Does commonality in illiquidity command a risk premium?\textsuperscript{1}

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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. In a more than fifty year long sample of NYSE stocks, we find that commonality risk carries a return premium of at least 2.0 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, transaction costs, as well as variations in illiquidity measurement.
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. Stocks that become more illiquid when market-wide liquidity dries up 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 premium to commonality risk, defined as the risk that a security becomes more illiquid when the market in general becomes more illiquid.

A substantial literature has established the existence of commonality. Chordia et al. (2000) and Huberman and Halka (2001) first documented commonality in stock market illiquidity for NYSE stocks. A large number of later studies have confirmed commonality in stock markets (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). Furthermore, Kamara et al. (2008) show that commonality in illiquidity on US stock markets has been increasing over time, perhaps due to the increased institutional-investor presence.

Models of market mechanisms that generate commonality are also well-known. Coughenour and Saad (2004), for example, suggest that commonality in illiquidity exists because suppliers and demanders of liquidity are exposed to similar underlying risk factors affecting all securities. One such factor is the cost of capital, a determinant of the cost of providing liquidity: interest rate changes affect illiquidity 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, leading 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.

Given the number of studies focusing on the existence and causes 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 should indeed carry a return premium. Nevertheless, empirical evidence by Acharya and Pedersen (2005), Lee (2011), and Hagstrømer 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.

A related literature has addressed the concept of systematic illiquidity, but its link to commonality risk is vague: such studies investigate the comovement between systematic illiquidity and individual asset returns, while commonality risk is defined as the comovement of systematic illiquidity and individual asset illiquidity. Studies that have assumed the existence of a systematic illiquidity factor and investigated how stock return comovement with systematic illiquidity affects expected returns include Amihud et al. (2015); Asparouhova et al. (2010); Brennan et al. (2013); Hasbrouck (2009); Korajczyk and Sadka (2008); Liu (2006); Pástor and Stambaugh (2003); and Sadka (2006).

We argue that studies of commonality risk must be designed with great care because such risk is highly correlated to the illiquidity level. Studies addressing the pricing of commonality risk typically have employed a portfolio-based approach, sorting portfolios on illiquidity level rather than commonality risk. In that setting, the commonality risk premium is reported as negligible. But sorting portfolios by illiquidity level may be inadequate to break the close correlation: 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 be an artifact of such techniques.
In this study, we apply a stratified portfolio formation 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. We show that commonality risk based on market depth is priced in the cross-section of portfolio returns, that its monthly return premium cannot be explained by common factor models, and that it persists in holding periods up to one year.

2 Literature on the pricing and existence of commonality risk

Investors should be concerned with commonality in illiquidity for two reasons. Firstly, the LCAPM by Acharya and Pedersen (2005) shows theoretically that commonality risk influences expected returns. According to the LCAPM, the conditional expected gross return of security $i$ can be decomposed into the risk-free rate of interest, the expected illiquidity cost, the market risk premium, and three different types of illiquidity risk premia.

Commonality risk is the first type of illiquidity risk, defined as the risk of holding a security that becomes more illiquid when the market in general becomes more illiquid. 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 becomes more illiquid when market returns are negative.

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 summarize the literature documenting the existence of commonality in illiquidity, and then present the prior evidence on the commonality risk premium.
2.1 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. 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.

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).

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.

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1For 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 (2010) for options.
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.

### 2.2 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, Hagström 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 Hagström 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 while controlling for illiquidity level. We then 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 and systematic illiquidity estimation.

3 Does commonality in illiquidity command a risk premium?

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. In the end of the section we provide a discussion of the economic significance of the results and put them in perspective by relating them to transaction costs and common factor models.

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). Excess returns are the monthly returns minus the risk-free rate, adjusted for delistings in the same way as in Acharya and Pedersen (2005), following Shumway (1997). We retrieve book value data from the Compustat database, to be used for book-to-market ratios, calculated as in Fama and French (1993).

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 mini-
mum tick size adds substantial noise to the returns on low-priced stocks, we include stocks priced $5 or higher only.

Our sample period includes 601 months, December 1962 – December 2012. For the same period, we also obtain monthly data on the market return factor ($MKT$), the size factor ($SMB$), the value factor ($HML$), the momentum factor ($MOM$), and the risk-free rate of interest from Kenneth French’s website.

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 the *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). Following Acharya and Pedersen (2005) we address potential non-stationarity and large outliers using the transformation

\[
\text{Price Impact} = \min(0.25 + 0.30 \times ILLIQ_i^{t}, P_{t-1}^M, 30.00),
\]

where \( ILLIQ_i^{t} \) is the average ratio of absolute returns and dollar trading volume (in millions) for stock \( i \) across all trading days in month \( t \), and \( P_{t-1}^M \) is the market portfolio capitalization at the end of month \( t - 1 \) divided by the market portfolio capitalization at the end of November 1962.

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 each illiquidity measure, and the monthly stock characteristics including market capitalization, book-to-market ratios, price, and turnover of eligible firms.

[Insert Table 2 about here]

The number of firms eligible for analysis varies between 1134 and 2253, and averages 1781. The Effective Spread is on average 0.89%. This implies that a trade of $100 on average incurs a cost of immediacy amounting to 89 cents. 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 transformation of the ILLIQ ratio underlying the *Price Impact* is meant to put it on a scale comparable to the effective spread, but the prevalence of outliers makes the mean much higher than that of the *Effective Spread*. As shown by the standard deviation, the *Price Impact* variation is much higher than that of the *Effective Spread*. Untabulated results show that the correlation between *Effective Spread* and *Price Impact* (across both time and cross-section) is 0.58.

As reference information, Table 2 also includes information on monthly market capitalization, monthly turnover, stock price, and book-to-market of the stocks in our sample.

### 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.

The estimated regression equation is

\[ l_{it}^{e} = \alpha_i + \beta_i l_{m}^{m} + u_{it}^{e}, \]  

where \( l_{it}^{e} \) and \( l_{m}^{m} \) denote innovations in illiquidity of security \( i \) and systematic illiquidity in month \( t \), \( \alpha_i \) is an intercept, \( \beta_i \) is the commonality beta, and \( u_{it}^{e} \) is the residual. Our commonality beta thus reflects the covariance between individual and systematic illiquidity innovations, scaled by the variance of systematic illiquidity innovations. The specification is consistent with Acharya and Pedersen (2005), except that they scale the covariance by the variance of the market returns minus the systematic illiquidity innovations.

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 and that have a non-zero variation in the *Price Impact* measure.\(^4\)

\(^4\)This restriction is due to that some illiquid stocks (<1% of the sample) where all observations are equal to the cap
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.\textsuperscript{5}

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 and to have a non-zero variation in the \textit{Price Impact} measure. 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 ($\hat{\beta}_i$), 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 $\beta_i$ as the commonality beta or commonality risk. In the portfolio application pursued below, the commonality betas are used for portfolio formation.

Panel (a) of Table 3 presents the results of the monthly commonality regressions for each illiquidity measure. In the columns of Table 3, we present the $R^2$ and $\hat{\beta}_i$ commonality metrics. Furthermore, we report the number of stocks eligible for the regression analysis and the systematic illiquidity estimation, respectively. Finally, we report the average cross-sectional Pearson or Spearman correlations between the level illiquidity and the commonality beta.

[Insert Table 3 about here]

For the \textit{Effective Spread}, we find that the degree of commonality is 0.03 on average, compared to 0.11 for the \textit{Price Impact}. The commonality in illiquidity is thus considerably stronger in the market depth dimension than in market tightness. This may indicate that commonality risk is priced higher for market depth than for market tightness.

\textsuperscript{5}We have repeated all estimations in the paper using a value-weighted systematic illiquidity estimator. The results are qualitatively the same.
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.

For both illiquidity measures we find that the commonality betas are positively correlated to the level of illiquidity. In particular, for *Price Impact* the Spearman rank correlation is high and positive, 0.70. This result implies that portfolios sorted on illiquidity level (e.g., as in Acharya and Pedersen, 2005) are likely to be dispersed in terms of both commonality betas and illiquidity level. The return difference between a highly illiquid and a highly liquid portfolio may then reflect both an illiquidity level premium and a commonality risk premium. In the portfolio formation pursued in Section 3.4 we seek to form portfolios that are dispersed in terms of commonality beta, but flat in terms of illiquidity level.

Panel (b) of Table 3 presents properties of the cross-sectional distribution of commonality betas. For each month we calculate percentiles of the commonality beta distribution. We report time-series averages for the percentiles corresponding to 1%, 10%, 25%, 50%, 75%, 90%, and 99%. We find that commonality betas feature substantial dispersion in the cross-section. In the subsequent analysis we investigate whether investors value such cross-sectional differences in commonality beta.

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 is in line with expectations.
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.

Due to the high cross-sectional correlation between commonality betas and level illiquidity, a traditional dependent double sorting procedure is not enough to separate the effects of illiquidity level and commonality betas. In unreported analysis we perform a five-by-five portfolio sort, first by illiquidity level and then by commonality beta. We find that such a procedure yields portfolios that are dispersed both in terms of illiquidity level and in terms of commonality betas. To separate the two we thus require a less conventional portfolio formation procedure.

We develop a stratified portfolio formation technique. We first divide the sample of stocks into 50 illiquidity level strata. We then rank the stocks of each stratum by their commonality beta, and from each stratum we put the top decile into portfolio 1, the second decile into portfolio 2, and so on. In this way, we retrieve 10 portfolios for each month with different commonality betas and with stocks drawn from 50 different levels of illiquidity.

We form the 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 3.6). 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 the Effective Spread, and Panel (b) holds the Price Impact portfolio properties. Portfolio 1 is the high commonality risk portfolio (HighBeta), and Portfolio 10 is the low commonality risk portfolio (LowBeta). Our primary interest among the portfolio properties is the portfolio return, but we also report the illiquidity level as well as other characteristics.

[Insert Table 4 about here]
The leftmost column of each panel reports monthly portfolio excess returns, calculated as equal-weighted averages of monthly excess returns. For both illiquidity measures, the portfolio returns are decreasing with the portfolio number, indicating that high commonality beta stocks have higher returns on average. Using a HighBeta – LowBeta strategy, being long in Portfolio 1 and short in Portfolio 10, an investor would get an average monthly return of 0.17% (0.53%) when commonality betas are based on the Effective Spread (Price Impact). In annual terms, at 2.0% (6.4%), 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 High-Low return premia are also statistically significant.

Importantly, the commonality risk portfolios are highly similar in terms of their level of illiquidity. In both panels of Table 4, we report that the LowBeta portfolio has a slightly higher illiquidity than the HighBeta portfolio, which is opposite to the general tendency of positively related commonality betas and illiquidity levels. That illiquidity level is virtually flat across the portfolios shows the merit of our stratified portfolio formation procedure and makes it unlikely that the return differences observed is due to illiquidity level.

We note also that both illiquidity measures are around 0.57% on average, which is lower than the central measures reported in Table 2. This is likely due to that excluded stocks tend to be relatively illiquid.

We also report the characteristics Size, Price, Turnover, and B/M for each portfolio. 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 lower market capitalization than the cross-sectional average have negative numbers.

We observe a clear size effect in our portfolios, indicating that commonality risk is decreasing in Size. The size effect is particularly strong for the Price Impact portfolios. There is also a tendency that portfolios featuring high commonality risk have lower Price and higher B/M. For Turnover we observe opposite tendencies for the two illiquidity measures, but overall the dispersion in Turnover across portfolios is relatively small.
The return difference between the HighBeta and LowBeta is interesting, but to confirm its relation to commonality risk, we need to control for other portfolio characteristics. In the next subsection we investigate if the commonality risk is priced in the cross-section of expected portfolio returns.

3.5 The commonality risk premium in the cross-section of expected returns

To investigate the role of the level of illiquidity and the commonality risk in the cross-section of portfolio returns, we jointly run GMM estimations of time-series regressions and cross-sectional regressions following Cochrane (2005), pp. 241-243. We modify his setup to allow for portfolio specific characteristics in the cross-sectional regressions (see, e.g., Hasbrouck, 2009). The GMM estimations are repeated for a panel of monthly equally weighted portfolios sorted on each of the two illiquidity measures, Effective Spread and Price Impact.

The time-series regressions determine the market return beta, $\beta_i^M$, and the commonality beta, $\beta_i^{IC}$, for each portfolio $i$ and are given by:

$$R_{it} = \alpha_i + \beta_i^M R^M_t + \beta_i^{IC} R^{IC}_t + \epsilon_{it}. \tag{3}$$

In Eq. (3), the dependent variable $R_{it}$ is the excess return for portfolio $i$, the factor $R^M_t$ is the excess market return and $R^{IC}_t$ is the return on a zero investment traded illiquidity commonality factor. The illiquidity commonality factor is constructed as the average return on the top 30% stocks in terms of commonality beta, minus the average return on the bottom 30% stocks on the same characteristic.

The cross-sectional regressions determine the risk-prices of market risk and commonality risk and are given by:

$$R_{it} = \delta_0 + \lambda_M \beta_i^M + \lambda_{IC} \beta_i^{IC} + \delta_{Illiq} Illiq_{it} + \delta_{Size} Size_{it} + \delta_{B/M} B/M_{it} + u_{it}. \tag{4}$$

In Eq. (4), the dependent variable $R_{it}$ is as in Eq. (3), and the independent variables $\beta_i^M$ and $\beta_i^{IC}$ are the estimated betas from Eq. (3), with corresponding risk-prices $\lambda_M$ and $\lambda_{IC}$. Because the portfolios are constructed in an attempt to isolate the illiquidity commonality risk from the illiquidity level...
effect, our main interest in the estimates concerns the significance of $\lambda_{IIIq}$ and $\delta_{IIIq}$.

We run three different versions of Eq. (4). Model (1), which includes only $\beta_{IM}^i$ and $\beta_{IC}^i$ as explanatory variables (the cross-sectional constant $\delta_0$ is included in all specifications); Model (2), which in addition includes the illiquidity level as an explanatory variable; and Model (3), which also includes the additional characteristics size, $Size_{it}$, and book-to-market, $B/M_{it}$. Model (1) is the baseline model. In Model (2), we add the illiquidity level characteristic to investigate whether it has explanatory power in the cross-section. This is further expanded in Model (3), with the addition of the size and book-to-market characteristics. It is well known that in the presence of (multiple) characteristics, the significance of the risk-prices may go away, which in turn could give some hints of which (if any) portfolio specific characteristics could help in explaining the expected portfolio returns. This serves as a secondary motivation for the specifications of Model (2) and Model (3).

We calculate HAC-consistent GMM standard errors for the regression coefficients, to correct for heteroscedasticity and autocorrelation, as well as for the ”generated regressors” estimation error in the beta values (see, e.g., Andrews, 1991 and Cochrane, 2005). Parameters estimates from the cross-sectional regressions are presented in Table 5. Parameter estimates for the time-series regressions are not reported, but they are available from the authors upon request. As expected, there is a strong gradient in the illiquidity commonality betas across portfolios. All portfolios have market betas close to one.

[Insert Table 5 about here]

Depending on the illiquidity measure employed, as expected, the cross-sectional regression results differ somewhat at a detailed level. However, the results have most elements in common, both across illiquidity measures and across models. First, and most importantly, the results strongly suggest that the illiquidity level lacks explanatory power in the cross-section. The coefficient on the level of illiquidity is far from being significant in any model or for any illiquidity measure. We therefore conclude that differences in illiquidity level are not the source of the documented cross-sectional dispersion in portfolio returns. Second, we observe that commonality risk is priced in the

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6We also estimate cross-sectional regressions with only the market beta as independent variable. To conserve space these results are not reported, but available from the authors upon request.
baseline model (Model (1)) for both illiquidity measures. Third, adding the illiquidity level as a characteristic (Model (2)) does not alter this result. Fourth, the price of market risk is significant in all specifications.

Further, we note that in Model (3), with multiple characteristics added, the price of illiquidity commonality risk is significant only for the transformed price impact measure, *Price Impact*, see Panel (b). For both illiquidity measures, all characteristics in Model (3) are statistically insignificant. The evidence in Panel (a) that the commonality risk price is no longer significant when the *Size* characteristic is added may indicate that commonality risk contributes to the size effect documented by Banz (1981).

Taken together, we find strong support for that illiquidity level is not the origin of the observed cross-sectional return dispersion, and reasonably strong support for that commonality risk is a priced systematic risk factor that is unrelated to the level of illiquidity.

### 3.6 Economic significance

Our results indicate a range for the annual commonality risk premium from 2.0% to 6.4%. This is much higher than what is reported in the previous literature on commonality risk. According to Acharya and Pedersen (2005), the 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. Hagström et al. (2013) study the same premium for a longer time period (1927-2010) and report it to be 1.74% to 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 study and the previous literature is the portfolio sorting. Whereas Acharya and Pedersen (2005) and Hagström 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 potential weakness of the methodology applied above is that transaction costs for imple-
menting the \textit{HighBeta – LowBeta} 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. In Panel (a), we show how the \textit{HighBeta – LowBeta} excess return develops as we extend the holding period gradually from one month to twelve months. All holding period return premia are annualized, such that the premia of different investment horizons are comparable. A horizontal line would imply that the same monthly return premium is earned in each of the twelve months after the portfolio formation, whereas a downward-sloping line would point to that the monthly return falls as the holding period is extended.

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 commonality betas based on the \textit{Effective Spread} the premium amounts to 1.5\% per year, which is slightly lower than the annualized premium for the one-month holding period. The commonality risk premium associated with the \textit{Price Impact}, on the other hand, is increasing somewhat with the length of the holding period. The twelve-month premium for \textit{Price Impact} amounts to 7.1\%. With the cost of a round-trip trade being around 0.57\% on average (see Table 4), the \textit{HighBeta – LowBeta} portfolio strategy outlined above, applied at a twelve-month holding period, yields positive returns net of transaction costs regardless which illiquidity measure is used.

In Panel (b) of Figure 1, we also present evidence controlling for a potential relation between the commonality risk premium and the short-term reversal effect (Jegadeesh, 1990, Lehmann, 1990). To investigate this relation, we skip one month between the portfolio selection (at the end of time \(t\)) and the portfolio performance start date (the beginning of time \(t + 2\)). The results for the \textit{Effective Spread} are slightly weaker for this specification, and for the \textit{Price Impact} they are
slightly stronger. The small differences lead us to conclude that the short-term reversal effect does not have a strong relation to the commonality risk premia that we document.

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 HighBeta – LowBeta 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 $MKT, SMB, HML$), and the four-factor momentum model by Carhart (1997; with the same factors as the three-factor model, adding $MOM$). Table 6 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 6 about here]

The results in Table 6 show that the commonality risk strategy is positively related to the market factor, the size factor and the momentum factor. For the value factor, the effect is positive for the portfolio based on the Effective Spread, but negative for the portfolio based on the Price Impact. The intercept for the Effective Spread commonality portfolio is not significant in any of the factor model specifications. In contrast, the intercept for the Price Impact commonality portfolio remains positive and significant in all factor model specifications.

The difference in results between the two illiquidity measures is consistent with the evidence in Table 3, showing that the degree of commonality is stronger for the Price Impact. It seems reasonable that if the systematic variation in illiquidity is higher for Price Impact, investors are also more concerned about that type of commonality beta. It is also important to note that the two measures are designed to capture different dimensions of illiquidity – they represent market tightness and market depth. Our evidence shows that commonality in market depth concerns investors more than commonality in market tightness.

A potential concern is that the return to the HighBeta – LowBeta strategy is due to other types of illiquidity risk than commonality risk. Acharya and Pedersen (2005) show that there are three
types of illiquidity risks that potentially influence the returns. They report, however, that the cross-sectional correlation at the individual stock level between the commonality risk and the other two illiquidity risks are low. They report correlations to the individual return-marketwide illiquidity beta at -0.07 and to the individual illiquidity-marketwide return beta at -0.27.

4 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 commonality risk premium remains positive net of transaction costs when the holding period is extended from one to twelve months. For long and short horizons, the results indicate that the commonality betas derived from a measure of the Price Impact yields more sustainable returns than corresponding betas based on the Effective Spread.

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 illiquidity level premium.

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| Reference                        | Market(s) | Data period | Liquidity measure(s)                                                                 | Data frequency | Liquidity frequency | Systematic estimator(s) | Commonality |
|---------------------------------|-----------|-------------|-------------------------------------------------------------------------------------|----------------|---------------------|-------------------------|-------------|
| Chordia et al. (2000)           | NYSE      | 1992        | Quoted and effective spread; depth at BBO                                         | Intraday       | Days               | EW, VW                  | Yes         |
| Hasbrouck and Seppi (2001)      | NYSE      | 1994        | Effective spread; order imbalance                                                  | Intraday       | 15 minutes         | PCA                     | Spreads: No; Order imb.: Yes |
| Huberman and Halka (2001)       | NYSE      | 1996        | Spread; volume. Quoted and effective spread; depth at BBO; volume                 | Intraday       | Days               | -                       | Yes         |
| Chordia et al. (2001)           | NYSE      | 1988–1998   | Quoted and effective spread; depth at BBO                                         | Intraday       | Days               | EW, VW                  | Yes         |
| Pstor and Stambaugh (2003)      | NYSE, AMEX| 1966–1999   | Return reversal coefficient                                                        | Days           | Months             | EW                      | Yes         |
| Coughenour and Saad (2004)      | NYSE      | 1999–2000   | Quoted and effective spread                                                        | Intraday       | 3 periods intraday | EW                      | Yes         |
| Kamara et al. (2008)            | NYSE, AMEX| 1962–2005   | ILLIQ                                                                               | Days           | Days               | EW, VW                  | Yes         |
| Korajczyk and Sadka (2008)      | NYSE      | 1983–2000   | Eight liquidity measures                                                           | Intraday       | Months             | PCA                     | Yes         |
| Hallin et al. (2009)            | S&P500    | 2004–2006   | Spread; volume                                                                      | Days           | Days               | Dynamic PCA             | Yes         |
| Corwin and Lipson (2011)        | NYSE      | 1997–1998   | Trading and order volume; spread; depth                                            | Intraday       | 15 minutes         | PCA                     | Yes         |
| Kang and Zhang (2013)           | NYSE      | 2003        | Spread; depth; LOB dispersion                                                       | Intraday       | Days               | EW                      | Yes         |
| Koch et al. (2012)              | NYSE, AMEX| 1980–2008   | ILLIQ; turnover                                                                     | Days           | Days               | EW, VW                  | Yes         |
(b) Studies of non-US equity markets

| Reference                        | Market                  | Data period       | Liquidity measure                                      | Data frequency | Liquidity frequency | Systematic estimator | Commonality |
|----------------------------------|-------------------------|-------------------|--------------------------------------------------------|----------------|---------------------|----------------------|-------------|
| Brockman and Chung (2002)        | HKEX, Hong Kong         | 1996–1999         | Spread; depth                                          | Intraday       | Days                | EW, VW               | Yes         |
| Domowitz et al. (2005)           | ASX 20 (Australia)      | 2000 (10 months)  | Spread; full order book depth; order flows; order types| Intraday       | Hours               | -                    | Yes         |
| Kempf and Mayston (2008)         | DAX30, Germany          | 2004              | Spread; volume                                         | Intraday       | 30 minutes          | PCA, EW              | Yes         |
| Beltran-Lopez et al. (2009)      | DAX30, Germany          | 2004 (3 months)   | Bid and ask price impact                               | Intraday       | Days                | PCA                  | Yes         |
| Galariotis and Giouvris (2007)   | FTSE100, UK             | 1996–2001         | Spread                                                 | Days           | Days                | EW                   | Yes         |
| Galariotis and Giouvris (2009)   | FTSE100, FTSE250, UK    | 1996–2001         | Spread                                                 | Days           | Days                | PCA                  | Yes         |
### Studies of multiple international equity markets

| Reference                  | Market       | Data period         | Liquidity measure | Data frequency | Liquidity frequency | Systematic estimator | Commonality |
|----------------------------|--------------|---------------------|-------------------|----------------|---------------------|----------------------|-------------|
| Brockman et al. (2009)     | 47 countries | 2002–2004           | Spread; depth     | Intraday       | Days                | EW, VW               | Yes         |
| Dang et al. (2015)         | 39 countries | 1996–2007           | Spread            | Intraday       | Days                | EW                   | Yes         |
| Karolyi et al. (2011)      | 40 countries | 1995–2004           | ILLIQ; turnover   | Days           | Days                | VW                   | Yes         |
Table 2: Descriptive statistics. Common stocks incorporated in the US, with primary listing at NYSE, with price in the range of USD 5 – 999, and a positive market capitalization are eligible for illiquidity measurement. *Number of stocks* is the number of eligible stocks each month. We report monthly level illiquidity and illiquidity innovations for two measures. *Effective Spread* is estimated from daily closing prices as in Holden (2009) and reported in percentage points. *Price Impact* is the Amihud (2002) illiquidity ratio, transformed to handle potential outliers and non-stationarity in the same way as in Acharya and Pedersen (2005). 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. *B/M* is the book-to-market ratio, defined as in Fama and French (1993); and *Price* is the stock price. The descriptive statistics are based on the full panel of stock-month 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              | -3.93E-03 | -1.01E-03 | 0.55  | -5.17 | 5.34  |
| Price Impact (%)               | 6.13  | 1.39   | 9.37  | 0.25  | 30.00 |
| ΔPrice Impact                  | 4.80E-04 | 0.00   | 3.41  | -23.69 | 22.73 |
| Market cap. (billion USD)      | 2.38  | 0.23   | 11.73 | 3.80E-04 | 581.10 |
| Turnover (monthly, %)          | 16.70 | 6.30   | 69.42 | 0.00  | 13937.81 |
| B/M                            | 0.83  | 0.67   | 1.22  | 0.00  | 283.96 |
| Price (USD)                    | 27.27 | 21.75  | 25.75 | 5.00  | 998.00 |
Table 3: Commonality in illiquidity. Commonality regressions are run for eligible stocks each month from Dec. 1965 - Dec. 2012. 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. To be eligible for commonality beta estimation in a given estimation window, a stock should satisfy the criteria listed in Table 2, have at least thirty observations for each illiquidity measure, and have positive variance in the Price Impact innovations. The model \( l_i^t = \alpha_i + \beta_i m_i^t + u_i^t \) is estimated with OLS for each stock \( i \) in each time period \( t \). Two illiquidity measures are considered: Effective Spread and Price Impact, both defined as in Table 2. All reported metrics are time-series averages across monthly observations. Panel (a) reports for each illiquidity measure the cross-sectional averages for \( \beta_i \) and \( R^2 \); the number of stocks included in the regression analysis and the calculation of systematic illiquidity (\( l_i^m \)), respectively; and the cross-sectional correlations (Pearson and Spearman) between the level illiquidity and \( \beta_i \). Panel (b) reports for each illiquidity measure distributional statistics of \( \beta_i \), considering the following percentiles: 1%, 10%, 25%, 50%, 75%, 90%, and 99%.

(a) Commonality regression properties

| Commonality       | \( \beta \) | \( R^2 \) | Number of stocks | Regressions | Systematic illiquidity | \( Cor(l_i,\beta) \) |
|-------------------|-------------|-----------|------------------|-------------|------------------------|----------------------|
| Effective Spread  | 1.21        | 0.03      | 1452.80          | 1110.13     | 0.28                   | 0.29                 |
| Price Impact      | 1.29        | 0.11      | 1452.80          | 1110.13     | 0.42                   | 0.70                 |

(b) Commonality beta distribution

| Commonality       | Commonality beta distribution percentiles |
|-------------------|-------------------------------------------|
|                   | 1%  | 10% | 25% | 50% | 75% | 90% | 99% |
| Effective Spread  | -3.63 | -0.57 | 0.09 | 0.75 | 1.84 | 3.63 | 9.81 |
| Price Impact      | -0.97 | 0.01  | 0.07 | 0.39 | 1.65 | 4.02 | 9.44 |
Table 4: Properties of commonality beta portfolios. We form portfolios that are stratified with respect to illiquidity level and sorted by commonality beta. Specifically, at the end of time period $t$, stocks are sorted by their level of illiquidity and divided into fifty strata. Within each stratum, stocks are sorted by their commonality beta and divided into decile portfolios. Commonality betas are estimated as described in Table 3. The decile portfolios are then merged across the fifty strata, yielding ten portfolios with different levels of commonality betas. The following metrics are reported for each of the ten portfolios as well as a portfolio that is long in portfolio 1 (HighBeta) and short in portfolio 10 (LowBeta). Excess returns are monthly portfolio excess returns for a holding period from $t$ to $t+1$, reported along with the $t$-statistic for the time-series average. Size is the natural log difference between the observed value and the median value for the current month; Price is the monthly average price; Turnover is the monthly average turnover defined as in Table 2; and $B/M$ is the monthly average book-to-market ratio defined as in Table 2; all reported as time-series averages for each portfolio. Each panel also reports the portfolio level illiquidity averaged across portfolio stocks and over time. Panels (a) and (b) hold results for two different illiquidity measures: Effective Spread and Price Impact, respectively, both defined as in Table 2.

(a) Portfolios based on the Effective Spread

| Portfolio       | Excess return | t-stat. | Effective Spread | Size  | Price  | Turnover | B/M |
|-----------------|---------------|---------|------------------|-------|--------|----------|-----|
| HighBeta 0.97   | 3.96          | 0.565   | -0.59            | 21.51 | 19.20  | 0.84     |
| 2               | 0.91          | 3.86    | 0.565            | -0.23 | 25.34  | 18.73    | 0.83 |
| 3               | 0.76          | 3.37    | 0.567            | -0.03 | 27.71  | 18.67    | 0.82 |
| 4               | 0.82          | 3.66    | 0.567            | 0.12  | 29.69  | 18.34    | 0.80 |
| 5               | 0.81          | 3.69    | 0.562            | 0.25  | 31.59  | 18.44    | 0.79 |
| 6               | 0.72          | 3.26    | 0.565            | 0.33  | 32.85  | 18.28    | 0.78 |
| 7               | 0.70          | 3.20    | 0.565            | 0.38  | 33.71  | 18.48    | 0.77 |
| 8               | 0.75          | 3.54    | 0.563            | 0.36  | 33.41  | 18.23    | 0.77 |
| 9               | 0.76          | 3.59    | 0.563            | 0.22  | 31.46  | 16.86    | 0.78 |
| LowBeta 0.80    | 3.89          | 0.566   | -0.18            | 26.83 | 16.49  | 0.82     |
| HighBeta – LowBeta | 0.17      | 2.24    | 0.000            | -0.42 | -5.32  | 2.71     | 0.02 |
(b) Portfolios based on the *Price Impact*

| Portfolio     | Excess return | t-stat. | Price Impact | Size  | Price | Turnover | B/M |
|---------------|---------------|---------|--------------|-------|-------|----------|-----|
| HighBeta      | 1.12          | 4.55    | 0.568        | -1.53 | 17.29 | 13.76    | 0.94|
| 2             | 0.95          | 4.02    | 0.569        | -1.14 | 20.48 | 14.82    | 0.91|
| 3             | 0.88          | 3.71    | 0.571        | -0.78 | 23.02 | 15.62    | 0.87|
| 4             | 0.89          | 3.86    | 0.569        | -0.40 | 25.53 | 16.65    | 0.84|
| 5             | 0.80          | 3.50    | 0.566        | 0.00  | 28.01 | 18.26    | 0.80|
| 6             | 0.78          | 3.43    | 0.569        | 0.40  | 30.67 | 19.56    | 0.78|
| 7             | 0.69          | 3.11    | 0.569        | 0.88  | 34.22 | 21.61    | 0.75|
| 8             | 0.63          | 2.97    | 0.567        | 1.36  | 38.38 | 22.43    | 0.73|
| 9             | 0.56          | 2.76    | 0.567        | 1.73  | 42.44 | 22.78    | 0.69|
| LowBeta       | 0.58          | 3.03    | 0.569        | 0.90  | 39.37 | 19.70    | 0.73|
| HighBeta – LowBeta | 0.53 | 4.92    | -0.001       | -2.42 | -22.07 | -5.94    | 0.21|
Table 5: The commonality risk premium in the cross-section of expected returns: GMM estimates. The factor loadings (the betas) are estimated in time-series regressions as described in Eq. (3). The cross-sectional regression coefficients are estimated in a panel as described in Eq. (4). The panel of commonality sorted portfolio returns are equally weighted and calculated on a monthly basis. Results for three different versions of Eq. (4) are reported for each illiquidity measure: (a) Effective Spread; and (b) Price Impact. Model (1) constrains all δ parameters to zero, and Model (2) constrains δ_{Size} and δ_{B/M} to zero. See Table 2 for definitions of the illiquidity level (Illiq) and book-to-market (B/M), and Table 4 for relative market capitalization (Size). A cross-sectional intercept is included in all three specifications. HAC-consistent GMM t-statistics are reported within parentheses. * and ** indicate that the coefficient is statistically significant at the 90% and 95% confidence levels, respectively.

(a) Portfolios based on Effective Spread

|       | (1)    | (2)    | (3)    |
|-------|--------|--------|--------|
| δ₀    | 0.276**| 0.080  | −0.679 |
|       | (3.00) | (0.17) | (−0.89)|
| λ_{M} | 0.428**| 0.428**| 0.435**|
|       | (2.15) | (2.14) | (2.18)|
| λ_{IC}| 0.156**| 0.156**| 0.032 |
|       | (2.89) | (2.87) | (0.43)|
| δ_{Illiq} | 0.351  | −0.227 |
|       | (0.43) | (−0.23)|
| δ_{Size} |        | −0.158 |
|       |        | (−0.92)|
| δ_{B/M} |        | 1.454  |
|       |        | (1.34)|
(b) Portfolios based on *Price Impact*

|       | (1)   | (2)   | (3)   |
|-------|-------|-------|-------|
| $\delta_0$ | 0.114 | 0.269 | -0.862 |
|        | (1.36) | (0.19) | (-0.54) |
| $\lambda_M$ | 0.430** | 0.430** | 0.432** |
|        | (1.98) | (2.36) | (2.37) |
| $\lambda_{IC}$ | 0.406** | 0.406** | 0.286** |
|        | (4.18) | (4.38) | (2.70) |
| $\delta_{\text{Iliq}}$ | -0.274 | -0.070 | (-0.03) |
|        | (-0.11) | (-0.03) | |
| $\delta_{\text{Size}}$ | 0.032 |       | (0.48) |
| $\delta_{B/M}$ | 1.346 |       | (1.52) |
Table 6: Commonality risk premium exposure to other risk factors: Factor models. Factor models are estimated on the commonality risk premium retrieved from pursuing a HighBeta – LowBeta strategy with respect to commonality betas, with monthly rebalancing. Panels (a) and (b) report results for commonality betas estimated for two illiquidity measures: Effective Spread and Price Impact, both defined as in Table 2. Four different factor model specifications are considered: (1) intercept only; (2) intercept and the market return factor MKT (as in the traditional CAPM); (3) intercept, MKT, the size factor SMB and the value factor HML (as in Fama and French, 1996); (4) intercept, MKT, SMB, HML, and the momentum factor MOM (as in Carhart, 1997). * and ** indicate that the coefficient is statistically significant at the 90% and 95% confidence levels, respectively. For each coefficient estimate, t-statistics are reported within parentheses.

(a) Portfolios based on the Effective Spread

|          | (1)    | (2)    | (3)    | (4)    |
|----------|--------|--------|--------|--------|
| (intercept) | 0.0017** | 0.0009 | 0.0010 | 0.0004 |
|          | (2.24) | (1.41) | (1.57) | (0.66) |
| MKT      | 0.1676** | 0.1160** | 0.1282** |    |
|          | (11.53) | (7.89) | (8.72) |      |
| SMB      | 0.1765** | 0.1766** |      |      |
|          | (8.51) | (8.66) |      |      |
| HML      | -0.0697** | -0.0490** |    |      |
|          | (-3.12) | (-2.18) |      |      |
| MOM      | 0.0641** |        |      |      |
|          | (4.47) |      |      |      |

(b) Portfolios based on the Price Impact

|          | (1)    | (2)    | (3)    | (4)    |
|----------|--------|--------|--------|--------|
| (intercept) | 0.0053** | 0.0048** | 0.0034** | 0.0032** |
|          | (4.92) | (4.50) | (4.61) | (4.23) |
| MKT      | 0.1305** | 0.0197 | 0.0243 |        |
|          | (5.69) | (1.16) | (1.41) |      |
| SMB      | 0.6126** | 0.6126** |      |      |
|          | (25.54) | (25.56) |      |      |
| HML      | 0.1028** | 0.1106** |    |      |
|          | (3.98) | (4.19) |      |      |
| MOM      | 0.0241 |        |      |      |
|          | (1.43) |      |      |      |
Figure 1: Commonality risk return period for different holding periods. The commonality risk premium is retrieved when pursuing a HighBeta – LowBeta strategy with respect to commonality betas. The figure plots results for commonality betas estimated on each of the two illiquidity measures: Effective Spread and Price Impact, both defined as in Table 2. Average monthly returns are calculated from portfolio formation to the end of the holding period, with different holding periods indicated by the horizontal axis in each panel. To facilitate comparison across holding periods, the returns are annualized and averaged across months. A horizontal curve thus indicates that all months of the holding period have the same average return. Panel (a) shows results for portfolios selected in the end of period \( t \) and held from \( t + 1 \) up to \( t + 12 \) (a holding period from one to twelve months). Panel (b) shows results for portfolios selected in the end of period \( t \) and held from \( t + 2 \) up to \( t + 12 \), implying hat there is a one-month gap between the portfolio selection and the start of the holding period. This is to control for the short-term reversal effect.