6 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 stock market return.

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 1 to portfolio 6, 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 1 are those with the lowest interest rate and function as funding currencies, while currencies in portfolio 6 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 6 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 1 have a positive beta on our noise measure, implying relative good performance during crises.

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

Panel A: Returns and Beta's				
Rank	exret (%)	β^N	β^M	Adj-R2 (%)
1	-0.20	0.27	-0.01	1.5
	[-1.50]	[1.91]	[-0.18]	
2	-0.06	0.07	0.04	0.9
	[-0.51]	[0.44]	[1.06]	
3	0.16	0.17	0.06	2.1
	[1.25]	[1.06]	[1.32]	
4	0.31	-0.07	0.07	2.5
	[2.33]	[-0.36]	[1.31]	
5	0.34	-0.04	0.12	6.0
	[2.41]	[-0.25]	[2.64]	
6	0.81	-0.43	0.14	8.3
	[4.47]	[-1.83]	[2.15]	
Panel B: Estimated Risk Premiums				
	constant	Noise	Market	month
estimate	4×10^{-6}	-0.82	2.93	276
t-stat	[0.003]	[-2.54]	[2.29]	

Portfolios are formed by sorting currencies by their forward discount. Currencies in portfolio 1 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 6 are often used as the asset currency. Returns are monthly in excess of the riskfree rate.

This specific pattern of differing expected returns and 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 6 over portfolio 1 could be contributed by the fact that carry portfolio 6 takes on more liquidity risk. Given that carry portfolio 6 also has more market exposure β^M, however, we need to test this idea more formally.

For this, we run monthly cross-sectional regressions:

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

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 "illiquidity" risk γ^N is -0.82% with a t-stat of -2.54, while the stock market risk premium γ^M is estimated to be 2.93 with a t-stat of 2.29. 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/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 liquidity risk factors obtained from other markets such as equity, corporate bonds and equity options show no explanatory power.

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