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Abstract

This paper investigates whether investors are compensated for taking on commonality risk in equity portfolios. A large literature documents the existence and the causes of commonality in illiquidity, but the implications for investors are less well understood. In a more than fifty year long sample of NYSE stocks, we find that commonality risk carries a return premium of around 2.6 per cent annually. The commonality risk premium is statistically and economically significant, and substantially higher than what is found in previous studies. It is robust when controlling for illiquidity level effects, different investment horizons, as well as variations in illiquidity measurement and systematic illiquidity estimation.

1 Introduction

Coinciding trading decisions across stocks, both among buy-side investors (liquidity demanders) and market makers (liquidity suppliers) cause comovement in illiquidity across stocks. Just as correlation in stock returns is important for expected portfolio returns, commonality in stock illiquidity is important for expected trading costs. At market downturns, the need for fast liquidation of positions increases as investors turn to safer assets. Stocks that turn illiquid at such times thus increase the expected trading cost, and will not attract investors unless they carry a return premium. The aim of this article is to quantify the commonality risk premium.

The commonality in stock market illiquidity is first documented by Chordia et al. (2000) and Huberman and Halka (2001) for NYSE stocks. Following their findings, an extensive literature confirms the existence of commonality in illiquidity in equity markets (see, e.g., Korajczyk and Sadka, 2008; Pástor and Stambaugh, 2003), as well as in other asset classes. Commonality is also found on numerous international stock markets by Brockman et al. (2009) and Karolyi et al. (2012). Overall, there is overwhelming evidence of the existence of commonality in illiquidity, and this is robust across differences in samples, data frequencies, illiquidity dimensions and estimation techniques. Furthermore, Kamara et al. (2008) show that commonality in illiquidity on US stock markets is increasing over time.

Given the number of studies focusing on the existence of commonality, the literature on implications of commonality is surprisingly small. The liquidity-adjusted capital asset pricing model (LCAPM; Acharya and Pedersen, 2005) demonstrates that commonality risk, the risk that an asset turns illiquid when the market as a whole turns illiquid, should indeed carry a return premium. Nevertheless, empirical evidence by Acharya and Pedersen (2005), Lee (2011), and Hagströmer et al. (2013) indicates that the commonality risk premium on US stock markets is close to zero. This mismatch between theoretical and empirical evidence motivates the current study.

The empirical studies that address the pricing of commonality risk sort portfolios on illiquidity level rather than commonality risk. In that setting, the commonality risk premium is reported as negligible. Our evidence shows that commonality risk is highly correlated to illiquidity level. Given that correlation, the return differences between portfolios sorted by illiquidity level may include compensation for both illiquidity level and commonality risk. The low commonality risk premium reported in previous studies may thus be misleading. In this study, we apply a double-sorting procedure to separate the illiquidity level premium from the commonality risk premium. Controlling for the illiquidity level, we report a commonality risk premium that is both economically and statistically significant.

Several studies rely on the existence of a systematic illiquidity factor and investigate how stock return comovement with systematic illiquidity affects expected returns (Amihud et al., 2015; Asparouhova et al., 2010; Brennan et al., 2013; Hasbrouck, 2009; Korajczyk and Sadka, 2008; Liu, 2006; Pástor and Stambaugh, 2003; Sadka, 2006). This line of research has delivered mixed evidence of a systematic illiquidity risk premium, but its link to commonality risk is vague. Whereas they investigate the comovement between systematic illiquidity and individual asset returns, commonality risk is defined as the comovement of systematic illiquidity and individual asset illiquidity.

Commonality risk estimates are subject to measurement error from at least three sources: measurement of individual asset illiquidity, estimation of systematic illiquidity, and estimation of the exposure of asset illiquidity to systematic illiquidity. We address these sources of measurement error in several ways. Firstly, we measure individual asset illiquidity as relative effective spreads (market tightness) and as price impact (market depth). Our main investigation is based on monthly illiquidity approximations, estimated from daily data on US stocks for the period December 1962 - December 2012. In robustness tests we also consider intraday data to measure illiquidity with higher accuracy, but for a shorter sample period. We consider three different systematic illiquidity estimators. The estimators are essentially different approaches to form weighted averages across stocks, including equal-weights, value-weights, and principal components. Finally, we consider different specifications of the regression model underlying the estimation of commonality risk, including daily and monthly illiquidity data frequencies. Overall, we find that our results are robust to these variations in illiquidity measure, data frequency, estimators as well as regression models.

The reason that commonality in illiquidity exists, according to Coughenour and Saad (2004), is that suppliers and demanders of liquidity are exposed to similar underlying risk factors affecting all securities. For example, the cost of capital is a determinant of the cost of providing liquidity, implying that interest rate changes affect liquidity across all securities. Theoretical support for supply-side explanations is provided by Brunnermeier and Pedersen (2009), who show that illiquidity commonality is particularly strong in down markets, where more investors hit their funding constraints, and therefore have to unwind their positions simultaneously. Cespa and Foucault (2014) show that illiquidity may be contagious because illiquidity in one asset makes the price information of that asset more noisy, which lead dealers of related assets to lower their liquidity supply. In contrast, Karolyi et al. (2012) present empirical evidence that is more consistent with demand-side explanations of commonality, e.g., higher observed commonality in times of market downturns, high market volatility and positive investor sentiment. Several articles show that commonality in illiquidity is induced by correlated actions taken by specific trader groups, such as mutual funds (Koch et al., 2012); program traders (Corwin and Lipson, 2011); and institutional investors and index traders (Kamara et al., 2008). Pascual et al. (2004) show that both the immediacy and the depth dimensions need to be considered to understand commonality in either one dimension. We think that the literature on the causes of commonality, just as the literature on its existence, is well developed. We argue, however, that research on the implications of commonality in illiquidity is scarce.

In the next section we provide a review of the theoretical framework showing that commonality risk should be priced. We also discuss the concept of systematic illiquidity and review the literature on the existence and estimation of commonality in illiquidity. In Section 3 we present our main investigation, a portfolio strategy assessing whether commonality risk carries a return premium. Section 4 holds robustness tests with respect to systematic illiquidity estimators, illiquidity measurement, and commonality risk estimation methods. Section 5 provides concluding remarks.

2 Literature on commonality risk

The implications of commonality in illiquidity are interesting to study from an investor perspective for two reasons. Firstly, the LCAPM by Acharya and Pedersen (2005) shows theoretically that commonality risk influences expected returns. Secondly, the multitude of studies showing the existence of commonality in illiquidity is in itself an indication of its importance. Pástor and

Stambaugh (2003, p.657) argue that the existence of commonality in illiquidity *"enhances the prospect that marketwide liquidity represents a priced source of risk"*. In this section we first present the theoretical foundation for commonality in illiquidity and its influence on asset returns. We then review the empirical literature on the topic.

2.1 The LCAPM

According to the LCAPM, the conditional expected gross return of security i is:

$$E_t\left[r^i_{t+1}\right] = r^f + E_t\left[c^i_{t+1}\right] + \lambda_t\beta_{1t} + \lambda_t\beta_{2t} - \lambda_t\beta_{3t} - \lambda_t\beta_{4t}, \tag{1}$$

where r^i is the security return, c^i is the security illiquidity cost, and r^f is the risk-free rate. The risk premium λ is defined by:

$$\lambda_t \equiv E_t\left[r^m_{t+1} - c^m_{t+1} - r^f\right],$$

where r^m and c^m are the return and the relative illiquidity cost of the market portfolio. Both the expected return and the risk premium are thus adjusted for expected illiquidity costs. The betas represent systematic sources of risk, defined as:

$$\beta_{1t} = \frac{cov_t\left(r^i_{t+1}, r^m_{t+1}\right)}{var_t\left(r^m_{t+1} - c^m_{t+1}\right)}$$

$$\beta_{2t} = \frac{cov_t\left(c^i_{t+1}, c^m_{t+1}\right)}{var_t\left(r^m_{t+1} - c^m_{t+1}\right)}$$

$$\beta_{3t} = \frac{cov_t\left(r^i_{t+1}, c^m_{t+1}\right)}{var_t\left(r^m_{t+1} - c^m_{t+1}\right)}$$

$$\beta_{4t} = \frac{cov_t\left(c^i_{t+1}, r^m_{t+1}\right)}{var_t\left(r^m_{t+1} - c^m_{t+1}\right)}.$$

The first beta reflects the traditional market risk. The three additional sources of risk are interpreted as different forms of illiquidity risk, with β_2 representing commonality risk. Commonality risk is the risk of holding a security that becomes illiquid when the market in general becomes illiquid. The positive sign of β_2 in Eq. (1) indicates that investors require compensation in terms of extra expected return for holding a security with commonality risk. The other two illiquidity betas reflect the risk of holding a security that yields a low return in times of high systematic illiquidity, and the risk of holding a security that turns illiquid when market returns are negative.

2.2 Empirical studies establishing commonality in illiquidity

In Table 1 we present a sample of the current empirical literature on equity market commonality in illiquidity, highlighting how the studies differ in research design.[1] Panel A presents studies that focus on the US equity market; Panel B holds studies on developed markets in Asia, Europe and Australia; and Panel C includes two cross-country studies that compare commonality in 47 and 40 countries, respectively. The time periods studied vary widely, from one month to 43 years.

[Insert Table 1 here]

Table 1 shows that virtually all empirical papers find that there is commonality in illiquidity. To our knowledge, the only exception is Hasbrouck and Seppi (2001), who study commonality in the very short term, 15-minute periods. In that setting, they find no significant commonality in the variation of bid-ask spreads. In spite of the near consensus with respect to results, the literature is methodologically diverse. In addition to sample differences, we identify three key variations in research design:

1. *Illiquidity measurement:* Most studies measure illiquidity either as market tightness or market depth. Market tightness is typically estimated as either the quoted or the effective bid-ask spread. The highest accuracy in spread measurement requires intraday data, but several approximation methods using daily data are available. Similarly, full limit order book data facilitates market depth measurement. In low-frequency settings many studies use the *ILLIQ* ratio proposed by Amihud (2002).

[1] For brevity, we restrict the overview here to studies on equity markets. For evidence in other asset classes, see Goyenko and Ukhov (2009) for bonds, Mancini et al. (2012) for foreign exchange, Marshall et al. (2013) for commodities, and Cao and Wei (2009) for options.

2. *Systematic illiquidity estimation:* Systematic illiquidity is some unobservable factor that influences the illiquidity of several assets simultaneously, inducing commonality. Systematic illiquidity is typically estimated as a weighted average of individual illiquidity across stocks. We refer to the weighting schemes for such averages as systematic illiquidity estimators. The most common approach is to give all stocks equal weights, but several studies also consider weights based on market capitalization (value-weighting) and principal components.

3. *Data frequency:* Typically, commonality is assessed by regressing individual stock illiquidity on systematic illiquidity and various control variables. The degree of commonality is then calculated as either the mean exposure to systematic illiquidity, or the mean explanatory power of the regressions. Following the pioneering paper by Chordia et al. (2000), the most common data frequency for such regression analysis is daily. Some papers, however, use intraday (e.g., Hasbrouck and Seppi, 2001) or monthly illiquidity measures (e.g., Korajczyk and Sadka, 2008).

Even though these differences in research design seem to lead to the same conclusion with respect to the existence of commonality, it remains an open question what approach is best suited when assessing investor valuation of commonality risk.

2.3 Empirical studies on the commonality risk premium

The LCAPM support for a commonality risk premium in combination with the abundant evidence on the existence of commonality motivates empirical research on the commonality risk premium. Surprisingly, the current literature shows that commonality has only a small influence on expected returns, if any. In their empirical investigation Acharya and Pedersen (2005) estimate an unconditional version of the LCAPM, finding that the annualized compensation for bearing commonality risk is economically insignificant at 0.08%. In an empirical assessment of the conditional LCAPM, Hagströmer et al. (2013) find an even lower commonality risk premium, estimated at 0.02%-0.04% per year. Further evidence is available in Lee (2011), who estimates an unconditional international LCAPM and finds that the compensation for commonality risk is statistically insignificant for the US market and for developed markets (but significant for emerging markets).

The evidence in Acharya and Pedersen (2005) and Hagströmer et al. (2013) is based on portfolios sorted by the level of illiquidity. That sorting procedure is appropriate for understanding the illiquidity premium in general, but it is not geared to identify a commonality risk premium. In this article we sort stocks by their commonality risk and study the return differential between high and low commonality risk portfolios. Reflecting the diversity in research design in the commonality literature seen in Table 1, we also consider variations in illiquidity measurement, systematic illiquidity estimation, and data frequencies for estimating commonality risk.

3 Does commonality risk matter to investors?

We use a portfolio approach to investigate whether commonality risk carries a return premium. The research design for our main results can be described in five steps. (1) Use daily data to measure two dimensions of monthly illiquidity, market tightness and market depth. (2) Estimate systematic illiquidity using the most commonly applied estimator, the equal-weighted average. (3) Use regression analysis to estimate commonality risk for each stock and each month. (4) Rank stocks by their commonality risk and divide them into decile portfolios. (5) Evaluate whether high commonality risk portfolios carry higher excess returns than low commonality risk portfolios.

This section shows the implementation of the five steps above in detail. Section 4 reports how variations in the different steps influence the end results.

3.1 Data

We use data from the Centre for Research in Security Prices (CRSP) to construct our proxies of illiquidity on monthly frequency. For all eligible stocks we retrieve daily closing prices and daily dollar trading volumes. We also retrieve monthly closing prices (for data filtering), monthly market capitalization, and monthly returns (adjusted for dividends). Our sample period includes 601 months, December 1962 – December 2012. For the same period, we also obtain monthly data on the market return factor and the risk-free rate of interest from Kenneth French's website. For a stock to be included in our analysis on a particular date, it should have share code 10 or 11. This excludes certificates, American depository receipts, shares of beneficial interest, units, companies incorporated outside the US, American trust components, closed-end funds, preferred stocks and REITs. To avoid differences in trading protocols across exchanges, we limit our sample to stocks with their primary listing at NYSE throughout the year. Finally, because the $1/8 minimum tick size adds substantial noise to the returns on low-priced stocks, we include stocks priced $5 or higher only.

3.2 Illiquidity measurement

We use two different measures of illiquidity, effective spread and price impact. For our main empirical analysis we use the effective tick by Holden (2009) to approximate the effective spread, and the ILLIQ ratio by Amihud (2002) to approximate price impact. In horseraces of several liquidity proxies, Goyenko et al. (2009) find effective tick and ILLIQ to be well suited to represent market tightness and market depth, respectively.[2]

Holden's (2009) measure of illiquidity builds on the empirical observation that trade prices tend to cluster around specific numbers, i.e., what is usually labeled rounder numbers (Harris, 1991; Christie and Schultz, 1994). On a decimal price grid, whole dollars are rounder than quarters, which are rounder than dimes, which are rounder than nickels, which are rounder than pennies. Harris (1991) gives a theoretical explanation for such price clustering. He argues that price clustering reduces negotiation costs between two potential traders by avoiding trivial price changes and by reducing the amount of information exchanged. To derive his measure, Holden (2009) assumes that trade is conducted in two steps. First, in order to minimize negotiation costs traders decide what price cluster to use on a particular day. Then, traders negotiate a particular price from the chosen price cluster. His proxy for the effective spread thereby relies on the assumption that the effective spread on a particular day equals the price increment of the price cluster used that day.[3]

[2]For market tightness, the Gibbs sampler estimator by Hasbrouck (2009) is an alternative to the effective tick. As Hasbrouck's (2009) measure is available only at an annual frequency, we use monthly estimates of Holden's (2009) effective tick proxy in this study.

[3]For the NYSE and AMEX stock used in this study, the possible price clusters are at $1/8, $1/4, $1/2 and $1 before July 1997, at $1/16, $1/8, $1/4, $1/2 and $1 from July 1997 up to January 2001, and at $0.01, $0.05, $0.10, $0.25 and $1 after January 2001.

Monthly Holden measures are formed as the time-series average across days in each month.

The ILLIQ ratio by Amihud (2002) relates daily absolute returns to daily trading volumes measured in dollars. Following the logic that deep markets are able to absorb large trading volumes without large price changes, this ratio is a proxy for market depth. We form monthly ILLIQ measures as the time-series average across days in each month, excluding days with zero volume (for which the ratio is undefined).

Due to the persistence of illiquidity over time, innovations in illiquidity are required for the commonality investigation. We calculate monthly illiquidity innovations as the first difference of the level illiquidity series. As both illiquidity measures are in terms of percent, the nominal innovations are in units of percent. The use of percentage changes in commonality regressions follows the specification of Chordia, Roll, and Subrahmanyam (2000). The illiquidity innovations are cross-sectionally winzorized, meaning that the observations beyond the 0.5% and 99.5% quantiles in each day are set equal to the 0.5% and 99.5% quantiles respectively.

Table 2 shows descriptive statistics for the number of eligible firms each month, the monthly level and innovation of effective spreads and price impacts, and the monthly market capitalization and turnover of eligible firms.

[Insert Table 2 here]

The number of firms eligible for analysis varies between 1134 and 2253, and averages 1781. Effective spreads are on average 0.89%. This implies that a trade of $100 would incur a cost of immediacy amounting to 89 cents, provided that the depth at the BBO can absorb the trade value. Due to the well-known effects of decimalization of tick sizes, automatization of trading systems, and financial innovation, effective spread innovations are negative on average in our sample. The ILLIQ ratio expresses the price impact of a one million dollar trade, amounting to 16.99% on average in our sample. The ILLIQ measure is however known to have large positive outliers, making the median a more appropriate central measure at 1.69%. As shown by the standard deviation, the price impact variation is much higher than that of effective spreads. Untabulated results show that the correlation between effective spreads and ILLIQ (across both time and cross-section) is 0.50.

As reference information, Table 2 also includes information on monthly market capitalization and monthly turnover of the stocks in our sample. Firm size varies widely, between \$0.4 million and \$581 billion, and is almost \$2.4 billion on average. The monthly stock turnover averages 16.7% of the market capitalization.

3.3 Commonality estimation

To estimate commonality risk for each stock and each month we run regressions on monthly illiquidity innovations. Following common practice in estimating market betas, we apply a 60 months moving estimation window (see, e.g., Groenewold and Fraser, 2000). To make the most of our sample, however, we begin the estimation in December 1965 using a 36 months estimation window, which is then expanded by one month for each month up until December 1967. Following Chordia et al. (2000) we include market return as a regressor to remove spurious dependence between return and liquidity measures. The estimated regression equation is thus

$$l_t^i = \alpha_i + \beta_{i,l} l_t^m + \beta_{i,r} r_t^m + u_t^i, \tag{2}$$

where l^i and l^m denote innovations in illiquidity of security i and systematic illiquidity, r^m is the market return, α_i is an intercept, $\beta_{i,l}$ is the commonality beta, $\beta_{i,r}$ is the illiquidity market beta, and u^i is the residual.

For any given month in each estimation window, we estimate the systematic illiquidity innovation as the equal-weighted average of illiquidity innovations of stocks that have no missing values in the estimation window. During 60 months, many stocks enter and exit the sample. By restricting the sample of stocks used for systematic illiquidity estimation to stocks that are available throughout the estimation window, our systematic illiquidity estimator is unaffected by time-variation in the sample size. We consider alternative estimators in Section 4.

For a stock to be included in the commonality regression analysis, we require it to have at least 30 non-missing illiquidity observations in the estimation window. The requirement for a stock to be included in the commonality analysis is thus less restrictive than the requirement to be included in the systematic illiquidity estimator.

The commonality regression analysis can be used to study either the stock illiquidity sensitivity to systematic illiquidity ($\widehat{\beta_{i,l}}$), or to assess how much of the variation in asset illiquidity is due to systematic illiquidity variation (R^2 of the regressions). Both metrics are referred to as commonality in illiquidity in the literature (see, e.g., Karolyi et al., 2012; and Brockman et al. 2009). To keep the metrics apart, we refer to the average R^2 of the regressions (averaged across stocks for each estimation window) as the degree of commonality, and to $\beta_{i,l}$ as the commonality beta or commonality risk. In the portfolio application pursued below, the commonality betas are used for portfolio formation.

Table 3 presents the results of the monthly commonality regressions based on effective spread (Panel A) and price impact (Panel B). We calculate monthly averages across all firms and report time series averages for three subperiods as well as for the full sample. In the columns of Table 3, we present the R^2 and $\widehat{\beta_{i,l}}$ commonality metrics, along with the fraction of $\widehat{\beta_{i,l}}$ each month that are positive, and positive and statistically significant at the 5% level. Furthermore, we report the number of stocks eligible for the regression analysis and the systematic illiquidity estimation, respectively.[4]

[Insert Table 3 here]

For effective spreads, we find that the degree of commonality is stable over time, varying between 0.042 and 0.059 and averaging 0.052. The average illiquidity sensitivity to systematic illiquidity ($\beta_{i,l}$) lies between 1.0 and 1.1. For price impact coefficients, the degree of commonality is decreasing over time, with average R^2 at 0.165 in Dec. 1965 - Dec. 1980, 0.118 in Jan. 1981 - Dec. 1995, and 0.094 in Jan. 1996 - Dec. 2012. The commonality betas are also decreasing over time. The commonality betas for both illiquidity measures exceed one on average. This is because the criterion for inclusion in the systematic illiquidity estimation is more restrictive than for the commonality regressions, leading to more illiquid stocks being included in the latter.

Commonality in illiquidity is in general explained in the literature by both demand-side and supply-side effects. Demand-side effects include index funds that buy and sell several stocks simultaneously in accordance with fund inflows and outflows (Koch et al., 2012). Supply-side ef-

[4] For brevity, the other coefficients estimated in the commonality regressions are not reported in Table 3.

fects include factors related to the cost of market making, such as interest rates, inventory costs and asymmetric information costs (Brunnermeier and Pedersen, 2009; Kamara et al., 2008; Karolyi et al., 2012). Given that none of the suggested rationales for illiquidity comovement suggests that a stock has a negative correlation with systematic illiquidity, the high prevalence of positive betas (on average 72.2% and 88.3% for effective spread and price impact, respectively) is in line with expectations.

The monthly illiquidity proxies are subject to estimation errors, and such estimation errors naturally carry over to commonality betas. As shown in Table 3, the commonality beta is positive and significant (at the 5% level) in only 16 % of the cases for the effective spreads, and 40% of the cases for the price impact. By improving the accuracy in illiquidity measurement, the statistical significance of commonality risk estimates can be improved. We pursue that in Section 5.

To investigate whether commonality betas matter to investors it is important to be able to disentangle commonality effects from effects of other variables. Acharya and Pedersen (2005) show that the correlations between commonality betas and other liquidity risks are low at the individual stock level. They report correlations to the individual return-marketwide illiquidity beta at -0.07 and to the individual illiquidity-marketwide return beta at -0.27. We show, however, that commonality betas are strongly correlated to level illiquidity. The rightmost columns of Table 3 show that the Pearson (Spearman rank) correlation between commonality beta and illiquidity is 0.39 (0.42) for effective spread and 0.55 (0.85) for price impact. Thus, we have to control for illiquidity effects in our portfolio application.

3.4 Commonality beta portfolios

To evaluate whether stocks with high commonality betas carry a return premium relative to stocks with low commonality betas we form portfolios based on commonality betas. For each month from December 1965 to November 2008, we form ten portfolios with different commonality betas. To control for level illiquidity, we first divide the sample of stocks into 50 illiquidity groups. For each of those 50 groups, we rank constituent stocks by their commonality beta and put the top decile in a high commonality portfolio, the second decile into another commonality portfolio, and so on. In this way, we retrieve 10 portfolios for each month with different commonality betas and with stocks sampled from 50 different levels of illiquidity. To avoid stocks with large estimation errors in the commonality betas, we exclude all stocks that have negative commonality betas in the portfolio formation month.

We form portfolios at the end of each month, using only data available at that time for illiquidity measurement and commonality beta estimation. The holding period is set to one month. For example, portfolios based on commonality betas in December 1965 are held for the duration of January 1966. At the end of January 1966, new rankings are made and new portfolios are formed and held for one month, and so on (we consider longer holding periods in Section 6). Thus, we allow the constituents of our ten portfolios to vary over time.

Table 4 displays properties for the 10 portfolios from January 1966 to December 2012. Panel A holds results for portfolios based on commonality betas retrieved using effective spreads, and Panel B holds the price impact portfolio properties. Portfolio 1 is the high commonality risk portfolio (*High*), and Portfolio 10 is the low commonality risk portfolio (*Low*). We are interested in the properties of these portfolios over time. Our primary interest among the portfolio properties is the portfolio return, but we also report size, illiquidity, and commonality betas for each portfolio (all measured post-formation, i.e., for the holding period of the portfolios).

[Insert Table 4 here]

The leftmost column of each panel reports monthly portfolio excess returns, calculated as equal-weighted averages of monthly stock returns taken from CRSP, and adjusted for the risk-free rate.[5] For both illiquidity measures, high commonality beta portfolios record higher returns than low commonality risk portfolios. Using a High-minus-Low strategy, being long in Portfolio 1 and short in Portfolio 10, an investor would get an average monthly return of 0.213% (0.330%) when commonality betas are based on the effective spread (price impact). In annual terms, at 2.6% (4.0%), these return premia are economically significant. For comparison, the annual average return on the market portfolio for the same period is 5.6%. As indicated by the t-test, the return premia are also statistically significant.

[5]As suggested by Shumway (1997), returns are also adjusted for delistings in the same way as in Acharya and Pedersen (2005).

In spite of the double sorting procedure aimed to retrieve commonality portfolios unrelated to level illiquidity, illiquidity is falling almost monotonously with portfolio numbers, both for effective spread portfolios and for price impact portfolios. The higher commonality risk, the more illiquid stocks are. However, relative to the standard deviation in illiquidity measures (see Table 2), the illiquidity differences observed between portfolios are small. For effective spread portfolios (price impact portfolios), the difference never exceeds 14% (10%) of the standard deviation in effective spreads (price impact).

Size is measured as the deviation in log market cap from cross-sectional median log market cap, a size measure proposed by Hasbrouck (2009) to control for inflation in market capitalization. A positive number indicates higher-than-median market capitalization, whereas stocks with less market capitalization than the cross-sectional average have negative numbers. Using this measure, we observe a clear size effect in our portfolios as well: commonality risk is decreasing in firm size.

Finally, we report post-formation commonality betas for each portfolio. To estimate portfolio commonality betas, we run time-series regressions of the type described in Eq. (2), using monthly observation for Jan. 1966 - Dec. 2012. The results confirm that the portfolio formation procedure leads to portfolios with statistically significant differences in exposure to commonality risk.

The conclusion of this portfolio application is that commonality risk commands a return premium in the sample at hand. Our evidence points to an average return of at least 2.6% annually, which is both economically and statistically significant. Commonality risk is shown to be related to both illiquidity and size. Thus, commonality risk may partially explain the return premia associated with illiquidity level and size (see Amihud and Mendelson, 1986; Banz, 1981). We discuss the magnitude and interpretation of the commonality risk premium further in Section 6. Before that, we consider two potentially important variations in the methodology: the choice of systematic illiquidity estimator and the choice between low-frequency and high-frequency data when approximating illiquidity.

3.5 Economic significance

Our results indicate a range for the annual commonality risk premium from 2.6% to 4.0%. This is much higher than what is reported in the previous literature on commonality risk. According to Acharya and Pedersen (2005), the total premium for illiquidity level and illiquidity risk combined amount to 4.6%, based on US stocks (for the years 1964-1999) sorted by their illiquidity level. Hagströmer et al. (2013) study the same premium for a longer time period (1927-2010) and report it to be 1.74%-2.08%. Both studies find that the commonality risk premium is the least important component of the total illiquidity premium. Pástor and Stambaugh (2003) find an illiquidity risk premium of 7.5% in US stocks, but their focus is not on commonality risk.

A key difference between our studies and the previous literature is the portfolio sorting. Whereas Acharya and Pedersen (2005) and Hagströmer et al. (2013) sort their portfolios to maximize dispersion in illiquidity level, our sorting procedure seeks to maximize dispersion in commonality risk while keeping illiquidity level flat across portfolios. The fact that the results with respect to commonality risk differ is thus not surprising.

A weakness of the methodology applied above is that transaction costs for implementing the High-minus-Low strategy are not accounted for. Given our focus on one-month holding periods, the cost of rebalancing may undermine the return premium. To limit transaction costs a real-world investor may be interested in longer holding periods. In line with this, we now consider holding periods for up to twelve months.

Figure 1 presents how the commonality risk premium (the return on the High-minus-Low strategy) holds up when the portfolios are not rebalanced monthly. All holding period return premia are annualized, such that the premia of different investment horizons are comparable.

[Insert Figure 1 here]

The main finding observed in Figure 1 is that the commonality return premium holds up well when the holding period is extended up to twelve months. For effective spreads the premium amounts to 3.1% per year, which is even higher than the annualized premium for the one-month holding period. The commonality risk premium associated with price impact, on the other hand, is falling with the length of the holding period, implying that the durability of this strategy is shorter than for effective spreads. The twelve-month premium for price impact amounts to 1.3%. With the cost of a round-trip trade being 0.89% on average (see the effective spread in Table 2), the High-minus-Low portfolio strategy outlined above is profitable net of transaction costs regardless which illiquidity measure is used.

To improve the understanding of the commonality risk premia, as a final application we investigate how the commonality risk strategy relates to systematic risk factors. We use monthly returns from the commonality risk High-minus-Low strategy as the dependent variable in various time-series factor models. The specifications considered include the three-factor model by Fama and French (1996; with the factors *MKT*, *SMB*, *HML*), the four-factor momentum model by Carhart (1997; with the same factors as the three-factor model, adding *MOM*), and the liquidity-augmented factor model by Liu (2006; with the *MKT* and *LIQ* factors).[6] Table 5 shows the factor model results. Panels A and B hold results for commonality betas estimated on the effective spread and price impact, respectively. For this application we use returns from portfolios with monthly rebalancing.

[Insert Table 5 here]

The results in Table 5 show that the commonality risk strategy is positively related to the size factor and the momentum factor. For the market factor, the value factor, and the liquidity factor, the results are mixed across illiquidity measures and factor model specifications. The intercepts show that the commonality risk premium is not explained by either the CAPM model or the Fama and French (1996) three-factor model. This is seen in that the intercepts of the model are not much lower than the average return presented above.

When the momentum factor is added, however, the intercept falls sharply and is no longer significantly different from zero. This result, which is consistent across the two illiquidity measures, indicates that the commonality risk strategy has features in common with the momentum strategy of Carhart (1997). The four-factor model does also record the highest explanatory power in terms

[6]The data for *MKT*, *SMB*, *HML*, and *MOM* are retrieved from Kenneth French's website. The *LIQ* factor was kindly provided by Weimin Liu in personal communication. The latter is available up until 2009.

of adjusted R^2. We want to emphasize, however, that this does not imply that the commonality risk premium is explained by momentum. Commonality risk has a theoretical foundation in the LCAPM by Acharya and Pedersen (2005). To our knowledge, there is no corresponding theoretical framework explaining the momentum effect.

Acharya and Pedersen (2005) point out that different types of illiquidity risks are highly correlated. In light of their evidence, it is important to note that the commonality risk premium is not explained by Liu's (2006) liquidity-augmented CAPM. This is seen in that the intercept of that model, for both illiquidity measures, is close to the average return on the commonality risk portfolio.

4 Robustness tests

In this section we confirm that the results presented above hold up to variations in the estimation of systematic illiquidity, to illiquidity measures based on intradaily rather than daily data, and to a change in data frequency in the commonality regressions.

4.1 The choice of systematic illiquidity estimator

As discussed in Section 2, there are several different systematic illiquidity estimators. The equal-weighted average used above is the by far most common in the empirical literature. The equal-weighted and the value-weighted estimators have in common that they are independent of the cross-sectional covariance structure of illiquidity that they are used to describe. Many studies conclude that equal-weighted and value-weighted systematic illiquidity estimators yield more or less the same outcome (e.g., Chordia et al. 2000; Kamara et al., 2008). Principal components and factor analysis estimators of systematic illiquidity are based on the covariance matrix of individual asset illiquidity innovations (see e.g., Hasbrouck and Seppi, 2001; Korajczyk and Sadka, 2008; Corwin and Lipson, 2011; and Hallin et al., 2011). Such estimators are by construction maximizing the degree of commonality in a sample.

We consider three systematic illiquidity estimators: the equal-weighted, the value-weighted, and the principal component estimator. As before, all stocks with no missing illiquidity observations within the estimation window are included in the calculation of the systematic illiquidity estimator. The principal component estimator is the first eigenvector of the illiquidity correlation matrix of each estimation window; normalized to unit length; and signed to have positive correlation to the equal-weighted and value-weighted estimators. We run the regressions based on Eq. (2) in exactly the same way as above, but with different systematic illiquidity estimators. This gives us estimator-specific commonality betas that we can use to form commonality portfolios.

Before applying the commonality betas to the portfolio formation procedure, we study the correlations between the estimators as well as the estimator-specific commonality betas. The correlation results are presented in Table 6. The two leftmost columns show correlations between systematic illiquidity estimators; and the two rightmost columns show correlations between estimator-specific commonality betas. We use Spearman rank correlations for the latter as it captures the extent of which the different estimators yield the same portfolio formations.

[Insert Table 6 here]

For effective spreads, the correlation between the equal-weighted and the value-weighted estimators is relatively high (0.72) compared to the correlation of the equal-weighted and value-weighted estimators to the principal component estimator (0.30 and 0.22, respectively). The corresponding correlations for the price impact is substantially higher, at 0.90, 0.86, and 0.87. The same pattern carries through to the rank correlations of commonality betas. Here, we see that the ranking of commonality betas based on price impact is virtually the same across estimators, with rank correlations of 0.96–0.97. For effective spreads, however, the rank correlations vary between 0.39 and 0.63. Based on these results, we proceed to check for differences in portfolio results between different effective spread systematic illiquidity estimators. Due to the high rank correlations observed for price impact, we do not pursue any further analysis for this measure.

Table 7, columns (a) and (b) contain the results for portfolios formed on effective spread commonality betas retrieved from value-weighted and principal component estimators. Except for the variation in the systematic illiquidity estimator, each step of the analysis is performed exactly as above. The return on the High-minus-Low commonality beta strategy remains both economically and statistically significant when the alternative estimators are used. The magnitude of the return premium is slightly smaller, 0.188% for the value-weighted estimator and 0.177% the principal components estimator, compared to 0.213% per month found for the equal-weighted estimator.

[Insert Table 7 here]

The investigation in this subsection shows that the equal-weighted systematic illiquidity estimator yields a commonality risk premium that is qualitatively similar to the premia associated with alternative estimators of systematic illiquidity. As the equal-weighted estimator is straightforward to implement and well established in the literature, we find no reason to use alternative estimators.

4.2 Illiquidity measures based on intraday data

The use of low-frequency data to measure monthly illiquidity is common in studies that require long time series, but the low-frequency illiquidity proxies have a disadvantage in measurement accuracy. In the commonality literature, where long time series are typically not required, most studies apply intraday data to measure daily illiquidity (see Table 1). As reduced measurement error in the illiquidity measures can potentially reduce commonality beta estimation error, we here repeat our portfolio strategy using illiquidity measures on intraday data.

For this application we use the Trades and Quotes database (TAQ) provided by the New York Stock Exchange. TAQ includes data on all trades and quote updates for US stocks. Our sample includes data for Jan. 1, 1993 – Dec. 31, 2008.[7] For our liquidity measurement based on intraday TAQ data, we adopt metrics for effective spread and price impact used by Hasbrouck (2009). For details about the filtering of TAQ data and calculation of illiquidity measures, as well as descriptive statistics for that sample, see the appendix.

We run commonality regressions in the same way as in Section 3, retrieving commonality betas for all eligible stocks and all months from Jan. 1996 to Dec. 2008. For the estimation of systematic illiquidity the equal-weighted average is used. Table 8 presents how the TAQ illiquidity measures and their corresponding commonality betas estimated here correlate to those based on

[7]Jan. 1, 1993 is the earliest date available in the TAQ database. The end date is due to restrictions in our access to the database.

low-frequency data. The two leftmost columns show correlations between illiquidity measures calculated from CRSP and TAQ data, respectively; and the two rightmost columns show correlations between commonality betas obtained using illiquidity measures from different data sources. As above, we use Spearman rank correlations for the latter as these capture the extent to which the different estimators yield the same portfolio formations.

[Insert Table 8 here]

The first row of Table 8 shows that the effective spread metrics estimated on CRSP and TAQ data have a correlation of 0.73. The price impact measures display a much lower correlation, 0.31. These non-perfect correlations between illiquidity measures (that are supposed to capture the same property) indicate that the results on commonality risk presented above may be subject to measurement error. The correlation between commonality betas estimated using different data sources is low (0.37) for the effective spread and high (0.77) for the price impact. These results imply that the portfolio sorts will differ depending on the type of data used to measure illiquidity.

In Table 7, columns (c) and (d) show the results of using intraday data to measure monthly illiquidity. The economic significance of the High-minus-Low commonality risk premium is roughly at the same level as above. For effective spreads, the High-minus-Low commonality strategy yields an excess return of 0.228% per month. For price impact, the return premium is 0.162% per month. The return premia observed here are not statistically significant, which is likely due to the shorter time period. Untabulated result for our main application, using the Jan. 1996 - Dec. 2008 time interval, is 0.347% for the effective spread and 0.221% for the price impact.

We conclude from this test of robustness that the intraday data yields illiquidity measures that differ from the low-frequency measures, and presumably have less measurement error. However, this improvement does not influence the return on the strategy in a material way.

4.3 Estimating commonality risk using daily data frequency

The use of intraday data also allows the derivation of illiquidity measures at frequencies higher than monthly. Calculating the same illiquidity measures on a daily frequency, we can repeat the commonality risk estimation for regressions run on daily frequency too. This approach has strong precedence in the literature documenting the existence of commonality in illiquidity, e.g., Chordia et al. (2000). Descriptive statistics for the daily illiquidity measures are available in Appendix A.

To be able to compare the results of daily illiquidity observations to those of monthly observations, we apply the same estimation window for the commonality regressions as above. This makes the number of observation for daily illiquidity about 21 times higher than for the monthly sample, in any given commonality regression, which may improve the precision of the commonality beta estimates. As above, the regressions are reestimated each month.

In the second and third row of Table 8 we present Spearman rank correlations between commonality betas based on daily and monthly illiquidity observations. We find considerable differences between the commonality betas of different data frequencies, with correlations less than 0.40 for the effective spread and less than 0.70 for the price impact.

Table 7, columns (e) and (f), show that the effective spread commonality risk premium is 0.269% per month, and the corresponding premium for price impact is 0.123% per month. Neither of these are statistically significant, and both are lower than what is retrieved using the low-frequency data to proxy illiquidity. We thus conclude that the gain in precision of illiquidity measures and commonality risk does not bring an edge in terms of return premia, at least not for the period considered here.

5 Conclusions

The commonality in illiquidity literature is vast when it comes to the existence and causes of commonality. The implications of commonality, however, are unclear. We address this gap in the literature by studying whether investors attach a premium to commonality risk.

Our investigation shows that a portfolio with high commonality risk earns a risk premium compared to a portfolio with low commonality risk. The return premium is significant both in the economical and the statistical sense, controlling for the illiquidity level effect. The results hold up to robustness tests with respect to illiquidity measurement, systematic illiquidity estimation, and commonality risk estimation. Even though the commonality risk estimates can be improved using intraday data, we find that low-frequency data proxies of illiquidity are enough for successful implementation of the strategy.

The commonality risk premium remains positive net of transaction costs when the holding period is extended from one to twelve months. For longer horizons, the results indicate that the effective spread yields more sustainable returns than do the price impact.

The high correlation between commonality risk and illiquidity level shows that long-term investors who seek to earn the illiquidity level premium are likely to also take on illiquidity commonality risk. Future research on the pricing of illiquidity should recognize the commonality risk premium as an important component of the illiquidity risk premium, and be careful to disentangle it from the illiquity level premium.

Appendix: TAQ data processing and illiquidity measures

We retain all trades, from all exchanges, that have positive trading volume. Trades that are cancelled, erroneous, out-of-sequence, or have conditions attached to them, are excluded. We filter the trades data set for outliers on a stock-day by stock-day basis, following the algorithm outlined by Brownlees and Gallo (2006). The outlier filter is based on that a trade with a price recorded more than three local standard deviations away from the local delta-trimmed mean is likely to be reported out of sequence. Trades that are reported in the same second are merged to be represented by one observation with the aggregate volume and the volume-weighted average price.

We also obtain all NYSE quote updates. Quotes where the bid-ask spread is either zero, negative, or exceeding $5 are excluded, and so are quotes with negative prices or volumes. When there are simultaneous quote observations (i.e., in the same second) the last observation in the second is retained.

The effective spread is the volume-weighted average (daily or monthly) distance between the transaction price and the midpoint of the bid-ask spread prevailing at the time of the trade, divided by the midpoint. In the depth dimension, we estimate a price impact coefficient $\lambda_{t,i}$ in the regression

$$\Delta p_{t,i,\tau} = \lambda_{t,i} q_{t,i,\tau} \sqrt{pv_{t,i,\tau}} + \epsilon_{t,i,\tau}, \tag{3}$$

where $\Delta p_{t,i,\tau}$ are log price changes (returns) of stock i in a 5-minute interval τ, the direction of trade is denoted $q_{t,i,\tau}$ (which is 1 [-1] for 5-minute intervals with more [less] buyer-initiated trades than seller-initiated trades, and zero if the buyer-initiated volume equals the seller-initiated volume), $pv_{t,i,\tau}$ is the dollar trading volume, and $\epsilon_{t,i,\tau}$ are regression residuals. Similar specifications are applied by Goyenko et al. (2009) and Hasbrouck (2009). We require at least 30 signed trade observations to run the regression. For consistency across illiquidity measures, we apply the same filter to the effective spread measure.[8]

We calculate liquidity measures from TAQ data on both daily and monthly frequency. For the effective spread, we calculate the monthly measure as the average of daily measures in a given month. For the monthly measure of price impact, we run the price impact regression on all five-minute periods of the month in question.

Table A1 presents descriptive statistics of the monthly (Panel A) and daily (Panel B) illiquidity measures estimated from TAQ data.

[Insert Table A1 here]

Reflecting that 1993-2008 in general is a time period with higher liquidity than in our full sample, the effective spread and the price impact coefficient are much lower than what is reported in Table 2. On average a $100 trade carries a transaction cost of 44 cents according to the monthly TAQ, and 30 cents according to the daily TAQ. A $1000 trade has a 5-minute price impact average (median) of 0.75% (0.29%) according to the monthly measure, and 0.45% (0.19%) according to the daily measure. A likely reason that the daily measures indicate higher liquidity is the restriction that illiquidity is only measured for stock-days with at least 30 trade observations. For the monthly sample, the same restriction is applied on stock-months, which is binding for fewer stocks.

Turnover and market capitalization are larger in 1993-2008 than in the full sample, and the average number of stocks considered each month is slightly lower than in the full sample.

[8] Matching of trades to prevailing quotes is required for both illiquidity measures. Trades occurring in 1997 or earlier are matched to quotes with a five-second delay. For trades after 1997 a one-second delay is applied. Whether a trade is buyer- or seller-initiated is determined on a trade-by-trade basis by the Lee and Ready (1991) algorithm.

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Table 1: Overview of literature on commonality in illiquidity

Panel A: Studies of US equity markets

Reference	Market(s)	Data period	Liquidity measure(s)	Data frequency	Systematic estimator(s)	Liquidity frequency	Commonality
Chordia et al. (2000)	NYSE	1992	Quoted and effective bid-ask spread; depth at BBO	Intraday	Equal-weighted, value-weighted	Daily	Yes
Hasbrouck and Seppi (2001)	NYSE	1994	Effective bid-ask spread; order imbalance	Intraday	Principal components	15 min periods	Spreads: No Order flow: Yes
Huberman and Halka (2001)	NYSE	1996	Bid-ask spread; volume.	Intraday	-	Daily	Yes
Chordia et al. (2001)	NYSE	1988-1998	Quoted and effective bid-ask spread; depth at BBO; volume	Intraday	Equal-weighted, value-weighted	Daily	Yes
Pástor and Stambaugh (2003)	NYSE, AMEX	1966-1999	Return reversal coefficient	Daily	Equal-weighted	Monthly	Yes
Coughenour and Saad (2004)	NYSE	1999-2000	Quoted and effective bid-ask spread	Intraday	Equal-weighted	3 periods intradaily	Yes
Kamara et al. (2008)	NYSE, AMEX	1962-2005	ILLIQ	Daily	Equal-weighted, value-weighted	Daily	Yes
Korajczyk and Sadka (2008)	NYSE	1983-2000	Eight liquidity measures	Intraday	Principal components	Monthly	Yes
Hallin et al. (2009)	S&P500	2004-2006	Bid-ask spread; volume	Daily	Dynamic princ-ipal components	Daily	Yes
Corwin and Lipson (2011)	NYSE	1997-1998	Trading and order volume; bid-ask spread; depth	Intraday	Principal components	15-min periods	Yes
Kang and Zhang (2013)	NYSE	2003	Bid-ask spread; depth; LOB dispersion	Intraday	Equal-weighted	Daily	Yes
Koch et al. (2012)	NYSE, AMEX	1980-2008	ILLIQ; turnover	Daily	Equal-weighted, value-weighted	Daily	Yes

Table 1 (continued)

Panel B: Studies of international equity markets

Reference	Market	Data period	Liquidity measure	Data frequency	Systematic estimator	Liquidity frequency	Commonality
Brockman and Chung (2002)	HKEX, Hong Kong	1996-1999	Bid-ask spread; depth	Intraday	Equal-weighted, value-weighted	Daily	Yes
Domowitz et al. (2005)	ASX 20 (Australia)	2000 (10 months)	Bid-ask spread; full order book depth; order flows; order types	Intraday	-	Hourly	Yes
Kempf and Mayston (2008)	DAX30, Germany	2004	Bid-ask spread; volume	Intraday	Principal components, equal-weighted	30 min periods	Yes
Beltran-Lopez et al. (2009)	DAX30, Germany	2004 (3 months)	Bid and ask price impact	Intraday	Principal components	Daily	Yes
Galariotis and Giouvris (2007)	FTSE100, UK	1996-2001	Bid-ask spread	Daily	Equal-weighted	Daily	Yes
Galariotis and Giouvris (2009)	FTSE100, FTSE250, UK	1996-2001	Bid-ask spread	Daily	Principal components	Daily	Yes

Panel C: Studies of multiple international equity markets

Reference	Market	Data period	Liquidity measure	Data frequency	Systematic estimator	Liquidity frequency	Commonality
Brockman et al. (2009)	47 countries	2002-2004	Bid-ask spread; depth	Intraday	Equal-weighted, value-weighted	Daily	Yes
Dang et al. (2015)	39 countries	1996-2007	Bid-ask spread	Intraday	Equal-weighted	Daily	Yes
Karolyi et al. (2011)	40 countries	1995-2004	ILLIQ; turnover	Daily	Value-weighted	Daily	Yes

Table 2: Descriptive statistics

Common stocks incorporated in the US, with primary listing at NYSE, with price in the range of $5 and $999, and a positive market capitalization are eligible for illiquidity measurement. The relative effective spread is estimated from daily closing prices as in Holden (2009), yielding a monthly average spread. The price impact is estimated from daily returns and volumes as in Amihud (2002), and averaged monthly. The effective spread is given in percentage form, and the price impact is stated in percent per million USD traded. Illiquidity innovations are calculated as the first-difference of level illiquidity, and are cross-sectionally winzorized at the 0.5% and 99.5% quantiles. Market capitalization is expressed in billion USD. Turnover is measured as the monthly dollar trading volume divided by the market capitalization. The descriptive statistics are based on monthly observations for the time period Dec. 1962 - Dec. 2012.

	Mean	Median	Sd	Min	Max
Number of firms	1780.93	1803.00	241.10	1134.00	2253.00
Effective spread (%)	0.89	0.64	0.91	0.00	23.18
ΔEffective spread (%)	-3.9E-03	-1.0E-03	0.55	-5.17	5.34
Price impact (%) x10^3	16.99	1.69	53.95	0.00	8917.66
ΔPrice impact (%) x10^3	4.3E-03	2.3E-06	20.62	-339.03	364.20
Market cap. (BUSD)	2.38	0.23	11.73	3.8E-04	581.10
Turnover (monthly, %)	16.70	6.30	69.42	0.00	13937.81

Table 3: Commonality in illiquidity

Commonality regressions are run for eligible stocks each month from Dec. 1965 - Dec. 2012. Eligible stocks have a closing price in the current month between $5 and $999, positive market capitalization and at least 30 monthly illiquidity observations in the estimation window. The estimation window is 36 months in Dec. 1965 and expands gradually to 60 months in Dec. 1967, after which it moves forward by one month for each step in time. The regression analysis has individual stock illiquidity innovations as the dependent variable and systematic illiquidity innovations and marketwide returns as independent variables. Panels A and B hold results for the relative effective spreads and the price impact, respectively. The fraction of commonality betas being positive and significant is determined using a 95% confidence level. Results are reported for three subperiods as well as the full sample. For each time period, the reported metrics are time-series averages calculated across cross-sectional averages.

Panel A: Effective spread results

		Commonality betas			Number of stocks		Correlation: illiquidity & commonality beta	
Time period	Degree of commonality	Coeff.	Positive	Positive & significant	Regressions	Systematic illiquidity	Pearson	Spearman
Dec.1965-Dec.1980	0.059	1.112	73.6%	15.7%	1614	1173	0.343	0.411
Jan.1981-Dec.1995	0.051	1.085	70.7%	12.4%	1444	1144	0.384	0.428
Jan.1996-Dec.2012	0.046	1.034	72.3%	12.3%	1344	1025	0.448	0.418
Dec.1965-Dec.2012	0.052	1.075	72.2%	13.4%	1462	1110	0.394	0.419

Panel B: Price impact results

		Commonality betas			Number of stocks		Correlation: illiquidity & commonality beta	
Time period	Degree of commonality	Coeff.	Positive	Positive & significant	Regressions	Systematic illiquidity	Pearson	Spearman
Dec.1965-Dec.1980	0.165	1.449	93.0%	51.6%	1614	1173	0.566	0.809
Jan.1981-Dec.1995	0.118	1.225	88.0%	39.6%	1444	1144	0.525	0.863
Jan.1996-Dec.2012	0.094	1.120	84.4%	28.9%	1344	1025	0.571	0.874
Dec.1965-Dec.2012	0.125	1.259	88.3%	39.6%	1462	1110	0.555	0.850

Table 4: Properties of portfolios based on commonality betas

The portfolios are formed in the end of the previous month with equal weights to each stock and held for one month. The portfolio formation procedure is as follows: Stocks are sorted by their level of illiquidity and divided in 50 groups. Within each group, stocks are sorted by their commonality beta and divided into decile portfolios. Such decile portfolios are then merged across the 50 groups, yielding ten portfolios with different levels of commonality betas. Returns, illiquidity, and market capitalization are time-series averages of holding period characteristics for the time period Jan. 1966 - Dec. 2012. Returns are in excess of the risk-free rate of interest. Market cap. is the natural log difference between the observed value and the median value for the current month. Commonality betas are estimated by regression analysis for the full monthly time series. Panel A and B hold results for the relative effective spreads and the price impacts, respectively.

Panel A: Effective spread results

Portfolio	Excess returns (%)	t	Effective spread (%)	Relative market cap.	Commonality beta	t
High	0.802	2.83	0.8779	-0.890	1.134	26.47
2	0.769	2.70	0.8180	-0.418	1.032	29.29
3	0.711	2.52	0.7844	-0.200	1.017	28.68
4	0.642	2.33	0.7702	-0.037	0.998	29.37
5	0.596	2.18	0.7484	0.105	0.918	29.76
6	0.638	2.33	0.7317	0.216	0.892	27.57
7	0.600	2.20	0.7210	0.303	0.868	29.12
8	0.566	2.06	0.7102	0.386	0.798	25.55
9	0.548	2.01	0.7070	0.418	0.814	27.18
Low	0.590	2.16	0.7075	0.433	0.812	26.47
High-Low	0.213	2.50	0.1704	-1.323	0.973	42.09

Panel B: Price impact results

Portfolio	Excess returns (%)	t	Price impact (%)	Relative market cap.	Commonality beta	t
High	0.870	2.87	21.511	-0.815	1.082	26.83
2	0.819	2.82	17.602	-0.411	0.887	29.79
3	0.681	2.43	15.384	-0.208	0.892	32.51
4	0.695	2.51	13.709	-0.058	0.887	38.31
5	0.624	2.28	12.485	0.065	0.812	38.43
6	0.636	2.34	11.571	0.183	0.771	39.87
7	0.564	2.08	10.449	0.281	0.688	36.93
8	0.551	2.05	10.237	0.386	0.746	36.16
9	0.534	1.98	9.533	0.478	0.638	32.74
Low	0.540	2.07	9.775	0.554	0.617	29.63
High-Low	0.330	2.65	11.735	-1.369	0.849	42.39

Table 5: Commonality risk premium exposure to risk factors

Factor models are estimated on the commonality risk premium retrieved from pursuing a high-minus-low strategy with respect to commonality betas, with monthly rebalancing. Panels A and B hold results for commonality betas estimated on the effective spread and price impact, respectively. Four different factor model specifications are considered: (i) intercept and MKT (as in the traditional CAPM); (ii) intercept, MKT, SMB and HML (as in Fama and French, 1996); (iii) intercept, MKT, SMB, HML and MOM (as in Carhart, 1997); (iv) intercept, MKT and LIQ (as in Liu, 2006). MKT, SMB, HML, MOM, and LIQ are traded risk factors. * indicates that the coefficient is statistically significant at the 95% confidence level.

Panel A: Effective spread

	Intercept	*MKT*	*SMB*	*HML*	*MOM*	*LIQ*	R^2
CAPM	0.2046 *	0.0185					0.00
FF3	0.2076 *	-0.0494 *	0.2376 *	-0.0856 *			0.15
FF3+MOM	0.0321	-0.0121	0.2379 *	-0.0223	0.1963 *		0.32
MKT+LIQ	0.1923 *	0.0658 *				0.0701 *	0.01

* Statistically significant at the 95% confidence level

Panel B: Price impact

	Intercept	*MKT*	*SMB*	*HML*	*MOM*	*LIQ*	R^2
CAPM	0.2413 *	0.2053 *					0.10
FF3	0.2855 *	0.0857 *	0.3572 *	-0.2162			0.30
FF3+MOM	0.0147	0.1434 *	0.3578 *	-0.1185	0.3030 *		0.49
MKT+LIQ	0.3173 *	0.1618 *				-0.0791	0.10

* Statistically significant at the 95% confidence level

Table 6: Correlations between metrics using different systematic illiquidity estimators

The table presents correlations between systematic illiquidity estimators and commonality betas retrieved using different systematic illiquidity estimators. Commonality betas are estimated in regressions using either the equal-weighted average, the value-weighted average, or the principal components as the systematic illiquidity estimator. The commonality betas are reestimated monthly using a rolling estimation window covering up to 60 months, using monthly observations as inpuys. The correlations are estimated in the cross-section of stocks each month and averaged across time, Jan. 1966 - Dec. 2012. The correlations between estimators are based on Pearson correlations, and the correlations between commonality betas are based on Spearman rank correlations. The two underlying illiquidity measures are the Effective spread and the Price impact.

	Pearson correlation between systematic illiq.		Spearman correlation between commonality betas	
	Effective spread	Price impact	Effective Spread	Price impact
Equal-weighted vs. value-weighted	0.72	0.90	0.63	0.97
Equal-weighted vs. principal components	0.30	0.86	0.48	0.96
Value-weighted vs. principal components	0.22	0.87	0.39	0.97

Table 7: Portfolios based on TAQ illiquidity measures

The table presents average monthly returns for portfolios sorted on commonality risk. The portfolios are formed in the end of the previous month with equal weights to each stock and held for one month. The portfolio formation procedure is as follows: Stocks are sorted by their level of illiquidity and divided in 50 groups. Within each group, stocks are sorted by their commonality beta and divided into decile portfolios. Such decile portfolios are then merged across the 50 groups, yielding ten portfolios with different levels of commonality betas. Columns (a)-(f) report portfolio returns, excess of the risk-free rate, for variations in the portfolio formation procedure. For each variation, the High-Low return is the outcome of being long in the High risk portfolio and short in the Low risk portfolio. The High-Low return is reported along with a t-statistic. Columns (a) and (b) use different estimators of systematic illiquidity, the value-weighted average and the principal components, both for the effective spread. Columns (c) and (d) use intraday (TAQ) data from 1993-2008 to measure monthly illiquidity. Columns (e) and (f) also use the same intraday data but calculate daily illiquidity measures rather than monthly, and then applies a daily frequency in the commonality regressions.

	Systematic illiquidity estimators		TAQ monthly illiquidity		TAQ daily illiquidity	
	(a)	(b)	(c)	(d)	(e)	(f)
Portfolio	Value-weighted average	Principal components	Effective spread	Price impact	Effective spread	Price impact
High	0.768	0.749	0.804	0.603	0.795	0.676
2	0.688	0.702	0.628	0.694	0.625	0.640
3	0.669	0.664	0.686	0.586	0.488	0.641
4	0.634	0.597	0.544	0.556	0.560	0.399
5	0.676	0.657	0.520	0.534	0.583	0.637
6	0.579	0.577	0.632	0.614	0.559	0.570
7	0.617	0.637	0.483	0.536	0.559	0.588
8	0.621	0.651	0.563	0.546	0.556	0.483
9	0.597	0.612	0.536	0.555	0.560	0.649
Low	0.580	0.572	0.575	0.442	0.526	0.554
High-Low	0.188	0.177	0.228	0.162	0.269	0.123
t stat(High-Low)	2.49	2.35	1.28	0.75	1.82	0.64

Table 8: Correlations between metrics using different data sources

The table presents correlations between illiquidity measures based on different data sources (CRSP and TAQ) and commonality betas retrieved using the illiquidity measures based on different data sources and data frequencies (CRSP monthly, TAQ monthly, TAQ daily). Commonality betas are estimated in regressions using the equal-weighted average as the systematic illiquidity estimator, and with either monthly or daily data frequency. Regardless of data frequency, the commonality betas are reestimated monthly using a rolling estimation window covering up to 60 months. The correlations are estimated in the cross-section of stocks each month and averaged across time, Jan. 1966 - Dec. 2012. The correlations between estimators are based on Pearson correlations, and the correlations between commonality betas are based on Spearman rank correlations. The two underlying illiquidity measures are the Effective spread and the Price impact.

	Pearson correlation between illiquidity measures		Spearman correlation between commonality betas	
	Effective spread	Price impact	Effective Spread	Price impact
CRSP (monthly) vs. TAQ (monthly)	0.73	0.31	0.37	0.77
CRSP (monthly) vs. TAQ (daily)	-	-	0.26	0.70
TAQ (monthly) vs. TAQ (daily)	-	-	0.40	0.68

Table A1: Descriptive statistics for illiquidity based on TAQ data

Common stocks incorporated in the US, with primary listing at NYSE, with price in the range of \$5 and \$999, and a positive market capitalization are eligible for illiquidity measurement. For monthly measures (Panel A) stock-months are required to contain at least 30 trade observations. For daily measures (Panel B) stock-days are required to have at least 30 trade observations. Trades that are erroenous, cancelled, out-of-sequence, or with conditions attached to them are not included. Trades occurring before (after) the end of 1997 are matched to the latest quote observation at least five (one) seconds before the trade. The effective spread is the distance between the transaction price and the midpoint of the bid-ask spread prevailing at the time of the trade, divided by the midpoint. The daily effective spread is calculated as the dollar volume-weighted average across trades in the day, and the monthly measure is the average across days. The price impact coefficient is estimated in a regression of five-minute stock returns against five-minute contemporaneous signed square root dollar trading volumes. For daily (monthly) measures, all five-minute periods during opening hours in a day (month) are considered. Innovations are calculated as the first-difference of level illiquidity, and are cross-sectionally winzorized at the 0.5% and 99.5% quantiles. Market capitalization is expressed in billion USD. Monthly turnover is measured as the dollar trading volume divided by the market capitalization.

Panel A: Monthly illiquidity measures based on TAQ

Measure	Mean	Median	Sd	Min	Max
Number of firms	1403.85	1356.00	126.97	1049.00	1690.00
Effective spread (%)	0.44	0.29	0.48	0.01	37.97
ΔEffective spread (%)	-3.3E-03	-2.2E-03	0.18	-2.83	2.91
Price impact (%) x10^3	0.75	0.29	1.31	-4.62	41.39
ΔPrice impact (%) x10^3	-5.5E-03	-7.6E-04	0.52	-5.52	5.51
Market cap. (BUSD)	5.39	0.97	19.98	3.8E-04	581.10
Turnover (monthly, %)	0.16	0.10	0.27	2.0E-05	29.84

Panel B: Daily illiquidity measures based on TAQ

Measure	Mean	Median	Sd	Min	Max
Number of firms	1115.32	1174.00	190.87	328.00	1403.00
Effective spread (%)	0.30	0.20	0.33	0.00	53.88
ΔEffective spread (%)	-5.3E-04	-1.3E-04	0.15	-5.35	6.96
Price impact (%) x10^3	0.45	0.19	0.80	-14.80	45.87
ΔPrice impact (%) x10^3	2.2E-04	2.4E-06	0.46	-8.32	9.14
Market cap. (BUSD)	4.97	0.86	19.60	3.8E-04	581.10
Turnover (monthly, %)	0.16	0.10	0.27	3.0E-05	29.84

Figure 1: Commonality risk premium over different holding periods

The commonality risk premium is retrieved when pursuing a High-minus-Low strategy with respect to commonality betas. The figure plots results for commonality betas estimated on the relative effective spreads and the price impacts, respectively. Cumulative returns are calculated from portfolio formation to the end of the holding period. The length of the holding period is given on the x-axis. All returns are annualized for comparability across holding periods.