Stockholm School of Economics
Department of Finance
Master's Thesis
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Investment Uncertainty, Liquidity Supply, and Pairs Trading Profitability[*]

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May 2013

ABSTRACT

In this paper, we examine a pairs trading strategy that speculates on the price-level divergence and convergence of paired stocks with similar risk-return characteristics. We explore whether time-variation in pairs trading returns is related to fluctuations in liquidity supply and investment uncertainty. The trading strategy is tested against a sample of 305 U.S. oil and gas stocks between January 1984 and December 2012. We document a significant negative time series and cross-sectional relationship between excess returns and several liquidity supply proxies. Our results also indicate that compensation per unit of risk peaks during periods of low liquidity supply. Pairs trading may consequently be thought of as a way of quantifying the costs of maintaining relative prices in markets with funding frictions. Based on regressions of monthly excess returns on four investment uncertainty proxies, we do not find evidence that fluctuations in pairs trading returns are associated with investors' behavioral biases.

Keywords: Pairs trading, statistical arbitrage, liquidity, behavioral bias, valuation uncertainty

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[*] We are grateful to our tutor Bige Kahraman, Assistant Professor of Finance at the Stockholm School of Economics and Research Fellow at the Institute for Financial Research in Stockholm (SIFR), for invaluable comments and guidance throughout the process of writing this thesis. We also thank Frej Andreassen, Peder Folke, Niklas Lyttkens and Addie Patterson for helpful remarks at the final stage. All errors are our own.

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1. Introduction

Pairs trading is a widely adopted statistical arbitrage strategy that uses the historical price paths of securities to predict future relative price movements. A basic strategy matches stocks with similar risk-return characteristics, sells the relative winner and buys the relative loser upon abnormal price-level divergence in a speculative bet that relative prices will converge to their historical equilibrium. If asset prices are path independent, statistical arbitrage opportunities would not be observed. Hence, evidence of such anomalies challenges the weak form of the efficient-market hypothesis, as defined by Fama (1970). Statistical arbitrage has attracted attention among researchers and market practitioners, as traditional asset pricing models have proved largely ineffective at explaining the time-variation in and magnitude of excess returns.

In the most notable paper on pairs trading, Gatev, Goetzmann & Rouwenhorst (2006) study a strategy that matches stocks into pairs based on minimum distance criteria in normalized price space. The authors find that the strategy generates annual excess returns of up to 11 percent and monthly Sharpe ratios of four to six times higher than the market (S&P 500), between 1962 and 2002. Substantial excess returns to pairs trading strategies have been shown to persist over time and across markets (Andrade, di Pietro & Seasholes (2005); Engelberg, Gao & Jagannathan (2009); Perlin (2009); Do & Faff (2010); Broussard & Vaihekoski (2012)).

Previous research attributes the strategy's profitability to delays in information diffusion and to uninformed demand shocks, but does not seek to explain the persistence of and time-variation in the pairs effect. In a recent working paper, Engelberg et al. (2009) find that some of the profitability to pairs trading can be explained by pair constituents' different price reactions to common information shocks. Market frictions create a lead-lag relationship between the paired stocks, which gives rise to relative return predictability. In an earlier working paper, Andrade et al. (2005) show that stocks which have historically fluctuated in step diverge when exposed to temporary price pressures caused by differential uninformed demand shocks. The finding suggests that pairs trading profits may constitute compensation for providing liquidity in markets with limited risk-bearing capacity.

The purpose of this paper is to broaden and extend the understanding of the factors that influence the magnitude of pairs trading profits. Our key contribution is to examine the merits of two different explanations for time-variation in pairs trading returns, which, to our knowledge, have not been extensively or directly tested. Firstly, we examine the relationship between pairs trading returns and liquidity supply. In light of Asness, Moskowitz & Pedersen's (2013) finding that funding liquidity is related to asset pricing anomalies, we expect that aggregate liquidity supply may play an important role in explaining pairs trading profitability. Liquidity provision is increasingly performed by nonconventional market makers such as algorithmic traders, quantitative hedge funds and individual investors (Kaniel, Saar & Titman (2008); Hendershott, Jones & Menkveld (2011)). Despite their engagement in sophisticated trading strategies, these market participants depend, to a large extent, on external banks and brokers (see e.g., Gromb & Vayanos (2002); Vayanos (2004); Brunnermeier & Pedersen (2009)). In times of market turmoil, risk-management constraints reduce the risk appetite of these financial intermediaries (Adrian & Shin, 2010), which may curtail arbitrageurs' ability to exploit profit opportunities. Funding constraints could therefore give rise to statistical arbitrage opportunities which otherwise are competed away and may serve as an explanation of the time-variation in pairs trading profitability.

Secondly, we seek to extend the understanding of the evidence in Engelberg et al. (2009) by examining the relationship between pairs trading excess returns and investors' behavioral biases. Frazzini (2006) finds that the tendency of investors to ride losses and realize capital gains (i.e., the disposition effect) induces stock prices to underreact to news. News travels slowly, which causes stock prices to drift in the wake of information events. The author shows that the steepness of the drift and the extent of the behavioral bias depend on the magnitude of gains (losses) experienced by stockholders on the event date. We conjecture that if the stockholders of pair constituents exhibit different levels of aggregate unrealized gains (losses), they may react differently to a common information shock. As a result, a pair may experience temporary price-level divergence that diminishes over time due to the stocks' skew post-shock drifts. A pairs trading strategy may exploit the temporary mispricing by opening a long-short position upon divergence and closing the position upon convergence.

Our empirical results are based on an out-of-sample implementation of the pairs trading strategy devised by Gatev et al. (2006) on a sample of 305 U.S. oil and gas stocks from January 1984 to December 2012. The reason for focusing on oil and gas stocks is twofold. Firstly, oil price changes have been shown to exhibit significant explanatory power in the cross-section of oil and gas stock returns (Mohanty & Nadha, 2011). High oil price volatility may thus cause investment uncertainty through high volatility among oil and gas stocks. Secondly, volatile stocks may induce uninformed trading activity and relative mispricings when arbitrageurs' market participation is constrained (Andrade et al., 2005). In particular, the pro-cyclical nature of the oil and gas industry may cause idiosyncratic price pressures in the cross-section of stocks as investors seek to de-risk or rebalance their portfolios upon fluctuations in the business cycle (Sadorsky, 2001).

We find that the pairs trading strategy generates average monthly excess returns of 1.86 (1.55) percent on equal-weighted (value-weighted) invested capital. Consistent with previous studies (Engelberg et al. (2009); Chen, Chen & Li (2012)), we find that the strategy generates significant alpha of 2.33 percent per month against the Fama-French Carhart four-factor model (Carhart, 1997) augmented with a short-term reversal factor and the Pástor-Stambaugh (2003) liquidity factor. The strategy's excess returns exhibit insignificant exposure to these common sources of risk, with the exception of negative but low exposure to momentum and the Pástor-Stambaugh liquidity factor.

We document a negative relationship between liquidity supply and returns to pairs trading, using four funding liquidity proxies: (i) idiosyncratic volatility, (ii) the Chicago Board Options Exchange's (CBOE) implied volatility index VIX, (iii) the U.S. Treasury-Eurodollar

(TED) spread and (iv) the 7-year swap spread over the 7-year U.S. Treasury bond rate. The results are significant for the computed excess return time series and in the cross-section of trades. We standardize the return series by its volatility, conditional on the TED spread, and find that the risk-return dynamics of the strategy have varied considerably over time. Our results indicate that the return per unit of risk peaks during times of low liquidity supply such as the financial crisis 2007-2009 and the stock market crash 1987.

We do not find evidence that aggregate investment uncertainty influences the time-variation in pairs trading returns. Kumar (2009) shows that investors exhibit stronger disposition bias when market-level uncertainty is higher and stocks are more difficult to value. Building on these findings, we regress the monthly pairs trading returns on four lagged investment uncertainty proxies: (i) idiosyncratic volatility, (ii) the VIX index, (iii) the University of Michigan Consumer Sentiment Index and (iv) the monthly oil price volatility. We find that the coefficient estimates bear the expected signs but that they are statistically insignificant at conventional levels.

This paper provides insight on the risk-return dynamics of pairs trading and adds to the literature on the systematic risk exposures of statistical arbitrage strategies.[1] Our findings suggest that time-variation in pairs trading profitability is partly attributable to financial intermediaries' sporadic funding constraints and, in corollary, arbitrageurs' market participation constraints. Pairs trading may consequently be thought of as a way of quantifying the costs of maintaining relative prices in markets with funding frictions.

The remainder of this paper is organized as follows. Previous literature on pairs trading and related topics are reviewed in Section 2. Our theoretical framework and hypotheses are outlined in Section 3, preceding the presentation and discussion of the data and methodology in Section 4. The empirical results are presented in Section 5, followed by our concluding remarks in Section 6.

2. Literature review

Contemporary financial research provides extensive evidence on the existence of strong return predictability over different horizons based on the historical price paths of individual securities. Statistical arbitrage strategies that are well documented include reversals (De Bondt & Thaler (1985); Jegadeesh (1990); Lehmann (1990)) as well as momentum (e.g., Jegadeesh & Titman (1993); Moskowitz, Hua Ooi & Pedersen (2012)). Pairs trading is, similar to these strategies, related to market efficiency theories and limits to arbitrage. The basic implementation of a pairs trading strategy is rather unsophisticated by nature. For this reason, it may appear

[1] For example, Asness et al. (2013) find that value loads positively on liquidity risk, whereas momentum loads either negatively or zero on liquidity risk, depending on the measure. Nagel (2012) shows that withdrawal of liquidity supply is associated with an increase in expected returns from short-term reversal strategies.

paradoxical that such a simple rule-based investment strategy can generate significant returns in an efficient market.

Gatev et al. (2006) examine a pairs trading strategy by matching stocks into pairs based on minimum distance between normalized prices. The authors form pairs during a 12-month formation window and allow for trading during a subsequent 6-month period. A long-short position in a stock pair is opened upon relative divergence exceeding two times the historical standard deviation of the normalized price spread and closed upon convergence or at the end of the trading window. The authors find that the strategy generates annual excess returns of up to 11 percent between 1962 and 2002. Do & Faff (2010) find that excess returns to the strategy have persisted in the U.S. stock market throughout the financial crisis. The trading strategy has also been shown to generate significant excess returns in markets such as Brazil (Perlin, 2009), Finland (Broussard & Vaihekoski, 2012) and Taiwan (Andrade, et al., 2005). These studies apply the basic methodology with no or minor modifications and report profits of similar magnitude as Gatev et al. (2006).[2]

The uniform finding that pairs trading strategies generate significant excess returns raises questions regarding the drivers of profitability. Previous studies have documented that pairs trading strategies are market-neutral and have no or negligible exposure to size and value (as defined by Fama & French (1993)). However, empirical results (Gatev et al. (2006); Engelberg et al. (2009)) indicate that excess returns to the strategy exhibit low but significant exposure to cross-sectional momentum (as defined by Carhart (1997)) and reversals (as defined by Lehmann (1990)).

The most explored explanation for the pairs effect is related to how information is incorporated into stock prices. Papadakis & Wysocki (2007) find that pair trades are frequently triggered around accounting information events and clustered analyst forecast events, and that these events affect the strategy's profitability. In line with this result, Engelberg et al. (2009) find that a divergence in the normalized prices of paired stocks is often caused by idiosyncratic news events or common information events that affect both stocks. By implementing a measure of information diffusion, the authors document that pairs trading profitability can partly be explained by differential responses to common information shocks. Market frictions like illiquidity and costly information acquisition creates a lead-lag relationship between the price movements of the constituent stocks, which creates a trading opportunity. In a working paper, Chen et al. (2012) make several findings consistent with the information diffusion explanation. The authors find that (i) pairs trading is more profitable in small firms, without media coverage, lower investor recognition and analyst coverage; (ii) pairs trading returns have diminished over time, suggesting that avid exploitation by arbitrageurs have reduced the efficacy of the strategy; and (iii) pairs trading returns do not persist beyond the first month, indicating that persistent fundamentals are unlikely to explain the returns.

[2] Andrade et al. (2005) limit trading to the top 20 pairs based on historical co-movement, while Perlin (2009) allow for trading in all available stocks. Broussard & Vaihekoski (2012) focus on the top 5 pairs but do not allow for overlapping portfolio trading.

Researchers have also sought to investigate pairs trading strategies' exposure to market liquidity factors. Engelberg et al. (2009) examine the factor exposure of a pairs trading strategy with value-weighted and equally-weighted versions of the Pástor-Stambaugh (2003) liquidity factor as well as the fixed cost and variable cost components of spreads liquidity constructed by Sadka (2006). The authors find that the equally-weighted Pástor-Stambaugh index and the variable-cost component of the Sadka spreads are negatively correlated with returns from pairs trading, especially for short holding periods. However, the R-squared from time series regressions are low and the alphas of pairs trading are largely unaffected by the inclusions of these liquidity risk factors.

Andrade et al. (2005) conjecture that pairs trading profits constitute compensation for providing liquidity in markets that have limited risk-bearing capacity. Specifically, it is argued that liquidity is demanded by uninformed traders and that this demand is observed as temporary pressure in stock prices. Based on Taiwanese stock data, the authors find that initial price divergences are highly correlated with uninformed idiosyncratic shocks to pair constituents and conclude that these shocks have an economically and statistically significant impact on asset prices.[3] Whilst Engelberg et al. (2009) provide indicative evidence that funding liquidity may help explain time-variation in pairs trading returns; the relationship is neither extensively tested nor explained.

The explanatory power of funding liquidity risk has been extensively examined in related studies on alternative trading strategies. In a recent paper, Asness et al. (2013) explore the role played by funding liquidity risk in explaining time-variation in value and momentum returns. The authors regress value and momentum returns on funding liquidity indicators such as the U.S. Treasury-Eurodollar (TED) spread, a global average of TED spreads, a global LIBOR-term repo spread and a global illiquidity index constructed from the other measures. The findings indicate that value loads positively on liquidity risk whereas momentum loads negatively or zero on liquidity risk, although a substantial part of the variation remains unexplained. Similarly, Brunnermeier, Nagel & Pedersen (2009) find that diminishing funding liquidity coincides with sudden unwinding of currency carry trade positions.

3. Theoretical framework and hypotheses

We explore the merits of two different explanations for the time-variation in pairs trading returns. Firstly, we hypothesize that excess returns to pairs trading are negatively associated with aggregate liquidity supply. Recent research has emphasized the importance of examining

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3 In order to arrive at this conclusion, Andrade et al. (2005) construct a net uninformed trading factor. The factor is defined as the daily change in the aggregate net shares held long on margin divided by total shares outstanding. Normalizing by total shares outstanding allows for comparison across stocks. The authors explain that this factor can be thought of as representing the flow of capital from the uninformed traders into, or out of, a company's stock.

the role played by funding liquidity in explaining the returns of other relative strength strategies (see e.g., Asness et al. (2013)). Secondly, we hypothesize that pairs trading profitability is positively associated with the level of market-wide behavioral biases affecting the speed at which new information is incorporated into prices. Similar hypotheses have been shown to have significant bearing on other relative strength strategies (see e.g., Hong & Stein (1999); Jegadeesh & Titman (2001); Grinblatt & Han (2002); Cooper, Gutierrez Jr. & Hameed (2004); Frazzini (2006)).

Pairs trading and liquidity supply. Liquidity provision in equity markets is increasingly performed by nontraditional market makers (or arbitrageurs) such as algorithmic traders, hedge funds and individual investors (Kaniel et al. (2008); Hendershott et al. (2011)). Brunnermeier & Pedersen (2009) propose a theoretical model which illustrates how trading patterns of market liquidity providing arbitrageurs are intertwined with the activities of funding liquidity providing financial intermediaries. Importantly, small arbitrageur losses can lead to discontinuous drops in market liquidity through mutually reinforcing margin and loss spirals.

The margin spiral manifests when a funding shock to arbitrageurs lowers market liquidity, increasing margin requirements and tightening funding constraints for arbitrageurs. Consequently, arbitrageurs are forced to unwind positions and de-lever during downturns. The loss spiral materializes if an arbitrageur holds a position that is negatively associated with the public's demand for liquidity. A funding shock reduces market liquidity, causing trading losses that compel arbitrageurs to close their positions. Consistent with these predictions, Ang, Gorovyy & van Inwegen (2011) and Ben-David, Franzoni & Moussawi (2012) find that hedge funds lose assets under management and reduce leverage in times of market turmoil and high market-wide volatility.

The unwinding of arbitrage positions creates price pressures that push market prices away from fundamental values, prompting higher margin requirements, exacerbating losses on other positions and ultimately causing yet greater funding problems for arbitrageurs. Consistent with these predictions, Mitchell, Pedersen & Pulvino (2007) find that capital shocks to liquidity providers cause substantial liquidity-driven market price deviations from fundamental values in convertible bond markets. Hence, funding liquidity constraints give rise to statistical arbitrage opportunities which otherwise are competed away, and we expect that this pattern may partly explain pairs trading returns.

Pairs trading and investors' behavioral biases. Frazzini (2006) shows that stock price drifts following information events can be attributed to the tendency of investors to ride losses and realize gains (i.e., the disposition effect). The author finds that the steepness of the drift depends on the magnitude of the capital gains or losses experienced by the stockholders on the event date. If the average investors in two paired stocks differ in terms of unrealized capital gains (losses), the stocks may respond differently to new information. The initial price-level divergence will diminish over time due to the skew post-event drifts of the pair constituents, thereby creating a pairs trading opportunity.

In order to operationally investigate the systematic relationship between pairs trading and investors' behavioral biases, we proxy the strength of market-wide disposition effects with the aggregate level of investment uncertainty. Using investor-level data, multiple investment uncertainty measures and several behavioral bias proxies, Kumar (2009) shows that investors exhibit stronger behavioral biases when market-level uncertainty is higher and stocks are more difficult to value. The evidence suggests that investors are more reluctant to realize losses and exhibit greater overconfidence when investment uncertainty is high, and that relatively better informed investors attempt to exploit these biases. In light of these findings, we conjecture that pairs trading profitability may be positively related to aggregate investment uncertainty.

Kumar (2009) identifies four mechanisms through which investment uncertainty may induce stronger disposition effects. Firstly, high idiosyncratic volatility increases the likelihood of observing high price-levels that investors may set as reference points when evaluating their stock holdings. Inflated reference points could induce a greater feeling of regret upon value deterioration thereby amplifying disposition effects (see e.g., Shefrin & Statman (1985)). Secondly, investment uncertainty may aggravate disposition effects through investors' beliefs in mean-reversion (Odean, 1998). Consistent with experimental evidence (Andreassen, 1988), investors seek to pocket trading profits when volatility is high because they believe that price reversals are more likely. Investors may thus exhibit a stronger disposition effect when there is greater uncertainty about the intrinsic values of stocks. Thirdly, investors with high risk appetite may opt to hold on to underperforming stocks and speculate in price recoveries when idiosyncratic volatility is high. In times of high uncertainty, such investors would be more reluctant to realize their losses and exhibit a stronger disposition effect. Fourthly, disposition effects may be amplified in uncertain environments through investor overconfidence. If investment uncertainty amplifies overconfidence by exacerbating biased self-attribution, overconfident investors would be unwilling to realize losses and accept investment mistakes.

4. Data and methodology

4.1 Trading strategy implementation

We describe the implementation of the distance method approach to pairs trading as devised by Gatev et al. (2006). From a practical point of view, the distance method is easy to conceptualize and implement. Since the method is non-parametric and independent of economic models, it is not subject to model misspecification and misestimation biases. The fundamental assumption of the method is that pair spreads exhibit mean-reversion. Accordingly, a price-level divergence is an indication of disequilibrium and distance is the measure of mispricing. From a theoretical perspective, we should only expect this relationship to be viable for pair constituents which are (close to) identical in terms of risk-return characteristics.

The distance method does not necessarily represent an optimal implementation of the pairs trading concept. For example, Gatev et al. (2006) note that constructing the trading strategy with baskets of stocks may potentially capture more price co-movement and yield better profits. Alternatively, one could seek to parameterize pairs trading by exploring the possibility of cointegration (Vidyamurthy, 2004). Although tampering the trading rules could increase profitability, we believe that the risk of data-snooping enhancements outweigh any potential insights that can be gained from higher profits.

Pairs formation. The pairs trading strategy in Gatev et al. (2006) is implemented in two stages. Pairs are formed during a 250-day (approximately 12-month) formation period and actively traded for a subsequent 125-day (approximately 6-month) trading period. We normalize closing prices for each stock by calculating a cumulative total return index over the moving formation period of 250 days. Formally, we compute

$$\tilde{P}_t^i = \prod_{\tau=1}^{t} (1 + r_\tau^i), \tag{1}$$

where $\tilde{P}_t^i$ is the normalized price of stock i at time t, r is the dividend-adjusted return of stock i at time τ, and τ is the index for all trading days between $t - 250$ and t. For each stock i, we find the stock j that minimizes the sum of squared deviations between the two normalized price series. The distance is thus defined as

$$D_t^{i,j} = \sum_t^{250} \left(\tilde{P}_t^i - \tilde{P}_t^j\right)^2, \tag{2}$$

where $D_t^{i,j}$ is the distance between the normalized prices of stock i and j over the formation period. This means that pairs are formed by exhaustive matching in normalized price space, where price is the daily closing price adjusted for dividends and splits. We rank all possible pairs by distance, identify the combinations with the highest measure of co-movement and monitor these pairs for the duration of the trading period. Similar to Gatev et al. (2006), we set the periodicity of pair updates to 20 days (approximately 1 month).

Pairs trading. The trading period begins on the day following the last day of the formation period. During the 125-day period, we monitor the top 20 pairs according to the minimum-distance criterion. A long-short position is opened when the distance exceeds a prespecified threshold based on a standard deviation metric. Similar to Gatev et al. (2006), we open a position when normalized prices diverge by more than two standard deviations. An open long-short position is closed either upon convergence in normalized prices, if a superior matching partner to either pair constituent is identified or at the end of the trading period regardless of outcome. The latter imposes a restriction on the investment horizon and functions as an automatic risk control mechanism.

Pairs that diverge and converge during the trading period will generate a positive cash flow when the position is unwound. If an open pair does not converge, the position will be closed and generate a positive or a negative cash flow at the end of the trading period. A pair that does not diverge by more than the prespecified threshold of two standard deviations does not give rise to any cash flows. The resulting payoff to the pairs trading strategy is thus a set of cash flows distributed randomly throughout and at the end of the trading period across the 20 monitored pairs.

Empirical data. Our implementation of the pairs trading strategy uses a sample of 305 U.S. oil and gas stocks for the sample period that runs from January 1983 to December 2012.[4] Focusing on oil and gas stocks may, for at least two reasons, facilitate our empirical investigation of the relationship between pairs trading returns on the one hand, and investment uncertainty and liquidity supply on the other. Firstly, fluctuations in the oil price have been shown to have significant explanatory power for oil and gas stock returns (Mohanty & Nadha, 2011). High oil price volatility may thus cause high investment uncertainty and exacerbate disposition effects. While companies may mitigate short-term uncertainty by hedging, we conjecture that forecasting of future cash flows and stock valuation is adversely affected by high volatility in oil prices. Secondly, the high idiosyncratic volatility among oil and gas stocks may induce uninformed trading activity and relative mispricings in times of low liquidity supply (Andrade et al., 2005). Such idosyncratic price pressures in the cross-section of stocks may aggravate if investors seek to divest pro-cyclical oil and gas stocks in response to business cycle downturns (Sadorsky, 2001).

We retrieve daily stock price data for currently traded NYSE, AMEX and NASDAQ oil and gas stocks from S&P Capital IQ. The dataset is complemented with delisted share price data from ThomsonReuters Datastream. All share prices are adjusted for splits and dividends. In each formation period, we remove illiquid stocks from the sample by excluding stocks with zero stock price standard deviation for at least five days. Stocks that are illiquid during one formation period but liquid during another are thus excluded from the former but included in the latter. Furthermore, any stock which lacks price data during one formation period is excluded from the pair formation process for that particular formation period. A comprehensive list of all stocks included in the final sample can be found in Appendix A1.

4.2 Excess return computation

The payoffs are calculated over long-short positions, meaning that they have the interpretation of excess returns. When calculating daily excess returns, we consider both the return on invested capital and the return on committed capital. The former represents the return on the actual capital employed in open pair portfolios and is calculated by dividing the sum of the payoffs by the number of open pairs. The return on committed capital takes into account

[4] Note that analyses of the pairs trading strategy's excess returns are based on the sample period that runs from January 1984 to December 2012 since no trading will occur during the initial formation period January to December, 1983.

capital allocated to pair portfolios that are not open and is calculated by scaling the payoffs by the total number of monitored pairs. As it incorporates the opportunity cost of having to commit to a strategy regardless of its current tradability, the return on committed capital is a more conservative measure of performance.

For both payoff measures, we calculate the equal-weighted and the value-weighted return. The equal-weighted return on invested (committed) capital is simply the average return across open (monitored) portfolios of pairs. The value-weighted return is calculated on a marked-to-market basis,

$$r_t^P = \sum_{i=1}^{N} \omega_t^i r_t(p^i), \tag{3}$$

where the weights $\omega_{i,t}$ are initially one after which they change according to the changes in the value of the underlying stocks,

$$\omega_{i,t} = \omega_{i,t-1}(1 + r_{i,t-1}). \tag{4}$$

Eq. 3 corresponds to the portfolio return of a buy-and-hold strategy with an equivalent capital allocation to each trade. The value-weighted return on invested capital represents the marked-to-market return on a portfolio of open long-short positions, each with an initial allocation of $1. The value-weighted return on committed capital on the other hand represents a capital allocation policy of committing $1 to each monitored pair.

4.3 Common factors in stock returns

To confirm that pairs trading returns cannot be explained by loadings on common risk factors in stock returns, we examine the excess return time series' systematic risk exposures using four factor model specifications. Firstly, we examine the strategy's factor loading against the one-factor Capital Asset Pricing Model (CAPM). Secondly, we regress the monthly excess returns on the Fama-French Carhart four-factor model (Carhart, 1997). The model includes the well-known size, value and momentum factors. Thirdly, we augment the Fama-French Carhart four-factor model with a short-term reversal factor.

In the last specification, we add the Pástor-Stambaugh (2003) liquidity factor to the augmented Fama-French Carhart four-factor model. The factor captures the liquidity dimension associated with temporary price changes accompanying order flow. The basic concept is that order flow (constructed simply as volume signed by the contemporaneous stock return in excess of the market) should be accompanied by a return that can be expected to partially reverse in the future if the stock is not perfectly liquid. The greater the expected reversal for a given dollar volume, the lower the stock's liquidity (Pástor & Stambaugh, 2003). The Pástor-Stambaugh factor is thus related to short-term reversals, but is not interpretable as a return (per dollar of capital) on a trading strategy. The independent variables in the regression analyses are defined as follows. [5, 6]

MKT. Market return in excess of the 1-month U.S. Treasury Bill rate. The market return is computed as the value-weighted return of NYSE, AMEX and NASDAQ stocks with CRSP share code 10 or 11 (i.e., common stock).

SMB. Fama & French's (1993) size factor calculated as the average return on three small portfolios minus the average return on three big portfolios.

HML. Fama & French's (1993) value factor calculated as the average return on two value portfolios minus the average return on two growth portfolios.

MOM. Cross-sectional momentum factor calculated as the average of the returns on two high prior return portfolios minus the average of the returns on two low prior return portfolios. Prior return is measured from month -12 to -2.

STREV. Short-term reversal factor calculated as the average of the returns on two low prior return portfolios minus the average of the returns on two high prior return portfolios. Prior return is measured from month -1 to 0.

LIQ. Pástor & Stambaugh's (2003) market liquidity factor constructed as the value-weighted return on a portfolio that is long the highest decile stocks and short the lowest decile stocks, sorted on historical liquidity betas.

4.4 Investment uncertainty

On examination of the relationship between pairs trading returns and investment uncertainty, we consider four alternative investment uncertainty proxies: (i) oil price volatility (OIL_VOL), (ii) idiosyncratic volatility (IDIO_VOL), (iii) the VIX index (VIX), and (iv) the University of Michigan Consumer Sentiment Index (SENTI). Kumar (2009) shows that (ii)-(iv) induces stronger behavioral biases in the form of disposition effects and overconfidence. The independent variables are lagged by one month, consistent with the author's finding that investment uncertainty in one period amplifies behavioral biases in the next. Note that IDIO_VOL and VIX may not only measure investment uncertainty but also aggregate liquidity constraints (we return to discuss the latter in the next section). However, estimating the

5 Monthly data for the market, size, value, momentum and short-term reversal factors is retrieved from Kenneth French's online data library (mba.tuck.dartmouth.edu/pages/faculty/ken.french).

6 We retrieve monthly data on the Pástor-Stambaugh liquidity factor, available from January 1984 to December 2011, from Luboš Pástor's research website (faculty.chicagobooth.edu/lubos.pastor/research).

individual and collective predictive power of multiple investment uncertainty proxies reduces the potential risk of misinterpreting regression outputs. Definitions and data sources for the independent variables are as follows.[7]

OIL_VOL. Oil price volatility is calculated as the monthly standard deviation in daily log returns on the NYMEX West Texas Intermediate (WTI) Light Sweet Crude Oil futures contract with the shortest maturity. Price data for the WTI futures is retrieved from S&P Capital IQ.

IDIO_VOL. Idiosyncratic volatility is measured as the monthly cross-sectional standard deviation in stock returns (cf., Nagel (2012)).

VIX. The Chicago Board Options Exchange's (CBOE) index of S&P500 index options' implied volatilities is a measure of expected market volatility over the next 30 days. Data is retrieved from CBOE (www.cboe.com).

SENTI. The University of Michigan Consumer Sentiment Index captures the current confidence of U.S. consumers. Data is retrieved from ThomsonReuters/University of Michigan's statistical database of consumer surveys (www.sca.isr.umich.edu).

The motivation for using WTI as the oil price benchmark is twofold. Firstly, WTI futures are among the world's most actively traded energy derivatives and the instruments are the most widely used oil price benchmarks in North America (Mohanty & Nadha, 2011). Secondly, price fluctuations in WTI futures have been shown to explain share price movements of firms operating in the U.S. oil and gas sector (Hammoudeh, Dibooglu & Aleisa (2004); Mohanty & Nadha (2011)).

Control variables. Similar to Kumar (2009), we include a set of macroeconomic variables as controls in order to ensure that shifts in investors' biases do not simply reflect changes in the general economy. Specifically, we include (i) the unemployment rate (UNEMP), (ii) unexpected inflation (UEI), (iii) growth in oil production (OIL_PROD), (iv) change in the term yield spread (ΔTS), and (v) change in the default risk premium (ΔRS). Among these variables, the U.S. unemployment rate and unexpected inflation may also serve as proxies for investment uncertainty (Kumar, 2009). Data sources and variable definitions are as follows.

UNEMP. U.S. unemployment rate as published by the U.S. Bureau of Labor Statistics (www.bls.gov).

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7 Since the VIX index was first available in 1990, analyses including the variable are confined to the period January 1990 to December 2012. All other variables in the analysis of pairs trading and investment uncertainty are available for the full sample period January 1984 to December 2012.

UEI. Unexpected inflation calculated as the monthly change in the Consumer Price Index (CPI), as published by the U.S. Bureau of Labor Statistics (www.bls.gov), minus the average change over the last twelve months.

OIL_PROD. Growth in oil production calculated as the year-on-year change in the U.S. oil production as published by the U.S. Energy Information Administration (www.eia.gov).

ΔTS. Change in the term yield spread calculated as the change in the rate spread between the 3-month U.S. Treasury Bill and the 10-year U.S. Government bond as published by the U.S. Federal Reserve (www.federalreserve.gov).

ΔRS. Change in the default risk premium calculated as the change in the rate difference between Moody's seasoned Aaa and Baa corporate bonds as published by the U.S. Federal Reserve (www.federalreserve.gov).

4.5 Liquidity supply

We examine the relationship between pairs trading profitability and liquidity supply using four different proxies: (i) idiosyncratic volatility, (ii) the VIX index, (iii) the Treasury-Eurodollar (TED) spread, and (iv) the 7-year swap spread. Idiosyncratic volatility may in particular be a constraint for imperfectly diversified market makers (Nagel, 2012). Definitions of and data sources for independent variables are as follows.[8]

IDIO_VOL. Idiosyncratic volatility is measured as the monthly cross-sectional standard deviation in stock returns (cf., Nagel (2012)).

VIX. The Chicago Board Options Exchange's (CBOE) VIX index of S&P500 index options' implied volatilities is a measure of expected market volatility over the next 30 days. Data is retrieved from CBOE (www.cboe.com).

TED. The U.S. Treasury-Eurodollar spread is calculated as the difference between the 3-month Eurodollar deposit rate and the 3-month U.S. Treasury Bill rate, based on data from the U.S. Federal Reserve's statistical database (www.federalreserve.gov).

SWAP_7Y. The 7-year swap spread is calculated as the difference between the International Swaps and Derivatives Association's (ISDA) 7-year mid-market swap rate and the 7-year

[8] Data on the VIX index is available from January 1990 to December 2012. Swap data used to compute SWAP_7Y is available from July 2000 to December 2012. IDIO_VOL and TED are available for the full sample period January 1984 to December 2012.

constant maturity U.S. Treasury Bond rate, based on data published by the U.S. Federal Reserve (www.federalreserve.gov).

VIX has been shown to be a useful predictor of financial intermediaries' risk-taking. This relationship does not, however, imply that the VIX index is the state variable generating returns from liquidity provision. Rather, the VIX index proxies for underlying variables that affect the propensity of market makers to provide liquidity. Based on the theories of Gromb & Vayanos (2002) and Brunnermeier & Pedersen (2009), Nagel (2012) argues that high volatility tightens funding constraints and reduces the liquidity-provision capacity of market makers. On a similar note, Adrian & Shin (2010) argue that the risk appetite of financial intermediaries decreases due to risk-management constraints in high market volatility environments. Empirical findings also suggest that hedge funds reduce leverage and experience capital outflows in times of high VIX (Ang et al. (2011); Itzhak et al. (2012)). Recent literature that relates various asset-pricing anomalies to VIX further indicates that the index is a relevant proxy for the risk-bearing capacity of financial intermediaries.[9]

The Treasury-Eurodollar (TED) spread is another popular proxy for funding costs of financial intermediaries (see e.g., Gârleanu & Pedersen (2011)). As the Eurodollar deposit rate reflects the implied credit risk of interbank lending and the U.S. Treasury Bill rate reflects the risk-free rate of return, the TED spread is an indicator of credit risk in the economy. If interbank lenders perceive that the risk of default on interbank loans has increased, they should require a higher rate of return on a risky investment or accept a lower rate of return on a risk-free investment in U.S. Government securities. Hence, an increase (decrease) in perceived systematic counterparty risk will lead to an increase (decrease) in the TED spread.

The 7-year swap spread is one of the liquidity measures tracked by IMF in its Global Financial Stability Report.[10] Since the swap rate is derived from floating payments based on interest rates that contain credit risk (e.g., LIBOR), the swap spread can be used as an alternative proxy of funding costs in the financial system. The swap rate is affected by the relative supply and demand for long-term U.S. Government securities and could also therefore also be considered an indicator of risk appetite and confidence in the stock market.

Control variables. In April 9, 2001, the U.S. Securities and Exchange Commission implemented a regulatory change that effectively forced all U.S. stock markets to migrate from a fraction-based price reporting and stock denomination system to a decimal system. To control for possible effects, we follow Nagel (2012) and employ a dummy (**Pre_decim**) for the pre-decimalization period in our empirical analysis of the relationship between pairs trading and liquidity supply.

Although the introduction of decimalization was associated with a significant decline in quoted bid-ask spreads, it did not reduce effective bid-ask spreads (Bessembinder, 2003).

9 See e.g., Bao, Pan & Wang (2011) on corporate bond liquidity, Brunnermeier et al. (2009) on foreign exchange carry trades, and Longstaff, Pan, Pedersen & Singleton (2007) on sovereign credit default swaps.

10 The IMF Global Financial Stability Reports are available online at www.imf.org/external/pubs/ft/gfsr.

However, it is likely that the control dummy will capture other significant changes in the institutional environment that occurred in the pre-decimalization period. Most importantly, a substantial change in the order-handling rules on NASDAQ in 1997 together with the U.S. Department of Justice investigation following Christie & Schultz's (1994) finding that NASDAQ dealers may implicitly have colluded to maintain wide spreads resulted in a significant decrease in bid-ask spreads and trading costs on NASDAQ (Barclay, Christie, Harris, Kandel & Schultz (1999)). Nagel (2012) note that these changes are likely to have affected the serial correlation properties of price changes for many stocks and thus the returns from liquidity provision.

5. Empirical results

5.1 Trading statistics and pairs trading excess returns

Table 1 summarizes the excess return and holding period per trade for the sample period that runs from January 1984 to December 2012. To provide a sensitivity test on the maximum holding period of the pairs trading strategy, we present trading statistics for both the baseline 125-day trading period (Panel A) and a 20-day trading period (Panel B).[11]

During the sample period, a total of 3,251 trades were executed. Panel A shows that the average (median) trade of the baseline strategy was held for 14.2 (12) days and generated a 1.08 (1.26) percent total excess return with a standard deviation of 11.02 percent. The high standard deviation in combination with the observed minimum and maximum excess return per trade of -81.77 and 112.97 percent, respectively, indicates substantial variation in trade returns. The mean (and median) excess return per trade is nevertheless economically significant and implies that the pairs trading strategy is profitable. Panel B shows that restricting the trading window to 20 trading days results in a slightly lower mean (median) return of 0.96 (1.02) percent per trade as well as a lower standard deviation of 10.28 percent. Tightening the maximum holding period creates a stricter stop-loss mechanism and, in this case, effectively improves the minimum excess return per trade by 8.90 percentage points, from -81.77 to -72.87 percent.

Table 2 provides summary statistics for the pairs trading strategy's monthly excess returns. As in Table 1, we show summary statistics for the baseline strategy with a 125-day trading window in Panel A and a 20-day trading window in Panel B. Excess returns are calculated on invested capital (i.e., solely on open pair portfolios) as well as committed capital. The return on committed capital reflects a capital allocation of $1 to each of the 20 pair portfolios and captures the opportunity cost of having to commit to the strategy *ex ante*. In

[11] Engelberg et al. (2009) test a pairs trading strategy using both a 125-day and a 20-day trading period. The authors find that excess returns are higher if the trading period is reduced to 20 days.

TABLE 1

Pairs trading strategy trade statistics

Summary statistics per trade of the pairs trading strategy for the sample period that runs from January 1984 to December 2012 (3,251 observations). Trading is based on the rule that opens a long-short position in a pair at the end of the day that the normalized prices of the stocks in the pair diverge by more than two standard deviations as estimated during the last 250 trading days. An open position is closed upon convergence, at the end of the 125-day trading window (Panel A) or at the end of the 20-day trading window (Panel B). Trading is restricted to the top 20 pairs ranked by distance in normalized prices with monthly rebalancing.

	Excess return	Holding period
Panel A. 125-day trading window		
Mean	0.0108	14.2
Median	0.0126	12.0
Standard deviation	0.1102	12.2
Minimum	-0.8177	1.0
Maximum	1.1297	102.0
N	3,251	3,251
Panel B. 20-day trading window		
Mean	0.0096	12.0
Median	0.0102	12.0
Standard deviation	0.1028	7.4
Minimum	-0.7287	1.0
Maximum	1.1297	20.0
N	3,251	3,251

addition, we compute returns on an equal-weighted and value-weighted basis. The former averages returns across positions while the latter weighs returns based on t minus one cumulative return indices.

For each excess return computation methodology, we provide summary statistics for the total trades and for the long and short legs, respectively. For equal-weighted return series, the total return is simply the return on the long leg plus the return on the short leg.[12, 13] The first and second row of Panel A show that the mean and median of the total excess returns are economically significant across computation methodologies. During the sample period, the equal-weighted return on invested capital has a monthly mean (median) of 1.86 (1.67) percent.

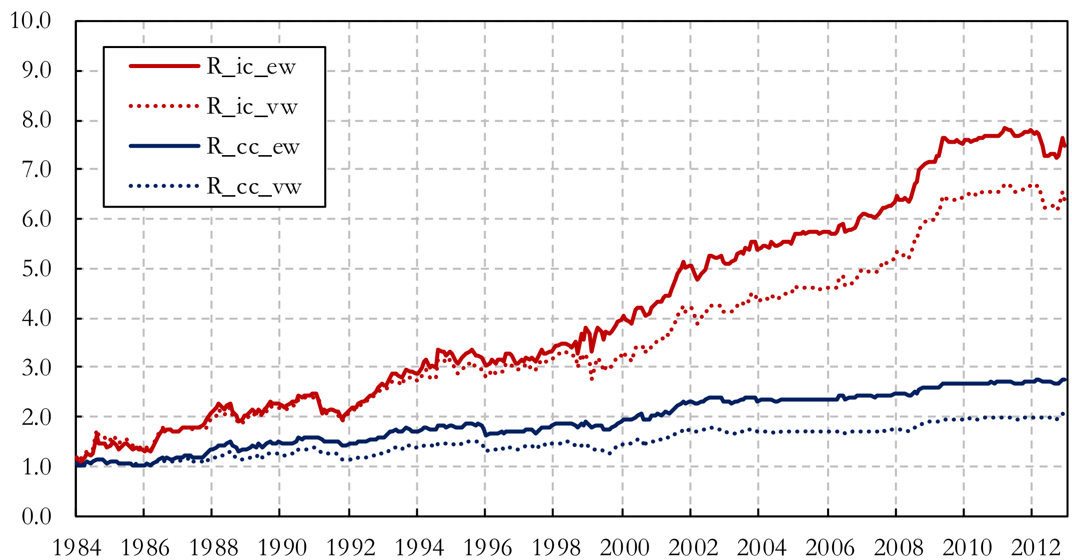
12 Note that the short leg return time series reflects a negative capital allocation and thus weight.

13 The intuition does not apply for value-weighted returns that are weighted based on t minus one cumulative returns and which instead reflect the return on positions that are marked-to-market daily.

FIGURE 1

Cumulative return indices for the pairs trading strategy

Cumulative return indices based on the pairs trading strategy's monthly excess returns for the sample period that runs from January 1984 to December 2012 (348 observations). Returns are calculated on invested capital (R_ic) (excluding closed pairs) and committed capital (R_cc) (including closed pairs), and on an equal-weighted (ew) and value-weighted (vw) basis.



The mean and median returns are positive both for the long and short return time series, indicating that both legs contributed positively to the strategy's excess return. The remainder of Panel A provides information on the distribution of the return time series.

Panel B summarizes the excess return statistics for the pairs trading strategy considering a maximum holding period of 20 trading days. Switching from a 125-day to a 20-day trading period has no fundamental impact on the general interpretation of the results. We also test the strategy's robustness to transaction costs and find that returns cannot be explained by the bid-ask bounce, consistent with Gatev et al. (2006) (for details, please see Appendix A2).

Figure 1 plots the cumulative return indices for all return computation methodologies (using the baseline strategy) for the sample period January 1984 to December 2012. The equal-weighted approach generates higher returns than the value-weighted approach. We expect that the value-weighted approach gives more weight to successful pairs for which the normalized price spread has partially converged, lowering the potential for additional pairs trading profits.

TABLE 2

Pairs trading strategy monthly excess returns

Summary statistics of the pairs trading strategy monthly excess return for the sample period that runs from January 1984 to December 2012 (348 observations). Trading is based on the rule that opens a long-short position in a pair at the end of the day that the normalized prices of the stocks in the pair diverge by more than two standard deviations as estimated during the last 250 trading days. An open position is closed upon convergence, at the end of the 125-day trading window (Panel A) or at the end of the 20-day trading window (Panel B). Trading is restricted to the top 20 pairs ranked by distance in normalized prices with monthly rebalancing. Returns are calculated on invested capital (R_ic) (excluding closed pairs) and committed capital (R_cc) (including closed pairs), and on an equal-weighted and value-weighted basis. Statistics are reported for the total return, the return on the long positions and the return on the short positions, respectively. Absolute kurtosis is reported.

	R ic ew			R ic vw			R cc ew			R cc vw		
	Total	Long	Short	Total	Long	Short	Total	Long	Short	Total	Long	Short
Panel A. 125-day trading window												
Mean	0.0186	0.0157	0.0029	0.0155	0.0154	0.0001	0.0050	0.0050	0.0000	0.0030	0.0043	-0.0005
Median	0.0167	0.0113	0.0018	0.0123	0.0169	0.0004	0.0048	0.0044	0.0007	0.0032	0.0036	0.0005
Standard deviation	0.0945	0.0934	0.0970	0.0890	0.0949	0.0918	0.0285	0.0301	0.0343	0.0265	0.0302	0.0329
Minimum	-0.3517	-0.2874	-0.3712	-0.3767	-0.3546	-0.3923	-0.1085	-0.1304	-0.1593	-0.0943	-0.1554	-0.1603
Maximum	0.3788	0.5139	0.3860	0.3787	0.6231	0.3258	0.0918	0.1120	0.1571	0.0862	0.1124	0.1448
Skewness	0.44	0.51	0.34	0.29	0.70	0.05	-0.37	-0.18	-0.05	-0.32	-0.33	-0.08
Kurtosis	6.3	6.4	5.7	7.0	9.0	5.3	5.0	5.1	7.8	5.2	6.1	7.8
Panel B. 20-day trading window												
Mean	0.0194	0.0171	0.0023	0.0155	0.0159	-0.0004	0.0045	0.0045	0.0000	0.0025	0.0039	-0.0005
Median	0.0190	0.0145	0.0030	0.0128	0.0182	0.0011	0.0044	0.0038	0.0000	0.0028	0.0034	-0.0004
Standard deviation	0.0971	0.0937	0.0971	0.0910	0.0930	0.0913	0.0242	0.0257	0.0292	0.0223	0.0258	0.0281
Minimum	-0.3517	-0.2782	-0.3712	-0.3767	-0.3535	-0.3923	-0.0810	-0.1211	-0.1593	-0.0730	-0.1461	-0.1603
Maximum	0.4042	0.4521	0.3698	0.3709	0.5083	0.3154	0.0819	0.1072	0.1510	0.0794	0.1071	0.1387
Skewness	0.42	0.58	0.33	0.13	0.49	0.10	-0.07	-0.14	0.15	-0.07	-0.40	0.06
Kurtosis	5.8	5.7	5.5	6.1	6.8	5.2	4.4	5.8	8.6	4.8	7.4	8.6

5.2 Alpha and factor loadings

To explore the systematic risk exposures of the pairs trading strategy, we regress the monthly excess returns on a market factor (MKT), Fama & French's (1993) size (SMB) and value (HML) factors, momentum (MOM), a short-term reversal factor (STREV) and the Pástor-Stambaugh (2003) liquidity factor (LIQ).[14]

TABLE 3

Alpha and factor loadings

The dependent variable is the pairs trading strategy monthly excess returns calculated as the equal-weighted return on invested capital. The independent variables are the excess market return (MKT), Fama-French's size (SMB) and value (HML) factors, cross-sectional momentum (MOM), short-term reversal (STREV), and the Pástor-Stambaugh liquidity factor (LIQ). Autocorrelation and heteroskedasticity consistent Newey-West HAC t-statistics (with three lags) are reported in parentheses. The sample period runs from January 1984 to December 2011.

	(1)	(2)	(3)	(4)
Intercept	0.020***	0.022***	0.022***	0.023***
	(4.12)	(4.50)	(4.50)	(4.51)
MKT	-0.073	-0.180	-0.188	-0.196
	(-0.52)	(-1.33)	(-1.32)	(-1.42)
SMB		0.267	0.264	0.251
		(1.62)	(1.60)	(1.51)
HML		-0.073	-0.078	-0.094
		(-0.45)	(-0.46)	(-0.54)
MOM		-0.311**	-0.309**	-0.304**
		(-2.21)	(-2.18)	(-2.15)
STREV			0.036	0.070
			(0.22)	(0.41)
LIQ				-0.233*
				(-1.88)
Adj. R^2	-0.002	0.012	0.009	0.014
F-statistic	0.40	1.99	1.60	1.79
T	336	336	336	336

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

14 Similar to previous studies (e.g., Gatev et al. (2006); Engelberg et al. (2009)), we base our analyses on the equal-weighted return on invested capital.

Table 3 documents the risk exposures using four different factor model specifications for the sample period January 1984 to December 2012. The results indicate that the monthly returns of the strategy cannot be fully explained by loadings on the common sources of risk. The intercepts in Table 3 are positive and statistically significant across the different specifications and the monthly risk-adjusted return amounts to 2.0-2.3 percent, which is substantially higher than the estimated monthly factor model-adjusted return of 0.8 percent reported in Gatev et al (2006).

In conformity with Gatev et al (2006), Engelberg et al. (2009) and Chen et al. (2012), we find that the exposures to market risk, size and value are statistically insignificant across the specifications. We expect the loading on the short-term reversal factor to be positive as the pairs trading strategy buys short-term underperforming stocks and sells short-term overperforming stocks. The evidence provided in Table 3 confirms the expectation although the coefficient estimates are statistically insignificant. If the strategy buys medium-term underperforming stocks and sells medium-term overperforming stocks, the returns could be explained by a momentum factor bearing a negative coefficient. We find that the economically significant coefficient estimates are of the expected sign and statistically significant at the 5 percent level. The statistical significance of the intercept after controlling for momentum, short-term reversals and other factors indicates however that pairs trading does not mimic these conventional contrarian strategies.

In specification 4, we include the Pástor-Stambaugh (2003) factor to measure the strategy's exposure to variations in market liquidity. The evidence in Table 3 suggests that the liquidity factor is negatively related to the pairs trading return series and the coefficient estimate is statistically significant on the 10 percent level. The negative factor exposure marginally increases the alpha of the factor model from 2.2 to 2.3 percent since the liquidity factor is positive on average.

5.3 Performance and investment uncertainty

We examine the systematic relationship between pairs trading and the aggregate level of investment uncertainty by regressing the monthly excess returns on four investment uncertainty proxies, lagged by one month. The proxies used in this analysis may not only reflect the current investment uncertainty. Notably, idiosyncratic volatility and the VIX index are also highly related to funding constraints. To provide convincing evidence, we rely on multiple proxies and expect all coefficient estimates to be statistically significant and carry the expected signs. To control for the possibility that variation in pairs trading returns reflects changes in the broad macroeconomic environment, we include a set of control variables. Table 4 documents the loadings of the strategy on the investment uncertainty proxies. For robustness, we evaluate each proxy variable individually and collectively and present the results using six different model specifications reporting Newey-West HAC t-statistics with three lags.

TABLE 4

Exposure to investment uncertainty proxies

The dependent variable is the pairs trading strategy monthly excess returns calculated as the equal-weighted return on invested capital. The independent variables are oil price volatility (OIL_VOL) calculated as the monthly standard deviation in the log return on the NYMEX WTI future contract with the shortest maturity, idiosyncratic volatility (IDIO_VOL) calculated as the monthly standard deviation in log returns across sample stocks, the CBOE S&P500 implied volatility index (VIX), the University of Michigan Consumer Sentiment Index (SENTI), the U.S. unemployment rate (UNEMP) published by the U.S. Bureau of Labor Statistics, monthly unexpected inflation (UEI) calculated as the monthly change in the Consumer Price Index published by the U.S. Bureau of Labor Statistics less the last twelve month average change, change in oil production (OIL_PROD) calculated as the year-on-year change in U.S. oil production published by the U.S. Energy Information Administration, change in term yield spread (ΔTS) calculated as the change in the yield spread between the 3-month U.S. Treasury Bill and the 10-year U.S. Government Bond, and change in default risk premium (ΔRP) calculated as the change in the yield spread between Moody's seasoned Aaa and Baa bonds. All independent variables are lagged one month. Autocorrelation and heteroskedasticity consistent Newey-West HAC t-statistics (with three lags) are reported in parentheses. The sample period runs from January 1984 to December 2012.

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.014	-0.006	-0.003	0.022	-0.011	0.082
	(1.50)	(-0.46)	(-0.22)	(0.55)	(-0.23)	(0.75)
Lagged OIL_VOL	0.236				-0.099	-0.335
	(0.51)				(-0.17)	(-0.55)
Lagged IDIO_VOL		0.637*			0.584	0.525
		(1.91)			(1.11)	(1.02)
Lagged VIX			0.001*		0.001	0.001
			(1.77)		(0.85)	(0.88)
Lagged SENTI				0.000	0.000	-0.001
				(-0.09)	(-0.14)	(-0.75)
Lagged UNEMP						-0.599
						(-1.03)
Lagged UEI						-0.525
						(-0.27)
Lagged OIL_PROD						-0.044
						(-0.39)
Lagged ΔTS						0.001
						(0.05)
Lagged ΔRP						0.000
						(-0.00)
Adj. R^2	-0.002	0.005	0.004	-0.003	-0.003	-0.016
F-statistic	0.32	2.62	2.01	0.01	0.79	0.53
T	347	347	275	347	275	275

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

In light of the finding that investment uncertainty aggravates investors' behavioral biases (Kumar, 2009), we expect to find a positive relationship between investment uncertainty and pairs trading returns. Through specification (1)-(3), we find that the coefficient estimates for oil price volatility (OIL_VOL), idiosyncratic volatility (IDIO_VOL) and the implied volatility index (VIX) carry the expected positive signs. With a Newey-West HAC t-statistic of 0.51, OIL_VOL lacks statistical significance. The coefficient estimate for IDIO_VOL (0.64) is economically meaningful and the Newey-West HAC t-statistic (1.91) indicates statistical significance at the 10 percent level. Likewise, the VIX variable is economically significant and statistically significant at the 10 percent level.

Conversely, we expect the coefficient estimate of the sentiment variable to be negative since consumer sentiment is high when market-wide uncertainty is low (Kumar, 2009). Specification (4) shows that the magnitude of the sentiment variable is minute and that its explanatory power in the regression is statistically insignificant. In specification (5), the oil volatility variable becomes negative and IDIO_VOL and VIX lose their statistical significance. Adding the macroeconomic control variables in specification (6) has limited impact on the explanatory value of the variables of interest. Note that the control variables UNEMP and UEI may be interpreted as uncertainty proxies (Kumar, 2009). However, the coefficient estimates do not carry the expected positive signs and both estimates are statistically insignificant. Finally, the low adjusted R-squared (-1.6 percent) of specification (6), indicates that the explanatory variables do not meaningfully contribute to explaining the variance in pairs trading returns.

5.4 Performance and liquidity supply

We regress the monthly excess returns from pairs trading on the level of four different liquidity supply proxies: (i) idiosyncratic volatility (IDIO_VOL), (ii) CBOE's implied volatility index (VIX), (iii) the Treasury-Eurodollar (TED) spread and (iv) the 7-year swap spread (SWAP_7Y). Columns (1)-(4) in Table 5 present the exposures individually and column (5) displays the multivariate specification. All specifications include a pre-decimalization dummy that takes on the value of one (zero) for the period before (after) April 9, 2001.

Our empirical results suggest that there is a strong relationship between pairs trading returns and the level of liquidity supply. High levels of idiosyncratic volatility, the VIX index, the TED spread and the 7-year swap spread should be associated with low liquidity supply and consequently high required returns from liquidity provision. Hence, we expect the coefficient estimates of the proxy variables to be positive in all specifications. The magnitude of the coefficient estimate for IDIO_VOL in column 1 (0.78) is economically meaningful and of the expected sign. An increase of one percentage point in idiosyncratic volatility is associated with an increase of 0.78 percentage points in excess pairs trading returns. The Newey-West HAC t-statistic (1.93) further indicates that the coefficient estimate is close to statistically significant at

TABLE 5

Exposure to liquidity supply proxies

The dependent variable is the pairs trading strategy monthly excess returns calculated as the equal-weighted return on invested capital. The independent variables are idiosyncratic volatility (IDIO_VOL) calculated as the monthly standard deviation in log returns across sample stocks, the CBOE S&P500 implied volatility index (VIX), the spread between the 3-month Eurodollar deposit rate and 3-month Treasury Bill rate (TED), the spread between the International Swaps and Derivatives Association 7-year mid-market swap rate and the 7-year constant maturity Treasury bond (SWAP_7Y), and a pre-decimalization dummy (Pre_decim) that takes on a value of one (zero) for the period before (after) April 9, 2001. VIX has been normalized to a monthly volatility measure by dividing it by $\sqrt{12}$. In regression specification (5), correlation among covariates have been removed through orthogonalization of VIX and SWAP_7Y. Autocorrelation and heteroskedasticity consistent Newey-West HAC t-statistics (with three lags) are reported in parentheses. The sample period runs from January 1984 to December 2012.

	(1)	(2)	(3)	(4)	(5)
Intercept	-0.007	-0.005	0.009	-0.018	-0.041
	(-0.48)	(-0.38)	(1.05)	(-1.03)	(-1.12)
IDIO_VOL	0.777*				1.461
	(1.93)				(1.26)
VIX		0.427**			-0.197
		(2.14)			(-0.51)
TED			2.314***		2.134*
			(2.93)		(1.90)
SWAP_7Y				9.464**	5.591
				(2.33)	(1.09)
Pre_decim	-0.006	-0.002	-0.009	-0.039	-0.030
	(-0.64)	(-0.23)	(-0.92)	(-1.24)	(-0.89)
Adj. R^2	0.006	0.003	0.012	0.031	0.042
F-statistic	2.05	1.40	3.14	3.38	2.31
T	348	276	348	150	150

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

the 5 percent level. The coefficient estimate for the VIX variable is also of the expected sign and statistically significant on the 5 percent level. The coefficient estimate for the TED spread (2.31) is positive and economically significant. One percentage point increase in the TED spread has substantial impact on the pairs trading excess returns due to the low average level of the explanatory time series. The Newey-West HAC t-statistic (2.93) implies that the relationship is statistically significant on the 1 percent level. Equivalently, the coefficient estimate for the 7-year swap spread is substantial in magnitude (9.46), of the expected sign and carries a Newey-West HAC t-statistic of 2.33, implying a statistically significant relationship at the 5 percent level.

Column (5) tabulates the regression results for the model specification including all liquidity supply proxies. In order to remove multicollinearity among regressors and facilitate inference, we orthogonalize the VIX and SWAP_7Y variables (for further details, please see Appendix A2). As a result of the factor orthogonalization, the only proxy variable to retain statistical significance in specification (5) is TED for which the estimated coefficient increases in magnitude. The pre-decimalization dummy variable has a negative sign across the regression specifications but remains statistically insignificant at conventional significance levels. The monthly adjusted R-squared for the multivariate model in column (5) is 4.2 percent, indicating that time-variation in liquidity supply accounts for only a small part of the time-variation in pairs trading returns.

To evaluate the robustness of our findings, we examine the cross-sectional relationship between the liquidity supply proxies and pairs trading returns on a trade-by-trade basis. Table 6 documents the results from the cross-sectional regressions of total excess returns per trade on the four liquidity supply proxies. Each proxy variable is measured as the level at the date of entry for each respective trade. We include the pre-decimalization dummy variable and a control variable for the holding period of each trade. Specification (1)-(4) examines the individual impact of each liquidity supply proxy and specification (5) includes all variables, where VIX and SWAP_7Y have been orthogonalized.

The results are consistent with our findings in the time-series regressions, as the coefficient estimates for the liquidity supply proxy variables are of the expected sign across specification (1)-(4). IDIO_VOL is statistically significant on the 10 percent level, whereas VIX, TED and SWAP_7Y are significant on the 1 percent level. In specification (5), all proxy variables retain statistical significance and positive signs. The coefficient estimate for the holding period variable is negative with statistically significant t-statistics ranging from 5.31 to 9.51 in absolute terms. The economic magnitude of the estimate implies that total trade return decreases by 0.2 percent for each additional holding day. The result is in line with previous findings documented by Engelberg et al. (2009) who find that pairs trading excess returns are short-lived and that positions with short holding periods contribute a substantial fraction of the profits. In contrast to the results from the time series regressions, the pre-decimalization dummy variable bears a positive sign, but of limited economic significance and of statistical insignificance.

The statistically significant intercepts across specifications (1)-(5) in combination with the low adjusted R-squared values (2.2-3.5 percent) indicates that fluctuations in liquidity supply does not fully explain the cross-sectional variation in pairs trading profits. However, the time series and cross-sectional analyses lend support to the hypothesis that the variation in pairs trading excess returns exhibits a significant negative relationship with the level of aggregate liquidity supply.

TABLE 6

Liquidity supply proxies and return per trade

The dependent variable is the pairs trading strategy total return per trade. The independent variables are holding period per trade (Hold_period) in days, idiosyncratic volatility (IDIO_VOL) calculated as the monthly standard deviation in log returns across sample stocks, the CBOE S&P500 implied volatility index (VIX), the spread between the 3-month Eurodollar deposit rate and 3-month Treasury Bill rate (TED), the spread between the International Swaps and Derivatives Association 7-year mid-market swap rate and the 7-year constant maturity Treasury bond (SWAP_7Y), and a pre-decimalization dummy (Pre_decim) that takes on a value of one (zero) for the period before (after) April 9, 2001. VIX has been normalized to a daily volatility measure by dividing it by √250. In regression specification (5), correlation among covariates have been removed through orthogonalization of VIX and SWAP_7Y. All independent variables (with the exception of Hold_period) are values per trade at the day of entry. T-statistics are reported in parentheses. The sample period runs from January 1984 to December 2012.

	(1)	(2)	(3)	(4)	(5)
Intercept	0.026***	0.014*	0.026***	0.013*	0.017**
	(5.54)	(1.90)	(6.22)	(1.68)	(2.30)
Hold_period	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(-9.51)	(-7.18)	(-9.68)	(-5.44)	(-5.31)
IDIO_VOL	0.127*				0.276**
	(1.84)				(1.98)
VIX		1.241***			1.200**
		(2.69)			(2.01)
TED			1.085***		0.988**
			(3.06)		(2.17)
SWAP_7Y				4.439***	4.283***
				(3.19)	(2.64)
Pre_decim	0.002	0.001	0.000	-0.015	-0.020
	(0.59)	(0.12)	(0.07)	(-1.32)	(-1.60)
Adj. R^2	0.028	0.022	0.030	0.030	0.035
F-statistic	32.00	20.19	34.05	13.71	8.40
N	3,251	2,514	3,251	1,239	1,239

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

5.5 Risk and return dynamics

The results presented in Section 5.4 indicate that returns to pairs trading have co-varied with liquidity supply throughout the sample period. The finding raises the question whether the pairs trading strategy also exhibits time-variation in compensation for risk. Documenting the relationship between return per unit of risk and variation in liquidity supply may potentially uncover information on the predictability of expected returns to pairs trading strategies. In order to investigate the risk-return dynamics of pairs trading, we examine how conditional Sharpe ratios vary with liquidity supply as proxied by the TED spread.

We follow the methodology in Nagel (2012) to estimate the conditional volatility using daily observations. Firstly, we specify the conditional mean of the pairs trading strategy as

$$E\left(R_t^{ic,ew} | TED_t\right) = \sigma_t \, \theta_t, \tag{5}$$

where $\sigma_t \equiv \sqrt{Var\left(R_t^{ic,ew} | TED_t\right)}$, and θ_t is the Sharpe ratio conditional on TED_t. We include the pre-decimalization dummy Pre_decim_t, assuming that σ_t and θ_t are linear in TED_t and Pre_decim_t,

$$\sigma_t = a_0 + a_1 TED_t + a_2 Pre\_decim_t, \tag{6}$$

$$\theta_t = b_0 + b_1 TED_t + b_2 Pre\_decim_t. \tag{7}$$

Note that the positive relationship between pairs trading profitability and TED could be explained either by $a_1 > 0$ or $b_1 > 0$. We estimate σ_t conditional on TED through the regression

$$\left|\tilde{R}_t^{ic,ew}\right| \times k = a_0 + a_1 TED_t + a_2 Pre\_decim_t + u_t, \tag{8}$$

where $\tilde{R}_t^{ic,ew}$ is the residual from the regression of pairs trading strategy returns on TED_t and Pre_decim_t. In order to account for the difference between standard deviation and expected absolute value, $\tilde{R}_t^{ic,ew}$ is scaled by

$$k = \frac{\sqrt{T^{-1} \sum_{t=1}^{T} \left(\tilde{R}_t^{ic,ew}\right)^2}}{T^{-1} \sum_{t=1}^{T} \left|\tilde{R}_t^{ic,ew}\right|}. \tag{9}$$

The fitted values of regression (8) are used as estimates for σ_t. Finally, we run the regression

$$\frac{R_t^{ic,ew}}{\sigma_t} = b_0 + b_1 TED_t + b_2 Pre\_decim_t + e_t. \tag{10}$$

The fitted values of regression (10) correspond to the conditional Sharpe ratios of the pairs trading strategy. The regression output is summarized in Table 7. To simplify interpretation, TED has been scaled by a factor of 100 in the regression such that the estimated coefficient corresponds to the marginal change in the conditional Sharpe ratio given a 1 percentage point change in the spread. The result implies that a 1 percentage point increase

TABLE 7

Conditional Sharpe ratios of the pairs trading strategy

The dependent variable is the pairs trading strategy excess return on day *t* standardized by its conditional volatility, which is estimated by regressing (scaled) absolute unexpected pairs trading strategy returns on lagged TED. The independent variables are the spread between the 3-month Eurodollar deposit rate and 3-month Treasury Bill rate (TED), and a pre-decimalization dummy (Pre_decim) that takes on a value of one (zero) for the period before (after) April 9, 2001. To simplify interpretation, TED has been scaled by a factor of 100 such that the estimated coefficient corresponds to the marginal change in the conditional Sharpe ratio given a 1 percentage point change in the spread. Autocorrelation and heteroskedasticity consistent Newey-West HAC t-statistics (with 20 lags) are reported in parentheses. The sample period runs from January 1984 to December 2012.

Intercept	2.634
	(1.54)
TED	2.747**
	(2.08)
Pre_decim	-2.178
	(-1.28)
Adj. R^2	0.000
F-statistic	1.59
T	7,315

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$

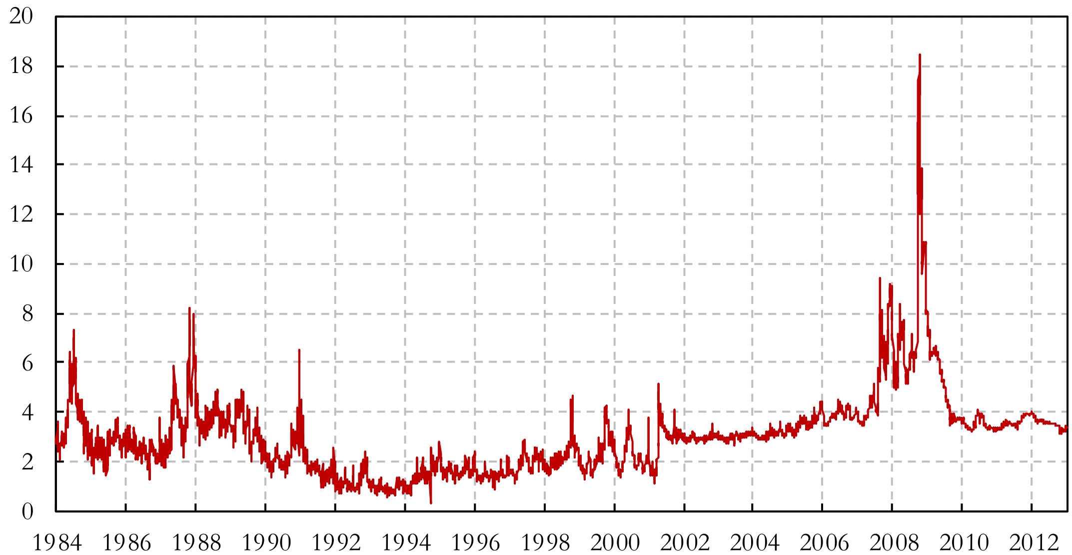
in the TED spread is associated with an increase in the annualized conditional Sharpe ratio of about 2.75. The economic magnitude of the estimated coefficient is substantial and the results are significant on the 5 percent level.

Figure 2 plots the fitted values of the regression. The plots indicate that the risk-return dynamics of the pairs trading strategy have varied considerably over time. The return per unit of risk accordingly reached its peak in October 2008 amidst the financial turmoil following the bankruptcy of Lehman Brothers. The figure also indicates substantial time-variation in return per unit of risk during the period 1998 to 2000 which notably includes the Long-Term Capital Management (LTCM) crisis as well as the burst of the dot-com bubble. Taken together, the results suggest that pairs trading profitability is negatively associated with aggregate liquidity supply and that reward-to-risk peaks in times when liquidity providers face funding constraints.

FIGURE 2

Conditional Sharpe ratios of the pairs trading strategy

Fitted values from the regression of the pairs trading strategy's conditional Sharpe ratios on the 3-month Eurodollar deposit rate and 3-month Treasury Bill rate (TED), and a pre-decimalization dummy (Pre_decim) that takes on a value of one (zero) for the period before (after) April 9, 2001. The sample period runs from January 1984 to December 2012.



6. Conclusion

In an extension of previous research on pairs trading, we investigate if and how time-variation in profitability is related to liquidity supply and investment uncertainty. Similar to previous studies (e.g., Gatev et al. (2006); Engelberg et al. (2009)), we find that a pairs trading strategy has low exposure to common sources of risk as long positions are, by construction, effectively hedged with offsetting short positions with similar factor loadings.

The evidence in Engelberg et al. (2009) implies that pairs trading profits can partly be explained by different responses to common information shocks. We hypothesize that pairs trading profitability is positively related to behavioral biases affecting the speed at which new information is incorporated into prices. Specifically, pair constituents may react differently to common information shocks due to differences in stockholders' propensity to ride losses and pocket capital gains. Such behavioral biases have been shown to amplify in times of high investment uncertainty (Kumar, 2009). Based on predictive regressions of pairs trading returns on multiple investment uncertainty proxies, however, we do not find significant evidence in support of this hypothesis. Since our analysis focuses solely on the systematic relationship, we emphasize that further robustness analysis on stock-level valuation uncertainty measures would be necessary to reject the hypothesis.

Recent literature on trading strategies indicates that low liquidity supply may facilitate statistical arbitrage opportunities that otherwise are competed away (see e.g., Nagel (2012); Asness et al. (2013)). Building on this research, we hypothesize that pairs trading returns are negatively associated with aggregate liquidity supply. We find evidence consistent with this conjecture, using both time series and cross-sectional regressions of pairs trading excess returns on multiple liquidity supply proxies. In addition, our results indicate that returns per unit of risk peak in times of market turmoil and low liquidity supply (i.e., when market participants can be expected to require higher compensation for providing liquidity). Despite the strong link between pairs trading profitability and the level of liquidity supply, a sizable share of the variance remains unexplained.

Our empirical results indicate that at least some of the time-variation in pairs trading profitability is attributable to financial intermediaries' intermittent funding constraints and, in effect, arbitrageurs' market participation constraints. Pairs trading may thus represent a way to quantify the costs of maintaining relative prices in markets with limited risk-bearing capacity. While providing insight on the risk-return dynamics of pairs trading and adding to the literature on the systematic risk exposures of statistical arbitrage strategies, our findings also raise some questions: Are the results applicable to other industries, geographical markets and asset classes? Are there other dormant factors which may help explain the variance in pairs trading profits? Are pairs trading returns correlated with payoffs to other statistical arbitrage strategies? What are the characteristics and trading patterns of arbitrageurs who provide liquidity in markets with limited risk-bearing capacity? At this point, we leave these questions for future research.

References

Adrian, T., & Shin, H. S. (2010), "Liquidity and Leverage", *Journal of Financial Intermediation*, **3**(19), 418-437.

Andrade, S. C., di Pietro, V., & Seasholes, M. S. (2005), "Understanding the Profitability of Pairs Trading". Working Paper. University of California, Berkeley and Northwestern University.

Andreassen, P. B. (1988), "Explaining the Price-volume Relationship: The Difference Between Price Changes and Changing Prices", *Organizational Behavior and Human Decision Processes*, **41**(3), 371-389.

Ang, A., Gorovvy, S., & van Inwegen, G. B. (2011), "Hedge Fund Leverage", *Journal of Financial Economics*, **102**(1), 102-126.

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013), "Value and Momentum Everywhere", *Journal of Finance* (forthcoming).

Bao, J., Pan, J., & Wang, J. (2011), "The Illiquidity of Corporate Bonds", *Journal of Finance*, **66**(3), 911-946.

Barclay, M. J., Christie, W. G., Harris, J. H., Kandel, E., & Schultz, P. H. (1999), "Effects of Market Reform on the Trading Costs and Depths of NASDAQ Stocks", *Journal of Finance*, **1**(54), 1-34.

Ben-David, I., Franzoni, F., & Moussawi, R. (2012), "Hedge Fund Stock Trading in the Financial Crisis of 2007-2009", *Review of Financial Studies*, **25**(1), 1-54.

Bessembinder, H. (2003), "Trade Execution Costs and Market Quality after Decimalization", *Journal of Financial and Quantitative Analysis*, **4**(38), 747-778.

Broussard, J. P., & Vaihekoski, M. (2012), "Profitability of Pairs Trading Strategy in an Illiquid Market with Multiple Share Classes", *Journal of International Financial Markets, Institutions and Money*, **22**(5), 1188-1201

Brunnermeier, M. K., & Pedersen, L. H. (2009), "Market Liquidity and Funding Liquidity", *Review of Financial Studies*, **6**(22), 2201-2238.

Brunnermeier, M. K., Nagel, S., & Pedersen, L. H. (2009), "Carry Trades and Currency Crashes", *NBER Macroeconomics Annual 2008*, 23, 313-347.

Carhart, M. (1997). "On Persistence in Mutual Fund Performance". *Journal of Finance*, **52**(1), 57-82.

Chen, H., Chen, S., & Li, F. (2012). "Empirical Investigation of an Equity Pairs Trading Strategy". Working Paper. University of British Columbia and University of Michigan at Ann Arbor.

Christie, W. G., & Schultz, P. H. (1994), "Why do NASDAQ Market Makers Avoid Odd-eighth Quotes?", *Journal of Finance*, **5**(49), 1813-1840.

Cooper, M. J., Gutierrez Jr., R. C., & Hameed, A. (2004), "Market States and Momentum", *Journal of Finance*, **59**(3), 1345-1365.

De Bondt, W. F., & Thaler, R. (1985), "Does the Stock Market Overreact?", *Journal of Finance*, **40**(3), 793-805.

Do, B., & Faff, R. (2010), "Does Simple Pairs Trading Still Work?", *Financial Analysts Journal*, **4**(66), 83-95.

Engelberg, J., Pengjie, G., & Jagannathan, R. (2009), "An Anatomy of Pairs Trading: The Role of Idiosyncratic News, Common Information and Liquidity". Working Paper. University of California, San Diego, University of Notre Dame and Northwestern University.

Fama, E. F. (1970), "Efficient Capital Markets: A Review of Theory and Empirical Work", *Journal of Finance*, **25**(2), 383-417.

Fama, E. F., & French, K. R. (1993), "Common Risk Factors in the Returns on Stocks and Bonds", *Journal of Financial Economics*, **1**(33), 3-56.

Frazzini, A. (2006), "The Disposition Effect and Underreaction to News", *Journal of Finance*, **61**(4), 2017-2046.

Gârleanu, N., & Pedersen, L. H. (2011), "Margin-based Asset Pricing and Deviations from the Law of One Price", *Review of Financial Studies*, **24**(6), 1980-2022.

Gatev, E., Goetzmann, W. N., & Rouwenhorst, K. G. (2006), "Pairs Trading: Performance of a Relative-value Arbitrage Rule", *Review of Financial Studies*, **19**(3), 797-827.

Grinblatt, M., & Han, B. (2002), "The Disposition Effect and Momentum", *NBER Working Papers 8734*, National Bureau of Economic Research, Inc.

Gromb, D., & Vayanos, D. (2002), "Equilibrium and Welfare in Markets with Financially Constrained Arbitrageurs", *Journal of Financial Economics*, **66**(2), 361-407.

Hammoudeh, S., Dibooglu, S., & Aleisa, S. (2004), "Relationships Among U.S. Oil Prices and Oil Industry Equity Indices", *International Review of Economics & Finance*, **4**(13), 427-453.

Hendershott, T., Jones, C. M., & Menkveld, A. J. (2011), "Does Algorithmic Trading Improve Liquidity?", *Journal of Finance*, **66**(1), 1-33.

Hong, H., & Stein, J. C. (1999), "A Unified Theory of Underreaction, Momentum Trading and Overreaction in Asset Markets", *Journal of Finance*, **54**(6), 2143-2184.

Jegadeesh, N. (1990), "Evidence of Predictable Behavior of Security Returns", *Journal of Finance*, **45**(3), 881-898.

Jegadeesh, N., & Titman, S. (1993), "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency", *Journal of Finance*, **48**(1), 65-91.

Jegadeesh, N., & Titman, S. (1995). "Overreaction, Delayed Reaction, and Contrarian Profits". *Review of Financial Studies*, **8**(4), 973-993.

Jegadeesh, N., & Titman, S. (2001), "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations", *Journal of Finance*, **56**(2), 699-720.

Kaniel, R., Saar, G., & Titman, S. (2008), "Individual Investor Trading and Stock Returns", *Journal of Finance*, **63**(1), 273-310.

Kumar, A. (2009). "Hard-to-value Stocks, Behavioral biases, and Informed trading". *Journal of Financial and Quantitative Analysis*, **44**(6), 1375-1401.

Lehmann, B. (1990), "Fads, Martingales and Market Efficiency", *Quarterly Journal of Economics*, **105**(1), 1-28.

Longstaff, F. A., Pan, J., Pedersen, L. H., & Singleton, K. J. (2007), "How Sovereign is Sovereign Credit Risk?", *NBER Working Papers 13658*, National Bureau of Economic Research, Inc.

Mitchell, M., Pedersen, L. H., & Pulvino, T. (2007), "Slow Moving Capital", *American Economic Review*, **97**(2), 215-220.

Mohanty, S. K., & Nadha, M. (2011), "Oil Risk Exposure: The Case of the U.S. Oil and Gas Sector", *Financial Review*, **1**(46), 165-191.

Moskowitz, T. J., Hua Ooi, Y., & Pedersen, L. H. (2012), "Time Series Momentum", *Journal of Financial Economics,* **104**(2), 228-250.

Nagel, S. (2012), "Evaporating Liquidity", *Review of Financial Studies*, **25**(7), 2005-2039.

Odean, T. (1998), "Are Investors Reluctant to Realize Their Losses?", *Journal of Finance*, **53**(5), 1775-1798.

Papadakis, G., & Wysocki, P. (2007), "Pairs Trading and Accounting Information". Working Paper. Boston University and Massachusetts Institute of Technology.

Pástor, L., & Stambaugh, R. F. (2003), "Liquidity Risk and Expected Stock Returns", *Journal of Political Economy*, **111**(3), 642-685.

Perlin, M. S. (2009), "Evaluation of Pairs Trading Strategy in the Brazilian Financial Market", *Journal of Derivatives & Hedge Funds*, **15**, 122-136.

Sadka, R. (2006), "Momentum and Post-earnings-announcement Drift Anomalies: The Role of Liquidity Risk", *Journal of Financial Economics*, **80**(2), 309-349.

Sadorsky, P. (2001), "Risk Factors in Stock Returns of Canadian Oil and Gas Companies", *Energy Economics*, **1**(23), 17-28.

Shefrin, H., & Statman, M. (1985), "The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence", *Journal of Finance*, **40**(3), 777-790.

Vayanos, D. (2004), "Flight to Quality, Flight to Liquidity, and the Pricing of Risk", *NBER Working Papers 10327*, National Bureau of Economic Research, Inc.

Vidyamurthy, G. (2004). "Pairs Trading – Quantitative Methods and Analysis". Hoboken, NJ: John Wiley & Sons, Inc.

Appendix

A1. Final sample

Our implementation of the pairs trading strategy uses daily stock price data for currently traded NYSE, AMEX and NASDAQ oil and gas stocks from S&P Capital IQ. The dataset is complemented with delisted share price data from ThomsonReuters Datastream. All share prices are adjusted for splits and dividends. In each formation period, we exclude illiquid stocks from the sample by removing stocks with zero stock price standard deviation for at least five days. Stocks that are illiquid during one formation period but liquid during another will thus be excluded from the former but included in the latter. Furthermore, any stock which lacks price data during a particular formation period will be excluded from the pair formation process for that particular formation period. Table A1 shows a list of all stocks included in the final sample.

TABLE A1

List of stocks included in the final sample

1. Abraxas Petroleum Corp.
2. Access Midstream Partners, L.P.
3. Adams Resources & Energy Inc.
4. Advantage Oil & Gas Ltd.
5. Alliance Holdings GP, L.P.
6. Alliance Resource Partners LP
7. Alon USA Energy, Inc.
8. Alon USA Partners, LP
9. Alpha Natural Resources, Inc.
10. American Midstream Partners LP
11. Amyris, Inc.
12. Anadarko Petroleum Corporation
13. Apache Corp.
14. Apco Oil & Gas International Inc.
15. Approach Resources, Inc.
16. Arch Coal Inc.
17. Atlas Energy, L.P
18. Atlas Pipeline Partners, L.P.
19. Atlas Resource Partners, L.P.
20. Barnwell Industries, Inc.
21. Basic PTL
22. Baytex Energy Corp.
23. Belden & Blake
24. Bellatrix Exploration Ltd.
25. Berry Petroleum Co.
26. Bill Barrett Corp.
27. BioFuel Energy Corp.
28. Blueknight Energy Partners, L.P.
29. Boardwalk Pipeline Partners, LP
30. Bonanza Creek Energy, Inc.
31. BP Prudhoe Bay Royalty Trust
32. BPZ Resources, Inc.
33. Breitburn Energy Partners L.P.
34. Buckeye Partners, L.P.
35. Cabot Oil & Gas Corporation
36. Callon Petroleum Co.
37. Calumet Specialty Products Partners LP
38. CAMAC Energy Inc.
39. Cameco Corporation
40. Canadian Natural Resources Limited
41. Capital Product Partners L.P.
42. Carrizo Oil & Gas Inc.
43. Cenovus Energy Inc.
44. Cheniere Energy Partners LP.
45. Cheniere Energy, Inc.
46. Chesapeake Energy Corporation

47. Chesapeake Granite Wash Trust
48. Chevron Corporation
49. Cimarex Energy Co.
50. Clayton Williams Energy, Inc.
51. Clean Energy Fuels Corp.
52. Cloud Peak Energy Inc.
53. Cobalt International Energy, Inc.
54. Comstock Resources Inc.
55. Concho Resources, Inc.
56. ConocoPhillips
57. CONSOL Energy Inc.
58. Constellation Energy Partners LLC
59. Contango Oil & Gas Company
60. Continental Resources, Inc.
61. Copano Energy LLC
62. Crestwood Midstream Partners LP
63. Crimson Exploration Inc.
64. Cross Timbers Royalty Trust
65. Crosstex Energy Inc.
66. Crosstex Energy LP
67. Cubic Energy Inc.
68. CVR Energy, Inc.
69. CVR Refining, LP
70. DCP Midstream Partners LP
71. Dejour Energy Inc.
72. Delek Logistics Partners, LP
73. Delek US Holdings, Inc.
74. Denbury Resources Inc.
75. Denison Mines Corp.
76. Devon Energy Corporation
77. DHT Holdings, Inc.
78. Diamondback Energy, Inc.
79. DLB Oil & Gas, Inc.
80. Dominion Resources Black Warrior Trust
81. Dorchester Minerals LP
82. Double Eagle Petroleum Co.
83. Drilex Intl.
84. Eagle Rock Energy Partners, L.P.
85. Earthstone Energy, Inc.
86. Eastern American Natural Gas Trust
87. ECA Marcellus Trust I
88. El Paso Pipeline Partners, L.P.
89. Emerald Oil, Inc.
90. Enbridge Energy Management LLC
91. Enbridge Energy Partners LP
92. Enbridge Inc.
93. Encana Corporation
94. Endeavour International Corporation
95. Enduro Royalty Trust
96. Energen Corp.
97. Energy Reserves
98. Energy Transfer Equity, L.P.
99. Energy Transfer Partners LP
100. Enerplus Corporation
101. Enterprise Products Partners L.P.
102. EOG Resources, Inc.
103. EPL Oil & Gas, Inc.
104. EQT Corporation
105. EQT Midstream Partners, LP
106. Equal Energy Ltd.
107. ERC Industries, Inc.
108. EV Energy Partners LP
109. Evolution Petroleum Corp.
110. EXCO Resources Inc.
111. Exxon Mobil Corporation
112. Fieldpoint Petroleum Corp.
113. Forest Oil Corporation
114. FX Energy Inc.
115. Garnet Resources Corporation
116. Gasco Energy Inc.
117. GasLog Ltd.
118. Gastar Exploration, Ltd.
119. Genesis Energy LP
120. GeoGlobal Resources Inc.
121. GeoPetro Resources Company
122. Gevo, Inc.
123. Global Partners LP
124. Goodrich Petroleum Corp.
125. Gran Tierra Energy, Inc.
126. Green Plains Renewable Energy, Inc.
127. Gulfport Energy Corp.
128. Halcón Resources Corporation
129. Hallador Energy Company
130. Hallwood Consolidated Resources Corp
131. Hallwood Energy Corporation
132. Harvest Natural Resources Inc.
133. Hess Corporation
134. Holly Energy Partners L.P
135. HollyFrontier Corporation
136. Hondo Oil & Gas Company
137. Houston American Energy Corp.
138. Hugoton Royalty Trust
139. Hyperdynamics Corporation
140. Imperial Oil Ltd.
141. Inergy Midstream, L.P.
142. Inergy, L.P.

143. Isramco Inc.
144. Ivanhoe Energy Inc.
145. James River Coal Co.
146. Kinder Morgan Energy Partners, L.P.
147. Kinder Morgan Management LLC
148. Kinder Morgan, Inc.
149. KiOR, Inc.
150. Kodiak Oil & Gas Corp.
151. L & L Energy, Inc.
152. Laredo Petroleum Holdings, Inc.
153. Legacy Reserves Lp
154. Lehigh Gas Partners LP
155. Linn Co, LLC
156. Linn Energy, LLC
157. Lone Pine Resources Inc.
158. LRR Energy, L.P.
159. Lucas Energy, Inc.
160. Magellan Midstream Partners LP
161. Magellan Petroleum Corporation
162. Magnum Hunter Resources Corp.
163. Marathon Oil Corporation
164. Marathon Petroleum Corporation
165. Marine Petroleum Trust
166. MarkWest Energy Partners, L.P.
167. Martin Midstream Partners LP
168. Matador Resources Company
169. McFarland Energy, Inc.
170. McMoRan Exploration Co.
171. Memorial Production Partners LP
172. Mesa Royalty Trust
173. Methes Energies International Ltd.
174. Mexco Energy Corporation
175. Mid-Con Energy Partners, LP
176. Midstates Petroleum Company, Inc.
177. Miller Energy Resources, Inc.
178. MPLX LP
179. Murphy Oil Corporation
180. MV Oil Trust
181. Natural Resource Partners LP
182. Navios Maritime Acquisition Corporation
183. New Source Energy Partners L.P.
184. Newfield Exploration Co.
185. NGL Energy Partners LP
186. Niska Gas Storage Partners LLC
187. Noble Energy, Inc.
188. North European Oil Royalty Trust
189. Northern Oil and Gas, Inc.
190. Northern Tier Energy LP
191. NuStar Energy L.P.
192. NuStar GP Holdings, LLC
193. Oasis Petroleum Inc.
194. Occidental Petroleum Corporation
195. Oiltanking Partners, L.P.
196. ONEOK Partners, L.P.
197. Oxford Resource Partners, L.P.
198. PAA Natural Gas Storage, L.P.
199. Pacific Coast Oil Trust
200. Pacific Ethanol, Inc.
201. Panhandle Oil and Gas Inc.
202. PBF Energy Inc.
203. PDC Energy, Inc.
204. Peabody Energy Corp.
205. Pembina Pipeline Corporation
206. Pengrowth Energy Corporation
207. Penn Virginia Corporation
208. Penn West Petroleum Ltd.
209. Permian Basin Royalty Trust
210. PetroQuest Energy Inc.
211. Phillips 66
212. Pioneer Natural Resources Co.
213. Pioneer Southwest Energy Partners L.P.
214. Plains All American Pipeline, L.P.
215. Plains Exploration & Production Company
216. PostRock Energy Corporation
217. PrimeEnergy Corp.
218. PVR Partners, L.P.
219. Pyramid Oil Company
220. QEP Resources, Inc.
221. QR Energy, LP
222. Quicksilver Resources Inc.
223. Range Resources Corporation
224. Recovery Energy, Inc.
225. Regency Energy Partners LP
226. Renewable Energy Group, Inc.
227. Rentech, Inc.
228. Resolute Energy Corporation
229. REX American Resources Corporation
230. Rex Energy Corporation
231. Rhino Resource Partners LP
232. Rose Rock Midstream, L.P.
233. Rosetta Resources, Inc.
234. Royale Energy Inc.
235. Rutherford-Moran Oil Corporation
236. Sabine Royalty Trust
237. San Juan Basin Royalty Trust
238. Sanchez Energy Corporation

239. SandRidge Energy, Inc.
240. SandRidge Mississippian Trust I
241. Sandridge Mississippian Trust II
242. SandRidge Permian Trust
243. Saratoga Resources Inc.
244. Scorpio Tankers Inc.
245. SemGroup Corporation
246. SM Energy Company
247. Solazyme, Inc.
248. Sonde Resources Corp.
249. Southcross Energy Partners, L.P.
250. Southwestern Energy Co.
251. Spectra Energy Corp.
252. StealthGas, Inc.
253. Stone Energy Corp.
254. Summit Midstream Partners, LP
255. Suncor Energy Inc.
256. Sunoco Logistics Partners L.P.
257. Susser Petroleum Partners LP
258. Swift Energy Co.
259. Synergy Resources Corporation
260. Syntroleum Corp.
261. Talisman Energy Inc.
262. Targa Resources Corp.
263. Targa Resources Partners LP
264. TC PipeLines, LP
265. Teekay Corporation
266. Tengasco Inc.
267. Tesoro Corporation
268. Tesoro Logistics LP
269. Texoil, Inc.
270. Top Ships Inc.
271. TransCanada Corp.
272. TransGlobe Energy Corp.
273. Transmontaigne Partners L.P.
274. Triangle Petroleum Corporation
275. Tsakos Energy Navigation Limited
276. Ultra Petroleum Corp.
277. Uranerz Energy Corp.
278. Uranium Energy Corp.
279. Uranium Resources, Inc.
280. UR-Energy Inc.
281. US Energy Corp.
282. USEC Inc.
283. Vaalco Energy Inc.
284. Valero Energy Corporation
285. Vanguard Natural Resources, LLC
286. Varco International, Inc.
287. Verenium Corporation
288. Vermilion Energy Inc.
289. Vertex Energy, Inc.
290. VOC Energy Trust
291. W&T Offshore Inc.
292. Warren Resources Inc.
293. Western Gas Equity Partners, LP
294. Western Gas Partners LP
295. Western Refining, Inc.
296. Westmoreland Coal Co.
297. Whiting Petroleum Corp.
298. Whiting USA Trust I
299. Whiting USA Trust II
300. Williams Companies, Inc.
301. Williams Partners L.P.
302. World Fuel Services Corp.
303. WPX Energy, Inc.
304. ZaZa Energy Corporation
305. Zion Oil & Gas, Inc.

A2. Robustness to transaction costs

Pairs trading involves pairing stocks and selling the relatively well performing constituent and buying the relatively poor performing constituent. Previous findings (e.g., Jegadeesh (1990); Jegadeesh & Titman (1995)) suggest that returns to such contrarian investment strategies may be upward biased due to the bid-ask bounce. Upon divergence, the stock price of the winner (loser) is more likely to be the ask (bid) quote. Vice versa, the stock price of the winner (loser) is more likely to the bid (ask) quote upon convergence. Since our implementation of pairs trading is based on daily adjusted closing prices, the returns may thus be upward biased.

To address this issue, we follow Gatev et al. (2006) and provide information on the pairs trading strategy's monthly excess return series when positions are opened one day after divergence and closed one day after convergence. The results are summarized for the 125-trading window in Panel A and for the 20-day trading window in Panel B, Table A2. When trading is shifted one day, the mean (median) total equal-weighted return on invested capital drops 0.23 (0.55) percentage points. The magnitude of the return drops are similar to those in Gatev et al. (2006) and implies that a nontrivial portion of profits may be driven by the bid-ask bounce. Gatev et al. (2006) note that it is difficult to quantify to what extent the drop in profitability is driven by bid-ask bounce rather than mean reversion in prices. The authors' results nonetheless suggest that pairs trading profits are resilient to conservative estimates of transaction costs, consistent with our finding.

TABLE A2

Pairs trading strategy robustness to transaction costs

Summary statistics of the pairs trading strategy monthly excess return for the sample period that runs from January 1984 to December 2012 (348 observations). Trading is based on the rule that opens a long-short position in a pair at the end of the day after the normalized prices of the stocks in the pair diverge by more than two standard deviations as estimated during the last 250 trading days. An open position is closed at the end of the day after convergence, at the end of the day after the end of the 125-day (Panel A) or 20-day (Panel B) trading window. Trading is restricted to the top 20 pairs ranked by distance in normalized prices with monthly rebalancing. Returns are calculated on invested capital (R_ic) (excluding closed pairs) and committed capital (R_cc) (including closed pairs), and on an equal-weighted and value-weighted basis. Statistics are reported for the total return, the return on the long leg and the return on the short leg, respectively. Absolute kurtosis is reported.

	R ic ew			R ic vw			R cc ew			R cc vw		
	Total	Long	Short	Total	Long	Short	Total	Long	Short	Total	Long	Short
Panel A. 125-day (1-day waiting)												
Mean	0.0163	0.0155	0.0008	0.0132	0.0146	-0.0014	0.0042	0.0043	-0.0001	0.0021	0.0037	-0.0008
Median	0.0112	0.0144	-0.0010	0.0062	0.0128	-0.0050	0.0033	0.0054	-0.0015	0.0020	0.0058	-0.0018
Standard deviation	0.0884	0.0993	0.0962	0.0849	0.0949	0.0870	0.0283	0.0336	0.0369	0.0258	0.0316	0.0328
Minimum	-0.2817	-0.3304	-0.4046	-0.3215	-0.3806	-0.2711	-0.1180	-0.1677	-0.1908	-0.0901	-0.1729	-0.1602
Maximum	0.3814	0.5607	0.4783	0.4669	0.6169	0.4773	0.1021	0.1043	0.2182	0.0941	0.1131	0.2131
Skewness	0.68	0.49	0.50	0.88	0.45	0.84	-0.25	-0.71	0.42	-0.04	-0.70	0.86
Kurtosis	6.2	7.0	7.1	8.1	9.5	6.9	6.1	7.0	10.3	5.4	7.1	10.3
Panel B. 20-day (1-day waiting)												
Mean	0.0163	0.0154	0.0009	0.0129	0.0139	-0.0011	0.0039	0.0038	0.0001	0.0019	0.0033	-0.0006
Median	0.0115	0.0093	-0.0009	0.0067	0.0128	-0.0073	0.0032	0.0038	-0.0014	0.0019	0.0043	-0.0019
Standard deviation	0.0895	0.0975	0.0953	0.0844	0.0924	0.0865	0.0236	0.0292	0.0318	0.0217	0.0271	0.0287
Minimum	-0.2817	-0.3360	-0.4046	-0.3215	-0.3829	-0.2169	-0.0741	-0.1739	-0.1528	-0.0840	-0.1724	-0.0824
Maximum	0.3473	0.4768	0.4705	0.4162	0.5649	0.4949	0.0822	0.1043	0.2178	0.0819	0.0906	0.2150
Skewness	0.65	0.34	0.62	0.62	0.31	1.02	0.08	-0.83	1.01	0.02	-0.88	1.55
Kurtosis	5.5	5.9	6.7	6.6	8.6	7.1	4.8	9.0	11.9	5.5	9.1	13.3

A3. Factor orthogonalization

The liquidity supply proxies used throughout this paper exhibit significant multicollinearity (see Table A3.1). To facilitate inference in multivariate regression analyses, we orthogonalize the VIX and SWAP_7Y variables with TED and IDIO_VOL as the independent variables. Firstly, we regress VIX on TED and IDIO_VOL. The residuals constitute the orthogonalized VIX factor. Secondly, we regress SWAP_7Y on TED, IDIO_VOL and the orthogonalized VIX factor. The residuals from the second regression specification constitute the orthogonalized SWAP_7Y factor. The regression output is reported in Table A3.2. The orthogonalization is performed on monthly (Panel A) as well as daily (Panel B) data.

TABLE A3.1

Correlation table of liquidity supply proxies

The variables are idiosyncratic volatility (IDIO_VOL) calculated as the monthly standard deviation in log returns across sample stocks, the CBOE S&P500 implied volatility index (VIX), the spread between the 3-month Eurodollar deposit rate and 3-month Treasury Bill rate (TED), the spread between the International Swaps and Derivatives Association 7-year mid-market swap rate and the 7-year constant maturity Treasury bond (SWAP_7Y). The sample period runs from January 1984 to December 2012.

	IDIO_VOL	VIX	TED	SWAP_7Y
Panel A. Monthly correlation				
IDIO_VOL	-	0.235	0.006	0.206
VIX	0.235	-	0.541	0.173
TED	0.006	0.541	-	0.441
SWAP_7Y	0.206	0.173	0.441	-
Panel B. Daily correlation				
IDIO_VOL	-	0.235	0.024	0.206
VIX	0.235	-	0.541	0.173
TED	0.024	0.541	-	0.441
SWAP_7Y	0.206	0.173	0.441	-

TABLE A3.2

Orthogonalization of liquidity supply proxies

The dependent variables are the CBOE S&P500 implied volatility index (VIX) in specification (1) and the spread between the International Swaps and Derivatives Association 7-year mid-market swap rate and the 7-year constant maturity Treasury bond (SWAP_7Y) in specification (2). The independent variables are idiosyncratic volatility (IDIO_VOL) calculated as the standard deviation in log returns across sample stocks, the spread between the 3-month Eurodollar deposit rate and 3-month Treasury Bill rate (TED), and the orthogonalized VIX (VIX_ORT) measured as the residuals from specification (1). The sample period runs from January 1984 to December 2012.

	(1)	(2)
Panel A. Monthly data		
Intercept	0.026***	0.001
	(4.05)	(1.21)
IDIO_VOL	1.805***	0.089***
	(5.14)	(2.58)
TED	0.577***	0.077**
	(3.71)	(2.37)
VIX_ORT		-0.037***
		(-3.64)
Adj. R^2	0.328	0.268
F-statistic	67.98	19.16
T	276	150
Panel B. Daily data		
Intercept	0.009***	0.003***
	(18.16)	(10.94)
IDIO_VOL	0.036***	0.017***
	(5.13)	(2.85)
TED	0.533***	0.150***
	(6.59)	(6.69)
VIX_ORT		-0.060***
		(-2.66)
Adj. R^2	0.319	0.223
F-statistic	1,356.26	301.58
T	5,797	3,143

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$