Figure 1: Years of Forecasts Used by PE Investors

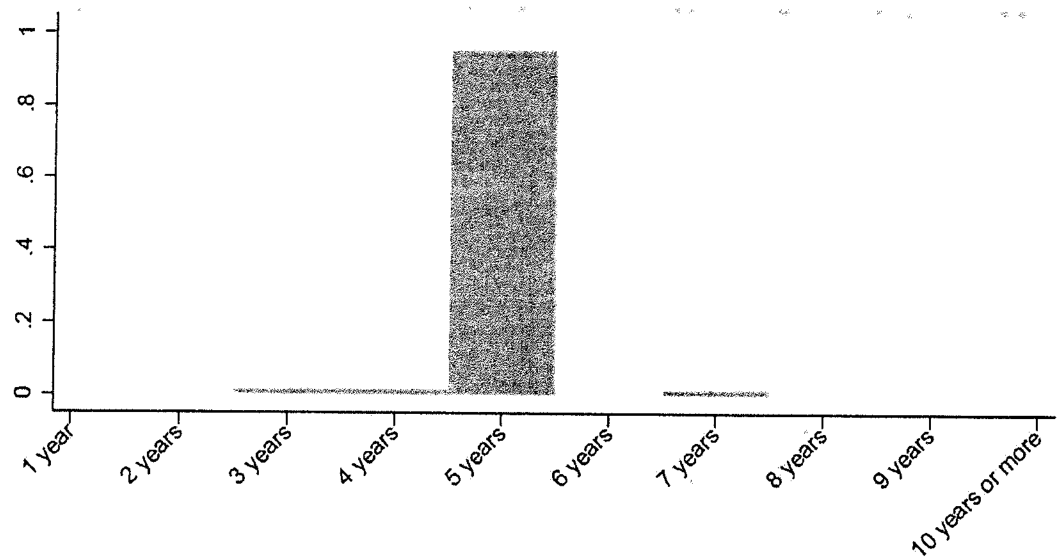

EXHIBIT QVLP-GS-6

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Private Equity Performance and Liquidity Risk

DP 06/2010-024 (revised version May 2011)

Private Equity Performance and Liquidity Risk

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May 12, 2011

Abstract

Private equity has traditionally been thought to provide diversification benefits. However, these benefits may be lower than anticipated. We find that private equity suffers from significant exposure to the same liquidity risk factor as public equity and other alternative asset classes. The unconditional liquidity risk premium is close to 3% annually and, in a four-factor model, the inclusion of this liquidity risk premium reduces alpha to zero. In addition, we provide evidence that the link between private equity returns and overall market liquidity occurs via a funding liquidity channel.

JEL classification: C51; G12; G23

Keywords: Private equity; Liquidity risk; Cost of capital

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1 Introduction

Investing in private equity is among the preferred choices for long-term investors, such as endowments and pension funds seeking to diversify their portfolios. Such long-term investors are clearly the best suited for holding an illiquid asset (i.e. one that cannot be readily traded) such as private equity. The diversification benefits of private equity, however, have not been widely documented. One issue in particular which has not been addressed so far is whether private equity performance, like that of other asset classes, is affected by liquidity risk (i.e. co-moves with unexpected changes in overall market liquidity).[1] The primary goal of this paper is to quantity this liquidity risk in private equity. In addition, the estimation of a factor model incorporating the liquidity risk factor allows us to compute the cost of capital for this asset class and test whether it is efficiently priced.

We use a unique, comprehensive dataset containing the exact cash flows generated by a large number of liquidated private equity investments. To clarify the unusual structure of our data from the outset, Table 1 shows a typical cash flow stream. There is an initial negative cash flow (the investment) followed by two positive cash flows (an intermediate distribution and the final dividend corresponding to the divestment). Note that we do not have intermediate valuations for the investment. This means that there is no time-series of returns, which precludes the use of the usual time-series regressions to estimate risk exposures. In such a context, as in Cochrane (2005), Korteweg and Sorensen (2010) and Driessen, Lin, and Phalippou (2011), we use variations in returns *across* investments to estimate the risk loadings and abnormal performance of the asset class.

We fit the four-factor model of Pástor and Stambaugh (2003) to the data and find significant loadings on the liquidity risk factor (0.64), market factor (1.3), and book-to-market factor (1.0), but not on the size factor. Exposure to these factors brings the alpha of this asset class to zero.

[1] A new strand of literature in asset pricing has established liquidity risk as a priced factor in public equity returns (e.g., Pástor and Stambaugh (2003), Acharya and Pedersen (2005), Sadka (2006)). This evidence has now been extended to emerging markets (Bekaert, Harvey, and Lundblad (2007)), bond markets (Beber, Brandt, and Kavajecz (2008), Chordia, Sarkar, and Subrahmanyam (2005), Li, Wang, Wu, and He (2009), and Acharya, Amihud, and Bharath (2010)), credit derivative markets (Longstaff, Mithal, and Neis (2005), Bongaerts, de Jong, and Driessen (2010), and Longstaff, Pan, Pedersen, and Singleton (2011)), and hedge funds (Sadka (2009) and Boyson, Stahel, and Stulz (2010)).

Importantly, the liquidity risk premium is about 3% annually, which implies an approximate 10% discount in the valuation of the typical investment (see Table 1). In addition, adapting Ferson and Harvey's (1999) approach, we find that the expected liquidity risk premium varies over time and is higher than 5% annually in one month out of four. We also note that a liquidity risk beta of 0.64 exceeds the corresponding estimate for the great majority (86%) of traded stocks.

These results suggest that private equity is significantly exposed to the same liquidity risk factor as public equity and other asset classes. Given this exposure to liquidity risk, the diversification gains potentially associated with private equity may be lower than previously thought.

Prompted by the finding of a significant loading on liquidity risk, we study the economic channel that connects private equity returns to market liquidity. We conjecture that due to their high leverage, private equity investments are sensitive to the capital constraints faced by the providers of debt to private equity, which are primarily banks and hedge funds. Brunnermeier and Pedersen (2009) develop a theory in which the availability of capital - which they term funding liquidity - is positively related to market liquidity. In our context, their argument suggests that times of low market liquidity are likely to coincide with times when private equity managers find it difficult to refinance their investments. In these periods, they may be forced to liquidate their investments or accept higher borrowing costs, which in turn translates into lower returns for this asset class. We then conjecture that the link between private equity returns and market liquidity occurs via a funding liquidity channel.

Empirically, we proxy for funding liquidity with the credit standards reported in the Federal Reserve's Senior Loan Officer Survey. Specifically, this survey asks loan officers at main banks whether they tightened or loosened their lending standards relative to the previous quarter. Axelson, Jenkinson, Strömberg, and Weisbach (2010) argue that, in the private equity context, "this measure captures non-price aspects of credit market conditions, such as debt covenants and quantity constraints." They find this measure to be strongly related to the amount of leverage used to finance private equity investments. In addition, Lown and Morgan (2006) present evidence that this variable strongly correlates with bank loans and is more important than interest rates in explaining loan volume.[2]

Turning to the empirical evidence on this channel, we first document a strong relationship between private equity investment returns and the average innovation in market liquidity (as measured by Pástor and Stambaugh (2003)) during the investment's life. The difference in performance for investments at the extreme deciles of market liquidity innovations is a striking 46% per year. This result is confirmed in a multiple regression setting, in which we control for investment characteristics and macroeconomic variables (credit spreads, M&A cycles, growth in industrial production, stock market volatility).

Next, we test our conjecture that funding liquidity provides the link between these two variables. We first show that returns are significantly related to the tightening of credit standards. A one-standard-deviation increase in this measure of the deterioration in funding liquidity decreases the annual return by 15.9%. Second, when including both the measure of funding liquidity and that of market liquidity, we observe that funding liquidity absorbs half of the market liquidity effect. In addition, we conduct a time-series test using the aggregate cash flows of all the private equity investments each month. Consistent with the cross-sectional evidence, we find that net cash flows (dividends minus investments) are lower at times when credit standards are tightened and times when liquidity conditions deteriorate.

We consider these results important for two related reasons. First, they improve our understanding of the economic channel underlying the relationship between private equity returns and market liquidity. Market liquidity is found to be closely related to a measure of funding liquidity, which in turn is a determinant of the ease of refinancing for leveraged deals as shown by Axelson, Jenkinson, Strömberg, and Weisbach (2010). Second, these results provide empirical support for Brunnermeier and Pedersen's (2009) theory relating funding liquidity to market liquidity. Our empirical evidence shows that there is indeed a negative relationship between a dry-up in funding liquidity (the tightening of credit standards) and innovations in market liquidity (the Pástor and Stambaugh measure).

[2] Leary (2008) also uses this measure to proxy for loan supply.

This study also contributes to the literature on the risk and return of private equity investments (e.g., Moskowitz and Vissing-Jorgensen (2002), Kaplan and Schoar (2005), Lerner, Schoar, and Wongsunwai (2007), Jones and Rhodes-Kropf (2004), Ljungqvist, Richardson, and Wolfenzon (2008), Hochberg, Ljungqvist, and Lu (2007)). Our investment-level data enable us to document new drivers of performance. In addition, previous research finds that private equity funds underperform public equity after fees (Kaplan and Schoar (2005), Phalippou and Gottschalg (2009)). Here, we report evidence that is consistent with previous research and show that accounting for systematic risk brings alpha (gross of fees) close to zero.

The paper continues as follows. Section 2 describes the data. Section 3 estimates different asset pricing models and computes the cost of capital and alpha for private equity. Section 4 relates private equity performance to market risk, funding liquidity, macroeconomic variables, and investment characteristics. Section 5 discusses the implications of our results and concludes.

[Insert Table 1 about here]

2 The data

In this section, we first detail how the data are collected, then document the coverage of our dataset relative to available commercial datasets, and gauge its representativeness in terms of performance. We next describe how we measure returns in our context, and finally provide some descriptive statistics of returns.

2.1 Data source

The dataset is provided by the Center for Private Equity Research (CEPRES), a private consulting firm established in 2001 as a joint venture between VCM Capital Management of Sal. Oppenheim Bank and the University of Frankfurt. The unique feature of these data is the information on the monthly cash flows generated by private equity investments.

CEPRES obtains data from private equity houses which make use of a service called

"The Private Equity Analyzer".[3] Participating firms are bound by contract to accurately report cash flows (before fees) generated for each investment they have made in the past. In return, the firms receive statistics such as risk-adjusted performance measures, which they use internally for various purposes such as bonus payments. CEPRES does not benchmark private equity houses to peer groups; this improves data accuracy and representativeness, as it eliminates incentives to manipulate cash flows or cherry-pick past investments.

CEPRES may also be hired by investors as an advisor. In such cases, it receives data on the past performance of private equity houses in which its clients are thinking of investing as limited partners. If permitted by the contractual agreement between the firm and the investor, CEPRES can add that firm's (investment level) track record to its database. If the firm already participates in the Private Equity Analyzer program, then CEPRES systematically cross-checks the data to verify that the existing contractual agreement is respected.

Earlier versions of this dataset have been utilized in previous studies. A subset covering mainly venture capital investments is used by Cumming, Schmidt, and Walz (2010), Cumming and Walz (2010) and Krohmer, Lauterbach, and Calanog (2009). For this study, CEPRES granted us access to all liquidated buyout investments in their database as of December 2007. The earliest investment in our sample starts in 1975 and the most recent in 2006. The total number of investments is 4,403.

We thus have access to a comprehensive, accurate panel of cash-flow streams generated by private equity investments. This enables us to construct precise measures of the investment performance and aggregate liquidity conditions over the investment's life, which is essential for estimating the relationship between performance and liquidity risk.[4]

[3] "Private equity houses" are organizations that run private equity funds which in turn make private equity investments in portfolio companies.

[4] Two proprietary databases similar to the CEPRES dataset are used in contemporary research. Ljungqvist, Richardson, and Wolfenzon (2008) have data from a large investor. Our data spans a similar time period to theirs, but contains about twice as many investments. Lopez-de-Silanes, Phalippou, and Gottschalg (2009)have a dataset containing the performance of private equity investments from hand-collected private placement memoranda, but do not have the detailed cash flows generated for each investment.

2.2 Data coverage and representativeness

To gauge coverage, we benchmark CEPRES to Standard & Poor's Capital IQ database. Capital IQ is now often perceived as the most comprehensive dataset at the investment level (Bernstein, Lerner, Sorensen, and Strömberg (2010) and Strömberg (2007)). Table 2 shows that CEPRES has a total of 7,198 private equity investments between 1975 and 2006 versus 14,011 in Capital IQ, i.e., 51%. During the early years, however, the coverage offered by CEPRES and Capital IQ is remarkably similar. From 1975 to 1994, CEPRES has slightly more investments than Capital IQ. After the mid-1990s, the number of investments in Capital IQ increases exponentially, while the rise is less pronounced for CEPRES. As noted above, we only use data on liquidated investments. Because investments are held for 4 years on average, the pre-2002 coverage is more informative. Table 2 shows that for the period 1975-1999, CEPRES coverage is 85% of Capital IQ. For the period 1975-2002 (non-tabulated) the coverage is about two thirds.

[Insert Table 2 about here]

Benchmarking performance in private equity is more difficult. The majority of previous studies have used Thomson Venture Economics, and private equity house performance is measured by a success ratio (the fraction of investments exited via IPO or M&A over the total number of investments).[5]

Results are displayed in Table 3. The success ratio is similarly distributed for the two datasets but the CEPRES dataset appears to contain firms that are slightly above average performance-wise. We also note that 10% of the investments in our dataset are bankrupt, which is similar to the rate reported by Strömberg (2007) for the Capital IQ dataset.

[Insert Table 3 about here]

[5] In order to compute a meaningful success ratio, we restrict investments to those made before 2002. It would not be fair to classify as unsuccessful investments made less than 5 years ago and not yet exited. We also require at least five investments per firm. CEPRES performed the calculations for us in order to preserve anonymity. They counted 117 firms in their dataset that satisfy these criteria. In Thomson Venture Economics, they counted 535 firms that satisfy these criteria but were not included in their database.

2.3 Performance Measures

As mentioned in the introduction, our data contain the series of cash flows generated by a given private equity investment. We begin by converting all the cash flows into US dollars. We note that this hardly changes performance: the correlation between performance in original currency and performance in US dollars is 99.8%. This is probably because investments last only four years on average, hence currency changes do not greatly affect performance. In addition, about half of the cash flows are already in US dollars.

To measure investment performance, we use a Modified Internal Rate of Return (MIRR). MIRR measures the geometric average return for an investor who deposits dividends (D_t) into, and draws her money for intermediate investments (I_t) from, an account that earns an interest rate x_t for each $t = 1, \ldots, T$, where T is the number of periods in the investment's life. The investment's MIRR is defined as follows:

$$
\begin{aligned}
(1 + MIRR)^T &= \frac{D_1 \prod_{t=1}^{T-1} (1 + x_t) + D_2 \prod_{t=2}^{T-1} (1 + x_t) + \cdots + D_{T-1} (1 + x_{T-1}) + D_T}{I_0 + \frac{I_1}{(1+x_0)} + \frac{I_2}{\prod_{t=0}^{1}(1+x_t)} + \cdots + \frac{I_T}{\prod_{t=0}^{T-1}(1+x_t)}} \\
&= \frac{FV(Div, x_t)}{PV(Inv, x_t)} \qquad (1)
\end{aligned}
$$

where $FV(\cdot, x_t)$ and $PV(\cdot, x_t)$ respectively denote the forward and present value of a stream of cash flows computed using the discount rate x_t. Note that when no cash is returned to investors (that is, the dividends are all zero), the MIRR equals -100%.

We now give a numerical example of MIRR construction and its sensitivity to the reinvestment rate x_t. To do so we use the typical cash flow pattern shown in the introduction (Table 1) and assume a constant reinvestment rate of 5% per semester. The final value of the dividends is:

$$FV\,(Inv, 5\%) = 50(1.05^3) + 150 = 208$$

The annualized MIRR is thus:

$$MIRR = \left(\frac{208}{100}\right)^{1/4} - 1 = 20\%$$

If we use a reinvestment rate of 0%, the MIRR would be 19%. Hence, the sensitivity of MIRR to the reinvestment assumption seems minor in our data. This is due to the relatively short life of the investments and the relatively small size of intermediate cash flows. In the analysis that follows, we use the S&P 500 index as a reinvestment rate. This reinvestment assumption should capture the fact that private equity investors tend to have highly-diversified portfolios. We also computed the MIRR of each investment using the risk-free rate as the reinvestment rate, and found a correlation coefficient of 99% between the two MIRRs.

2.4 Descriptive statistics - Performance

To provide aggregate performance figures, we group investments by their starting year and country of location. Next, we sum the cash flows of all the investments in the group month by month. Finally, we compute the MIRR of each (pooled) cash flow stream. This measures the actual rate of return of a buy-and-hold investor who selects all the investments of a certain country/region over a certain time period.

Table 4 - Panel A shows the results. Overall, we find little difference across countries/regions and across time. Returns are highest for Europe (ex-UK) in the second half of the 1990s at 25% annually, but returns in Europe were low in the first half of the 1990s at 14% annually. Returns are stable over time in the US, except for more recent years when they drop to 13%. An investor buying all the investments in our sample would have earned 19% annually. The carried interest payable with such a return is about 4% and management fees on invested capital are at least 3%.[6] Hence, after fees, the performance is around 12%, which is similar to the return documented by Kaplan and Schoar (2005) for net-of-fees (fund level) returns. This further demonstrates that our data are similar performance-wise to those used in previous research.

Table 4 - Panel B shows that our observations are almost evenly distributed across regions: US (37%), UK (29%) and the rest of Europe (25%).

[6] This is an approximation. Carried interest equals 20% of the returns. The 2% management fee is charged on a mix of capital invested and committed, and is typically equivalent to a 3% fee on capital invested (see Metrick and Yasuda (2010) and Phalippou (2009) for details).

[Insert Table 4 about here]

3 The liquidity risk premium in private equity returns

As pointed out by Acharya and Pedersen (2005), among others, liquidity varies over time and displays commonality across securities and asset classes. Recent theoretical and empirical research suggests that this commonality in liquidity is a priced risk factor (liquidity risk). Pástor and Stambaugh (2003) propose a four-factor asset pricing model which includes liquidity risk. If we assume that the public and private equity markets are integrated then this asset pricing model and its corresponding pricing kernel can be applied to private equity to evaluate its cost of capital, which is naturally an important question for such a large asset class. In addition, the finding of a significant loading on the liquidity risk factor would cast a different light on the diversification benefits of private equity.

In this section, we begin by detailing our methodology to estimate a factor model for private equity returns. Next, we provide the estimates of the risk exposures, the alpha, and the resulting cost of capital. Finally, we extend the analysis to time-varying factor loadings and risk premia.

3.1 Methodology

3.1.1 The estimation of risk exposures

Because private equity investments are not continuously traded, we cannot compute a time-series of returns and use a traditional time-series approach to estimate risk exposures. Instead, we have cash flow streams for a cross-section of investments that we use to compute rates of returns, as described in Section 2.3. This cross-sectional data structure fits into the approach developed by Cochrane (2005), which we adjust to our context.[7]

[7] Cochrane (2005) and Korteweg and Sorensen (2010) highlight the role played by sample selection bias when estimating risk models for venture capital investments. In their context, valuations are observed only infrequently, although more often for well-performing investments. Explicit modeling of the selection mechanism is thus required to obtain unbiased estimates of factor loadings and alphas. Because our data do not suffer from such a severe sample selection bias, we can simplify their approach and simply estimate the factor models with OLS regressions.

To start from the simplest case, let us assume that the cash flows of each project i consist of an initial investment, V_0^i, and a final dividend, $V_{T_i}^i$, which is paid at date T_i. Following Cochrane (2005), we assume that one-period returns are log-normal and exhibit a linear factor structure (in logarithm)

$$\ln R_{t+1}^i = \ln \frac{V_{t+1}^i}{V_t^i} = \gamma + \ln R_{t+1}^f + \delta' f_{t+1} + \varepsilon_{t+1}^i, \tag{2}$$

where γ is a constant, R^f is the gross risk-free rate, f_{t+1} is a vector of k risk factors (e.g. the three factors of Fama-French), δ is a k-vector of risk factor loadings, and ε_{t+1}^i is normal with mean zero and variance σ^2 and is independent of the risk factors.[8]

Given equation (2), the natural logarithm of the (gross) geometric average return on the investment (R_g^i) is given by

$$\ln(R_g^i) = \frac{1}{T_i} \ln \frac{V_T^i}{V_0^i} = \gamma + \frac{1}{T_i} \sum^{T_i} \ln R_{t+1}^f + \delta' \frac{1}{T_i} \sum^{T_i} f_{t+1} + \frac{1}{T_i} \sum^{T_i} \varepsilon_{t+1}^i. \tag{3}$$

The variance of the error term in equation (3) is $\frac{1}{T_i}\sigma^2$. To eliminate this source of heteroskedasticity, we multiply each side of equation (3) by $\sqrt{T_i}$

$$\sqrt{T_i} \ln(R_g^i) = \gamma\sqrt{T_i} + \frac{1}{\sqrt{T_i}} \sum^{T_i} \ln R_{t+1}^f + \delta' \frac{1}{\sqrt{T_i}} \sum^{T_i} f_{t+1} + \frac{1}{\sqrt{T_i}} \sum^{T_i} \varepsilon_{t+1}^i. \tag{4}$$

This is a GLS transformation that we can perform because we know the form of heteroskedasticity.[9] Equation (4) is the specification that we bring to the data. Notice that the right-hand side is linear in the parameters of interest. We can therefore simply apply a standard OLS regression. The dependent variable is the scaled natural logarithm of gross

[8] Given the monthly frequency of the factors, we set the interval length to one month. This decision has no material consequences, except for interpretation of the reported coefficients. Notice also that, unlike Cochrane (2005), we choose to express normally distributed factors in levels rather than logs. The reason is that factors are based on long-short strategies and can take negative values, for which logarithmic transformation is not possible. This fact causes minor deviations from Cochrane in the formulas for factor loadings and alphas that we derive in the Appendix.

[9] GLS is the most efficient estimation method with non-spherical disturbances. A less efficient alternative to GLS is to estimate equation (3) by OLS and correct the standard errors using the White-Huber correction. In untabulated results, we find that this procedure also produces statistically significant estimates of liquidity risk.

returns. The explanatory variables are the time-series averages of the risk factors during the investment's life (multiplied by $\sqrt{T_i}$). The specification does not include a constant, but it includes the square root of the investment duration as an additional explanatory variable, which is used to estimate γ. In the tables, however, we report the estimate of γ and label it 'Constant' for simplicity. As the constant is not included, the values of the R-squared from the OLS estimation are not meaningful and we do not report them.

Because the parameters in equation (2) pertain to the logarithm of returns, we need to derive expressions for alpha and factor loadings for the level of returns. In other words, we need to convert (γ, δ) from equation (2) into the familiar (α, β), which are defined by the equation

$$E\left(R^i_{t+1}\right) = R^f_{t+1} + \alpha + \beta' E\left(f_{t+1}\right). \tag{5}$$

In Appendix 1, we show that the formulas for conversion from the parameters in the log of returns to the parameters in the level of returns are

$$\beta = R_f \delta e^{\gamma + \delta' \mu_F + \frac{1}{2}\delta' \sigma_F^2 \delta + \frac{1}{2}\sigma^2} \tag{6}$$

$$\alpha = R_f \left(e^{\gamma + \delta' \mu_F + \frac{1}{2}\delta' \sigma_F^2 \delta + \frac{1}{2}\sigma^2} (1 - \delta\prime\mu_F) - 1 \right) \tag{7}$$

where μ_F is the k-vector of factor means and σ_F^2 is the $k \times k$ variance-covariance matrix of the factors. Because β turns out to be quite close to δ, we only report the latter in our empirical results.

The approach described above is motivated by the specific structure of the data. As we do not observe periodic valuations of the investment, we cannot construct a time-series of investment returns R^i_{t+1}. Instead, we observe the investment cash flows, which can be used to construct a summary measure of performance over the investment's life, that is, the geometric average return R^i_g. This explains why, in equation (4), we relate the average investment return to the average realization of the factor over the investment's life (with a correction for heteroskedasticity).

This approach amounts to considering each investment as a separate realization of the returns on the asset class, then the variation in returns across investments is used to estimate the risk loadings and the abnormal performance of the asset class. This cross-sectional approach for non-traded assets is essentially the same as in Cochrane (2005), Korteweg and Sorensen (2010) and Driessen, Lin, and Phalippou (2011). As in these papers, the identification comes from investments that are realized over partly non-overlapping time periods.

3.1.2 Forming portfolios

To measure the geometric return in equation (4), we use the investment's MIRR (see previous section for calculation details) and three issues must be addressed. First, the logarithm of MIRR is not defined for 10% of the investments (those with a return of -100%). Second, as is well-known in the empirical asset pricing literature, the high idiosyncratic risk of individual stocks/investments may induce substantial noise in risk estimates. Third, we use the assumption of normality of log-returns in order to derive alphas and betas, but the distribution of individual investment returns fails a D'Agostino, Belanger, and D'Agostino Jr. (1990) chi-squared normality test. Figure 1 shows the histogram of MIRRs; the probability mass on the tails of the distribution, especially on the left one, clearly explains the rejection of normality.

To overcome these three issues, we adopt the standard approach in the Asset Pricing literature and group individual investments into portfolios.[10] As mentioned above, the statistical identification comes from observing investment returns at different moments in time. It is therefore natural to group together investments that start at the same date (at the monthly frequency). To ensure that portfolios are sufficiently diversified, we require a minimum of twenty investments per portfolio. If the number of investments starting in the same month is below this minimum, we include investments that are started the next month, and continue until the number of investments is at least twenty.[11] Portfolio cash flow streams are obtained by summing the cash flows of the individual investments each

[10]In a recent paper, Ang, Liu, and Schwarz (2010) compare the cost and benefits of portfolio formation in a two-step Fama-McBeth procedure. Forming portfolios improves the estimation of beta but reduces the precision for the estimation of the risk premium. Since we only estimate betas, Ang, Liu, and Schwarz (2010) provide further support for the use of portfolios as opposed to individual investments.

[11]In the appendix tables, we show robustness to different choices for the minimum number of investments per portfolio.

month. Finally, we compute the MIRR of each portfolio.

By grouping investments based on their starting dates, we reduce idiosyncratic risk and preserve sufficient dispersion in the explanatory variables. In addition, forming portfolios results in a better-behaved distribution of returns and the normality assumption is not rejected (p-value is 0.44). Finally, no portfolios are observed with MIRR of -100%, meaning that the logarithm of the MIRR is always defined. We can thus estimate equation (4) by OLS at the portfolio level.

3.2 Empirical estimates of risk exposures and alpha

3.2.1 The factor models

We build up our estimate of the risk premium for private equity by moving from the simplest model to a four-factor model that includes liquidity risk. We start with the CAPM, which is the model that Cochrane (2005) estimates for venture capital. Then, recognizing that private equity investments tend to be made predominantly in value companies, we consider the Fama and French (1993) three-factor model. Finally, we augment the three-factor model with the Pástor and Stambaugh (2003) traded liquidity factor. This factor is equal to the return on a portfolio that goes long the tenth liquidity-beta-decile portfolio and short the first liquidity-beta-decile portfolio. Liquidity betas are obtained by regressing individual stock returns on innovations in aggregated liquidity; and aggregate liquidity is the sum of stock-level OLS slopes of daily returns on signed daily trading volume within a given month.

Assuming that markets are integrated, or more specifically that there is a unique pricing kernel for private and public equity, allows us to compute the prices of risk for the four factors from their realizations in the public equity market. Table 5 presents the correlation and distribution of these factors during our sample time period (October 1975 to December 2007). In particular, it shows the time-series mean for each factor. We use these means as estimates of the factor risk premia to compute the cost of capital. Multiplying the values in Table 5 by twelve, the liquidity premium is 4.5% annually. The market risk premium is 7.5% annually. The HML and SMB premia are 4.9% and 2.9% annually, respectively. The (unreported) risk-free rate is 5.8% annually.

[Insert Table 5 about here]

3.2.2 Empirical results

Panel A of Table 6 reports the estimates of equation (4) for each of the factor models. In the first specification, the estimate of the CAPM beta is close to one and statistically significant. This number is consistent with the approach used by Kaplan and Schoar (2005), who measure private equity performance by a public market equivalent with a beta of one. The second column in Panel A reveals that, after accounting for the other Fama and French (1993) factors, the loading on the market increases. This is because private equity investments load positively and significantly on HML and that HML and the market factor are negatively correlated. The loading on SMB is positive, but not statistically different from zero.

Finally, the last column in Panel A reports the estimates of the model including liquidity risk. The liquidity beta is approximately 0.64 and statistically significant at the 1% level. We also note that the slope on HML increases, suggesting that in the previous model the importance of HML is mitigated by the negative correlation between HML and the liquidity factor.[12]

For each of the factor models, Panel B of Table 6 reports the total risk premium, the cost of capital, and alpha estimates calculated by transforming the model in logs to the model in levels according to equations (5) and (7). Each estimated factor risk premium is the product of the estimated factor loading times the average realization of the factor in the sample (described in the previous sub-section).

The first line shows the sum of all the risk premia for each factor model. It varies from 7.3% with the CAPM to 18% with the four-factor model. The cost of capital is the sum of the risk-free rate and the total risk premium. The average risk-free rate in the sample is fairly high (especially compared to current levels). It increases the cost of capital by

[12] The residuals of portfolios based on investment starting dates that are close in time may be correlated because of common time effects. In such a case, the estimates of the standard errors would be biased. To address this concern, we also compute Newey and West (1987) standard errors with eleven lags. The residuals of portfolios with starting dates that are one year apart can thus be correlated. The corresponding t-statistics are only slightly smaller (non-tabulated).

approximately 6% for all the factor models.

Finally, we present estimates of alpha. Alpha can be interpreted as the portion of expected returns that is not explained by the chosen asset pricing model. The CAPM leaves a high 9.3% of expected returns unexplained. In the second column, once the risk premia on the book-to-market factor and size factor are taken into account, the alpha drops to 3.1%, which is still economically (although not statistically) significant. In the model with liquidity risk (third column of Panel B), the premia on the four factors entirely account for average private equity returns. The alpha is virtually zero, both economically and statistically, while the risk premium and the cost of capital are approximately 18% and 24% per year, respectively.[13] The liquidity risk premium thus appears to be an essential component to fully account for average private equity returns.[14]

[Insert Table 6 about here]

3.2.3 Economic significance

Implications for company valuation. In the total risk premium, we note that the lion's share belongs to the market risk premium (10%). The book-to-market premium is 5.2%, while the size premium is insignificant. The liquidity risk premium amounts to a statistically significant 2.9% per year.

A simple way to assess the economic significance of a liquidity risk premium for private equity is to use the representative investment cash-flow pattern shown in Table 1 and value this investment using either a 15% discount rate or 18% discount rate. The present values of this representative investment under the two alternative assumptions are 119 and 108 respectively, showing a 10% difference. This simple algebra reveals that even a 3% liquidity

[13]Notice that adding the estimates of alpha and the cost of capital in Panel B of Table 6 gives an estimate of 24% for the expected return on private equity. This estimate is larger than the 19% average return that we report in Panel A of Table 4. The spread is due to the fact that Table 4 shows the average geometric return (R_g^i), whereas the 24% estimate refers to arithmetic returns (R_{t+1}^i). Whenever the volatility of returns is not zero, the geometric return is smaller than the arithmetic return.

[14]As mentioned above, our choice of a minimum number of twenty investments per portfolio may be considered arbitrary. To address this concern, Tables A-I and A-II in the appendix report the results with alternative choices for this minimum numbers. The threshold cannot drop below five investments, or we would have a portfolio with a -100% return. With a threshold of fifty investments per portfolio, the number of portfolios drops to sixty-eight, so we do not raise the threshold further. In general, results seem stable throughout the spectrum of chosen thresholds.

premium has important economic implications when valuing investments. In addition, in the next subsection, we use a conditional asset pricing framework and find that, in some periods, the liquidity risk premium far exceeds the unconditional value of 3%.

Comparing public equity and private equity liquidity risk exposures. It is also interesting to compare our estimate of liquidity risk for private equity with that of public equity. To do so, we simply compute the liquidity beta of all the stocks in CRSP with a standard time-series regression between January 1966 and December 2008 using the Pástor and Stambaugh (2003) four-factor model. We sort all the stocks by their loading on the liquidity factor and show the resulting histogram in Figure 2. The private equity liquidity beta of 0.638 corresponds to the 86th percentile of the beta distribution for publicly listed equities (as shown by the vertical line in Figure 2). This result indicates that the liquidity risk in private equity is high compared to that of most publicly-traded companies.[15]

The finding of a higher liquidity risk premium for private equity than for the average listed company can be rationalized within the classic Amihud and Mendelson (1986) framework.[16] To simplify, assume there are only two assets: one liquid (which could be public equity) and one illiquid (which could be private equity). If investors have different holding periods, in equilibrium, there is a clientele effect. Investors with longer horizons hold the more illiquid security. We believe the same logic applies to liquidity risk. The intuition is that absent an additional premium, the asset with poorer liquidity properties, be it lower liquidity level or higher liquidity risk, will not be held in equilibrium, because even long horizon investors are better off with the asset that offers better liquidity properties (public equity in this example). It thus seems reasonable that the liquidity risk premium is higher

[15]Note that the 7.5% liquidity risk premium reported by Pastor and Stambaugh (2003) is the beta of a long-short position on the top and bottom decile stocks by liquidity betas, not the liquidity risk premium paid by the average stock. By construction, the aggregate public equity portfolio will have a zero beta on the liquidity factor, SMB and HML, and a beta of one on the market factor in a four-factor model. Hence any asset class with a liquidity beta higher than zero will have a greater liquidity risk than the public equity portfolio. Furthermore, notice that in our sample (October 1987 - December 2007) the Pastor-Stambaugh factor pays a 4.5% premium, which is less than the 7.5% in the 1963-1999 sample used in the original Pastor and Stambaugh (2003) paper. This observation gives more economic significance to the 2.9% liquidity premium that we calculate for private equity.

[16]In a private equity context, Lerner and Schoar (2004) develop a model in which investors with higher tolerance for illiquidity hold private equity.

for private equity than for most publicly traded stocks.

[Insert Figure 2 about here]

3.3 Conditional analysis

One issue which is always present when estimating risk exposures is that factor loadings may be correlated with factor realizations. A significant covariance between factor loadings and risk premia would cause the unconditional estimates to be biased (e.g., Jagannathan and Wang (1996) and Lewellen and Nagel (2006)). In our context, we can expect that fund managers anticipating poor funding conditions may choose (or be forced) to reduce their exposure to refinancing risk, for example by reducing the leverage ratio. This behavior may ultimately induce positive correlation between liquidity risk realizations and loadings, which biases the estimates of alphas and betas, if left unmodeled. To verify whether this is a valid concern, we follow Ferson and Harvey (1991) and Ferson and Harvey (1999), and let the betas be a linear function of conditioning information. In addition, this conditional analysis allows us to document the extent to which the liquidity risk premium varies over time.

3.3.1 Empirical framework

Estimating the conditional risk premium for an asset involves a separate estimation of: i) the conditional beta and ii) the conditional factor risk premium. The conditional risk premium of the asset is the product of the two.

To estimate conditional betas, we adjust the approach of Ferson and Harvey (1999) to our context. We modify equation 4 and let the loading for factor k at time t be a linear function of a set of instruments Z_t

$$\delta_{k,t} = b_{k,0} + b'_{k,1} Z_t. \tag{8}$$

Similarly, the γ in equation 4 is allowed to vary over time with the same set of instruments Z_t

$$\gamma_t = a_0 + a_1' Z_t. \tag{9}$$

We obtain estimates of $b_{k,0}$, $b_{k,1}$ from this modified version of equation 4 on the same portfolio data as in the previous sub-section, using the same four risk factors. The time-varying risk loadings are then calculated by interacting the estimates of $b_{k,0}$, $b_{k,1}$ with the instruments Z_t.

To estimate the conditional factor risk premia, we run predictive rolling-window regressions. The rolling-window framework is adopted to allow for instability in the coefficients of the predictive regression. The dependent variable is the average realization of the factor in the forty-eight months between t and $t+47$,[17] the independent variables are the instruments Z_{t-1} (measured at time $t-1$). The estimation sample ranges from month $t-60$ to month $t-1$. The predicted risk premium at time t is then constructed by multiplying the slopes from this predictive regression by the instruments measured at time t. The Pástor and Stambaugh (2003) factor is only available up to December 2008. Hence, for the predictive regressions, t ranges between October 1975 and December 2004. As suggested by Campbell and Thompson (2008), the predicted factor risk premium is constrained to be positive.

Empirical results with the five instruments of Ferson and Harvey (1999). First, we use the same five instruments as Ferson and Harvey (1999). These are: (1) the holding period return between time $t-1$ and time t for a three-month T-bill in excess of the return on a one-month T-bill (Bb3, data from CRSP); (2) the dividend yield on the S&P 500 (DY, data from Prof. Shiller's website); (3) the spread between Moody's Baa and Aaa corporate bond yields (Credit Spread, data from the St. Louis Fed); (4) the spread between a long-term (5-year) Treasury bond and one-year Treasury bond yields (Term Spread, data from CRSP); (5) the yield on a one-month T-bill at time t (Y1M).

In Table 7 - Panel A, we report the slopes on the instruments from the conditional estimation of the four betas. Panel B has the results from the predictive regressions of the four-factor risk premia. To avoid reporting 200 regression results here, we report the

[17]We use a forty-eight month measurement window for the factor realizations to match the average life of a private equity investment.

estimates for December 1975, December 1985, December 1995 and December 2004 (the last month for which the regression is possible). The standard errors are computed as in Newey and West (1987) with forty-seven lags to account for the autocorrelation of residuals due to the overlap in the dependent variable. We note that the instruments display some predictive power for the factors. However, the magnitude and sign of the slopes change over time, which justifies our choice of using rolling windows for the estimation sample.

Panel C reports the distribution of the monthly conditional liquidity risk premium for private equity. We focus first on the results obtained with the conditional forecasts of the factor risk premium. We notice that while the average conditional risk premium is 2.7% per year[18], it ranges between 0% (at the 25th percentile) and 5.4% (at the 75th percentile). In other words, the liquidity risk premium exceeds 5.4% in a quarter of the sample months. We also report statistics on the fraction of the total conditional risk premium of private equity (computed as the sum of the risk premia from the four factors) that is explained by liquidity risk. This ratio can be computed only in the months when both the numerator and denominator are positive. The ratio is 37.8% on average and ranges between 11.9% (at the 25th percentile) and 56.7% (at the 75th percentile). This shows that oftentimes liquidity risk can account for more than half of the cost of capital.

Since there is no consensus in the literature on the predictability of factor risk premia (see, e.g., Goyal and Welch (2008)), Panel C - Table 7 also shows the results we obtain when the forecasted risk premium is simply equal to the unconditional mean of the forty-eight month factor realizations. The variation in the conditional liquidity risk premium is naturally smaller than the figure reported above. Yet, at times, liquidity risk is still an important component of the total risk premium for private equity.

Empirical results with a restricted set of instruments. In Table 7, we note that no instrument is individually significant. We attribute the lack of significance to the low power of these tests given that the estimation sample consists of only 139 portfolios. For this

[18]Note also that the average conditional liquidity risk premium differs from the 3% unconditional liquidity risk premium reported in the main analysis. The fact that the mean of the conditional premium does not necessarily equal the product of the unconditional beta times the unconditional factor risk premium has been documented in the literature. The two quantities are different whenever the covariance between the conditional beta and the conditional factor risk premium is not zero (see, e.g., Lewellen and Nagel (2006)).

reason, we also show results with a narrower set of conditioning variables. The instruments with the best predictive power for the conditionals betas are the credit spread and Y1M. Table 8 shows the results when we use only these two instruments. As expected, in Panel A, the statistical significance of the instruments is higher than in the previous table. In particular, we notice that the relationship between liquidity risk beta and the credit spread is marginally significant at the 10% level. As in the previous table, Panel B shows the predictive regressions for the factor risk premia and we observe that the instruments are stronger predictors of the factors.

Finally, in Panel C - Table 8, we notice that the variation in the conditional liquidity risk premium is of similar magnitude to what reported in Table 7; whether or not we use conditional forecasts of the factor risk premia.

To summarize, we show that in some periods of our sample the conditional liquidity premium goes well beyond the 3% unconditional estimate. The dependence of the betas on conditioning information appears to be marginal, with much of the time-variation resulting instead from time-variation in the factor risk premia. The finding that the betas are insignificantly related to the conditioning variables that drive the risk premia likely suggests that the covariance between factor loadings and factor risk premia is negligible. This fact, in turn, implies that the asset pricing model holds conditionally as well as unconditionally (see, e.g., Jagannathan and Wang (1996) and Lewellen and Nagel (2006)). This conclusion addresses the concern that motivated us to pursue the conditional analysis, and legitimates the results of the unconditional estimation above.

[Insert Tables 7 and 8 about here]

4 The source of liquidity risk in private equity

The factor model estimation in Section 3 shows that a liquidity risk factor is a significant determinant of private equity returns. The premium attributable to liquidity risk explains the abnormal performance of this asset class and is an important component of the cost of capital.

In this section, we set out to identify the channel that links variation in aggregate liquidity to private equity performance. First, we develop our main hypothesis. Second, we test it empirically using the cross-section of investment return data. Third, we provide consistent evidence from a time-series test.

4.1 Hypothesis development

The Pástor and Stambaugh (2003) traded liquidity factor that we use in Section 3 is based on a measure of stock market liquidity. The question naturally arises of why private equity returns are related to the liquidity of public equity markets. Our hypothesis is based on two complementary arguments.

The first argument is provided by Brunnermeier and Pedersen (2009) who postulate a relationship between market liquidity and funding liquidity, i.e. the availability of trading capital for investors. For our purposes, the focus is on banks and hedge funds because they are the main providers of finance to private equity companies. Brunnermeier and Pedersen (2009)'s theory suggests that times of low funding liquidity are also characterized by poor market liquidity. In their mechanism, labeled a liquidity spiral, a negative shock to investors' trading capital triggers margin calls and forced liquidations which, in turn, reduce market liquidity and exacerbate the initial trading losses. Consequently, poor market liquidity conditions, captured by the Pástor and Stambaugh (2003) factor, may reflect a dry-up in funding liquidity.

The second argument is that shocks to funding liquidity may be related to the return of the private equity companies. One crucial characteristic of private equity investments, which distinguishes them from public companies, is their higher leverage (e.g. Axelson, Strömberg, and Weisbach (2009)). The fact that these loans need to be refinanced or renegotiated (e.g., following a breach of covenant) makes private equity investments sensitive to the availability of capital from the debt providers (Axelson, Jenkinson, Strömberg, and Weisbach (2010), Kaplan and Strömberg (2009)). The providers of debt finance to private equity are mainly banks and hedge funds and are certainly exposed to variations in funding liquidity of the type described by Brunnermeier and Pedersen (2009). At times of low liquidity, private equity houses may thus find it difficult to refinance their companies and may be forced to liquidate their investments or accept higher financing costs. This argument relates the returns of private equity companies to funding liquidity. In Appendix 2, we provide anecdotal evidence on the workings of the funding liquidity channel in private equity from a Standard & Poor's (2009) study. This report shows that the performance of LBO transactions sharply deteriorated as a result of the liquidity crisis in 2008-2009 and defaults increased substantially due to covenant breaches with serious implications for the ability to refinance the deals.

Taken together, these two arguments suggest that private equity returns correlate with market liquidity through the refinancing risk channel. In other words, the observed link between private equity returns and market liquidity results from the dependence of private equity performance on the availability of capital from debt providers (funding liquidity), and from the link between funding liquidity and market liquidity.

In order to test this conjecture using our data, we need to find a proxy for funding liquidity that is especially relevant for private equity. Axelson, Strömberg, and Weisbach (2009) propose the 'Senior Loan Officer Opinion Survey on Bank Lending Practices' as an indicator of the credit availability for private equity investments. The survey asks loan officers whether they tightened or loosened their lending standards relative to the previous quarter.[19] Axelson, Jenkinson, Strömberg, and Weisbach (2010) argue that "this measure captures non-price aspects of credit market conditions, such as debt covenants and quantity constraints." They find this index to be strongly related to the amount of leverage used to finance private equity investments. Also, Lown and Morgan (2006) present evidence that this variable strongly correlates with bank loan changes and is more important than interest rates in explaining loan volume. Leary (2008) uses this measure to proxy for loan supply. He finds that it helps to explain differences in leverage between firms with and without bond market access. The tightening of credit standards thus has the double advantage of having been used and advocated in a private equity context and having strong empirical support. We therefore expect it to be a potentially accurate instrument to measure funding

[19]This survey is conducted quarterly by the US Federal Reserve Board and asks commercial banks in what direction they have changed their "standards of credit worthiness for loans to non-financial businesses" and "their willingness to make term loans to businesses" (http://www.federalreserve.gov/boarddocs/SnloanSurvey/)

liquidity.

Given the above arguments, we conjecture that the tightening of credit standards is negatively related to private equity performance as a manifestation of refinancing risk. Furthermore, we postulate that the observed relationship between private equity returns and the Pástor and Stambaugh (2003) measure results from the link between funding liquidity and market liquidity. Hence, our chosen measure for the change in funding liquidity (the tightening of credit standards) should empirically explain part of the negative relationship between private equity returns and market liquidity.

4.2 Cross-sectional evidence

In this sub-section, we empirically test the above conjecture using the cross-section of individual investments.

4.2.1 Main results

We first need to verify that, consistent with the finding of liquidity being a priced factor, unexpected market liquidity shocks are correlated with contemporaneous return. We adopt the measure of unexpected market liquidity shocks provided by Pástor and Stambaugh (2003). Second, we need to verify that the tightening of credit standards explains part of this relationship. This analysis is best conducted at the individual investment level, which we now discuss.

Working with individual investment returns. In contrast to Section 3 where we study portfolio returns, we now cast our analysis at the investment level. Investment characteristics are important control variables when identifying the relationship between private equity returns and macroeconomic variables. Forming portfolios would result in a loss of this investment level information. In addition, the advantages of forming portfolios, which we stated in Section 3, do not apply to the present analysis.

The investment returns are measured by the annualized MIRR (with S&P 500 reinvestment rate) described in Section 2. This measures the performance over the life of the investment. We thus simply compute our explanatory variables as the average realization between the investment's starting and ending date. For instance, we relate the MIRR of an investment to i) the average realization of market liquidity innovations over the life of that investment (labelled "P&S liquidity conditions"), ii) the average change in credit standards during the life of that investment (labelled "Tightening of credit standards"), etc.

As we observe outliers on the right tail of returns, we winsorize the MIRR at the 95th percentile.[20] Also, because the Federal Reserve's Survey of Loan Officers is continuously available only from April 1990, we focus on the investments that started after that date.[21] This reduces the sample from the original 4,403 observations to 3,763 investments.

Shocks to market liquidity and investment returns. Figure 3 provides a graphical illustration of the relationship between investment returns and liquidity conditions, plotting the average MIRR by deciles of P&S liquidity conditions. The relationship is almost monotonic and the difference in performance between investments experiencing bad versus good liquidity conditions is a striking 46% per year.

[Insert Figure 3 about here]

Of course, this relationship does not account for a number of other potentially important determinants of private equity returns. To this purpose, Table 9 shows the results from a multiple regression analysis. All specifications include a set of control variables. These are investment-level variables such as stage (a dummy variable that is one if it is a growth investment), size (equity invested, expressed in January 2007 in US dollars), private equity house age, country of investment location, industry of the investment, and stock market return (CRSP universe).[22] All the explanatory variables are standardized.[23] In addition,

[20] The 95th percentile is 135% annually and the 99th percentile is 400% annually. Winsorizing at the 99th percentile leads to slightly stronger results.

[21] The finding that liquidity conditions and returns are negatively related holds for the full sample starting in October 1975. Corresponding tables are available in a web appendix.

[22] We control for the country and industry of the investment with fixed effects. A growth investment is an investment undertaken to finance the growth of a company. It usually involves less leverage than leveraged buyouts and is usually a minority stake (unlike leveraged buyouts). As both firm age and investment size increase over time, we subtract the annual mean from each observation. In addition, as there are some outliers in terms of investment size, we winsorize this variable at the 95th percentile.

[23] The coefficients can then be interpreted as the impact of a one-standard-deviation change in the explanatory variable on annual returns. Importantly, inference is not affected by the transformation. The t-statistics are exactly the same with and without the standardization.

the standard errors are clustered at the investment's starting year, because the performance of investments starting at the same time may be driven by unobserved common factors.

In the first specification in Table 9, the effect of liquidity conditions on private equity performance is economically and statistically significant. A one-standard-deviation increase in liquidity conditions raises the annual MIRR by 11.4%. This confirms the results in Section 3 and Figure 3. A deterioration in market liquidity negatively affects private equity returns.

Shocks to funding liquidity and investment returns. The next step is to test of our conjecture that the effect of market liquidity on private equity returns originates from the relationship between these two variables and funding liquidity. Hence, in the second specification in Table 9, we regress the MIRR on the tightening of credit standards (our chosen measure for deteriorating funding liquidity) and the same set of control variables as above. Consistent with our hypothesis, when credit standards are tightened performance is significantly lower.

In the third specification, we test whether the funding liquidity channel explains the impact of market liquidity on private equity performance. Confirming our conjecture, credit conditions absorb half of the Pástor and Stambaugh liquidity effect. The coefficient on liquidity conditions decreases from 11.4% to 5.1% when we add the tightening of credit standards, and remains significant at the 5% confidence level. This robust and significant effect of market liquidity may be interpreted as a sign that the tightening of credit standards is an imperfect measure of funding liquidity. It is also possible that channels other than refinancing risk explain the relationship between market liquidity and private equity performance, which opens up an area for future research.[24]

[24] Acharya and Pedersen (2005) argue that liquidity risk originates from uncertainty about the transaction costs associated with selling an asset. A simple example shows how this can be relevant in a private equity context. Let us consider the uncertainty about transaction costs for an investor selling two different equity positions: A and B. A is a $10 million position in a S&P 500 company. B is a $10 million investment representing 100% ownership of a privately-held business. When selling A, an investor has some flexibility to manage transaction costs: for example, he can limit the price impact by splitting the order (Chan, Jegadeesh, and Lakonishok (1995), Vayanos (2001)). This is not possible for asset B. In addition, market depth is probably better for A. The number of potential investors in A certainly varies over time, but there are always enough investors willing to purchase a $10 million stake in a S&P 500 company at a reasonable price. In contrast, the market for full ownership of a privately-held business is significantly smaller. To exit

The close connection between credit conditions and liquidity conditions is also apparent from the correlation matrix in Table 10. The variable most tightly linked to P&S liquidity conditions is the tightening of credit standards (-63% correlation), followed by stock market returns (46%). The other variables are only weakly related to credit conditions.

We consider these results important for two related reasons. First, they deepen our understanding of the economic channel underlying the relationship between private equity returns and market liquidity. The market liquidity variable is closely related to a measure of funding liquidity, which in turn is a determinant of the ease of refinancing for leveraged deals as shown by Axelson, Jenkinson, Strömberg, and Weisbach (2010).

Second, as a by-product of our analysis, we find some empirical support for the theory put forward by Brunnermeier and Pedersen (2009) relating funding liquidity to market liquidity. Our evidence shows that there is a negative relationship between a dry-up in funding liquidity (the tightening of credit standards) and innovations in market liquidity (the Pástor and Stambaugh measure).

[Insert Tables 9 and 10]

4.2.2 Robustness

Controlling for the risk of economic conditions. The liquidity effect just shown can be the result of a positive 'macroeconomic' environment which fosters both good private equity performance and good liquidity conditions. With the goal of testing alternative explanations for the effect of liquidity conditions, we add controls for the most obvious macroeconomic variables.

Chen, Roll, and Ross (1986) show that two macro factors are priced in the cross-section of expected returns for public equity: the change in credit spreads and the growth in industrial production. According to these authors, the credit spread proxies for the expected risk premium and industrial production growth proxies for changes in future profitability.

a privately-held investment, the two main routes are a trade sale or an IPO. Both of these exit channels have proven to be cyclical in the past. When exiting during a trough in the IPO or M&A cycle, transaction costs are probably substantial, but they will be minimal in a buoyant IPO or M&A market. We partly test this story in the robustness analysis by adding the M&A cycles variables. In combination with credit tightening and the other controls, this regressor reduces the significance of P&S liquidity conditions (see the last specification in Table 9).

We thus include these two variables in specifications three and four in Table 9. Neither variable impacts the significance of P&S liquidity conditions. An increase in credit spreads has a negative, although not significant, impact on private equity returns, confirming that credit conditions matter for private equity returns. However, the change in credit spreads appears to be dominated by the tightening of credit standards as a measure of funding liquidity (see also the last specification in Table 9). This is probably due to the fact that the credit spread is a price-based variable which combines demand and supply effects, unlike the change in credit standards which is a measure of credit supply. This point is probably best illustrated in the context of the recent financial crisis. It is reasonable to say that in the second semester of 2007, refinancing constraints were probably tight. But the credit spreads hardly changed. In fact, they even decreased (0.97% in the first semester of 2007 vs. 0.89% in the second semester of 2007). Credit spreads spiked in January 2008 and December 2008, but in the other months of 2008, they were at similar levels to 2002.

To capture the cyclicality in exit opportunities we include a measure of M&A waves in column six. The effect of liquidity conditions remains significant with a somewhat lower t-statistic, while the M&A variable is not significant. Spiegel and Wang (2005) and Bandi, Moise, and Russel (2008) argue that the effects on returns of aggregate liquidity and aggregate volatility are closely (negatively) related. Consequently, in the seventh specification, we control for the change in long-term (4-year) realized volatility. This control leaves the significance of the credit standards unaffected and is not significant.

Finally, in the last column of 9, all the control variables are included. Liquidity conditions are now significant only at the 10% level. This reduced significance probably reflects the combined effect of controlling for tightening of credit standards and M&A waves. The fact that the M&A wave variable reduces slightly the significance of P&S liquidity conditions weakly supports the time-varying liquidity of the M&A market as another channel for liquidity risk in private equity (see also footnote 24).

Asymmetric effect of liquidity conditions. One potential refinement of our measure of liquidity risk is to allow liquidity conditions to affect private equity performance asymmetrically. The intuition stems from the effect of refinancing constraints. If liquidity has mild positive and negative shocks during the investment's life, then the refinancing constraint will never be very tight and the investment return should not be greatly affected. On the other hand, a large negative shock followed by a large positive shock may lead to the same average liquidity (over time) but will have made the refinancing constraint binding at one point, with a potentially significant impact on performance.

The literature on market timing (e.g.,Henriksson and Merton (1981)) captures asymmetric exposures by simply breaking down factor returns into positive and negative realizations. We follow this lead to create both a "negative-liquidity-condition" variable and a "positive-liquidity-condition" variable. The "negative-liquidity-condition" variable results from multiplying each shock by a dummy variable that takes the value zero if a shock is positive and one otherwise. The "positive-liquidity-condition" variable is defined symmetrically. Then, as usual, we take the average realization of these variables over the investment's life.

Table 11 shows the results when we use these two asymmetric measures of liquidity conditions instead of the symmetric measure. All the specifications mirror those in the previous table. Consistent with the above intuition, the negative-liquidity-condition variable has a larger effect than the average liquidity condition variable (shown in Table 9). For example, in the first column, a one standard-deviation decrease in the negative-liquidity-conditions variable reduces returns by 14% annually. This is a 23% difference in magnitude relative to the slope of the original liquidity variable. When all controls are included, in the last specification, the difference is even larger. In addition, and still consistent with the above intuition, the positive-liquidity-condition variable is not significant. Controlling for the tightening of credit standards once again halves the effect of market liquidity on private equity returns.

[Insert Table 11]

Other robustness tests. In the appendix, we replicate our analysis using two other market liquidity measures. The Acharya and Pedersen (2005) measure (see also Acharya, Amihud, and Bharath (2010)) is equal to the cross-sectional average of the monthly illiquidity of individual stocks.[25] Stock illiquidity is measured with the Amihud (2002) ratio, which is the average ratio over the month of absolute daily returns over daily trading volume.

The Sadka (2006) (also see Sadka (2010)) liquidity measure is a market-wide aggregation of estimated price impact at the stock level. This price impact consists of one permanent and one transitory part. These two components are estimated from a micro-structure model and use stock transaction data. According to Sadka (2006), it is the permanent component that is priced in public equity and we therefore use that one here.

Panel A of Table A-III has the results with the Acharya and Pedersen measure. We find that this measure also leads to statistically significant results. We also note that when using the Acharya and Pedersen measure, the liquidity effect is fully explained by our measure of funding liquidity. The results with the Sadka measure in Panel B of Table A-III follow a similar pattern to the other two liquidity measures.

In the appendix Table A-IV, we show the same specifications as in Table 9 for the sub-sample of US investments. Although the sample is only half as big, the economic and statistical significance is remarkably similar.

Averaging shocks over long periods of time naturally leads to a reduction in the dispersion of liquidity conditions across investments and thus a reduction in statistical power. In the web appendix, we re-run our main regressions over sub-samples of investments based on investment duration. The results suggest that taking the average realization of the explanatory variables reduces the statistical power with respect to the longest-duration investments. Still, there seems to be enough power left to identify a significant effect of liquidity risk and tightening of credit standards for all other investments.

Finally, in the web-appendix, we extend the set of control variables to additional proxies for the risk of macroeconomic conditions (IPO cycles, VIX, inflation) without impacting the main results and show that the liquidity conditions variable retains significance in the long sample (October 1975 - December 2007) for which the tightening of credit standards is not available.

[25] Their original variable is measures market illiquidity. We change its sign for consistency with our other measures.

4.3 Time-series evidence

An alternative approach to the cross-sectional analysis used in the previous sub-section is to generate an aggregate time-series of private equity payoffs and correlate it with the measures of market liquidity, funding liquidity, etc.

We first aggregate the cash flows (positive and negative) every month. Because of the growth of the private equity industry, this series shows a strong upward trend. We thus detrend it by scaling the investments so that exactly $100 million is invested each year. The scaling is pro-rata based on investment size, such that the cash flows are comparable over time. As shown in Figure 4, the time-series of cash flows appears stationary and clearly reveals the private equity cycles (to reduce volatility, the graph also shows the twelve-month moving average of the series). We notice the low-yielding years around the 1991 crisis, after which dividends increased faster than investments (mid-1990s). The downturn in the 2000-2003 period is also visible. The large dividends in 2004-5 triggered extensive fund-raising and large investments, which lowered the net cash flows in 2006. These investments started to give large payoffs in the early part of 2007. Finally, in late 2007 we see the collapse of private equity payoffs, coinciding with the onset of the financial crisis.

Table 12 shows the results from regressing the time-series of aggregate private equity cash flows on the same macroeconomic variables (including the liquidity measures) as in the cross-sectional analysis. Since the "tightening of credit standards" variable is available from April 1990 onwards, the sample starts in April 1990.

We find that the net cash flows are significantly and positively related to the innovations in the Pástor and Stambaugh measure of market liquidity. Also consistent with the previous analysis, the tightening of credit standards, which we interpret as a deterioration in funding liquidity, is negatively related to private equity net cash flows. As in the cross-sectional analysis, the tightening of credit standards is the most significant explanatory variable for private equity performance.

These results show that higher net distributions from private equity houses occur during periods of higher liquidity shocks. They bring further empirical support for our hypothesis and above findings. Finally, this exercise has generated an aggregate measure of private equity payoffs that can be used in other applications.

[Insert Figure 4 and Table 12]

5 Conclusions

Inspired by the recent literature that identifies a liquidity risk factor in the expected returns of stocks and alternative assets, this paper investigates whether private equity returns load on liquidity risk.

Using a new and comprehensive dataset containing the cash flows from liquidated private equity investments, we find a positive and significant loading of private equity returns on the Pástor and Stambaugh (2003) traded liquidity factor. The magnitude of the private equity liquidity beta exceeds the corresponding estimate for 86% of publicly listed stocks. The unconditional liquidity risk premium is approximately 3% annually, the total risk premium is 18%, and the alpha (gross-of-fees) is not statistically different from zero. In a conditional framework, the premium related to liquidity risk is larger than 5% for a quarter of the sample periods and can at times represent more than half of the total risk premium.

We explore a potential explanation for the observed link between private equity performance and liquidity risk. Private equity investments are sensitive to credit market liquidity because their debts are occasionally refinanced or renegotiated. According to the theory put forward by Brunnermeier and Pedersen (2009), the funding liquidity of private equity lenders (mainly banks and hedge funds) is related to market liquidity, which is the quantity we measure with the Pástor and Stambaugh (2003) factor. Our main conjecture is therefore that the relationship between market liquidity and private equity returns is a reflection of the effect of funding liquidity on private equity performance. We test this hypothesis by using the tightening of credit standards from the Federal Reserve's Senior Loan Officer Survey as a measure of the evolution of funding liquidity. Consistent with our conjecture, this variable is strongly related to private equity returns and accounts for a significant portion of the liquidity effect on returns. This indicates that funding liquidity is an important source of liquidity risk in private equity. Furthermore, as a by-product of our analysis, we find supporting evidence for the link between market and funding liquidity postulated by

Brunnermeier and Pedersen (2009).

The results in this paper are relevant for academics, practitioners, and regulators, as we quantify the systematic risks and pricing efficiency of an asset class that has gained increasing importance in financial markets. Our evidence suggests that the apparently high performance of private equity investments can be largely explained as compensation for the different risk factors to which returns are exposed, and liquidity risk is one important source of this risk premium.

Our results provide practitioners with a hurdle rate to evaluate private equity. Using such a benchmark, they can assess the NPV of their track record. At approximately 18% above the risk-free rate, the cost of capital that we estimate is in sharp contrast to the widely-used hurdle rate of 8%. In addition, our results may call current compensation practices into question. Fund managers (GPs) and, oftentimes, the private equity team within the investor's organization, receive performance-based compensation if they achieve returns above 8% per annum, but this hurdle rate seems low in view of our findings. Knowing the risk profile of private equity investments is also important for portfolio risk management. In times of liquidity crises, these investments may not offer the diversification investors may expect of them.

Regulators may also find some useful insights in our results. Solvency II and Basel II require insurance companies and banks to set aside a provision for the risk on their private equity investments (see Bongaerts and Chalier (2009)). As the current method of weighting assets by risk does not reflect the large exposure to liquidity risk, this may result in too low a provision.

Finally, for academics, this paper finds that the liquidity risk factor identified in public equity is consistently related to private equity performance. This contributes to the recent literature showing the pervasiveness of liquidity risk across asset classes.

Appendix 1

In this appendix, we provide the explicit derivation of equations (6) and (7) in the text. The reported formulas differ slightly from the formulas in Cochrane (2005), because we have a multifactor model and the factors are not in logarithmic form.

From equation (2), R^i_{t+1} is the exponential of a normally distributed variable:

$$R^i_{t+1} = R^f_{t+1} e^{\gamma+\delta' f_{t+1}+\varepsilon^i_{t+1}}$$

Also, by assumption, the factors are normal. Hence, the expression of the expected return is

$$E\left(R^i_{t+1}\right) = R^f_{t+1} e^{\gamma+\delta'\mu_F+\frac{1}{2}\delta'\sigma^2_F\delta+\frac{1}{2}\sigma^2} \quad \text{(A-1)}$$

Applying Stein's lemma, the covariance can be expressed as

$$\begin{aligned} Cov\left(f_{t+1}, R^i_{t+1}\right) &= Cov(f_{t+1}, \delta' f_{t+1} + \varepsilon^i_{t+1}) E\left(R^i_{t+1}\right) \\ &= Cov\left(f_{t+1}, \delta' f_{t+1} + \varepsilon^i_{t+1}\right) R^f_{t+1} e^{\gamma+\delta'\mu_F+\frac{1}{2}\delta'\sigma^2_F\delta+\frac{1}{2}\sigma^2} \\ &= Var\left(f_{t+1}\right) \delta R^f_{t+1} e^{\gamma+\delta'\mu_F+\frac{1}{2}\delta'\sigma^2_F\delta+\frac{1}{2}\sigma^2} \end{aligned}$$

where, for the last step, we use the fact that ε^i_{t+1} and f_{t+1} are uncorrelated. The expression for beta then follows:

$$\begin{aligned} \beta &= Var\left(f_{t+1}\right)^{-1} Cov\left(f_{t+1}, R^i_{t+1}\right) \\ &= Var\left(f_{t+1}\right)^{-1} Var\left(f_{t+1}\right) \delta R^f_{t+1} e^{\gamma+\delta'\mu_F+\frac{1}{2}\delta'\sigma^2_F\delta+\frac{1}{2}\sigma^2} && \text{(A-2)} \\ &= \delta R^f_{t+1} e^{\gamma+\delta'\mu_F+\frac{1}{2}\delta'\sigma^2_F\delta+\frac{1}{2}\sigma^2} && \text{(A-3)} \end{aligned}$$

To compute alpha we use the standard definition

$$\alpha = E\left(R^i_{t+1}\right) - R^f_{t+1} - \beta' E\left(f_{t+1}\right) \quad \text{(A-4)}$$

where $E(f_{t+1}) = \mu_f$. Replacing the expressions for the expected return in (A-1) and beta in (A-3), we get

$$\alpha = R_f \left(e^{\gamma + \delta' \mu_F + \frac{1}{2}\delta' \sigma_F^2 \delta + \frac{1}{2}\sigma^2} (1 - \delta \prime \mu_F) - 1 \right) \tag{A-5}$$

Although we do not use them in the estimation, it is interesting to derive the continuous time limits for α and β. These are:

$$\begin{aligned} \beta &= \delta & \text{(A-6)} \\ \alpha &= \gamma + \frac{1}{2}\delta' \sigma_f^2 \delta + \frac{1}{2}\sigma^2. & \text{(A-7)} \end{aligned}$$

To obtain these formulas, we start from the continuous time equivalent of equation (2)

$$d \log(V_t) = \gamma dt + r_f dt + \delta' df_t + \sigma dZ_t \tag{A-8}$$

where $df_t = \mu_f dt + \sigma_f dZ_{f,t}$, Z_t and $Z_{f,t}$ are independent vectors of standard Brownian motions, and r_f is the instantaneous risk-free rate. Then, apply Ito's lemma to equation (A-8) to obtain the process for the return in levels

$$\frac{dV_t}{V_t} = \left(\gamma + r_f + \delta' \mu_f + \frac{1}{2}\left(\sigma^2 + \delta' \sigma_f^2 \delta \right) \right) dt + \sigma dZ_t + \delta' \sigma_f dZ_f. \tag{A-9}$$

Then, from equation (A-9), we obtain beta using the standard definition

$$\begin{aligned} \beta &= Var(df_t)^{-1} Cov\left(df_t, \frac{dV_t}{V_t} \right) \\ &= \left(\sigma_f^2\right)^{-1} \sigma_f^2 \delta \\ &= \delta. & \text{(A-10)} \end{aligned}$$

Finally, to obtain equation (A-7), use the definition of alpha and the result in (A-10)

$$\begin{aligned} \alpha dt &= E\left(\frac{dV_t}{V_t}\right) - r_f dt - \beta' E(df_t) \\ &= \left(\gamma + \frac{1}{2}\left(\sigma^2 + \delta' \sigma_f^2 \delta \right) \right) dt. \end{aligned}$$

Appendix 2

Extracts from the Standard & Poor's study "LBO Performance In Europe Falls Behind Expectations As Recession Bites", RatingsDirect, September 9, 2009.

We see that when debt for these transactions was marketed to investors during the boom years of 2005-2007, transactions were structured and sold on the basis of solid growth prospects, whether they were first-time LBOs, secondary or tertiary buyouts, or recapitalizations. We therefore believe that a shortfall in sales and EBITDA growth will have serious implications for covenant compliance and the ability to refinance an overleveraged balance sheet.

(...)

Many companies in our study were experiencing severe underperformance by the end of 2008, with 45% more than 10% behind forecast EBITDA. This trend is reflected in the increase in defaults in 2008. Of our sample, 11 companies, or 12.2%, have experienced a payment default, filed for insolvency, or are undergoing a restructuring. The median EBITDA performance for these companies was 29% behind the original forecast at year-end 2008, while the median sales figure was down 18.6%. And 18 companies (20%), including those that have defaulted, have either breached covenants or asked lenders for a waiver or amendment to covenants. This compares with the last update of our study in December 2008, when 12.5% of companies in the study had covenant-related problems.

(...)

In our opinion, the majority of reported covenant breaches in 2008 were technical. What we see as very aggressive plans to deleverage through EBITDA growth meant that companies breached covenants even if their operating performance was healthy. Now, however, most breaches no longer fit in this category. Rather, they are triggered by true operating difficulties. We see that in many cases this results in liquidity problems for management, because companies are usually unable to rely on undrawn revolving credit facilities when in breach.

(...)

Waivers and resets, which were relatively easy and quick to agree on in early 2008, have become harder to obtain. As a consequence, toward the end of 2008 and throughout 2009, covenant breaches have often led more quickly to defaults. In the second half of 2008, the average time from a financial covenant breach to a payment default, distressed debt exchange, or restructuring contracted to 2.0 months from 7.5 months in the first half of the year.

(...)

Default rates have risen substantially in 2009 and we believe that the peak in Europe may occur later in 2009 as the full 12 months of trading following the bankruptcy of Lehman Brothers translates into a higher level of defaults. This will, in our view, cause more companies to breach covenants and force them into standstills and restructuring negotiations with lenders.

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Table 1: Cash flows of a typical investment. The table shows the cash flows of a representative investment. It lasts for four years, pays a final dividend equal to 1.5 times the original investment, and pays an intermediate dividend in year 2.5 which equals half of the initial investment. We show the computation of the modified IRR with a re-investment rate of 5% per semester. At the bottom of the table we report the present value of the dividends using two different discount rates.

Date (in years)	Cash flows	Re-invested dividend (at 5% per semester)
0	-100	0
0.5	0	0
1	0	0
1.5	0	0
2	0	0
2.5	50	50
3	0	53
3.5	0	55
4	150	208

MIRR = $(208/100)^{1/4}$-1 = 20%
IRR = 21%

Present value of dividends at 15% discount rate	119
Present value of dividends at 18% discount rate	108

Table 2: Data coverage. The table compares the coverage of the CEPRES dataset to that of Capital IQ. It shows the number of investments, their total size (equity invested) and their average multiple (size-weighted). Multiple is the sum of all the dividends divided by the sum of all investments. Statistics are shown for both the sample of liquidated investments and the sample of non-liquidated investments. Statistics are also broken down by investment periods.

	Liquidated			Non-liquidated			Total CEPRES	Capital IQ	Fraction
	Number Investments	Size ($ million)	Multiple Mean (VW)	Number Investments	Size ($ million)	Multiple Mean (VW)	Number Investments	Number Investments	CEPRES vs Capital IQ
1975-1989	592	4,581	3.30	10	237	3.56	602	581	1.04
1990-1994	1,320	17,354	3.03	52	1,523	2.20	1,372	1,102	1.25
1995-1999	1,702	38,059	2.38	665	28,569	1.65	2,367	3,416	0.69
2000-2006	789	27,027	2.26	2,068	140,003	1.66	2,857	8,912	0.32
Total	4,403	87,021	2.52	2,795	170,332	1.67	7,198	14,011	0.51

Table 3: Data representativeness. This table compares the success rates of PE houses included in the CEPRES dataset and of PE houses that are not included in the CEPRES dataset. The universe of PE houses and their success ratio comes from Thomson Venture Economics. Successful exit rate is the fraction of investments exited via IPO or M&A over the total number of investments. Only investments made before 2002 and PE houses with more than 5 investments are considered.

	CEPRES (1)	TVE (ex-CEPRES) (2)	Difference (1) minus (2)
Number of PE houses	117	535	-418
Successful-exit rate			
20th percentile	0.43	0.39	0.04
50th percentile	0.61	0.56	0.05
80th percentile	0.75	0.72	0.03
Mean	0.59	0.55	0.04

Table 4: Performance by year and region. The table reports the modified IRR of a group of investments. Groups are based on the year of the investment's starting date and the region where the investment is located. Performance is computed on the pooled cash flows of each group. The reinvestment rate is the return on the S&P 500 index.

Panel A: Modified Internal Rates of Return (S&P as re-investment rate)

	1975-1989	1990-1994	1995-1999	2000-2006	1975-2006
US	0.18	0.18	0.19	0.13	0.18
UK	0.17	0.16	0.17	0.20	0.17
Europe (ex-UK)	0.17	0.14	0.25	0.21	0.20
Rest of the world	0.21	0.15	0.18	0.17	0.17
All countries	0.18	0.17	0.21	0.21	0.19

Panel B: Number of Investments

	1975-1989	1990-1994	1995-1999	2000-2006	1975-2006
US	323	533	534	237	1627
UK	172	440	526	139	1277
Europe (ex-UK)	68	269	499	246	1082
Rest of the world	17	23	121	152	313
All countries	592	1320	1702	789	4403

Table 5: Correlations and distributions of the traded factors. This table shows the correlation matrix and summary statistics for the (time-series of the) four traded risk factors: the illiquid-minus-liquid factor constructed by Pástor and Stambaugh (2003), the excess market return, HML, and SMB. The time period is from October 1975 to December 2007. The frequency is monthly. Returns are in percentages.

	IML_PS	Rm-Rf	HML	SMB
Correlations:				
IML_PS	1.000			
Rm-Rf	-0.100	1.000		
HML	-0.276	-0.460	1.000	
SMB	0.042	0.236	-0.341	1.000
Mean	0.375	0.630	0.417	0.241
St. Deviation	4.138	4.320	3.009	3.166
5th percentile	-5.767	-6.410	-3.960	-4.180
Median	0.608	0.940	0.370	0.120
95th percentile	5.530	7.010	5.330	4.800