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Does commonality in illiquidity matter to investors?☆

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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 understood. We find a return premium for commonality risk in NYSE stocks that is both economically and statistically significant. The commonality risk premium is independent of illiquidity level effects, and robust to variations in illiquidity measurement and systematic illiquidity estimation. We also show that precision in commonality risk estimation can be increased by the use of daily illiquidity measures, instead of monthly.

Keywords: commonality, commonality risk premium, asset illiquidity, systematic illiquidity, liquidity, effective tick
JEL: G11, G12

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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 focus of this article is on implications of commonality in illiquidity for investors, in particular to investigate the economic significance of the commonality return premium. This contrasts to previous literature that almost exclusively is devoted to the existence of commonality in illiquidity and its potential causes.

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. Thus, the low commonality risk premium reported in previous studies may 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 (Asparouhova et al., 2010; 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 2008. We also consider intraday data to measure illiquidity with higher accuracy, but for a shorter sample period. Secondly, 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. Thirdly, 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. Interestingly, we find that the use of daily illiquidity measures (based on intraday data) improves the commonality risk estimates, and that the improved risk estimates lead to higher return premia.

The reason that commonality in illiquidity exists is that suppliers and demanders of liquidity are exposed to similar underlying risk factors affecting all securities (Coughenour and Saad, 2004). 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. This logic is particularly important in down markets, where more investors hit their funding constraints, and therefore have to unwind their positions simultaneously (Brunnermeier and Pedersen, 2009). Another supply-side oriented explanation of commonality is given by Kamara et al. (2008), who suggest that commonality is affected by the concentration of market makers and the amount of institutional investing and index trading. 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. Koch et al. (2012) also support the demand-side explanations, showing that the correlated trading patterns among mutual funds induce commonality. 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. That is the gap that we aim to fill with this study.

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 and 5 hold robustness tests with respect to systematic illiquidity estimators, illiquidity measurement, and commonality risk estimation methods. In Section 6 we discuss the magnitude of the commonality risk premium and relate it to other risk factors. Section 7 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 *”en-*

hances 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:

$$E_t\left[r_{t+1}^i\right] = r^f + E_t\left[c_{t+1}^i\right] + \lambda_t\beta_{1t} + \lambda_t\beta_{2t} - \lambda_t\beta_{3t} - \lambda_t\beta_{4t}, \qquad (1)$$

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:

$$\lambda_t \equiv E_t\left[r_{t+1}^m - c_{t+1}^m - r^f\right],$$

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:

$$\begin{aligned}
\beta_{1t} &= \frac{cov_t\left(r_{t+1}^i, r_{t+1}^m\right)}{var_t\left(r_{t+1}^m - c_{t+1}^m\right)}\\
\beta_{2t} &= \frac{cov_t\left(c_{t+1}^i, c_{t+1}^m\right)}{var_t\left(r_{t+1}^m - c_{t+1}^m\right)}\\
\beta_{3t} &= \frac{cov_t\left(r_{t+1}^i, c_{t+1}^m\right)}{var_t\left(r_{t+1}^m - c_{t+1}^m\right)}\\
\beta_{4t} &= \frac{cov_t\left(c_{t+1}^i, r_{t+1}^m\right)}{var_t\left(r_{t+1}^m - c_{t+1}^m\right)}.
\end{aligned}$$

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] 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.

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).

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. Is commonality risk valued by investors?

We use a portfolio approach to investigate whether commonality in illiquidity is valued by investors. The research design for our main results can be described in five steps (variations of these steps are considered in subsequent sections of the article). Firstly, we use daily data to measure two dimensions of monthly illiquidity, market tightness and market depth. Secondly, we estimate systematic illiquidity using the most commonly applied estimator, the equal-weighted average. Thirdly, we use regression analysis to estimate commonality risk for each stock and each month. Next, we rank stocks by their commonality risk and divide them into decile portfolios. Finally, we evaluate whether high commonality risk portfolios carry higher excess returns than low commonality risk portfolios.

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 553 months, December 1962 – December 2008. 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. Furthermore, to avoid differences in trading protocols across exchanges, we limit our sample to stocks with their primary listing at NYSE throughout the year. Finally, only stocks with prices in the range from \$5 to \$999 are included in our sample.

3.2. Illiquidity measurement

We use two different measures of illiquidity, effective spread and price impact. For our main empirical analysis, based on CRSP data, we use the effective tick by Holden (2009) to approximate the effective spread, and the ILLIQ ratio by Amihud (2002) to approximate market depth. 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] 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

[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.

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]

In an average month in our sample there are 1740 firms eligible for analysis, varying between 1210 and 2129. Effective spreads are on average 0.93%. This implies that a trade of $100 would incur a cost of immediacy amounting to 93 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 2.8% 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 0.3%. 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 0.51.

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 $2.2 billion on average. The monthly stock turnover averages around 6.2% 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 0.05 and 0.07 and averaging 0.06. 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 0.17 in Dec. 1965 - Dec. 1980, 0.12 in Jan. 1981 - Dec. 1995, and 0.08 in Jan. 1996 - Dec. 2008. The commonality betas are also decreasing over time.

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 effects 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 73% and 89% 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

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

Section 5.

To investigate whether commonality betas matter to investors it is important to be able to disentangle commonality effects from other 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 0.35 (0.40) 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 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 2008. 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 0.218% (0.438%) when commonality betas are based on the effective spread (price impact). In annual terms, at 2.6% (5.3%), these return premia are economically significant. 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. 2008. 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.

4. 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; and Hallin et al., 2011). Such estimators are by construction maximizing the degree of commonality in a sample. In applications investigating whether commonality exists, the choice of systematic illiquidity estimator is perhaps secondary. When commonality risk is used as a decision variable in a portfolio strategy, however, it is important to consider what estimator yields the smallest estimation error in the commonality beta.

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 rerun the regressions based on Eq. (2) with the different estimators to obtain estimates of commonality risk for each stock in each months. The results of these regressions are available from the authors upon request.

Before applying the commonality betas to portfolio formation procedures as described above, we study the correlations between estimators as well as commonality betas. The correlation results are presented in Table 5, Panel A. The two leftmost columns show correlations between systematic illiquidity estimators; and the two rightmost columns show correlations between commonality betas obtained using different systematic illiquidity estimators. 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 5 here]

Overall, correlations between estimators are high and positive. For effective spreads, the correlation between the equal-weighted and the value-weighted estimators is 0.8. The correlation of the equal-weighted and value-weighted estimators to the principal component estimators are lower, 0.40 and 0.35, respectively. The corresponding correlations for the price impact is substantially higher, at 0.91, 0.88, and 0.88. As can be expected, 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 at 0.97. For effective spreads, however, the rank correlations vary between 0.48 and 0.69. Based on these results, we proceed to check for differences in portfolio results between different effective spread systematic estimators. Due to the high rank correlations observed for price impact, we do not pursue any further analysis for this measure.

Panel B and C of Table 5 contain the results for portfolios formed on commonality betas retrieved from value-weighted and principal component estimators. Except for the change in estimator, everything is the same as in Table 4. 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 roughly the same as for the equal-weighted estimator. The value-weighted estimator yields slightly lower returns (0.16%) and the principal components estimator slightly higher (0.26%) than the 0.22% per month found for the equal-weighted estimator.

The illiquidity and size effects are present with these estimators too, though the latter is somewhat weaker than when the equal-weighted estimator is used.

We also report the post-formation portfolio commonality beta. For comparability across estimators, we estimate this beta as the exposure of portfolio illiquidity to the equal-weighted systematic illiquidity estimator, regardless of which estimator is used to estimate the pre-formation commonality betas. The results show that the High-minus-Low portfolio based on the value-weighted estimator has a significant post-formation commonality beta. The High-minus-Low portfolio based on the principal component estimator, on the other hand, does not display a significant post-formation commonality beta.

The investigation in this section 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.

5. Illiquidity measurement accuracy and frequency

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 exercise using illiquidity measures on intraday data. As the intraday data allows us to derive daily illiquidity measures, we also consider commonality regressions on daily frequency.

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.

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.

For our liquidity measurement based on intraday TAQ data, we adopt metrics for effective spread and price impact used by Hasbrouck (2009). 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.[6]

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 6 presents descriptive statistics of the monthly (Panel A) and daily (Panel B) illiquidity measures estimated from TAQ data, as well as correlation statistics of the monthly illiquidity measures estimated on CRSP and TAQ data

[6]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.

(Panel C).

[Insert Table 6 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% (0.28%) 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.

The correlation analysis in Panel C of Table 6 shows that the panel correlation between the effective spread and the price impact is much higher when we use TAQ data (0.75) than when CRSP data is used (0.32). Furthermore, the effective spread metrics estimated on CRSP and TAQ data, respectively, have a correlation of 0.72. 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 sensitive to the data used as input for the illiquidity measurement.

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. Following the results in Section 4 we apply the equal-weighted estimator of systematic illiquidity to the commonality regressions. The estimation windows applied are of the same chronological length for both daily and monthly illiquidity measures, making the number of observation for daily illiquidity about 21 times higher than for the monthly sample. Results corresponding to Table 3 for the TAQ data set are available from the authors upon request. Table 7, Panel A, presents how the commonality betas estimated here correlate to those based on low-frequency data.

[Insert Table 7 here]

For effective spreads, the commonality betas retrieved from the three different data sets have positive but rather low cross-sectional Spearman rank correlations. Again, this is the type of correlation that indicates whether the different approaches to estimate commonality betas would lead to the same portfolios. With no correlation coefficient exceeding 0.40, the different data sets are likely to lead to rather different outcomes when we implement our portfolio application. The low rank correlations can be taken to indicate that the estimation error in betas estimated on low-frequency data.

For price impact, the rank correlations between ILLIQ and the price impact coefficients estimated in different regressions are in general higher than those observed for effective spreads, from 0.68 to 0.77.

Panel B and C of Table 7 show the commonality risk portfolio results based on monthly TAQ measures of 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 0.19% per month and a significant exposure to commonality risk. For price impact, the return premium is 0.33% per month, and the commonality risk exposure is strongly significant. Our economical conclusions from Section 3 are thus not driven by the low-frequency data. The return premia observed here are, however, not statistically significant, perhaps due to the shorter time period. Illiquidity and size effects remain present but small for both illiquidity measures.

Panel D and E of Table 7 show the corresponding results of portfolios based on commonality betas estimated using daily illiquidity measures. The accuracy of these betas is subject to a trade-off of utilizing more information and the risk that daily measures contain more noise than monthly measures. The return premia retrieved from these betas are higher than those based on monthly illiquidity measures. The effective spread commonality risk premium is 0.32% per month, and the corresponding premium for price impact is 0.54% per month. In spite of the short sample, both return premia are statistically significant.

The investigation presented in this section shows that the commonality betas estimated from illiquidity proxies based on low-frequency data have positive but far from perfect correlations to the same betas based on illiquidity measures with higher accuracy. Furthermore, we find that the commonality risk retrieved when using daily illiquidity measures is higher than the premium found when using monthly measures. Taken together, these findings indicate that the use of low-frequency illiquidity proxies introduces estimation error in strategies involving commonality risk.

6. Economic significance of the commonality risk premium

Our results indicate a monthly commonality risk premium of at least 0.16% and for one specification 0.54%. In annual terms these premia are substantial, from 1.9% to 6.5%, in particular in relation to the previous literature. 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 agree 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.

In this next two subsections we seek to further the sustainability and understanding of the commonality risk premium.

6.1. Extending the holding period

Some of the return premia found in this paper are remarkably high. A weakness of the methodology applied is that we do not consider the transaction costs for implementing the High-minus-Low strategy. Given our focus on one-month holding periods, the cost of rebalancing may undermine the return premium. To maximize the returns, a real-world investor would 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. Panel A displays results for effective spreads and Panel B holds price impact results. In each panel, we present results for illiquidity measures based on CRSP and TAQ data. The solid red line represents CRSP results for the full sample, whereas the dashed red line is for the same measure but for the subperiod that is comparable to TAQ (1996-2008). The TAQ results are given for commonality betas estimated on monthly data (blue line) as well as daily data (black line). For comparability, all holding period return premia are annualized.

[Insert Figure 1 here]

Panel A shows that the average return premium for commonality betas estimated on monthly betas holds up well when the holding period is extended up to twelve months. The 12-months holding period return for 1996-2008 is 2.4% for TAQ data and 2.5% for CRSP data. For the full CRSP sample the premium amounts to 3.2% per year. When the commonality betas are estimated on daily data, the return premium on short holding periods is substantially higher, but it deteriorates quickly when the holding period is extended. On a twelve-month holding period that premium amounts to 1.5%.

The commonality risk premia associated with price impact (Panel B) are falling with the length of the holding period, implying that the durability of this strategy is shorter than for effective spreads. This holds regardless of data source and data frequency for the commonality beta estimation. Here, the daily data frequency outperforms the monthly frequency at all considered investment horizons. On the twelve-months investment horizon, the return to the daily TAQ data strategy is 1.7%, as compared to the monthly TAQ data at 1.1%. For price impact we also note that the low-frequency data source CRSP yields a much lower return premium (essentially zero for 1996-2008) than the high-frequency data source TAQ.

The conclusion from extending the holding period is that the highest commonality risk return premia reported above are not sustainable for longer horizons, and on short horizons they may be undermined by transaction costs. Nevertheless, the twelve-month holding period return premia demonstrate that commonality risk is an important risk for investors to understand and to monitor.

6.2. Expsoure to other risk factors

To further improve the understanding of the commonality risk premia, as a final application we investigate in a time-series factor model setting 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 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).[7]

[Insert Table 9 here]

Table 9 shows the factor model results. As above, we consider results based on different illiquidity measures, each presented in separate panels (Panels A–F). For this application we use returns from portfolios with monthly rebalancing. In each panel we consider the four factor models listed above.

Panels A and D show the results based on CRSP data for the full sample, for effective spreads and price impact respectively. We observe here that in spite of the long-short strategy, most models display a positive and significant exposure to the market factor (*MKT*). The commonality risk strategy is also exposed to the size factor (*SMB*), but not to the value factor (*HML*). There is also a positive and significant exposure to the momentum factor (*MOM*), but no significant exposure to the liquidity factor (*LIQ*). These results are consistent

[7]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.

across the two illiquidity measures, though the exposures are in general higher for the strategy based on price impact.

Looking at the intercepts of the five models, these remain positive and significant for all models except the four-factor momentum model. 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 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.

For the commonality risk premium based on TAQ data, the factor model results differ substantially between the monthly and the daily frequency. As for the return premia presented in Table 7, the short time period makes the factor model intercepts associated with the monthly TAQ data insignificantly different from zero (see Table 9, Panels B and E). The magnitude of the intercepts is, however, comparable to the CRSP results. For the daily TAQ factor models, the intercepts are statistically different from zero in all models, for both effective spreads and price impacts. The only risk factor to which these strategies are significantly exposed is *MOM*, and again the four-factor model is the factor model registering the highest adjusted R^2.

7. Conclusions

The commonality in illiquidity literature is vast when it comes to the existence and causes of commonality. The implications of commonality, however, are not clear from the current literature. We address this gap in the literature by studying whether investors associate commonality risk with a return premium.

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.

We thoroughly analyze how different approaches to illiquidity measurement, systematic illiquidity estimation, and commonality risk estimation influence the commonality risk premium. Overall, we find that the commonality risk premium is robust to such variations in methodology. For short holding periods, we find that the commonality risk premium is higher when we use the price impact rather than the relative effective spread as illiquidity measure. For longer holding periods (that may be motivated by transaction costs), the premium associated with the relative effective spread is more persistent.

Our findings also indicate that commonality risk is estimated with better precision when daily rather than monthly illiquidity measures are used. This is demonstrated in that a higher fraction of the beta estimates are positive, which they should be according to theories explaining the existence of commonality. In addition, the commonality risk premium is higher when risk estimates based on daily data is used, at least for holding periods up to three months. Thus, investors who monitor the commonality risk of their portfolios may be adviced to use daily illiquidity measures rather than monthly.

Finally, we find that when the commonality risk premium is based on monthly illiquidity data, it is positively related to the market return, the size premium, and the momentum premium. When instead daily illiquidity data is used for commonality risk estimation, the only other risk factor that it relates to is momentum.

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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 principal components	Daily	Yes
Koch et al. (2010)	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
Karolyi et al. (2011)	40 countries	1995-2004	ILLIQ; turnover	Daily	Value-weighted	Daily	Yes

Table 2: Descriptive statistics of individual stocks

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. Illiquidity innovations are calculated as the first-difference of level illiquidity, and are cross-sectionally winzorized at the 0.5% and 99.5% quantiles. 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. 2008.

Measure	Mean	Median	Sd	Min	Max
Number of firms	1740	1762	187	1210	2129
Effective spread (%)	0.927	0.666	0.927	0.001	23.176
ΔEffective spread (%)	-0.0038	-0.0012	0.566	-8.752	5.7877
Price impact (%) $x10^6$	2.838	0.308	8.793	0.000	1509.076
ΔPrice impact (%) $x10^6$	0.0006	0.0000	3.405	-56.296	44.9664
Market cap. (MUSD)	2153.3	219.2	11022.9	0.4	581098.9
Turnover (%)	6.188	3.350	10.300	0.000	2995.744

Table 3: Commonality in illiquidity using different illiquidity measures and different time periods

Commonality regressions are run for eligible stocks each month from Dec. 1965 - Dec. 2008. 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: liquidity & commonality beta	
Time period	R^2	Coeff.	Positive	Positive and significant	Regressions	Systematic liquidity	Pearson	Spearman
Dec. 1965 - Dec. 1980	0.059	1.115	73.6%	15.8%	1549	1131	0.350	0.415
Jan. 1981 - Dec. 1995	0.051	1.086	70.7%	12.2%	1388	1108	0.384	0.428
Jan. 1996 - Dec. 2008	0.070	1.038	75.4%	19.9%	1356	1040	0.301	0.347
Dec. 1965 - Dec. 2008	0.060	1.082	73.1%	15.8%	1435	1095	0.347	0.399

Panel B: Price impact results

		Commonality betas			Number of stocks		Correlation: liquidity & commonality beta	
Time period	R^2	Coeff.	Positive	Positive and significant	Regressions	Systematic liquidity	Pearson	Spearman
Dec. 1965 - Dec. 1980	0.166	1.449	93.0%	51.7%	1549	1131	0.565	0.809
Jan. 1981 - Dec. 1995	0.119	1.220	88.2%	39.9%	1388	1108	0.526	0.862
Jan. 1996 - Dec. 2008	0.083	1.145	83.9%	26.7%	1356	1040	0.571	0.869
Dec. 1965 - Dec. 2008	0.125	1.278	88.6%	40.1%	1435	1095	0.553	0.845

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. 2008. 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	0.806	3.27	0.892	-0.677	1.083	28.39
2	0.673	2.77	0.847	-0.297	1.023	32.02
3	0.667	2.81	0.829	-0.107	1.090	33.98
4	0.599	2.54	0.817	0.045	1.020	31.35
5	0.537	2.33	0.793	0.151	0.916	28.22
6	0.584	2.52	0.782	0.234	0.934	29.88
7	0.555	2.42	0.772	0.298	0.844	26.69
8	0.536	2.30	0.768	0.343	0.823	24.87
9	0.539	2.36	0.766	0.367	0.846	25.96
Low	0.588	2.59	0.769	0.380	0.791	23.77
High-Low	0.218	2.66	0.122	-1.056	0.293	5.21

Panel B: Price impact results

Portfolio	Excess returns (%)	t	Price impact (%)	Relative market cap.	Commonality beta	t
High	0.846	3.17	2.765	-0.713	0.912	28.46
2	0.809	3.29	2.449	-0.321	0.801	32.87
3	0.645	2.74	2.310	-0.132	0.828	38.97
4	0.688	2.96	2.217	0.010	0.806	36.46
5	0.574	2.53	2.133	0.119	0.792	38.46
6	0.599	2.63	2.084	0.223	0.809	35.95
7	0.553	2.43	2.030	0.304	0.731	31.14
8	0.432	1.91	1.951	0.380	0.779	33.82
9	0.429	1.91	1.970	0.429	0.733	31.89
Low	0.408	1.87	2.029	0.458	0.739	30.47
High-Low	0.438	3.52	0.736	-1.172	0.173	3.78

Table 5: Influence of the choice of systematic illiquidity estimator on portfolio results

Correlations between systematic illiquidity estimators (equal-weighted average; value-weighted average; principal components) as well as between commonality betas estimated on different systematic illiquidity estimators, are given in Panel A. Correlations are estimated in the cross-section of stocks each month and averaged across time, Jan. 1966 - Dec. 2008. The portfolio results in Panels B and C follow the same methodology as in Table 4, except that the commonality betas are estimated as exposure to the value-weighted estimator (Panel B) and the principal component estimator (Panel C) rather than the equal-weighted estimator. All results are based on the relative effective spreads. 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, using an equal-weighted average of illiquidity as systematic illiquidity estimator.

Panel A: Correlations between estimators and between commonality betas

	Pearson correlation between systematic illiq.		Spearman correlation between commonality betas	
	Effective spread	Price impact	Effective Spread	Price impact
Equal-weighted vs. value-weighted	0.795	0.906	0.690	0.973
Equal-weighted vs. principal components	0.401	0.883	0.560	0.966
Value-weighted vs. principal components	0.345	0.883	0.480	0.968

Panel B: Commonality beta portfolios based on effective spread and value-weighted systematic illiquidity

Portfolio	Excess returns (%)	t	Effective spread (%)	Relative market cap.	Commonality beta	t
High	0.697	2.88	0.863	-0.487	1.016	29.63
2	0.717	3.06	0.825	-0.128	1.033	31.56
3	0.608	2.59	0.800	0.054	0.991	29.63
4	0.601	2.57	0.781	0.179	0.959	31.45
5	0.522	2.28	0.769	0.265	0.928	28.46
6	0.570	2.47	0.759	0.323	0.923	27.67
7	0.594	2.62	0.753	0.365	0.894	27.38
8	0.614	2.67	0.754	0.382	0.871	27.30
9	0.565	2.44	0.747	0.386	0.864	25.07
Low	0.535	2.34	0.743	0.377	0.761	22.72
High-Low	0.162	2.11	0.120	-0.864	0.256	4.92

Table 5 (continued)

Panel C: Commonality beta portfolios based on effective spread and principal component systematic illiquidity

Portfolio	Excess returns (%)	t	Effective spread (%)	Relative market cap.	Commonality beta	t
High	0.730	3.07	0.854	-0.446	0.904	21.84
2	0.699	2.97	0.823	-0.175	0.847	22.78
3	0.580	2.55	0.804	-0.011	0.911	24.71
4	0.625	2.68	0.796	0.087	0.883	24.79
5	0.515	2.25	0.784	0.175	0.818	22.21
6	0.562	2.43	0.779	0.254	0.870	25.72
7	0.577	2.54	0.779	0.293	0.884	23.25
8	0.615	2.67	0.774	0.315	0.830	22.04
9	0.531	2.26	0.780	0.315	0.850	21.62
Low	0.472	2.02	0.772	0.303	0.828	20.06
High-Low	0.258	3.00	0.082	-0.749	0.076	1.23

Table 6: 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. Monthly turnover is measured as the dollar trading volume divided by the market capitalization. Correlation statistics are Pearson correlations pooled panels of monthly illiquidity measures. The time period considered is Jan. 1993 - Dec. 2008.

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 (%)	0.4400	0.2944	0.4825	0.0144	37.969
ΔEffective spread (%)	-0.0033	-0.0022	0.1848	-2.8314	2.908
Price impact (%) x10^3	0.7532	0.2868	1.3124	-4.6153	41.389
ΔPrice impact (%) x10^3	-0.0055	-0.0008	0.5215	-5.5165	5.5087
Market cap. (MUSD)	5412.9	950.3	17794.5	1.5	310715.1
Turnover (monthly, %)	10.4	6.7	12.8	0.0	549.5

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 (%)	0.3033	0.2038	0.3283	0.0015	53.883
ΔEffective spread (%)	-0.0005	-0.0001	0.1531	-5.3464	6.962
Price impact (%) x10^3	0.4472	0.1918	0.8017	-14.8024	45.875
ΔPrice impact (%) x10^3	0.0002	0.0000	0.4649	-8.3220	9.1431
Market cap. (MUSD)	5326.8	866.1	20487.3	1.5	581098.9
Turnover (monthly, %)	10.9	7.0	13.7	0.0	651.1

Panel C: Panel correlations between monthly illiquidity measures

	ES (CRSP)	PI (CRSP)	ES (TAQ)	PI (TAQ)
Effective spread (CRSP)	1			
Price impact (CRSP)	0.316	1		
Effective spread (TAQ)	0.721	0.221	1	
Price impact (TAQ)	0.649	0.313	0.758	1

Table 7: Commonality in illiquidity using different types of data for illiquidity measurement

Commonality regressions are run for eligible stocks each month Jan. 1996 - Dec. 2008. Illiquidity is estimated on a monthly frequency using CRSP data, and on a monthly and a daily frequency using TAQ data, as described in Tables 2 and 6. 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 Jan. 1996 and expands gradually to 60 months in Jan. 1998, after which it moves forward by one month for each step in time. As the estimation window is limited by dates, regressions on daily data employ more observations than regressions on monthly data. The regression analysis has individual stock illiquidity innovations as the dependent variable and systematic illiquidity and marketwide returns as independent variables. Panel A and B hold results for the relative effective spreads and the price impacts, respectively. The fraction of commonality betas being positive and significant is determined using a 95% confidence level. All reported metrics are time-series averages of cross-sectional estimates.

Panel A: Effective spread results

		Commonality betas			Number of stocks		Correlation: liquidity & commonality beta	
Jan. 1996 - Dec. 2008	R^2	Coeff.	Positive	Positive and significant	Regressions	Systematic liquidity	Pearson	Spearman
CRSP (monthly)	0.070	1.038	75.5%	19.9%	1356	1040	0.301	0.347
TAQ (monthly)	0.153	1.328	91.6%	52.6%	1083	591	0.472	0.543
TAQ (daily)	0.042	1.189	95.6%	80.6%	1083	591	0.355	0.438

Panel B: Price impact results

		Commonality betas			Number of stocks		Correlation: liquidity & commonality beta	
Jan. 1996 - Dec. 2008	R^2	Coeff.	Positive	Positive and significant	Regressions	Systematic liquidity	Pearson	Spearman
CRSP (monthly)	0.083	1.145	83.9%	26.7%	1356	1040	0.571	0.869
TAQ (monthly)	0.140	2.135	91.3%	49.6%	1083	591	0.561	0.712
TAQ (daily)	0.015	1.362	90.5%	61.0%	1083	591	0.531	0.685

Table 8: Portfolios based on TAQ illiquidity measures

Correlations between illiquidity measures based on different data sources and estimated on different frequencies (CRSP monthly, TAQ monthly, TAQ daily) are given in Panel A. Correlations are estimated in the cross-section of stocks each month and averaged across time, Jan. 1966 - Dec. 2008. The portfolio results in Panels B-C follow the same methodology as in Table 4, except that the commonality betas are estimated on TAQ data instead of CRSP. The portfolio results in Panels D-E are based on daily illiquidity measures (estimated from TAQ data). As the estimation window is limited by dates, regressions on daily data employ more observations than regressions on monthly data. 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, using an equal-weighted average of illiquidity as systematic illiquidity estimator.

Panel A: Spearman rank correlations between commonality betas of different data sets

	Effective spread	Price impact
CRSP (monthly) vs. TAQ (monthly)	0.307	0.769
CRSP (monthly) vs. TAQ (daily)	0.222	0.699
TAQ (monthly) vs. TAQ (daily)	0.398	0.684

Panel B: Effective spread results for TAQ (monthly)

Portfolio	Excess returns (%)	t	Effective spread (%)	Relative market cap.	Commonality beta	t
High	0.658	1.65	0.150	-0.2098	0.874	23.67
2	0.595	1.40	0.145	0.0477	0.840	26.54
3	0.418	1.02	0.142	0.1990	0.905	33.97
4	0.426	1.09	0.141	0.2737	0.779	24.09
5	0.461	1.14	0.140	0.3063	0.809	27.43
6	0.449	1.09	0.141	0.3448	0.875	28.68
7	0.543	1.34	0.137	0.3981	0.777	24.96
8	0.195	0.47	0.138	0.4221	0.822	23.57
9	0.393	0.98	0.138	0.3827	0.880	19.71
Low	0.464	1.22	0.141	0.2686	0.726	17.94
High-Low	0.194	1.09	0.009	-0.4784	0.148	2.43

Table 8 (continued)

Panel C: Price impact results for TAQ (monthly)

Portfolio	Excess returns (%)	t	Price impact (%)	Relative market cap.	Commonality beta	t
High	0.567	1.34	0.449	-0.5726	0.833	18.55
2	0.427	1.06	0.419	-0.1572	0.645	16.18
3	0.550	1.40	0.403	0.0408	0.680	19.83
4	0.344	0.88	0.388	0.1995	0.672	20.17
5	0.536	1.36	0.383	0.3013	0.701	24.10
6	0.405	1.02	0.377	0.3819	0.607	18.90
7	0.323	0.80	0.368	0.4707	0.696	22.12
8	0.479	1.14	0.367	0.5422	0.698	18.87
9	0.378	0.92	0.370	0.5985	0.613	16.38
Low	0.234	0.58	0.383	0.6237	0.592	15.62
High-Low	0.333	1.55	0.066	-1.1963	0.241	3.77

Panel D: Effective spread results for TAQ daily

Portfolio	Excess returns (%)	t	Effective spread (%)	Relative market cap.	Commonality beta	t
High	0.664	1.80	0.147	-0.1059	0.850	31.13
2	0.497	1.36	0.141	0.1198	0.849	29.41
3	0.395	1.00	0.139	0.1713	0.818	30.47
4	0.393	1.02	0.140	0.2291	0.781	24.56
5	0.451	1.08	0.137	0.2854	0.778	29.37
6	0.495	1.19	0.137	0.3112	0.762	30.94
7	0.378	0.94	0.137	0.3474	0.752	27.49
8	0.433	1.00	0.140	0.3642	0.838	31.47
9	0.402	0.95	0.137	0.3585	0.826	23.43
Low	0.347	0.85	0.139	0.2666	0.835	23.73
High-Low	0.317	2.41	0.008	-0.3726	0.015	0.32

Panel E: Price impact results for TAQ daily

Portfolio	Excess returns (%)	t	Price impact (%)	Relative market cap.	Commonality beta	t
High	0.704	1.87	0.405	-0.4385	0.681	17.09
2	0.524	1.34	0.378	-0.0725	0.618	20.46
3	0.331	0.85	0.366	0.1334	0.551	17.84
4	0.385	1.01	0.350	0.2824	0.617	21.07
5	0.536	1.42	0.343	0.3948	0.606	18.38
6	0.394	1.00	0.350	0.4707	0.628	21.43
7	0.389	0.94	0.349	0.5508	0.682	23.91
8	0.502	1.20	0.345	0.6271	0.555	19.03
9	0.573	1.32	0.367	0.5969	0.570	14.15
Low	0.160	0.36	0.355	0.5921	0.646	17.47
High-Low	0.544	2.80	0.050	-1.0306	0.035	0.65

Table 9: 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. Each panel holds results for commonality betas estimated on different illiquidity measures (effective spreads and price impacts) and different data sources (CRSP and TAQ). 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.

Panel A: Monthly effective spread based on CRSP data (1962-2008)

	Constant	*MKT*	*SMB*	*HML*	*MOM*	*LIQ*	R2
MKT	0.0019 *	0.0733 *					0.03
FF3	0.0018 *	0.0180	0.2050 *	-0.0438			0.16
FF3+MOM	0.0003	0.0411 *	0.2044 *	-0.0011	0.1527 *		0.26
MKT+LIQ	0.0020 *	0.0705 *				-0.0056	0.03

* Statistically significant at the 95% confidence level

Panel B: Monthly effective spread based on TAQ data (1993-2008)

	Constant	*MKT*	*SMB*	*HML*	*MOM*	*LIQ*	R2
MKT	0.0017	0.1173 *					0.06
FF3	0.0020	0.0254	0.2001 *	-0.1572			0.29
FF3+MOM	0.0010	0.0648	0.1826 *	-0.1297	0.0964 *		0.34
MKT+LIQ	0.0029	0.0231				-0.1266	0.08

* Statistically significant at the 95% confidence level

Panel C: Daily effective spread based on TAQ data (1993-2008)

	Constant	*MKT*	*SMB*	*HML*	*MOM*	*LIQ*	R2
MKT	0.0033 *	-0.0832					0.05
FF3	0.0038 *	-0.1094	-0.0326	-0.0953			0.07
FF3+MOM	0.0025 *	-0.0581	-0.0554	-0.0595	0.1256 *		0.22
MKT+LIQ	0.0034 *	-0.0894				-0.0084	0.05

* Statistically significant at the 95% confidence level

Panel D: Monthly price impact based on CRSP data (1962-2008)

	Constant	*MKT*	*SMB*	*HML*	*MOM*	*LIQ*	R2
MKT	0.0037 *	0.2070 *					0.11
FF3	0.0042 *	0.0989 *	0.2732 *	-0.1946			0.25
FF3+MOM	0.0010	0.1461 *	0.2721 *	-0.1075	0.3116 *		0.45
MKT+LIQ	0.0043 *	0.1748 *				-0.0651	0.11

* Statistically significant at the 95% confidence level

Table 9 (continued)

Panel E: Monthly price impact based on TAQ data (1993-2008)

	Constant	*MKT*	*SMB*	*HML*	*MOM*	*LIQ*	R2
MKT	0.0032	0.0811					0.01
FF3	0.0034	-0.0083	0.1948 *	-0.1528			0.16
FF3+MOM	0.0009	0.0932 *	0.1497 *	-0.0820	0.2486 *		0.39
MKT+LIQ	0.0043	-0.0101				-0.1225	0.03

* Statistically significant at the 95% confidence level

Panel F: Daily price impact based on TAQ data (1993-2008)

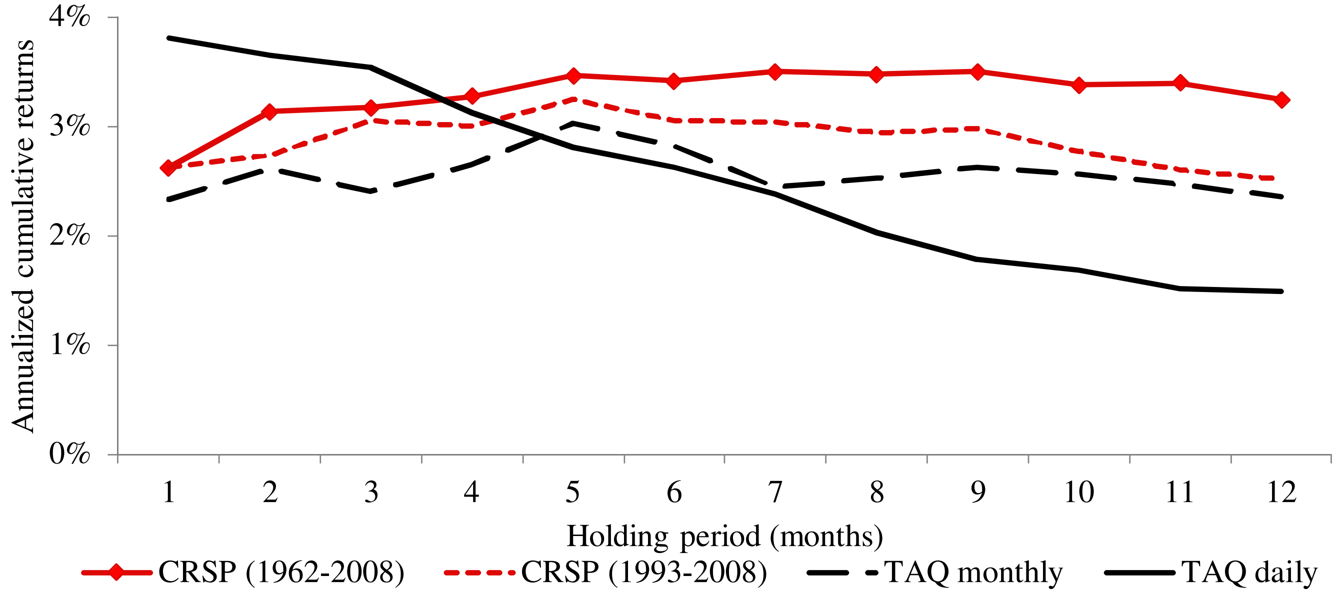
	Constant	*MKT*	*SMB*	*HML*	*MOM*	*LIQ*	R2
MKT	0.0058 *	-0.1774					0.11
FF3	0.0060 *	-0.2306	0.0981	-0.1008			0.16
FF3+MOM	0.0041 *	-0.1520	0.0633	-0.0459	0.1924 *		0.33
MKT+LIQ	0.0068 *	-0.2589				-0.1095	0.13

* Statistically significant at the 95% confidence level

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. Panels A and B hold results for commonality betas estimated on the relative effective spreads and the price impacts, respectively. Within each panel, four different sets of commonality betas are considered: (i) monthly illiquidity based on CRSP data from 1962-2008; (ii) monthly illiquidity based on CRSP data from 1993-2008; (iii) monthly illiquidity based on TAQ data from 1993-2008; (iv) daily illiquidity based on TAQ data from 1993-2008. 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.

A. Effective spread results



B. Price impact results