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An index-based measure of liquidity

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ABSTRACT

The liquidity shocks of '08–'09 revealed that measures of liquidity risk being used in most financial institutions turned out to be woefully inadequate. The construction of long-short portfolios based on liquidity proxies introduces errors such as extraneous risk factors and hedging error. We develop a new measure for liquidity risk using exchange-traded funds (ETFs) that attempts to minimize this error. We form a theoretically-supported measure that is long ETFs and short the underlying components of that ETF, i.e., long and short a similar set of underlying securities with the same weights. Pricing discrepancies between the long and short positions are driven by liquidity differences between the ETF and its underlying components. Constructing liquidity risk factors in a number of markets, we undertake several tests to validate our new liquidity metric. The results show that our illiquidity measure is strongly related to other measures of illiquidity, explains bond index returns, and reveals a systematic illiquidity component across fixed-income markets.

1. Introduction

The two years beginning in August 2007 demonstrated to the world the enormous destructive effects that global financial shocks can have, not only on the financial markets and institutions but on the real economy. It has become widely acknowledged that a substantial part of these shocks were a series of liquidity events that occurred in a contagion-like manner in a number of financial markets, beginning with the credit markets, and had a substantial negative impact on the balance sheets of most financial institutions. As a result, many financial institutions during this period (including banks, insurance companies, hedge funds, endowments, and pension funds) discovered to their detriment just how sensitive their balance sheets were to liquidity risk.[2] While liquidity risk has become a topic of greater interest for academics and practitioners in the last few years, one of the most difficult aspects of this risk is its measurement—it is a latent risk factor and so it is not possible to directly observe it. Most measures of liquidity risk that have been developed are confounded by the fact that they mix liquidity risk with varying amounts of other risk factors, i.e., it is difficult to know whether one has really captured pure liquidity risk. As a result, even those investors who were utilizing measures of liquidity risk in their risk management processes prior to the financial crisis discovered that their measures did not adequately capture the true level of liquidity risk in their balance sheets.

In this paper, we develop a new measure of liquidity risk which attempts to isolate liquidity risk from all other risk factors. We do so by constructing a portfolio that is long and short an identical set of securities, weighted in an identical manner. One set of securities is constructed by investing in an exchange traded fund (ETF), while the other set of securities is constructed by investing in the exact same securities that are in the ETF, with the exact same portfolio weights. The difference between the prices of the two securities may be attributed to liquidity differences. We devote much of the paper to demonstrating that the measure we derive by this method does indeed capture liquidity. Subsequently with our liquidity measure, we also run tests to check for the pricing of liquidity risk as well as test the extent of the liquidity exposure that one class of financial institutions with purportedly high liquidity levels of liquidity exposure, hedge funds, have on their balance sheets.

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[2] One of the most widely used quotes during this time period was provided by the "sage of Omaha," Warren Buffet, who said "You only find out who is swimming naked when the tide goes out" (Chairman's Letter, 2001 Berkshire Hathaway Annual Report). One interpretation of this quote is that one can only tell how much and what types of risk a firm is really carrying in its balance sheet when the downside of that risk manifests itself. In hindsight, it appears that many financial institutions had substantial liquidity risk in their balance sheets and the crisis of '07–'09 caused the "tide to go out" and make it clear which ones had the largest quantities of this risk.

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1.1. Background

Liquidity is a fundamental need of all investors at some point in time. The need for liquidity can be equated to the need for immediacy in doing a transaction, whether buying or selling. Liquidity risk is essentially the risk that an investor may need transaction immediacy at a particularly convenient or inconvenient time in the markets, i.e., when the price of transaction immediacy is particularly low or high, respectively.

Not all investors face the same degree of liquidity risk. Investors with long-dated liabilities, for example, face less risk of suddenly needing transaction immediacy in the short-term. Investors like these, who face little risk of requiring sudden liquidity, should then be able to collect a premium for providing liquidity to those investors who do.

Many financial institutions utilize this concept and structure their balance sheets to essentially provide these liquidity services (and thereby bear liquidity risk) to other investors in return for a premium—a liquidity premium. Consider for example a convertible arbitrage hedge fund. Convertible arbitrage involves a hedging strategy of forming portfolios that are long corporate bonds and short equities in such a way as to be market neutral. While this long-short position may reduce market risk, this strategy in fact increases the proportion of liquidity risk in the portfolio and magnifies (with leverage) the quantity of liquidity risk. The liquidity risk in the strategy comes from the fact that corporate bonds are typically several orders of magnitude more illiquid than equities. Hence the long and short positions are mismatched on the dimension of liquidity risk. This liquidity mismatch in the portfolio gives rise to a long exposure to liquidity risk, which cannot be hedged. Therefore, convertible arbitrage funds – and in fact, virtually all funds with long-short positions where the long and short positions are not carefully matched on liquidity risk – end up bearing considerable liquidity risk in their portfolios.[3] If this liquidity risk is priced, i.e., if there is a liquidity premium, then at least a part of the performance of convertible arbitrage funds is due to compensation for bearing this liquidity risk in the portfolio.[4]

A convertible arbitrage hedge fund is merely an example. Virtually all financial institutions have assets and liabilities and run liquidity mismatches between these assets and liabilities, either intentionally or unintentionally (because it is virtually impossible to precisely asset-liability match on the liquidity risk dimension)—in either case, the mismatch results in a liquidity premium.[5]

The approach we take in this paper for measuring liquidity risk utilizes precisely this same concept of mismatching the liquidity of assets and liabilities. We measure the level of liquidity risk by the difference in price between two assets which are otherwise similar except for the level of liquidity of each asset. Essentially, we calculate the value of a long-short portfolio where the long and short positions are identical but their prices are not because the long position is more liquid than the short—in the theoretical development that follows, we will show how these positions may be interpreted as call and put options on trading immediacy. Our methodology is very general and applies to any market in which an exchange-traded fund (ETF) is traded.

[3] Aragon (2007) studies hedge funds from the perspective of liquidity service provision.

[4] It is also interesting to note that any performance evaluation tests that fail to account for this liquidity risk/premium will mistakenly attribute the compensation for this liquidity risk as alpha.

[5] One effect of the prevalence of liquidity risk on the balance sheets of financial institutions and the interconnections of these institutions (the liabilities of many financial institutions are the assets of other financial institutions) is the widespread transmission of liquidity shocks around the world—such as the one we just experienced from mid-2007 thru 2009.

1.2. Existing literature

The academic papers that have been written to measure and analyze liquidity risk have used this same concept of mismatching asset and liability liquidity risk to create net liquidity risk on a balance sheet. The difficulty with liquidity risk is that it is a latent risk factor—it cannot be directly observed. Therefore, existing papers have used characteristics about securities to essentially instrument for liquidity risk, and then created long-short portfolios where the long and short positions are mismatched on these characteristics. This, in turn, gives rise to a portfolio with liquidity risk whose return can therefore be viewed as a liquidity premium—essentially a liquidity index. The problem, of course, is that because liquidity risk is not observable, especially situations of high liquidity risk, one is never sure whether the characteristics being used as instruments are also instrumenting for other risk factors. If they are, then the resulting long-short portfolio is a mix of liquidity risk and other risk factors.

While liquidity risk has received considerable attention recently in the academic literature, owing primarily to financial market disruptions in late Summer 2007 caused by liquidity problems in the mortgage securitization market, there had already been a growing literature addressing this issue well before the recent market turbulence. Many papers have investigated the importance of liquidity for explaining returns, using data from the equity markets. Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Brennan et al. (1998), Datar et al. (1998) and Chordia et al. (2002) have all found positive relationships between stock returns and overall liquidity as measured by spreads, depth, and volume. However, Chordia et al. (2001) find a negative relationship between liquidity and expected returns, while Hasbrouck and Seppi (2001) find no relationship. Ben-David et al. (2014) examine the relationship of ETF introduction on the volatility of the underlying equity, and find that the existence of ETFs raises volatility appreciably, and raises regulator concern that this may damage liquidity in the ETFs as well, see also Trainor (2010). Runs on ETFs may damage financial system stability (Ramaswamy, 2011). Finally, Huberman and Halka (2001) and Pastor and Stambaugh (2003) examined the question of whether liquidity risk is systematic. Both papers find substantial systematic components in liquidity risk. More recent work, for example from Acharya and Pedersen (2005), Sadka (2006), Korajczyk and Sadka (2008), Li et al. (2007) and Das and Hanouna (2010), seem to find more positive results for the pricing of liquidity risk, though in many cases the pricing is small.

The mixed results on liquidity pricing in the equity markets is likely the result of performing liquidity tests in a market where liquidity is typically pervasive and therefore, an unimportant characteristic. In fact, next to the Treasury market, the US equity market is the most liquid in the world. Work done in markets where the effects of illiquidity are pronounced, seems to indicate that liquidity risk is in fact priced. For example, Chacko (2009), utilizing holdings data instead of trading data, analyzes the question of whether liquidity risk is priced in the US corporate bond market.[6] Using data for the corporate bond market (excluding convertible corporate bonds), he finds strong evidence for a systematic liquidity risk factor. Longstaff et al. (2005), Ericsson and Renault (2006) and Chen et al. (2007) try to relate corporate bond liquidity to yield spreads as a way of ascertaining the pricing of liquidity risk—and all find some evidence that liquidity risk is priced.[7]

[6] See Goodhart and O'Hara (1997) and Edwards et al. (2007).

[7] Elton et al. (2001) and Huang and Huang (2003) on the other hand find evidence that the tax effects play a greater role than liquidity, while Campbell and Taksler (2003) find equity volatility to be more important than liquidity. Das and Hanouna (2009) find that equity liquidity is important even in explaining credit default swap spreads.

1.3. Our approach

In all of the papers on liquidity, a common factor is that security characteristics such as turnover, bid-ask spread, etc., are used to proxy for liquidity, as liquidity is unobservable directly. These papers directly or indirectly define liquidity risk as being long a set of securities that have a "high" characteristic measure and short a set of securities that have a "low" characteristic measure. Such an approach results in risk factors beyond just liquidity affecting the long-short portfolio, and hence the true risk factor that is measured is a blend of liquidity and other risk factors. While authors attempt to control for these extraneous risk factors by hedging, it is difficult to do this well due to our inability to measure all of the other possible risk factors as well as measurement error in determining contemporaneous exposure using historical data. One strong piece of evidence for this is the observation that if one calculates the correlations of the various risk factors produced by these papers in the same markets and time periods, they typically range from 0.1 to 0.3. Assuming the papers are all taking reasonable approaches for calculating liquidity, i.e., they are in fact picking up a true liquidity signal, one would expect these correlations to be much higher. Our interpretation is that there is material error being introduced into the liquidity risk calculation process.

We introduce a methodology to calculate liquidity risk that is not based on characteristic-based measures. The goal of this approach is to minimize the error introduced through extraneous factors and, as a result, produce a liquidity measure that is less contaminated than characteristic-based approaches. Our approach for measuring liquidity risk in a particular market is to form a portfolio that is long an ETF in that market and short the individual securities of that ETF—the securities of the short portfolio are weighted in a manner that is identical to the weighting scheme of those securities in the ETF. So, essentially we are going long and short the exact same securities except that the long positions are obtained through an ETF while the short positions are obtained through direct shorting of the individual securities.

Absent any frictions, this long-short portfolio should produce zero return always. However, we know that by almost any liquidity measure, ETFs and their underlying securities are different in liquidity. As a result, in practice we observe systematic pricing discrepancies between the ETF and its underlying components. Because we are long and short the same securities, there can reasonably be only two explanations for systematic pricing discrepancies: (1) the market is inefficient and these pricing discrepancies represent arbitrages, or (2) the long and the short positions differ in their levels of liquidity. As we will assume, like other papers in this area, that widespread, systematic arbitrages are not possible, the pricing discrepancy must be due to the liquidity-based explanation. Essentially the more liquid security will have a higher price due to a lower liquidity premium, while its illiquid counterpart has a lower price due to a higher liquidity premium. Indeed in a recent paper, Madhavan and Sibczyk (2014) estimate the price discrepancy in a cross-section of almost a thousand ETFs and attribute this to liquidity.[8]

1.4. Organization of this paper

In the next section, Section 2, we define the data and process that we use to construct sample ETF-based long-short portfolios. We present an options-based analysis that generates a formula for liquidity, and we also connect this formula to the literature on differences in price adjustment speeds.

In Section 3, we run a number of empirical tests to demonstrate that the time-series of these long-short portfolios are in fact related to liquidity risk. As our methodology for calculating liquidity risk hedges out other risk factors and frictions, we argue that liquidity is the predominant remaining risk factor—and the empirical results provide evidence for this argument. The main results are as follows. One, we find high correlation between our illiquidity measures for various fixed-income markets, even though the return correlation in these markets' ETFs is low. Two, our new measure of bond illiquidity correlates highly with two other measures of price impact, i.e., the Amihud (2002) illiquidity measure, and the absolute return on XLF, a financial institutions' ETF. Three, we find that our illiquidity measure is strongly related to market volatility (VIX) and the TED spread, both metrics being known to generate illiquidity. Four, the bond illiquidity measure is significantly correlated with the Chacko (2009) measure of latent liquidity, even though both are generated from very disparate methodologies. Five, a principal components analysis of our bond illiquidity measures reveals a major component that explains two-thirds of the common variation, supporting the existence of systematic illiquidity in bond markets. Six, we find that bond illiquidity correlates significantly with equity market illiquidity, with the latter tending to lead the former. And seven, we show that bond illiquidity explains the returns on bond indices (investment-grade and high-yield) even after controlling for several other asset-pricing factors.

Finally, in Section 4 we use these liquidity measures to test a widely held view that liquidity risk is related to the performance of hedge funds. We find that liquidity risk is indeed a systematic risk factor in explaining the returns of many hedge fund strategies, and we also find that hedge funds seem to have substantially reduced the liquidity risk on their balance sheets after the financial crisis of 2008–2009. Section 5 then concludes.

2. Methodology and data

In this section we lay out the basic methodology for calculation of our liquidity measure and, subsequently, our liquidity factor. We then provide details about the data on which we apply this methodology to generate our empirical findings.

2.1. An options approach to illiquidity

Most liquidity factors involve the utilization of liquidity measures that inadvertently include other risks beyond just liquidity. This results in a noisy liquidity measure. Our methodology for calculating liquidity in a market is fairly simple and avoids the problem of residual risk factors. Essentially, we take a traded index, an ETF, and compare the price of the index to the price of a portfolio (NAV) containing the same underlying components as the ETF. The NAV is calculated by using the end-of-day prices of the bonds in the index.[9] Because the index and the portfolio contain identical securities with identical weightings, the difference between their

[8] A structural explanation is that if market-wide illiquidity is high, then arbitraging between the underlying components and the ETF will be difficult, resulting in a pricing gap between the two. The greater the illiquidity in the markets, the higher this gap will become. Thus the pricing gap is an endogenous effect of illiquidity, and we utilize this result to measure illiquidity.

[9] One problem that occurs with credit market data is the general lack of trading in this market (for example, the median bond issue trades less than once per year). In such situations, non-trading or asynchronous trading can potentially create biases in liquidity measures. This problem is mitigated in the implementation in this paper because the securities that go into most ETFs are in the liquid segments of the credit markets due to the criteria that most indices use. For example, to be included in most indices a bond must have an issuance size of $1billion, must be able to settle internationally through Euroclear, and have daily bid and ask prices available from an inter-dealer broker. Bonds that satisfy these requirements typically experience reasonably high daily trading volumes, and thus the asynchronous trading problem is mitigated.

prices can be attributed mainly to liquidity differences.[10] Essentially, the portfolio of ETF underlying components has a different level of liquidity than the ETF itself and this difference varies through time; therefore, investors face liquidity risk when buying the portfolio. These investors therefore are only willing to purchase these securities at a discount that compensates for the higher liquidity risk.

There are several metrics that we can use to compare the ETF price and the value of the portfolio of its components, or NAV. We look to the theoretical market microstructure literature to guide us in the determination of this mathematical function. A large literature exists that explores the inventory cost model of transaction costs (Garman, 1976; Stoll, 1978; Amihud and Mendelson, 1986; Ho and Stoll, 1981). An interesting line of this literature (Copeland and Galai, 1983; Harris, 2003) has utilized contingent claims to model bid and ask prices. Chacko et al. (2008) showed that bid and ask prices could be modeled specifically as perpetual American calls and puts. The intuition behind their approach is to recognize that when a bid or an ask price is put out into the market the agent quoting the bid or ask price[11] is essentially writing an American option. For example when a sell limit order is put out by an investor, the investor has written an American call option to the market maker. The call option is written on the fundamental value of the security, and the exercise price is the limit price set by the investor. When the fundamental value of the security exceeds the limit price, or exercise price, by a sufficient, optimal amount, the option is exercised by the market maker, and a transaction takes place. Therefore, the value of the call option essentially represents the bid price of a security, and the value of the corresponding put option represents the ask price. Because a bid-ask spread is used as a proxy for the level of illiquidity in a market, we can use the value of the call and the value of the put to measure the liquidity in the market.

In applying a contingent-claims approach to our setting, we can think of illiquidity as the value of an option to exchange the ETF for the NAV, i.e., the difference between the ETF and the NAV upon exercise of the option is the effective transaction cost, and therefore the value of this option is the value of liquidity. If the transaction is initiated by a buyer of the ETF—say, by placing a limit order—then, an option to exchange the ETF for the NAV is written by the prospective buyer, i.e., a seller into the limit order would exercise a put of the ETF at strike NAV. On the other hand, if the transaction is initiated by a seller of the ETF, then an option to exchange the NAV for the ETF is written by the prospective seller, i.e., a buyer would exercise a call of the ETF at strike NAV. Empirically whenever a transaction occurs, we do not know if the transaction was buyer or seller initiated. However when a transaction occurs, we do know that one of the options has non-zero value because it is being exercised.[12] Therefore, we use the sum of the call and the put as our measure of liquidity because only one of them will have a positive value on exercise:

$$Illiquidity = Call(ETF, NAV) + Put(ETF, NAV) \quad (1)$$

where $Call(x, y)$ denotes an American call option with an exercise price of y written on an underlying security with a value of x, and $Put(x, y)$ similarly denotes an American put option with a exercise price of y written on an underlying security with a value of x. Because illiquidity should not depend on the level of the ETF and NAV, we modify our measure above by dividing through by the level of NAV:

$$Illiquidity^* = Call\left(\frac{ETF}{NAV}, 1\right) + Put\left(\frac{ETF}{NAV}, 1\right) \quad (2)$$

In order to simplify the interpretation of our liquidity measure, we now use the following transformation to define a new liquidity measure in a way that is analogous to a bond yield:

$$\begin{aligned} BILLIQ &= -10,000 \times \log\left[\frac{1}{1 + Illiquidity^*}\right] \\ &= -10,000 \times \log\left[\frac{1}{1 + Call(\frac{ETF}{NAV}, 1) + Put(\frac{ETF}{NAV}, 1)}\right] \end{aligned} \quad (3)$$

where $\log[\cdot]$ is the natural logarithm function.

The *BILLIQ* measure will be the bond illiquidity measure that we use throughout this paper. The main advantage of the form of this illiquidity measure is that *BILLIQ* can be interpreted as a continuously-compounded rate (quoted in basis points). When the financial markets are perfect and there is zero illiquidity, the value of the call and put are zero and *BILLIQ* takes on a value of 0. As illiquidity increases in the market, *BILLIQ* increases in value and is unbounded from above.

When a buy or sell transaction occurs, the call option or put option is exercised and the other is worthless. Therefore we can write

$$\begin{aligned} Illiquidity^* &= Call\left(\frac{ETF}{NAV}, 1\right) + Put\left(\frac{ETF}{NAV}, 1\right) \\ &= \max\left[\frac{ETF}{NAV} - 1, 0\right] + \max\left[1 - \frac{ETF}{NAV}, 0\right] \\ &= \left|\frac{ETF}{NAV} - 1\right| \end{aligned} \quad (4)$$

Substituting this result into Eq. (3), we get the following equation:

$$BILLIQ = -10,000 \times \log\left[\frac{1}{1 + |\frac{ETF}{NAV} - 1|}\right] \quad (5)$$

We then re-arrange to derive the formula we use to calculate *BILLIQ* in the paper.

$$BILLIQ = -10,000 \times \log\left[\frac{NAV}{NAV + |ETF - NAV|}\right] \quad (6)$$

As one would expect, the core of our illiquidity measure is the difference between the ETF value and NAV—essentially long the ETF and short the underlying components of the ETF. This measure implies that the greater the difference between the ETF and NAV, the higher the value of this metric, i.e., the greater the illiquidity. When there is a higher disparity between the ETF and portfolio NAV in a market, it means that investors are commanding a larger premium in that market for holding the portfolio of components rather than the NAV. Therefore, there is a large liquidity premium and our illiquidity measure takes on a high value. On the other hand, if the ETF and NAV are identical, then investors are pricing the ETF and its components the same, and there is no liquidity premium in that market. In this case, the *BILLIQ* measure takes on a value of zero.[13]

[10] We say "mainly" here because there are some institutional differences between ETFs and the underlying securities, such as management fees, capital gains tax basis, etc. Later in this paper when we develop a liquidity measure, we will test empirically whether the price differences are due to liquidity effects or other factors such as these.

[11] Bid and ask prices could be quoted by either a market maker or an investor. For example in bond markets the market maker, or bond dealer, puts out bid and ask quotes for the bonds in which he is willing to deal. On the other hand in equity markets investors can put out bid and ask quotes through the mechanism of limit orders. Thus, equity investors could actually become de facto market makers if their buy and sell limit order prices are inside the quotes of the market makers, or specialists. The label of market maker versus investor is simply determined by who has the least need for transaction immediacy or lower inventory costs.

[12] Actually, it is being *early* exercised because these are both perpetual American options in the contingent-claims framework.

[13] In passing, we also note that the BILLIQ measure is calculated daily using only NAV and ETF prices for that day. Unlike several other liquidity measures in the literature, BILLIQ does not need a time series of data to produce any one day's illiquidity score. It does not require trading volume data, nor data on bid-ask spreads. This makes it extremely easy to produce for real-world applications.

It is important to note that this measure of illiquidity is partly endogenous just as most illiquidity measures derived in the literature. While the long-short portfolio itself is constructed based on external characteristics (whether a security is a component of an ETF or not), the illiquidity measure itself and the subsequent generation of a time series of illiquidity, or an illiquidity factor, is endogenous. The illiquidity measure is created by the taking the difference in performance between the long and short sides of this portfolio, but this performance difference is a consequence of the illiquidity difference between the two sides.

In illiquid markets it is often the case that pricing is based on quoted prices rather than traded prices. In such a case, if the market experiences a sudden liquidity shock, the ETF usually experiences a quick negative shock, but the underlying portfolio NAV will not experience this shock—essentially, the price adjustment process for the less liquid NAV is slower than that of the more liquid ETF. The same occurs for positive shocks as well. Hence, the absolute difference between ETF and NAV in the denominator of our measure reflects this fact. Because the price-adjustment of the NAV is slower than that of the ETF, the difference in rates of price adjustment is picked up by our formula, irrespective of the direction of the price move—see Amihud and Mendelson (1989) for a formal derivation of the difference in price adjustment processes between an index and underlying securities. We believe that our derivation here is the first to connect the price of immediacy that is option-based with the literature on differences in price-adjustment speeds.[14]

2.2. Data

For our empirical testing, we use fourteen bond ETFs along with an equity ETF.[15]

A typical bond ETF aims to mimic the underlying index as closely as possible at low cost. For instance, the US Aggregate Bond Index ETF (AGG) holds over a thousand securities comprising US Government Treasuries, investment grade corporate debt, mortgage pass-throughs, and publicly available asset-based securities (ABS). All of these are fixed-rate, taxable, non-convertible, and have maturities greater than one year. The ETF's prospectus usually contains details about the risks entailed in investing in the ETF, and reports its top ten holdings, the sector, maturity, and rating breakdown of the assets. Individual fund shares represent a partial ownership in an underlying portfolio of assets, and are sold on national securities exchanges and hence have market prices that can deviate from net asset value (NAV). The NAV is determined once daily, Monday through Friday, usually at close (i.e., 4 pm EST) and is the price at which the ETF issues and redeems shares. The NAV is based on unadjusted, observable, quoted prices for the assets if possible (Level 1 prices) that are provided by market data providers or dealers, or on prices based on observable comparables after adjustment (Level 2), or are determined by models and judgment using unobservables (Level 3).

ETFs aim to replicate an underlying index in four ways: full, optimized, derivative, and blended. In the "full" version, the ETF holds 90% or more members of the index; in the "optimized" case, the ETF holds a representative sample of the index with less than 90% of members of the index, aiming for low tracking error. The "derivative" version uses swaps or futures to synthetically replicate the index return, and the "blended" version uses a combination of derivatives and index members. We use ETFs that are of the full type so that we extract the illiquidity of the underlying market as directly as possible. For the sake of comparison, we also use ETFs of the optimized type. Half our sample is made up of each type, and we do not include any ETFs of the deriviative or blended types. The full-type ETFs do not keep a sub-portfolio of only the liquid underlying components (as some ETFs do in order to minimize the effect of redemption risk), thereby minimizing the commingling of the risk of market liquidity with the risk of funding liquidity.

Table 1 provides a description of the ETFs we use throughout this paper. The main differences among the various bond ETFs are primarily in the durations of the ETFs and their average credit qualities. We try to use ETFs which span different parts of the duration/credit quality matrix such as LQD, which represents the investment grade, medium-duration space, and HYG, which represents the below investment grade, medium-duration space. We have AGG, which covers the entire investment grade space and is therefore the most comprehensive ETF. We include ETFs that capture the mortgage-backed securities markets and emerging-market debt markets, MBB and EMB, respectively. Finally, we utilize an equity ETF, the IVV, which represents the S&P 500, as a way to compare the liquidity measures generated in the fixed-income markets with one generated in the equity markets and see how much of liquidity risk is systemic across markets. We also include the more recently introduced Vanguard ETFs.

In subsequent sections, we utilize the time series of the *BILLIQ* measured above as calculated with these ETFs and their underlying components. Fig. 1, Panel A presents a graph of these *BILLIQ* time series as examples to help readers visualize the liquidity measures that are generated by our procedure. The graphs show that during 2002–2015, the financial markets experienced four liquidity shocks. One occurred in the Summer of 2007, and slowly receded during the remainder of 2007 and the first half of 2008. Then, the second liquidity shock hit in the second half of 2008, driven by the collapse of Lehman Brothers. It is also interesting to see that financial market volatility and the downturn in 2007–2009 was very different than that of 2001–2003. The 2001–2003 period was not driven by a liquidity shock, while the 2007–2009 period clearly was. The third liquidity shock occurred in the third and fourth quarters of 2011 and was followed by the fourth shock in mid 2013. Both of these latter shocks were less salient than the ones in the crisis. In fact, they almost seem like ripples following from the major shock in 2008. In Fig. 1, Panel B, we present the BILLIQ series for LQD and HYG only, for the period 2007–2009, smoothed by taking a monthly moving average—as expected, the illiquidity of the HYG series is greater than that of LQD. In times of greater market stress, the relative illiquidity of HYG to LQD increases.

In Table 2 we provide descriptive statistics of the ETFs. Because the ETFs were created and launched at different times, we have quite a long time series with some of the ETFs, like the iShares Investment Grade Bond Fund that was launched in July 2002, and shorter time series with others, like the iShares Credit Bond Fund, CFT, which was launched in January 2007. For all of the empirical tests we do subsequently, when we need to use multiple data series we use only the time periods for which all of the series overlap. The iShares High Yield Bond Fund ETF, HYG, has the largest volume because of active trading in the crisis. Because the iShares Aggregate Bond Fund (AGG) has the broadest coverage of all of the fixed income ETFs, we will use the liquidity measure generated from this ETF to make statements about liquidity in the fixed income markets as a whole. The lower panel of the table shows the return correlations between the ETFs. We see that the

[14] Based on Amihud and Mendelson (1989), the autocovariance of the NAV should be higher than that of the ETF because the latter is liquid and has faster price adjustment. We found that in nine of the ten ETFs in our sample (barring CIU), the NAV had a higher return autocovariance than that of the ETF.

[15] Note that while our procedure works for any ETF, we chose primarily corporate bond funds due to the illiquidity of that market (relative to equity markets, for example). If one is doing work on illiquidity risk, it is best to utilize markets where that risk is substantial, though obviously not so substantial that no trading occurs in the market.

Table 1
Data description. This table provides a description of each of the ETFs used in the study to compute bond illiquidity measures. All the ETF time series run up to September 1, 2015. Fund Turnover is the percentage of the portfolio that was changed or replaced over a one year time period. This one year is the fiscal year of the Fund. Fund Turnover is updated from annual reports. In the bottom panel, we show five pairs of iShares and Lyxor ETFs that are matched, and whose liquidity measure based on our model are significantly correlated, even though all correlations are not always high, see the numbers in square brackets.

Ticker	Full title	Issuer/industry	Replication
LQD	iShares iBoxx $ Investment Grade Bond Fund	Corp/Pref-Inv Grade	Optimized
HYG	iShares iBoxx $ High Yield Corporate Bond Fund	Corp/Pref-High Yield	Full
CSJ	iShares Barclays 1–3 Year Credit Bond Fund	Government/Corporate	Full
CFT	iShares Barclays Credit Bond Fund	Government/Corporate	Full
CIU	iShares Barclays Intermediate Credit Bond Fund	Corp/Pref-Inv Grade	Optimized
AGG	iShares Barclays Aggregate Bond Fund	Government/Corporate	Optimized
GBF	iShares Barclays Government/Credit Bond Fund	Government/Corporate	Optimized
GVI	iShares Barclays Intermediate Government/Credit Bond Fund	Government/Corporate	Full
MBB	iShares Barclays MBS Bond Fund	Asset Backed Securities	Full
EMB	iShares JP Morgan USD Emerging Markets Bond Fund	Emerging Market-Debt	Full
IVV	iShares S&P500 Index (NYSE)	Equity	Full
BIV	Vanguard Intermediate-Term Bond ETF	Govt/Corp Intermediate	Optimized
BLV	Vanguard Long-Term Bond ETF	Govt/Corp Long Term	Optimized
BND	Vanguard Total Bond Market ETF	Government/Corporate	Optimized
BSV	Vanguard Short-Term Bond ETF	Govt/Corp Short Term	Optimized

Ticker	Rating focus	Maturity focus	Start date	Turnover
LQD	Investment Grade	Intermediate Term (3–10 yr)	7/25/98	9
HYG	Speculative Grade/High Yield	Intermediate Term (3–10 yr)	4/10/03	11
CSJ	Investment Grade	Short Term (1–3 yr)	1/10/03	17
CFT	Investment Grade	Short/Intermediate Term	1/10/03	10
CIU	Investment Grade	Intermediate Term (3–10 yr)	1/10/03	7
AGG	Investment Grade	No Restriction	9/25/99	318
GBF	Investment Grade	Short/Intermediate Term	1/10/03	15
GVI	Investment Grade	Short/Intermediate Term	1/10/03	22
MBB	Investment Grade	No Restriction	3/15/03	936
EMB	Mixed	Intermediate/Long Term	12/18/03	52
IVV	N/A	N/A	5/15/00	4
BIV	Investment Grade	Intermediate Term (3–10 yr)	4/10/07	70
BLV	Investment Grade	Long Term (>10 yr)	4/10/07	50
BND	Investment Grade	Intermediate/Long Term	4/10/07	73
BSV	Investment Grade	Short/Intermediate Term	4/10/07	50

Bloomberg ticker	ETF name	Exch	CCY	Replication [Corr]	Expense ratio	30 day avg vol	Industry subgroup
LQD US equity	iShares IBOXX Investment Grade	US	USD	Optimized	0.15	3,345,122	Corp/Pref-Inv Grade
CRP FP equity	Lyxor ETF Euro Corporate Bond	FP	EUR	Derivative [0.34]	0.2	4973	Corp/Pref-Inv Grade
CSJ US equity	iShares 1–3 Year Credit Bond	US	USD	Full	0.2	576,894	Govt/Corp Short Term
CRPE IM equity	Lyxor ETF Euro Corporate Bond	IM	EUR	Derivative [0.09]	0.2	4,583	Corp/Pref-Inv Grade
HYG US equity	iShares IBOXX USD High Yield	US	USD	Full	0.5	9,123,272	Corp/Pref-High Yield
YIEL LN equity	Lyxor UCITS ETF iBoxx EUR Liquid High Yield 30 Ex-Financial	LN	EUR	Derivative [0.34]	0.45	10,163	Govt/Corp High Yield
GVI US equity	iShares Intermediate Government	US	USD	Full	0.2	237,684	Govt/Corp Intermediate
MTC FP equity	LYXOR UCITS ETF EuroMTS 5-7Y Investment Grade	FP	EUR	Full [0.50]	0.165	54,971	Govt/Corp Intermediate
AGG US equity	iShares Core U.S. Aggregate	US	USD	Optimized	0.08	3335052	Government/Corporate
LYXECB GY equity	Lyxor UCITS EuroMTS Covered Bond Aggregate	GY	EUR	Derivative [0.09]	0.165	1225.867	Sector Fund-Debt

correlations of most pairs of ETFs are significant when taken over as long a sample as possible.

3. Empirical results

3.1. Properties of the illiquidity measure

One of the difficulties of demonstrating whether one has a good measure of liquidity is that we do not have a universally agreed-upon definition of liquidity. Therefore, we cannot simply check whether the liquidity measure in this paper agrees with that definition.[16] However, we do have some generally agreed-upon characteristics that any good measure of liquidity should pick up; for example, we believe that liquidity should be related to volatility and price impact of trades. In this section, we conduct a number of empirical tests to provide evidence that the liquidity risk measure we are generating displays these characteristics.

In Table 3, we calculate correlations between the liquidity measures calculated from each of the fixed income ETFs. These correlations are calculated over periods where the two ETF return series for which we are calculating a correlation overlap (in the upper triangle of the correlation matrix) or periods where all of the ETF return series overlap (the lower triangle of the correlation matrix). As expected, the correlations in Table 3 reveal that all of the fixed income liquidity measures are highly correlated with each other. This seems to suggest that there is a strong systematic component to the individual liquidity measures—we will explore this further in subsequent empirical testing. The liquidity measures from the emerging markets bond index, EMB, and the mortgage-backed bond index, MBB, have very low correlations with other liquidity measures. This is probably because these two markets are quite

[16] In addition, this paper presents a reduced-form model of illiquidity rather than a structural model of liquidity such as Chordia et al. (2008) and others who use a Kyle (1985) and Admati and Pfleiderer (1988) setting. With a structural model, one can use the underlying structure to generate testable hypotheses. The cost of this approach is that no such liquidity measure has yet gained any widespread use because of the difficulty of implementation. The benefit of a reduced-form approach is that it has the potential to become immediately and widely useable.

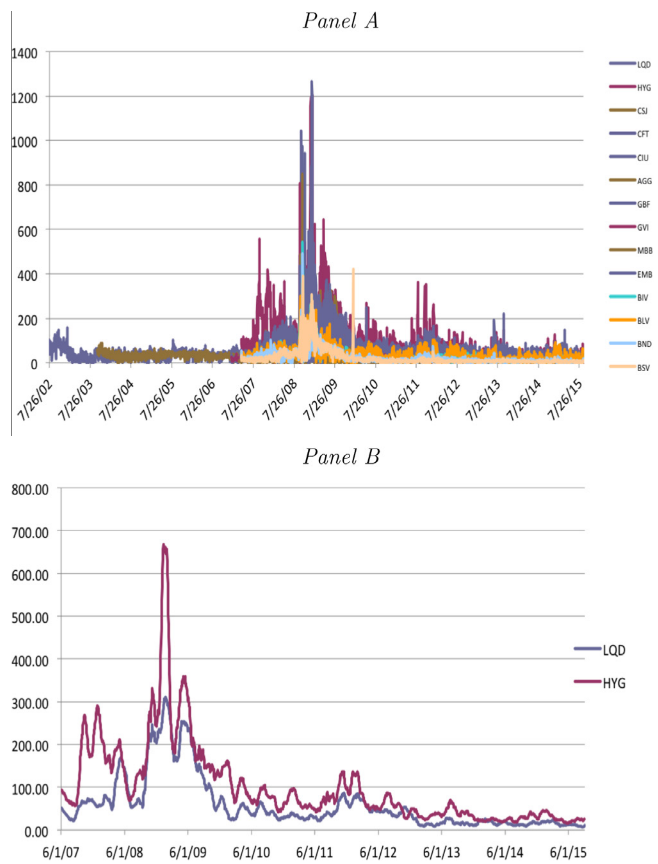

Fig. 1. BILLIQ time series. This graph presents the time series of the various BILLIQ measures extracted from the ETFs. All series are presented in the upper graph. Data runs from July 2002 to August 2015. See Table 1 for a description of the different series. The lower graph shows the 30-day moving average of the illiquidity series for the investment grade sector (LQD) and high-yield sector (HYG) from June 2007 to August 2015. Illiquidity is expressed in basis points.

different from the other markets, which are composed entirely of corporate and US government bonds. We also examined if our liquidity measures computed using iShares ETFs (based on "full" and "optimized" replication) were correlated to similar ETFs from Lyxor in Europe. We used five iShares ETFs, listed in the lower panel in Table 1 and found them to be significantly correlated to Lyxor ETFs even though there are substantial differences in the venues, trading volumes, and replication techniques. Therefore, this suggests that extracting liquidity metrics from varied sources might be a successful endeavor, and also that liquidity behavior is similar for different providers of ETFs in similar markets.

We also examined whether the Treasury–Eurodollar (TED) spread was related to our illiquidity measures. The TED spread is known to widen when there is systematic illiquidity in the interest-rate markets, and we see from Table 3 that there is a statistically significant relationship between the TED spread and most of our measures of liquidity.

Illiquid markets are characterized by high price impact of trades. As a robustness check of price impact, we expect that our liquidity measures will be highly correlated with the most widely used measure of illiquidity, i.e., the *ILLIQ* metric of Amihud (2002)—this metric computes the price change per dollar volume of trading. The correlation of all our *BILLIQ* series is significantly positive with the Amihud *ILLIQ* and is shown in Table 4. As another check of price impact, we expect that the absolute percentage price change in the financial sector will be positively correlated with illiquidity, i.e., our *BILLIQ* measures.[17] Therefore, in Table 4, we also present the results of a regression of the absolute returns of the financial sector ETF, i.e., the XLF, on each of our illiquidity metrics. The correlation is positive for all regressions and only two are not statistically significant. Hence, illiquidity clearly correlates with greater price impact.

Virtually every theoretical model of liquidity predicts that illiquidity should be positively correlated with volatility, i.e., as volatility increases so should illiquidity—see O'Hara (2004). We test this prediction with the BILLIQ measure. We calculate the time series of BILLIQ for each of our ETFs and then to run a time-series regression of each ETF BILLIQ against a volatility index. We use the VIX, the implied volatility of at-the-money S&P 500 options, as our proxy for systemic volatility. Table 5 shows that our BILLIQ measure is related to volatility—the *t*-stats on the VIX coefficients are significant for most of the illiquidity series, even after accounting for the high level of autocorrelation in the BILLIQ (we undertake Cochrane-Orcutt autocorrelation corrections after which the Durbin-Watson statistics are all close to 2). The CSJ, and CIU indices have low and insignificant correlations to the VIX. If we think of the VIX as proxying for systemic liquidity, it would appear that these indices have the least liquidity effects, i.e., are least likely to be affected by liquidity shocks. It is widely felt in the bond markets and verified in many fixed income papers that bonds of lower maturity and higher credit quality have higher liquidity—see Alexander et al. (2000). This certainly can explain the low sensitivity of CSJ to volatility, and possibly the results for CIU as well. Similar results are shown for the relationship of our illiquidity measures to 10-year and 30-year bond futures implied volatility, complementing the findings for the VIX.

In Table 6 we look directly at how our liquidity measure performs relative to another liquidity measure. Specifically, we compare the liquidity measure that is generated by our approach, i.e., the time series of the *BILLIQ* measure, against the liquidity measure that is generated in Chacko (2009), denoted *ILLIQFAC*. The Chacko measure is based on security holdings rather than trade-based characteristics, and that paper applied its liquidity measure in the corporate bond market to generate a liquidity factor for that market. Our measure has the advantage that it does not use proprietary data like that paper, but of course it is forced to confine itself to the more liquid parts of markets (where we observe trading). In Table 6 we see that despite the fact that the two measures are calculated using very different approaches, they are in fact highly correlated. In all cases the *t*-statistic of *ILLIQFAC* is significant (the *F*-statistics for the regressions are also highly significant) indicating that this measure of liquidity is important in explaining some part of the liquidity measures that we are generating, with the amount explained depending on how closely the ETF we use matches the Chacko (2009) paper in terms of coverage of the US credit markets.

3.2. Commonalities in liquidity across bond markets

Each of the ETFs generate a different liquidity measure—this is clear from the correlations in Table 3. However, a natural question arises as to whether there are common, or global, components to the individual liquidity measures. The global component that is the "most important" by some metric may be considered as a global liquidity factor for the fixed income markets. Therefore, we perform a principal components analysis (PCA) and rotate the

[17] Recall our discussion in Section 1.1 of the liquidity mismatch between assets and liabilities that naturally exists in the balance sheets of financial institutions. As we discussed, this mismatch gives rise to liquidity risk to the residual claimants (equity holders) of financial institutions.

Table 2
Descriptive statistics of ETF series. The data is daily. The number of observations is the number of days for which it was possible to compute *BILLIQ* for each ticker. *BILLIQ* is represented in basis points. Price and NAV are in dollars. Volume is the number of units of the ETF that are traded per day. The second panel displays the correlations of returns amongst the ETFs. The lower triangle of the correlation matrix below comprises correlations computed for only the period over which all series had complete observations. In contrast, the upper triangle of the correlation matrix presents the pairwise correlations for all observations where complete data is available for the pair of ETFs. Hence, the upper triangle comprises correlations computed off more observations than the lower triangle. Italicized correlation numbers are *non-significant* at the 5% level.

Ticker	Mean price	Mean NAV	Mean volume	Mean BILLIQ	No of obs
LQD	109.94	109.50	944,614	50.54	3300
HYG	90.17	89.47	2,427,205	99.84	2116
CSJ	103.74	103.24	414,768	51.46	2177
CFT	105.07	104.49	58,915	62.25	2172
CIU	105.20	104.64	223,522	57.29	2173
AGG	104.64	104.42	746,165	26.69	3005
GBF	108.49	108.24	12,785	33.77	2162
GVI	107.74	107.47	41,670	28.21	2173
MBB	106.11	106.04	266,999	10.36	2131
EMB	106.85	106.16	481,221	77.91	1938
BIV	82.48	82.24	198,057	32.46	2117
BLV	83.42	83.17	74,878	36.83	2117
BND	80.37	80.20	1,088,398	24.18	2117
BSV	79.73	79.58	614,474	21.83	2117
IVV	133.39	133.38	2,906,255	7.51	3297

	LQD	HYG	CSJ	CFT	CIU	AGG	GBF	GVI	MBB	EMB	BIV	BLV	BND	BSV
LQD	1.000	0.378	0.402	0.641	0.591	0.623	0.519	0.532	0.480	0.270	0.598	0.549	0.575	0.264
HYG	0.399	1	0.250	0.181	0.173	0.154	−0.046	*0.023*	*−0.011*	0.359	*0.005*	−0.089	0.058	−0.094
CSJ	0.393	0.263	1	0.479	0.427	0.452	0.277	0.380	0.264	0.211	0.361	0.191	0.389	0.224
CFT	0.643	0.191	0.476	1	0.653	0.687	0.597	0.562	0.535	0.224	0.720	0.615	0.698	0.425
CIU	0.581	0.182	0.414	0.646	1	0.624	0.564	0.501	0.519	0.251	0.666	0.531	0.628	0.415
AGG	0.589	0.157	0.444	0.689	0.624	1	0.624	0.606	0.606	0.222	0.747	0.671	0.769	0.461
GBF	0.511	−0.046	0.261	0.592	0.564	0.596	1	0.624	0.588	0.161	0.729	0.708	0.671	0.441
GVI	0.517	*0.024*	0.363	0.550	0.501	0.588	0.612	1	0.624	0.215	0.702	0.605	0.692	0.455
MBB	0.470	*−0.021*	0.248	0.529	0.519	0.597	0.576	0.582	1	0.624	0.670	0.572	0.664	0.513
EMB	0.270	0.359	0.211	0.223	0.251	0.221	0.162	0.214	0.153	1	0.624	0.111	0.247	*0.012*
BIV	0.588	*0.002*	0.348	0.721	0.666	0.742	0.723	0.690	0.661	0.190	1	0.624	0.846	0.568
BLV	0.539	−0.100	0.176	0.612	0.531	0.666	0.704	0.595	0.559	0.110	0.796	1	0.624	0.420
BND	0.564	0.056	0.377	0.698	0.628	0.762	0.663	0.679	0.652	0.246	0.840	0.721	1	0.624
BSV	0.243	−0.096	0.204	0.415	0.415	0.445	0.425	0.433	0.504	*0.012*	0.554	0.408	0.416	1

Table 3
Bond liquidity series correlations. The lower triangle of the correlation matrix below comprises correlations computed for only the period over which all series had complete observations. In contrast, the upper triangle of the correlation matrix presents the pairwise correlations for all observations where complete data is available for the pair of ETFs. Hence, the upper triangle comprises correlations computed off more observations than the lower triangle. The last line and column of the table shows the correlations of the various liquidity series with the Treasury-Eurodollar (TED) spread.

	LQD	HYG	CSJ	CFT	CIU	AGG	GBF	GVI	MBB	EMB	BIV	BLV	BND	BSV	TED
'LQD'	1	0.725	0.764	0.782	0.785	0.475	0.616	0.702	0.544	0.573	0.697	0.578	0.725	0.672	0.551
'HYG'	0.755	1	0.682	0.677	0.702	0.557	0.576	0.693	0.563	0.658	0.691	0.552	0.685	0.672	0.554
'CSJ'	0.772	0.717	1	0.869	0.919	0.546	0.706	0.815	0.490	0.653	0.759	0.635	0.781	0.786	0.433
'CFT'	0.790	0.698	0.873	1	0.885	0.654	0.731	0.800	0.497	0.608	0.797	0.668	0.788	0.717	0.525
'CIU'	0.791	0.731	0.920	0.887	1	0.526	0.712	0.834	0.514	0.627	0.769	0.649	0.757	0.772	0.442
'AGG'	0.540	0.560	0.560	0.666	0.537	1	0.586	0.598	0.438	0.487	0.678	0.504	0.655	0.585	0.510
'GBF'	0.622	0.602	0.707	0.733	0.710	0.604	1	0.740	0.484	0.547	0.692	0.594	0.645	0.664	0.407
'GVI'	0.707	0.720	0.816	0.803	0.834	0.608	0.741	1	0.598	0.639	0.800	0.660	0.771	0.772	0.523
'MBB'	0.565	0.580	0.511	0.515	0.534	0.446	0.498	0.618	1	0.477	0.542	0.408	0.512	0.607	0.567
'EMB'	0.574	0.659	0.653	0.608	0.627	0.487	0.547	0.640	0.477	1	0.659	0.525	0.658	0.624	0.446
'BIV'	0.702	0.720	0.764	0.803	0.773	0.688	0.698	0.803	0.557	0.660	1	0.725	0.837	0.765	0.571
'BLV'	0.584	0.573	0.639	0.674	0.652	0.511	0.596	0.662	0.417	0.525	0.727	1	0.657	0.622	0.426
'BND'	0.732	0.702	0.794	0.796	0.767	0.661	0.654	0.776	0.521	0.658	0.843	0.662	1	0.730	0.602
'BSV'	0.675	0.706	0.789	0.722	0.775	0.596	0.666	0.773	0.631	0.624	0.768	0.625	0.733	1	0.573
'TED'	0.607	0.539	0.497	0.570	0.492	0.603	0.456	0.576	0.606	0.447	0.631	0.472	0.633	0.636	1

individual liquidity measures generated from each of the ETFs in order to extract a set of orthogonal components driving these individual liquidity measures.

Fig. 2 shows the percentage of the common variation of the individual liquidity measures that is explained by each of the orthogonal components generated by the PCA. This figure shows that almost three-fourths of the variation of the individual liquidity measures is explained by a single orthogonal principal component (PC1). The second and third principal components, PC2 and PC3, respectively, each explain less than 10% of the common variation.

In Table 7, we take the first three orthogonal components and test how they perform in the VIX regressions that we ran in Table 5. From the first regression we see that the VIX is not contemporaneously correlated with the primary orthogonal component. The second and third regressions allow us to conduct a Granger causality test. Because lagged values of the primarily orthogonal component

Table 4
Relationship between *BILLIQs* and measures of price impact. We report the correlation between our bond illiquidity time series and the illiquidity measure of Amihud (2002), as well as the absolute returns on an ETF of financial institutions (i.e., the XLF). The Amihud illiquidity measure is computed for the investment grade, high-yield, and combined bond returns. The measure is the absolute price return divided by trading volume for the day, and this is then averaged over the required period. Finally the measure is scaled by multiplying it by 10,000 to prevent the numbers from being too small. Return is calculated from daily price history where available, and is divided by the trading volume (approximated by the trading volume in share times the closing price. Since price impact increases with illiquidity, we expect the correlations reported here to be statistically significant. All correlations are positive and significant.

Ticker	Correlation with			
	Amihud (All US Bonds)	Amihud (Inv Grade)	Amihud (High Yield)	Abs (XLF)
LQD	0.73	0.66	0.66	0.63
HYG	0.75	0.80	0.58	0.49
CSJ	0.81	0.81	0.71	0.58
CFT	0.82	0.84	0.70	0.64
CIU	0.79	0.78	0.70	0.57
AGG	0.75	0.84	0.48	0.48
GBF	0.76	0.76	0.66	0.60
GVI	0.86	0.86	0.74	0.59
MBB	0.73	0.81	0.52	0.40
EMB	0.73	0.82	0.51	0.49
BIV	0.85	0.89	0.68	0.60
BLV	0.78	0.81	0.65	0.60
BND	0.89	0.92	0.73	0.64
BSV	0.89	0.91	0.74	0.58

do not seem to explain the VIX, while lagged values of the VIX do seem to explain the primary orthogonal component, it seems that volatility is a precursor to illiquidity—consistent with the predictions of the Chacko et al. (2008) model. Thus, this table lends evidence to the primary orthogonal component being a less noisy liquidity factor. The second principal component PC2 appears to be contemporaneously negatively correlated to the VIX (opposite in sign to PC1) but neither variable Granger causes the other. The third component PC3 has no relation to the VIX, not even contemporaneously.

We conduct a similar set of regressions with the Chacko liquidity measure and the primary orthogonal component in Table 8. The primary orthogonal component is significantly and highly contemporaneously correlated to the Chacko measure (ILLIQFAC) indicating that both seem to be capturing the same economic factor. The Granger regressions reveal that ILLIQFAC forecasts our new measure BILLIQ PC1, and both are related to lagged values of both measures, indicating that perhaps both are metrics of fundamental liquidity. The second principal component appears to have a similar relationship to ILLIQFAC, but of opposite sign to the first component, but the third component has no relationship to the Chacko measure at all.

3.3. Returns and illiquidity

Next, we do a check of whether our illiquidity measure detects liquidity risk in financial markets. We use the the US fixed-income markets as our test market. It is widely felt in practice that these markets have significant amounts of illiquidity—fewer than 50% of the securities in the credit markets trade in any given year, and less than 1% of the securities are traded every day. Therefore, we conjecture that there is considerable liquidity risk in these markets.

In Table 9 we regress returns of various bond indices, representing different sectors of the credit markets, against the bond illiquidity measure (in changes) from the aggregate bond index, AGG (a yield rate for illiquidity), and several other commonly used risk

Table 5
Relationship of *BILLIQ* to volatility. Results of each ETF *BILLIQ* on volatility. The regression equation is $BILLIQ_t = b_0 + b_1\ Volatility_t + \epsilon$. The three panels relate to three different volatility measures: VIX, 30-year bond futures implied volatility, and 10-year bond futures implied volatility. We report the coefficients, *t*-statistics, *R*-squares, and the *P*-values of the *F*-statistics. The Durbin–Watson (DW) statistic is reported after making a Cochrane–Orcutt correction, showing that there is no residual autocorrelation in errors. The number of observations for the VIX is 1683.

Ticker	b_0	b_1	b_0 tstat	b_1 tstat	R^2 (%)	*P*-value	DW
Panel A: VIX							
LQD	−27.8565	3.9112	(6.33)	20.19	11.00	0.00	2.34
HYG	74.7154	1.1527	5.03	2.07	0.20	0.04	2.48
CSJ	60.2540	−0.4095	4.63	(1.64)	0.12	0.10	2.51
CFT	−1.4917	2.9713	(0.23)	11.36	5.62	0.00	2.36
CIU	59.5740	−0.1163	5.06	(0.46)	0.01	0.64	2.42
AGG	2.3781	1.2533	0.91	10.63	3.63	0.00	2.27
GBF	10.5173	1.0840	3.35	8.46	3.21	0.00	2.30
GVI	−4.5537	1.5288	(1.51)	12.62	6.84	0.00	2.49
MBB	−0.8092	0.5179	(0.98)	15.12	9.70	0.00	2.30
EMB	17.1790	2.7765	1.76	7.19	2.61	0.00	1.96
BIV	−3.0091	1.6364	(1.04)	13.92	8.40	0.00	2.10
BLV	0.5857	1.6734	0.23	15.82	10.59	0.00	2.20
BND	−14.9892	1.8063	(6.32)	18.61	14.07	0.00	2.21
BSV	−6.4635	1.3061	(1.97)	9.86	4.40	0.00	2.45
Panel B: 30-year bond futures implied volatility							
LQD	8.9739	3.9171	1.37	6.99	1.48	0.00	2.45
HYG	41.4458	5.1753	2.32	3.73	0.67	0.00	2.47
CSJ	62.3454	−0.9690	4.65	(1.69)	0.13	0.09	2.50
CFT	−9.1390	6.3971	(1.02)	8.99	3.65	0.00	2.41
CIU	64.5536	−0.6667	5.13	(1.14)	0.06	0.25	2.42
AGG	5.2748	2.0393	1.41	6.18	1.28	0.00	2.31
GBF	−0.6368	3.0809	(0.15)	8.98	3.66	0.00	2.32
GVI	−5.9732	3.0604	(1.38)	8.80	3.50	0.00	2.54
MBB	−1.2772	1.0339	(0.97)	9.31	3.97	0.00	2.38
EMB	−9.2852	7.5124	(0.68)	6.92	2.46	0.00	1.97
BIV	5.4899	2.3853	1.19	6.39	1.93	0.00	2.18
BLV	−9.9269	4.1412	(2.49)	12.41	6.89	0.00	2.25
BND	−4.5811	2.5426	(1.12)	7.61	2.71	0.00	2.35
BSV	−11.3940	2.9413	(2.39)	7.61	2.71	0.00	2.51
Panel C: 10-year bond futures implied volatility							
LQD	6.6146	6.8598	1.03	7.54	1.73	0.00	2.45
HYG	29.0550	10.8840	1.75	4.87	1.13	0.00	2.46
CSJ	61.7124	−1.5845	4.66	(1.70)	0.14	0.09	2.50
CFT	−21.1176	12.9373	(2.64)	11.62	5.96	0.00	2.38
CIU	59.5213	−0.3777	4.91	(0.40)	0.01	0.69	2.42
AGG	−4.3004	4.9601	(1.25)	9.69	3.09	0.00	2.28
GBF	−2.7710	5.6672	(0.71)	10.16	4.64	0.00	2.30
GVI	−10.5416	6.0083	(2.65)	10.83	5.21	0.00	2.52
MBB	−3.6708	2.1605	(3.12)	12.63	7.08	0.00	2.33
EMB	−15.4973	14.1570	(1.26)	8.26	3.46	0.00	1.96
BIV	−2.0691	5.2991	(0.50)	9.04	3.79	0.00	2.15
BLV	−10.2718	7.2347	(2.73)	13.28	7.82	0.00	2.23
BND	−15.9486	6.1579	(4.59)	12.41	6.89	0.00	2.29
BSV	−19.4601	6.3411	(4.61)	10.63	5.15	0.00	2.46

factors in benchmark performance regressions. The regressions in this table are interpreted as factor models. We use them to test whether liquidity risk is priced as a factor or not, and whether we have a complete asset pricing model. In Panel *A* of the table, we use the difference in long-term and short-term Treasury returns to proxy for a risk-less bond market factor, and in Panel *B*, we use pure long-term Treasury returns. The results are similar across specifications.

As one would expect, the excess long-term Treasury return (Try LS, Panel A), and the long-term Treasury return (Try LT, Panel B), are important for explaining the returns of high credit quality corporate bonds. However, these interest-rate related factors become significantly less important as credit quality decreases; this is when the role of the equity markets ($R_m - R_f$ and SMB) becomes more important in explaining corporate bond returns. Equity market performance, while small and statistically insignificant in explaining investment grade bond returns, becomes large in

Table 6
Relationship of *BILLIQ* to another bond illiquidity measure. Results of regressing *BILLIQ* for each ETF on the reciprocal of the Chacko illiquidity measure. We denote this measure *ILLIQFAC*. The regression equation is $BILLIQ = b_0 + b_1\ ILLIQFAC + \epsilon$. We report the coefficients, *t*-statistics, adjusted *R*-squareds, and the *P*-values of the *F*-statistics. The construction of *ILLIQFAC* is described in Chacko (2009). The *ILLIQFAC* series is monthly and so we have regressed the average *BILLIQ* for each month on *ILLIQFAC*. The regressions have been adjusted for autocorrelation using the Cochrane–Orcutt correction. There are 156 observations of *ILLIQFAC*.

Ticker	b_0	b_1	b_0 tstat	b_1 tstat	*R*-sq (%)	*P*-value	DW
LQD	(128.69)	647.63	(1.49)	2.09	2.1	0.04	2.22
HYG	(482.32)	2,331.21	(5.67)	6.89	31.9	0.00	2.07
CSJ	(292.05)	1,397.47	(3.02)	3.62	10.6	0.00	1.36
CFT	(298.57)	1,457.90	(4.10)	5.02	19.2	0.00	1.85
CIU	(386.65)	1,786.36	(4.58)	5.32	21.1	0.00	1.64
AGG	(45.59)	265.38	(2.78)	4.44	11.6	0.00	2.29
GBF	(106.76)	564.39	(3.42)	4.54	16.1	0.00	2.19
GVI	(156.10)	739.14	(4.84)	5.76	24.0	0.00	2.24
MBB	(22.21)	131.37	(1.78)	2.63	5.6	0.01	2.11
EMB	(297.56)	1,506.52	(4.72)	6.00	27.8	0.00	1.99
BIV	(140.79)	696.45	(4.04)	5.01	19.6	0.00	2.06
BLV	(115.68)	611.21	(4.29)	5.70	24.1	0.00	2.03
BND	(126.50)	608.20	(4.01)	4.84	18.5	0.00	2.03
BSV	(154.57)	711.44	(3.68)	4.24	14.7	0.00	2.06

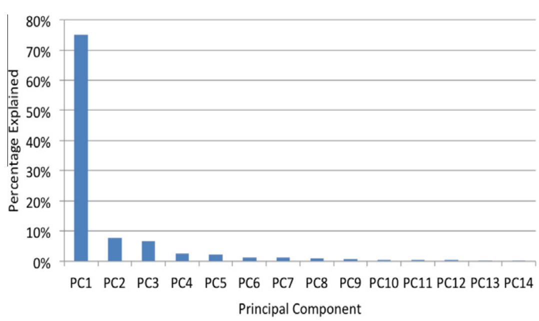

Fig. 2. Principal component analysis. A principal components analysis is undertaken using all the ETF *BILLIQ* measures. The data is daily. This figure presents the percentage of common variation explained by each principal component.

magnitude and statistically significant in explaining high yield bond returns. This is not surprising as all theoretical models of credit risk, beginning with the Merton (1974) model, predict that equity performance is a proxy for default risk. As one would expect, the decrease in the role of interest rate risk relative to credit risk is muted a bit as we move to longer maturity bonds, where longer durations would imply that interest-rate risk should matter more.

The most interesting result in the table is the role of liquidity risk in explaining bond returns. Changes in our illiquidity measure in Table 9, $\Delta BILLIQ_{AGG}$, is strongly statistically significant in all of the regressions for all sectors of high-yield bonds, and also for long-term investment-grade bonds, and only slightly less strong for shorter maturity investment-grade bonds. Its sign indicates that when illiquidity increases, the credit markets produce negative returns—as expected. The fact that the signs of the coefficients do not change—they are all consistently negative and significant—reinforces the notion that this measure is picking up something separate from simple equity or bond market performance (if not the sign would change as we go from investment-grade to high yield). The statistical significance of the $BILLIQ_{AGG}$ coefficients in corporate bond returns is an important result—it is an indication that liquidity risk is priced, i.e., that it is a systematic risk factor.

It is also interesting to see that though liquidity risk decreases in importance as default risk decreases, it remains a statistically significant component of the returns, especially of *all long-maturity* corporate bonds. This is likely because many financial institutions such as insurance companies and pension funds that buy credit instruments do so at the long end of maturity structure, for asset-liability matching reasons (in fact, these institutions are the majority of buyers in long-maturity instruments). Furthermore, because most of their liabilities are long-dated, these institutions tend to be buy-and-hold investors—thereby reducing liquidity in long-maturity bonds, even in investment-grade ones. Therefore, we see some evidence that the long investment horizon nature of the participants in certain markets tend to make those markets more susceptible to liquidity risk.

As a cross-check, in Panels C and D of Table 9 we replaced the BILLIQ factor with the first three principal components of the same factor, mirroring Panels A and B, respectively. The first principal

Table 7
The principal component and volatility. This table presents three regressions relating the first three principal components (PC1, PC2, PC3) of *BILLIQ* to the VIX. A principal components analysis is undertaken using all the ETF *BILLIQ* measures. The data is daily, and there is a common period spanning all the ETFs dates with data for all ETFs in the sample. We undertake three regressions for each PC here: (1) shows the lack of contemporaneous relationship of PC1 and VIX. (2) shows that PC1 is predictable using lagged values of VIX. (3) shows that VIX is predictable using its own lagged value but not that of PC1. Hence regressions (2) and (3) are Granger regressions suggesting that volatility forecasts illiquidity. (4) shows a strong negative contemporaneous relationship of PC2 and VIX. (5) shows that PC2 is not predictable using lagged values of VIX, but loads on its own lagged value. (6) shows that VIX is predictable using its own lagged value but not that of PC2. Hence, the second principal component is not Granger caused by VIX. (7–9) show that the VIX and the PC3 are not related in any way, though they are both autocorrelated. The numbers below the coefficient values are *t*-statistics. Results are reported after applying a Cochrane–Orcutt correction for autocorrelation.

Dependent variable	(1) PC1(t)	(2) PC1(t)	(3) VIX(t)	(4) PC2(t)	(5) PC2(t)	(6) VIX(t)	(7) PC3(t)	(8) PC3(t)	(9) VIX(t)
Intercept	−1.0897	−25.7458	0.5137	31.2569	3.0323	0.3492	−0.9947	−1.0087	0.3432
	−0.03	−7.17	3.94	4.06	1.49	3.55	−0.19	−0.37	3.53
VIX (t)	−0.0841			−1.4393			0.0517		
	−0.03			−4.6984			0.2374		
VIX ($t-1$)		1.1728	0.9766		−0.1424	0.9842		0.0505	0.9844
		7.54	173.05		−1.69	242.06		0.45	245.66
PC1 ($t-1$)		0.9266	0.0006						
		117.63	1.94						
PC2 ($t-1$)					0.8022	−0.0003			
					58.90	−0.4196			
PC3 ($t-1$)								0.5053	0.0000
								25.76	0.07
Adjusted R^2	−0.0005	0.9396	0.9688	0.0108	0.6517	0.9690	−0.0005	0.2553	0.9690
F-stat *p*-value	0.90	0	0	0	0	0	0.81	0	0
DW	2.38	2.03	2.01	2.21	2.01	2.02	2.02	2.00	2.02

Table 8
The principal component and the bond illiquidity measure. This table presents three regressions each relating the first three principal components of *BILLIQ* to the *ILLIQFAC* factor. A principal components analysis is undertaken using all the ETF *BILLIQ* measures. The data is daily and there is a common period spanning all the ETFs resulting in 1934 dates with data for all ETFs in the sample. The first principal component extracted is denoted PC1. The value of PC1 is then averaged monthly because the *ILLIQFAC* data is monthly – this results in 93 monthly observations. We undertake three regressions here: (1) shows the strong contemporaneous relationship of PC1 and *ILLIQFAC*. (2) shows that PC1 is predictable using lagged values of *ILLIQFAC*. (3) shows that *ILLIQFAC* is predictable using its own lagged value but not that of PC1. (4) shows a negative contemporaneous relationship of PC1 and *ILLIQFAC*. (5) shows that PC2 is predictable using lagged values of *ILLIQFAC*. (6) shows that *ILLIQFAC* is predictable using its own lagged value but not that of PC2.The numbers below the coefficient values are *t*-statistics. Regressions (7)–(9) show no relationship between ILLIQFAC and PC3. Results are reported after applying a Cochrane–Orcutt correction for autocorrelation.

Dependent variable	(1) PC1 (t)	(2) PC1 (t)	(3) ILLIQFAC (t)	(4) PC2 (t)	(5) PC2 (t)	(6) ILLIQFAC (t)	(7) PC3 (t)	(8) PC3 (t)	(9) ILLIQFAC (t)
Intercept	−1105.16	−1893.95	0.02	125.88	108.45	0.00	1.74	3.69	0.01
	−5.38	−6.19	2.00	3.33	3.16	0.66	0.06	0.18	0.97
ILLIQFAC (t)	4427.79			−509.25			−2.67		
	5.40			−3.39			−0.02		
ILLIQFAC ($t-1$)		7633.89	0.92		−438.14	0.98		−12.37	0.97
		6.29	23.07		−3.21	33.23		−0.16	33.80
PC_j ($t-1$)		−0.04	0.00		0.17	0.00		0.36	0.00
		−0.44	1.85		1.65	1.53		3.69	1.94
Adjusted R^2	0.2366	0.3013	0.9275	0.1034	0.1684	0.9263	(0.0111)	0.1146	0.9270
DW	1.99	2.00	2.04	1.97	2.00	2.09	1.99	1.98	2.16

component behaves in exactly the same way as does BILLIQ (which is not surprising given the results in Tables 7 and 8), showing the same sign, magnitude, and significance of coefficients. Interestingly, the third principal component mirrors the first, whereas the second one gives significant results but is opposite in sign. It does not appear that the various principal components capture any different aspects of liquidity.

We replicated the analyses in Table 9, but used six individual bonds instead. The bonds are for American Express (rated BBB2), Nucor (A3), Walmart (AA2), Cemex (B1), Sprint (B1), and Constellation (BB1). We reproduced Panels A and B of Table 9, and found that BILLIQ is significant also in explaining returns for individual bonds, though not at all as significant as we found with index returns. This is only to be expected, since individual bonds have less systematic risk, and are also much less frequently traded, and are expected to have liquidity effects that are less synchronous with returns than indexes would have. As expected BILLIQ is more significant for below investment grade bonds than for investment grade ones, mimicking the results for bond index returns in Table 9.[18]

Finally, we wanted to make sure that *BILLIQ* was not substitutable by other variables with which it may be related, such as the VIX. In order to check this, we included the VIX in our regressions explaining bond index returns. To examine whether Amihud's illiquidity measure would push out the *BILLIQ* we also included this variable in the regression. Panels E and F of Table 9 show the results, and correspond to Panels A and B with these additional controls. We see that the *BILLIQ* variable remains significant, and the VIX is also significant. The Amihud measure is not generally significant, but is so for investment grade returns but with the opposite sign. Therefore, it appears that our new illiquidity measure is robust to these controls.

3.4. Liquidity across markets

As our *BILLIQ* measure captures illiquidity, an interesting question arises as to how liquidity in the bond markets is related to liquidity in other markets. As a test, we calculate a liquidity measure in the equity markets in the exact same way as the *BILLIQ* measure and then compare the equity market liquidity measure against the bond market liquidity measure. We call the equity market liquidity measure *EILLIQ*, and we compute it using the S&P 500 iShares ETF.

Table 10 contains regressions of the liquidity measures generated using each of our fixed income ETFs on the liquidity measure generated by the equity ETF. For all but GVI and BSV, there is a statistically strong relationship between the equity market liquidity measure and bond market liquidity measures. However, the R^2s for all of the regressions are small indicating that much of liquidity risk is market specific and only a small component of liquidity measures are common across the bond and equity markets. An important implication of this is that while in theory the Merton (1974) model of credit risk predicts a tight relationship between equities and corporate bonds,[19] market-specific liquidity conditions in each market—particularly the corporate bond market—are one important reason that the empirical relationship is not as tight as one might expect.

In the second panel of Table 10, we conduct vector autoregressions (VARs) using the equity market liquidity measure and the bond market liquidity measure $BILLIQ_{AGG}$. We see from the VAR that there is a strong relationship between lagged values of both $BILLIQ_{AGG}$ and *EILLIQ* and the current value of $BILLIQ_{AGG}$. This relationship is also present and statistically significant between lagged values of both $BILLIQ_{AGG}$ and *EILLIQ* and the current value of *EILLIQ*; however, the R^2 for the latter regression is is very small. So to the weak extent that equity and bond market liquidity are linked, it appears that the bond market liquidity measure is driven by the equity market liquidity measure and to a lesser extent the other way around. The structural VAR confirms this result where equity market illiquidity has a greater impact on bond market illiquidity.

4. Liquidity Risk and Hedge Funds

It has been hypothesized that hedge funds earn a major portion of their returns from taking liquidity risk.[20] For example, convertible arbitrage and capital structure arbitrage involve taking a long

[18] Results not reported as tables in the text in order to prevent a huge increase in the number of tables.

[19] The Merton (1974) model predicts that equities and the credit portion of corporate bonds are simply a call option and a short put option, respectively, on the assets of the issuing firm. Because both the call and put have the same underlying—the enterprise value of the firm—they should be highly correlated.

[20] See for example Sadka (2009) and Chacko (2009). Additionally Fung and Hsieh (1997), Fung and Hsieh (2001) and Agarwal and Naik (2004) have considered the use of option-based factors to explain hedge fund returns. Because Chacko et al. (2008) shows that liquidity risk can be modeled as an option, these papers also imply that there could be a liquidity premium in hedge fund returns.

Table 9
Regression of bond index returns on pricing factors. Using the bond illiquidity measure for the aggregate bond market ETF (ticker: AGG), we regressed the BofA Merrill Lynch bond index returns for six series on the standard Fama–French factors, and the bond illiquidity series (denoted $BILLIQ_{AGG}$). The factors are the short-term risk free bond return (R_f), the excess performance of the equity market ($R_m - R_f$), the performance of small size firms relative to large size firms (SMB), the performance of high book-to-market ratio firms relative to low book-to-market ones (HML), and a bond market factor, Try LT-ST or Try LT Ret—Treasury long-term minus short-term return in Panel A, or Treasury long-term returns in Panel B. The regression is run on 3300 daily returns for the entire period spanned by the AGG ETF. The *F*-statistic for the regression is significant at the 99% level. The *F*-statistic for the incremental explanatory power of the changes in $BILLIQ_{AGG}$ series over the Fama–French factors is also significant at the same level. *t*-statistics are reported below the parameter estimates. We use six bond return series, all pertaining to US Corporates, investment grade and high-yield, further broken down into intermediate maturity and long-term bonds. The significant negative coefficient on $\Delta BILLIQ_{AGG}$ indicates that bonds perform poorly in illiquid markets. Results are reported after applying a Cochrane–Orcutt correction for autocorrelation. Panels C and D correspond to Panels A and B, but replace the BILLIQ variable with its three principal components. Results remain the same. Finally, Panels E and F correspond to Panels A and B, but with additional controls, i.e., the VIX and Amihud's illiquidity measure. Again, BILLIQ remains strong as an explanatory variable.

Independent variables	USCorp Inv grade All	USCorp Inv grade Intermediate	USCorp Inv grade Long Term	USCorp High Yield All	USCorp High Yield Intermediate	USCorp High Yield Long Term
PANEL A: Dependent variables						
Intercept	0.000146	0.000154	0.000134	0.000364	0.000350	0.000508
T-stat	2.75	3.21	1.72	3.23	3.16	3.89
R_f	−0.006012	−0.005265	−0.008868	−0.016198	−0.015261	−0.026527
T-stat	(0.99)	(0.95)	(0.99)	(1.25)	(1.20)	(1.77)
$R_m - R_f$	−0.000014	−0.000049	0.000114	0.000287	0.000277	0.000384
T-stat	(0.53)	(1.81)	3.55	7.45	7.38	6.95
SMB	−0.000017	0.000017	−0.000121	−0.000354	−0.000369	−0.000180
T-stat	(0.34)	0.33	(1.99)	(4.83)	(5.15)	(1.71)
HML	0.000026	0.000045	−0.000032	−0.000073	−0.000105	0.000268
T-stat	0.48	0.81	(0.48)	(0.91)	(1.34)	2.33
$\Delta BILLIQ_{AGG}$	−0.000008	−0.000007	−0.000014	−0.000016	−0.000016	−0.000020
T-stat	(6.94)	(5.48)	(10.06)	(9.38)	(9.46)	(8.18)
Try LS	0.411086	0.258030	0.868544	−0.010288	−0.025261	0.134351
T-stat	94.30	57.65	161.61	(1.59)	(3.99)	14.46
Adj R^2	77.50%	56.79%	90.85%	6.02%	6.77%	9.57%
DW	2.06	2.03	2.12	2.10	2.11	2.09
PANEL B: Dependent variables						
Intercept	0.000131	0.000142	0.000111	0.000364	0.000351	0.000505
T-stat	2.49	3.01	1.41	3.23	3.17	3.87
R_f	−0.009443	−0.007340	−0.016194	−0.016103	−0.015041	−0.027659
T-stat	(1.55)	(1.35)	(1.79)	(1.24)	(1.18)	(1.84)
$R_m - R_f$	0.000036	−0.000003	0.000193	0.000287	0.000276	0.000397
T-stat	1.57	(0.12)	6.39	7.43	7.32	7.14
SMB	−0.000066	−0.000011	−0.000221	−0.000353	−0.000366	−0.000195
T-stat	(1.53)	(0.24)	(3.86)	(4.81)	(5.11)	(1.85)
HML	0.000020	0.000041	−0.000018	−0.000073	−0.000106	0.000271
T-stat	0.43	0.81	(0.28)	(0.91)	(1.35)	2.36
$\Delta BILLIQ_{AGG}$	−0.000008	−0.000006	−0.000015	−0.000016	−0.000016	−0.000020
T-stat	(7.83)	(5.72)	(11.53)	(9.37)	(9.43)	(8.27)
Try Long-term	0.396063	0.255859	0.814148	−0.008802	−0.022868	0.125389
T-stat	110.75	66.85	172.60	(1.46)	(3.87)	14.48
Adj R^2	82.54%	63.53%	91.88%	6.01%	6.75%	9.58%
DW	2.09	2.05	2.13	2.10	2.11	2.09
PANEL C: Dependent variables						
Intercept	0.000223	0.000226	0.000224	0.000451	0.000436	0.000626
T-stat	3.18	3.62	2.19	2.98	2.92	3.64
R_f	(0.092739)	(0.079605)	(0.129896)	(0.153403)	(0.148778)	(0.200401)
T-stat	(3.46)	(3.32)	(3.31)	(2.64)	(2.60)	(3.03)
$R_m - R_f$	−4.68E-05	−8.25E-05	8.19E-05	0.000277086	0.00	0.00
T-stat	(1.52)	(2.59)	2.09	5.88	5.93	4.99
SMB	(0.000008)	0.000030	(0.000108)	(0.000449)	(0.000470)	(0.000229)
T-stat	(0.13)	0.49	(1.42)	(4.89)	(5.23)	(1.71)
HML	(0.000034)	(0.000016)	(0.000081)	(0.000090)	(0.000121)	0.000274
T-stat	(0.54)	(0.25)	(1.00)	(0.93)	(1.28)	1.95
$\Delta PC1$	(0.000004)	(0.000004)	(0.000007)	(0.000010)	(0.000010)	(0.000012)
T-stat	(6.98)	(5.64)	(9.41)	(10.23)	(10.19)	(8.74)
$\Delta PC2$	0.000005	0.000004	0.000005	0.000009	0.000009	0.000013
T-stat	6.10	5.60	5.50	8.02	7.87	7.74
$\Delta PC3$	(0.000004)	(0.000004)	(0.000003)	(0.000011)	(0.000010)	(0.000012)
T-stat	(6.37)	(6.33)	(4.46)	(12.34)	(12.34)	(9.89)
Try LS	0.37831	0.22609	0.83022	(0.02488)	(0.03722)	0.11151
T-stat	74.75	43.37	128.67	(3.20)	(4.88)	9.86
Adj R^2	78.25%	56.17%	91.11%	14.77%	15.58%	13.47%
DW	2.06	2.03	2.12	2.08	2.09	2.07
PANEL D: Dependent variables						
Intercept	0.000208008	0.000214836	0.000196864	0.000452178	0.000437	0.000623
T-stat	2.95	3.45	1.92	2.99	2.93	3.62
R_f	−0.100073041	−0.083697782	−0.14394165	−0.153032102	−0.148227337	−0.202379329
T-stat	(3.70)	(3.50)	(3.66)	(2.64)	(2.59)	(3.06)
$R_m - R_f$	0.000003	(0.000040)	0.000166	0.000275	0.000271	0.000352
T-stat	0.12	(1.33)	4.33	5.80	5.83	5.09

(*continued on next page*)

Table 9 (*continued*)

Independent variables	USCorp Inv grade All	USCorp Inv grade Intermediate	USCorp Inv grade Long Term	USCorp High Yield All	USCorp High Yield Intermediate	USCorp High Yield Long Term
SMB	(0.000063)	(0.000000)	(0.000220)	(0.000446)	(0.000465)	(0.000244)
T-stat	(1.17)	(0.00)	(2.97)	(4.86)	(5.17)	(1.82)
HML	(0.000018)	(0.000010)	(0.000018)	(0.000092)	(0.000124)	0.000283
T-stat	(0.32)	(0.16)	(0.23)	(0.95)	(1.31)	2.01
$\Delta PC1$	(0.000005)	(0.000004)	(0.000008)	(0.000010)	(0.000009)	(0.000012)
T-stat	(8.09)	(6.09)	(10.88)	(10.20)	(10.15)	(8.84)
$\Delta PC2$	0.000005	0.000004	0.000005	0.000009	0.000009	0.000013
T-stat	6.78	6.00	5.69	8.02	7.86	7.74
$\Delta PC3$	(0.000004)	(0.000004)	(0.000004)	(0.000011)	(0.000010)	(0.000012)
T-stat	(7.56)	(7.11)	(5.30)	(12.32)	(12.31)	(9.93)
Try Long-term	0.367760	0.226065	0.787711	(0.023394)	(0.035027)	0.104610
T-stat	85.08	49.13	132.66	(3.18)	(4.86)	9.77
Adj R^2	82.24%	61.71%	91.59%	14.77%	15.57%	13.39%
DW	2.07	2.04	2.13	2.08	2.09	2.07
PANEL E: Dependent variables						
Intercept	0.000755	0.000631	0.001130	0.002185	0.002149	0.002346
T-stat	6.64	6.05	6.83	9.15	9.16	8.43
R_f	−0.018434	−0.015589	−0.027123	−0.046436	−0.045395	−0.055174
T-stat	(2.91)	(2.70)	(2.93)	(3.46)	(3.44)	(3.55)
$R_m - R_f$	−0.000037	−0.000068	0.000079	0.000228	0.000219	0.000329
T-stat	(1.42)	(2.54)	2.45	5.89	5.80	5.92
SMB	−0.000021	0.000011	−0.000121	−0.000347	−0.000363	−0.000171
T-stat	(0.43)	0.22	(2.01)	(4.80)	(5.13)	(1.64)
HML	0.000009	0.000027	−0.000046	−0.000082	−0.000115	0.000263
T-stat	0.17	0.49	(0.69)	(1.03)	(1.48)	2.31
$\Delta BILLIQ_{AGG}$	−0.000008	−0.000007	−0.000014	−0.000016	−0.000015	−0.000020
T-stat	(6.99)	(5.53)	(10.05)	(9.26)	(9.35)	(8.06)
Try LS	0.411253	0.258212	0.868735	−0.009966	−0.024946	0.134858
T-stat	94.87	57.96	162.66	(1.56)	(3.99)	14.66
Amihud BILLIQ	0.006332	0.006667	0.004557	−0.000573	0.000202	−0.006051
T-stat	3.33	3.48	1.91	(0.20)	0.07	(1.47)
VIX	−0.000034	−0.000028	−0.000051	−0.000085	−0.000085	−0.000082
T-stat	(6.41)	(5.64)	(6.78)	(8.13)	(8.24)	(6.50)
Adj R^2	77.76%	57.20%	90.96%	8.29%	9.03%	11.38%
DW	2.06	2.03	2.12	2.12	2.12	2.10
PANEL F: Dependent variables						
Intercept	0.000815	0.000657	0.001206	0.002185	0.002149	0.002349
T-stat	7.24	6.45	7.24	9.15	9.16	8.45
R_f	−0.022860	−0.018193	−0.035545	−0.046341	−0.045173	−0.056353
T-stat	(3.64)	(3.22)	(3.81)	(3.45)	(3.42)	(3.63)
$R_m - R_f$	0.000011	−0.000024	0.000157	0.000229	0.000218	0.000342
T-stat	0.47	(0.95)	5.15	5.89	5.75	6.13
SMB	−0.000069	−0.000016	−0.000219	−0.000346	−0.000360	−0.000185
T-stat	(1.60)	(0.35)	(3.85)	(4.78)	(5.09)	(1.77)
HML	0.000006	0.000024	−0.000028	−0.000082	−0.000116	0.000267
T-stat	0.14	0.48	(0.45)	(1.04)	(1.49)	2.34
$\Delta BILLIQ_{AGG}$	−0.000008	−0.000006	−0.000015	−0.000016	−0.000015	−0.000020
T-stat	(7.86)	(5.78)	(11.49)	(9.25)	(9.32)	(8.14)
Try LT	0.396232	0.256042	0.814387	−0.008386	−0.022467	0.126099
T-stat	111.58	67.26	173.93	(1.41)	(3.86)	14.71
Amihud BILLIQ	0.005674	0.006376	0.003001	−0.000556	0.000244	−0.006242
T-stat	3.35	3.59	1.33	(0.19)	0.09	(1.52)
VIX	−0.000037	−0.000029	−0.000054	−0.000085	−0.000085	−0.000082
T-stat	(7.19)	(6.17)	(7.26)	(8.13)	(8.23)	(6.52)
Adj R^2	82.79%	63.93%	92.00%	8.28%	9.00%	11.42%
DW	2.08	2.04	2.14	2.12	2.12	2.10

The following indexes were used to construct this table:

Code	Description.
G1O2	The BofA Merrill Lynch 1-3 Year US Treasury Index.
G9O2	The BofA Merrill Lynch 10+ Year US Treasury Index.
C0A0	The BofA Merrill Lynch US Corporate Index.
C9A0	The BofA Merrill Lynch 10+ Year US Corporate Index.
C5A0	The BofA Merrill Lynch 1-10 Year US Corporate Index.
J0A0	The BofA Merrill Lynch US Cash Pay High Yield Index.
J9A0	The BofA Merrill Lynch 10+ Year US Cash Pay High Yield Index.
J5A0	The BofA Merrill Lynch 1-10 Year US Cash Pay High Yield Index.

Table 10
Bond market liquidity and equity market liquidity. Results of regressing *BILLIQ* for each ETF on equity market illiquidity as represented by *EILLIQ*. Equity market illiquidty is computed in the same way as *BILLIQ*, but the ETF used was the iShares S&P500 Equity Index (ticker IVV). The regression equation is $BILLIQ = b_0 + b_1\,EILLIQ + \epsilon$, and is run over 1682 observations. We report the coefficients, *t*-statistics, and adjusted R-squareds. These regression results are shown in Panel A. In Panel B, vector autoregressions are performed using $BILLIQ_{AGG}$ and *EILLIQ* as endogenous variables. Coefficients are reported, with *t*-statistics shown below each respective coefficient. Results are reported after applying a Cochrane–Orcutt correction for autocorrelation.

Ticker	b_0	b_1	b_0 tstat	b_1 tstat	Adj R-sq	DW
Panel A: Regressions of BILLIQ on EILLIQ						
LQD	45.7462	0.6214	13.68	13.21	5.00%	2.50
HYG	96.4169	0.6148	10.18	4.32	0.83%	2.49
CSJ	50.3207	0.2063	4.59	4.13	0.73%	2.51
CFT	59.8825	0.4162	10.23	5.58	1.37%	2.52
CIU	55.2334	0.3390	5.43	6.72	2.00%	2.43
AGG	25.2361	0.2057	17.08	6.72	1.45%	2.32
GBF	32.5642	0.2213	16.11	4.83	1.03%	2.40
GVI	27.8464	0.0621	10.43	1.64	0.08%	2.65
MBB	9.9290	0.0824	20.07	4.01	0.70%	2.45
EMB	74.9703	0.5929	11.99	4.28	0.89%	2.03
BIV	30.9772	0.2658	13.32	6.22	1.75%	2.25
BLV	35.0720	0.3229	20.07	5.63	1.43%	2.37
BND	22.1364	0.3528	11.20	8.72	3.43%	2.40
BSV	22.1208	−0.0668	8.53	(1.48)	0.06%	2.60

	Dependent variables VAR		Structural VAR	
Indep variables	$BILLIQ_{AGG}$	*EILLIQ*	$BILLIQ_{AGG}$	*EILLIQ*
Panel B: vector auto-regression				
Intercept	5.704	4.048	4.027	3.437
	11.20	15.57		
$BILLIQ_{AGG}$				0.107
EILLIQ			0.414	
$BILLIQ_{AGG}$ Lag1	0.728	0.070	0.699	−0.008
	57.69	10.84		
EILLIQ Lag1	0.227	0.132	0.173	0.108
	6.24	7.10		
Adj R-square	57.32%	7.47%		
F-statistic	2016.55	122.16		
F-stat *P*-value	0.0000	0.0000		

position in corporate bonds and short positions in equities. As a result, the asset and liability sides of a convertible arbitrage fund's or a capital structure arbitrage fund's balance sheet is heavily mismatched on liquidity—the corporate bonds are orders of magnitude more illiquid than equities.[21] Thus the fund bears significant liquidity risk, which is borne by the fund's investors, and a portion of the fund's return is fair compensation for bearing this risk. As another example, consider long-short equity funds. Most such funds are careful to have significantly more liquidity in their short positions than their long positions. This is because a short position can be called at any time, or there may be a sudden short squeeze in the markets, requiring the fund to liquidate a short position quickly. The risk of this need for transaction immediacy in turn compels funds to keep very liquid short positions – much more liquid, on average, than the liquidity of the median stock in the equity markets. As a result, the long positions of long-short equity funds are on average less liquid than the short position of these funds. As with convertible arbitrage, this liquidity mismatch in the balance sheet results in liquidity risk, which is borne by the equity capital, i.e., the fund's investors, and at least some portion of the fund's return is compensation for bearing this risk.

In fact, this liquidity mismatch is present in all funds that take long and short positions. Unless the long and short positions are carefully constructed so as to equate the liquidity of the long positions with the liquidity of the short positions—something very few funds do[22]—there will inevitably be a liquidity mismatch between the two. Therefore, virtually all funds taking long and short positions will have liquidity risk in their balance sheets, and a portion of all such funds' returns is simply fair compensation for bearing this risk.

We can use the liquidity risk measures developed in this paper to test the idea that hedge funds' returns can be attributed partly to bearing liquidity risk. To test this, we regressed the returns from eleven hedge fund strategies on our equity illiquidity measure, *EILLIQ*, as well as our wide bond market illiquidity measure, $BILLIQ_{AGG}$, to see whether hedge fund returns reacted adversely to liquidity shocks. We used data over the 2000–2015 time period. However, it is widely acknowledged that hedge funds greatly reduced the liquidity mismatch on their balance sheets soon after the financial crisis of 2008–2009 (by requiring greater liquidity in any positions held on the left hand sides of their balance sheets). Therefore, we split the sample into two time periods: 1) the time period before hedge funds increased the liquidity of their balance sheets, and 2) the time period after this change. We used the end of 2009 as the point at which this regime change occurred.

The results of regressing the various hedge fund strategies against $BILLIQ_{AGG}$ and *EILLIQ* are reported in Table 11 in Panels A and B (Panel A presents the pre-crisis results, while Panel B reports the post-crisis results). When illiquidity in the markets decreases hedge funds lose money, and when illiquidity increases they make money. Looking at the coefficients and *t*-stats associated with *EILLIQ* in Panel A, we see that all but two of the hedge fund strategies load in a strongly significant manner on the equity market illiquidity factor. This seems to indicate that the equity market illiquidity factor is strongly related to hedge fund performance as is widely hypothesized. The two strategies which are not strongly significant are dedicated short-bias funds and managed futures funds. The managed futures strategy generally confines itself to the very liquid parts of financial markets for both its long and short positions, and therefore its lack of dependence on the liquidity factor is expected and confirms that the liquidity factor is functioning as it should. Dedicated short-bias funds do not hold long positions; therefore, there can only be at best a small liquidity mismatch between the long and short positions on their balance sheets (the long positions are typically just cash). As a result, the lack of strong significance in the liquidity coefficient in this strategy is also very much expected.

Substantially fewer hedge fund strategies load significantly on fixed income liquidity factor, $BILLIQ_{AGG}$. Only two out of the eleven hedge fund strategy returns show strongly significant negative reactions to increases in bond market illiquidity. This seems to indicate that equity market illiquidity is substantially more important in explaining hedge fund performance than bond market illiquidity.

In looking at Table 11 and comparing the results in Panel B with those of Panel A, we see that after the financial crisis of 2009–2010, the amount of illiquidity decreased significantly. All of the *t*-stats on *EILLIQ* (as well as $BILLIQ_{AGG}$) drop substantially as we go from Panel A to Panel B. In addtion, the R^2 and *F*-stat values also drop substantially for each of the regressions in Panel B in comparison to those in Panel A. This seems to provide evidence for the widely rumored result that hedge funds substantially decreased the liquidity mismatch on their balance sheets immediately following the financial crisis. If hedge funds did not execute this rebalancing by decreasing the liquidity of the right hand sides of their balance

[21] See, for example, Edwards et al. (2007) and Chacko (2009).

[22] One reason for this is the lack of good liquidity risk measures.

Table 11
Hedge fund returns and liquidity risk. Results of regressing different hedge fund strategies, represented by the CS Tremont Hedge Fund sub-indices, against the $BILLIQ_{AGG}$ and *EILLIQ* measures, which capture aggregate bond market and equity market liquidity, respectively. In Panels A and B, the specific regression equations are of the form $Return_{Strategy} = b_0 + b_1\ BILLIQ_{AGG} + b_2\ EILLIQ + \epsilon$. Panel A uses data from 2000 thru 2009, while Panel B uses data from 2010 thru August, 2015. The table contains the coefficients, *t*-statistics, adjusted R-squareds, *F*-statistics, the *P*-values of the *F*-statistics, and Durbin–Watson statistics. In Panel C, the regression is expanded to include the Sadka liquidity factors and Fung–Hsieh hedge fund factors as well, and we do not split the data sample into pre- and post-crisis. Results are reported after applying a Cochrane–Orcutt correction for autocorrelation.

Strategy	b_0	b_1	b_2	b_0 tstat	b_1 tstat	b_2 tstat	R^2	*F*-stat	*P*-value	DW
PANEL A: PRE-CRISIS										
Convertible Arbitrage	0.0266	0.0000	(0.0025)	3.44	0.31	(4.68)	25.8%	12.33	0.000	2.10
Dedicated Short Bias	(0.0366)	0.0003	0.0022	(2.89)	1.34	2.10	12.5%	5.08	0.009	1.95
Emerging Markets	0.0464	(0.0003)	(0.0027)	5.78	(1.80)	(4.07)	30.1%	15.32	0.000	2.13
Equity Market Neutral	0.0545	(0.0009)	(0.0019)	5.37	(4.08)	(2.17)	33.0%	17.49	0.000	2.22
Event Driven	0.0199	0.0001	(0.0016)	4.08	0.92	(4.30)	21.3%	9.59	0.000	2.28
Fixed Income Arbitrage	0.0309	(0.0003)	(0.0016)	5.33	(3.29)	(3.79)	36.8%	20.68	0.000	2.06
Global Macro	0.0205	0.0000	(0.0013)	4.08	0.05	(3.20)	14.5%	6.02	0.004	1.93
Long Short Equity	0.0278	(0.0000)	(0.0021)	4.34	(0.15)	(3.95)	21.2%	9.57	0.000	2.10
Managed Futures	0.0008	0.0004	(0.0012)	0.09	2.11	(1.50)	6.5%	2.47	0.092	1.92
Multi-Strategy	0.0152	0.0002	(0.0017)	2.72	1.94	(4.69)	23.7%	11.01	0.000	2.16
CS/Tremont Blue Chip	0.0208	0.0000	(0.0017)	4.15	0.55	(4.43)	23.1%	10.68	0.000	2.23
PANEL B: POST-CRISIS										
Convertible Arbitrage	0.0118	0.0003	(0.0034)	2.44	1.07	(2.63)	10.0%	3.57	0.034	2.05
Dedicated Short Bias	(0.0250)	(0.0012)	0.0084	(1.57)	(1.34)	1.80	5.7%	1.93	0.154	1.94
Emerging Markets	0.0154	0.0009	(0.0066)	1.90	1.97	(2.79)	12.4%	4.52	0.015	1.97
Equity Market Neutral	0.0068	0.0000	(0.0016)	1.33	0.12	(1.03)	1.7%	0.57	0.570	1.99
Event Driven	0.0197	0.0005	(0.0065)	2.60	1.23	(3.20)	14.1%	5.25	0.008	2.10
Fixed Income Arbitrage	0.0086	0.0001	(0.0016)	3.21	0.98	(2.25)	7.7%	2.68	0.076	2.17
Global Macro	0.0042	0.0003	(0.0009)	1.11	1.52	(0.81)	3.6%	1.18	0.314	1.87
Long Short Equity	0.0181	0.0005	(0.0056)	2.30	1.21	(2.45)	8.8%	3.08	0.053	1.98
Managed Futures	0.0189	0.0003	(0.0056)	1.70	0.43	(1.67)	4.2%	1.41	0.251	1.94
Multi-Strategy	0.0142	0.0002	(0.0031)	3.40	0.91	(2.66)	9.9%	3.54	0.035	2.01
CS/Tremont Blue Chip	0.0139	0.0003	(0.0040)	2.79	1.16	(2.74)	10.6%	3.79	0.028	1.96

Strategy	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}	b_{11}	b_{12}	b_{13}	R^2	*F*-stat
PANEL C: PRE- AND POST-CRISIS																
Convertible Arbitrage	0.006	(0.000)	2.159	0.106	(0.002)	(0.011)	(0.011)	(0.001)	(0.001)	0.023	(0.095)	(0.007)	(0.045)	0.126	69.3%	16.71
Dedicated Short Bias	(0.005)	0.001	(1.848)	0.878	0.006	(0.001)	(0.009)	(0.012)	(0.007)	(0.621)	(0.523)	(0.011)	0.002	(0.064)	73.4%	20.33
Emerging Markets	0.004	(0.000)	2.930	0.093	(0.005)	(0.004)	(0.002)	(0.006)	0.007	(0.104)	(0.042)	(0.002)	(0.014)	0.398	89.9%	65.96
Equity Market Neutral	0.006	(0.002)	18.796	0.007	(0.100)	0.027	0.047	0.014	(0.004)	0.191	0.009	(0.007)	(0.026)	(0.026)	42.4%	5.43
Event Driven	0.005	(0.000)	2.159	0.111	(0.011)	0.013	(0.002)	(0.003)	0.001	0.068	0.033	0.022	(0.013)	0.123	78.0%	26.11
Fixed Income Arbitrage	0.008	(0.001)	1.440	(0.021)	0.001	(0.011)	0.008	(0.003)	(0.000)	0.079	(0.115)	(0.011)	(0.040)	0.057	66.9%	14.93
Global Macro	0.012	(0.001)	(2.143)	0.210	0.008	0.003	0.019	(0.005)	0.013	(0.077)	(0.128)	0.003	(0.008)	0.142	39.7%	4.87
Long Short Equity	0.003	(0.000)	0.725	0.157	(0.004)	0.006	0.002	0.001	(0.002)	0.088	0.033	0.021	(0.002)	0.236	86.3%	46.45
Managed Futures	0.013	(0.001)	(3.626)	0.370	0.041	0.030	0.046	(0.002)	0.027	(0.049)	(0.020)	0.031	0.020	0.165	25.5%	2.52
Multi-Strategy	0.007	(0.000)	2.551	0.126	(0.016)	0.003	(0.000)	(0.002)	0.003	0.020	(0.057)	0.007	(0.020)	0.125	79.3%	28.38
CS/Tremont Blue Chip	0.006	(0.000)	1.769	0.169	(0.007)	0.008	0.009	(0.002)	0.004	0.032	(0.017)	0.012	(0.011)	0.158	80.7%	30.90

Strategy	b_0	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}	b_{11}	b_{12}	b_{13}	DW
PANEL D: T-STATISTICS FOR PANEL C COEFFICIENTS															
Convertible Arbitrage	1.83	(1.43)	0.67	0.51	(0.16)	(1.26)	(0.96)	(0.21)	(0.08)	0.39	(1.53)	(0.87)	(5.01)	3.58	2.00
Dedicated Short Bias	(0.91)	1.01	(0.34)	2.52	0.30	(0.07)	(0.48)	(1.23)	(0.35)	(5.95)	(4.98)	(0.85)	0.16	(1.04)	2.01
Emerging Markets	1.90	(0.95)	1.31	0.65	(0.62)	(0.66)	(0.29)	(1.57)	0.81	(2.49)	(0.99)	(0.36)	(2.21)	16.20	2.00
Equity Market Neutral	1.01	(2.21)	2.33	0.01	(3.53)	1.23	1.82	1.06	(0.14)	1.39	0.06	(0.41)	(1.27)	(0.32)	2.03
Event Driven	2.08	(0.29)	1.15	0.93	(1.50)	2.66	(0.35)	(0.93)	0.13	1.87	0.93	4.69	(2.36)	5.68	2.10
Fixed Income Arbitrage	2.93	(2.36)	0.58	(0.13)	0.07	(1.61)	0.96	(0.69)	(0.04)	1.65	(2.41)	(1.84)	(5.56)	2.02	1.98
Global Macro	3.97	(1.83)	(0.74)	1.15	0.71	0.38	1.92	(0.92)	1.22	(1.42)	(2.32)	0.47	(1.00)	4.42	1.99
Long Short Equity	1.17	(0.55)	0.37	1.26	(0.58)	1.21	0.36	0.18	(0.21)	2.30	0.90	4.25	(0.41)	10.44	1.92
Managed Futures	1.99	(1.20)	(0.54)	0.86	1.65	1.64	1.99	(0.14)	1.09	(0.39)	(0.16)	1.90	1.07	2.24	1.99
Multi-Strategy	3.78	(2.29)	1.34	1.04	(2.27)	0.63	(0.01)	(0.54)	0.44	0.58	(1.55)	1.65	(3.74)	6.04	2.00
CS/Tremont Blue Chip	3.25	(1.87)	1.03	1.55	(1.02)	1.73	1.46	(0.49)	0.64	0.98	(0.52)	2.86	(2.20)	8.16	2.00

The various coefficients are as follows. b_0: intercept; b_1: EILLIQ; b_2: Sadka factor 1 (Fixed-Transitory); b_3: Sadka factor 2 (Variable-Permanent); b_4: Return of PTFS Bond lookback straddle; b_5: Return of PTFS Currency Lookback Straddle; b_6: Return of PTFS Commodity Lookback Straddle; b_7: Return of PTFS Short Term Interest Rate Lookback Straddle; b_8: Return of PTFS Stock Index Lookback Straddle; b_9: SPX Total return; b_{10}: Russell 2000 index monthly total return – Standard & Poors 500 monthly total return; b_{11}: change in the 10-year treasury constant maturity yield; b_{12}: change in the Moody's Baa yield less 10-year treasury constant maturity yield; b_{13}: MSCI Emerging Market index monthly total return. Note: These indexes were developed in: William Fung and David A. Hsieh, "The Risk in Hedge Fund Strategies: Theory and Evidence from Trend Followers," *Review of Financial Studies*, 14 (2001), 313–341. The data may be accessed at: http://faculty.fuqua.duke.edu/ dah7/DataLibrary/TF-FAC.xls. The script that produces this dataset can be found at https://github.com/tammer/scrapers/blob/master/hsieh.rb.

sheets (which is highly likely), then they must have achieved this rebalancing by taking on positions of much higher liquidity on the left hand sides of their balance sheets, which is the result that has been widely hypothesized.[23]

For robustness and completeness of our analysis, we also included in the baseline regression both the liquidity risk factors developed in Sadka (2006). In addition, we included ten hedge fund risk factors from Fung and Hsieh (2001). The results of the regressions are shown in Panel C of Table 11. Unfortunately, with so many liquidity factors, no conclusions can be drawn. Neither *EILLIQ* nor any of the liquidity factors from other papers are significant in systematically explaining any of the hedge fund strategies; however, there may be issues of multi-collinearity in these regressions. An interesting result to note is that the MSCI Emerging Markets index comes in as significant in explaining all but two of the hedge fund strategies. It is possible that this index is capturing market illiquidity better than any of the other liquidity factors and therefore subsumes all of the other factors. The levels of the coefficients of the MSCI Emerging Markets index in comparison to the levels of the other factors' coefficients seems to lend credence to this possibility.

5. Conclusion

Most papers that have generated and analyzed liquidity measures suffer from the problem that they are not able to fully filter out non-liquidity market risk factors. In fact, given the low correlations amongst the various liquidity factors generated by the different approaches in papers, it would appear that the signal-to-noise ratios for most liquidity measures are quite low.

In this paper, we created a liquidity measure in a way that tries to deal as effectively as possible with the noise created by non-liquidity factors. Our methodology involved creating a portfolio by going long and short the exact same set of securities. We created a liquidity measure by going long a traded index of securities and simultaneously going short the same individual securities that make up that index. Because we were going long and short the exact same set of securities, almost all systematic market risk factors had effectively been hedged away from the time series of the portfolio's equity value. We therefore interpreted the portfolio's equity value, which is the price difference between the very liquid index and the relatively illiquid components of the index, to be a liquidity measure—it was essentially a measure of the liquidity gap between the index and its underlying components. An appealing feature of this approach is that the formula may be applied each day and does not depend on a time series, or require a regression, nor does it depend on trading volume.

We performed a non-linear transformation of this long-short portfolio to create a liquidity measure that could be interpreted in a manner similar to an interest rate (i.e., a yield rate for illiquidity). We then applied this measure to a number of bond ETFs to create liquidity measures for various segments of the fixed income markets. While it is difficult to determine whether a risk factor truly represents liquidity risk, we conducted a number of checks. We found high correlations between our illiquidity measures for various fixed-income markets, even though the return correlation in these markets' ETFs is low. Our new measure of bond illiquidity correlated well with measures of price impact, i.e., the Amihud (2002) illiquidity measure, and the absolute return on XLF, a financial institutions' ETF. Our illiquidity measure is related to market volatility (VIX), the TED spread, and the Chacko (2009) measure of latent liquidity. A principal components analysis of our bond illiquidity measures revealed a principal component that explained two-thirds of the common variation, supporting the existence of systematic illiquidity in bond markets. Bond illiquidity correlated significantly with equity market illiquidity, with the latter tending to lead the former. Bond illiquidity was priced, in that it explained the returns on bond indices (investment-grade and high-yield) even after controlling for several other asset-pricing factors.

Finally, we used our liquidity risk measures to test whether hedge funds are exposed to liquidity risk and found compelling evidence that these funds are indeed significantly exposed to liquidity mismatch in their long and short positions.

The shortcoming of this measure is that it may only be constructed for asset classes on which ETFs trade. Therefore, illiquid asset classes such as private equity, hedge funds, and real estate are currently out of the scope of this measure. However, with the expanding coverage of asset classes by ETFs, this limitation may be mitigated over time. In conclusion, we found that the formula derived in this paper appears to have substantial merit for measuring liquidity and generating a liquidity factor. There are close to a thousand ETFs covering many markets; therefore, this approach has the potential to be applied very widely.

[23] A more careful examination of this rebalancing is out of the scope of this paper; therefore we leave this as a hypothesis to be followed up in more detail in another paper.

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