ACCOUNTING
& FINANCE

afaanz

Accounting & Finance

Pairs trading and idiosyncratic cash flow risk

Binh Do[a], Robert Faff[b]

[a]Monash Business School, Monash University, Caulfield East, VIC, Australia
[b]UQ Business School, University of Queensland, St Lucia, QLD, Australia

Abstract

We uncover idiosyncratic cash flow risk as a dominant driver for pairs trading performance. The convergence probability and pairs payoff are negatively associated with pairwise idiosyncratic cash flow volatility. Further, pairs portfolio returns load negatively on market-wide idiosyncratic cash flow volatility. This latter time-series evidence helps explain a substantial part of the decline in pairs trading profitability in the US equity market since the 1990s. Our results are consistent with idiosyncratic risk representing a major holding cost for arbitrageurs when substitutes are close but imperfect.

Key words: Pairs trading; Relative value arbitrage; Idiosyncratic cash flow risk

JEL classification: G11, G12, G14

doi: 10.1111/acfi.12697

1. Introduction

Pairs trading is a relative value arbitrage play, designed to profit from price differentials that occasionally arise among 'co-moving' securities. In a seminal study, Gatev *et al*. (2006) show that a 'disarmingly simple' version of this Wall Street trading strategy yields an average return in the order of 0.9 percent per

The authors acknowledge helpful comments from participants at the 2014 FMA Annual Meeting, the 2016 FMCG Conference, the 2016 AFBC Conference, as well as seminar participants at Macquarie University, Monash University, and Florida State University. We particularly thank Neal Galpin, Yuri Tserlukevich, Lyndon Moore, Stephen Brown, Carole Comerton-Forde, Bruce Grundy, John Wei and Pedro Barroso for insightful conversations and Bong-Soo Lee, who contributed to an earlier draft. Do acknowledges financial support from AFAANZ research grants.

Please address correspondence to Binh Do via email: binh.do@monash.edu

month against a standard deviation of just 1.5 percent.[1] They suggest that the documented profit represents a compensation to arbitragers enforcing the law of one price in equity markets. The literature spawned by their paper has since focused on characterising the determinants of pairs trading profits. Notably, Engelberg *et al*. (2009) find that pairs returns are positively related to illiquidity and negatively affected by arrival of firm-specific news. Jacobs and Weber (2015) identify market-wide limits to arbitrage and investor attention as additional determinants of the strategy's profitability. While these findings generally point to trading frictions as the source of pairs trading profits, we contend that this is only part of the story.

We extend this literature by identifying a new and dominant driver of this phenomenon, namely idiosyncratic cash flow risk. Our investigation is motivated by the fact that pairs trading operates on the premise that close substitutes, or fundamentally similar businesses, exist. Since most stocks do not have reasonably close substitutes (e.g. Roll, 1988; Wurgler and Zhuravskaya, 2002), this premise should only hold in a relative sense. Accordingly, pairs trading profitability should depend crucially on the extent to which the traded portfolio comprises close substitutes. To date, the literature is largely silent on this aspect, implicitly presuming the pair matching in the price space delivers close substitutes with little temporal variation. By focusing on idiosyncratic cash flow risk, we present evidence against this presumption.

We argue that idiosyncratic cash flow risk is a natural measure of fundamental similarity. In pairs that display high idiosyncratic cash flow risk, a great portion of price innovation is due to firm-specific factors. Such pairs are hardly close substitutes. Moreover, consistent with Pontiff's (2006) view that idiosyncratic risk is the key factor that makes real world arbitrage costly, our intuition is that high idiosyncratic risk has a direct and adverse effect on the profitability of pairs trading. Based on a simple empirical model that combines discounted cash flow valuation with a noise term, we demonstrate a negative relation between idiosyncratic cash flow risk and pairs trading performance.

Consistent with this central hypothesis, we find that among pairs that have exhibited price co-movement over the past one year, pairwise idiosyncratic cash flow risk over the subsequent period is strongly and negatively related to pairs trading performance, after controlling for variables that are known to affect pairs trades cross-sectionally. The relation is highly statistically significant and economically large. For example, in the case of our baseline portfolio of pairs, a one standard deviation increase in the idiosyncratic cash flow risk measured during the trading period reduces the probability of convergence by 6 percentage points and the per-trade payoff by 0.7 percentage point (compared to an average per trade payoff of 1.59 percent). We show that the effect is

[1]As a point of comparison, momentum delivers a similar magnitude of returns but against a standard deviation of about 4%, i.e. a variability of returns double that seen for pairs trading.

distinct from the firm-specific news effect documented in Engelberg *et al*. (2009) and Jacobs and Weber (2015).

A predictive analysis reveals that past idiosyncratic cash flow risk, measured over the formation period, also negatively predicts future pairs trading success. While the magnitude of the economic significance of this predictive relation is weaker (compared to that of the contemporaneous relation), it shows a level of predictability that savvy investment practitioners will not easily ignore. One standard deviation increase in the formation-period idiosyncratic cash flow risk reduces the convergence rate by 1.5 percentage points and per trade payoff by 0.2 of a percentage point. Most notably, the consistency across both sets of results (i.e. based on either contemporaneous or on historical cash flow risk) indicates that idiosyncratic cash flow risk is a persistent pairwise attribute.

Yet, our story becomes even more compelling. Not only does idiosyncratic cash flow risk affect the cross-sectional performance of pairs, it also drives the time-series variation of the strategy's profitability. We find that high market-wide idiosyncratic cash flow volatility is associated with low pairs portfolio returns. This time-series result is consistent with the expectation that during periods of high cross-sectional variation in idiosyncratic cash flow shocks, close substitutes are hard to find, which works to the detriment of pairs trading. As it turns out, market idiosyncratic cash flow volatility has increased considerably from the 1970s to the early 2000s, as first documented by Irvine and Pontiff (2009). These authors attribute the trend to a corresponding increase in competition in the product markets over the same period.[2] Figure 1 shows that market idiosyncratic cash flow volatility reduces in a few years subsequent to Irvine and Pontiff's (2009) sample period, but picks up again thereafter and, generally, remains at a higher level than most parts of the 1970s and 1980s.

As pairs trading returns are negatively affected by this time series, the sharp increase in the latter has contributed to the downtrend in pairs trading profits. We present an attribution analysis based on the time series regression estimates, and it reveals that the increase in the market level idiosyncratic cash flow volatility over two equally split sub-periods accounts for about 40 percent of the decline in pairs trading profits over the same horizon. The Fama and French (2015) five-factor model, as well as momentum, short-term reversals and Pástor and Stambaugh's (2003) liquidity factor do not explain any of the decline; nor do the alternative factor models by Hou *et al*. (2020a) and Stambaugh and Yuan (2017).

Several prior studies have noted the continual decline in the strategy's profitability since the 1990s (Gatev *et al*., 2006; Do and Faff, 2010, 2012; Jacobs and Weber, 2015; Chen *et al*., 2019). Gatev *et al*. (2006) find that this declining

[2]Their argument is that certain forms of competition lead to increased idiosyncratic cash flow risk. For example, when customers demonstrate less loyalty to a firm due to lower search costs, the firm loses sales to the benefit of another firm in the industry, inducing a lower correlation between the firms' cash flows.

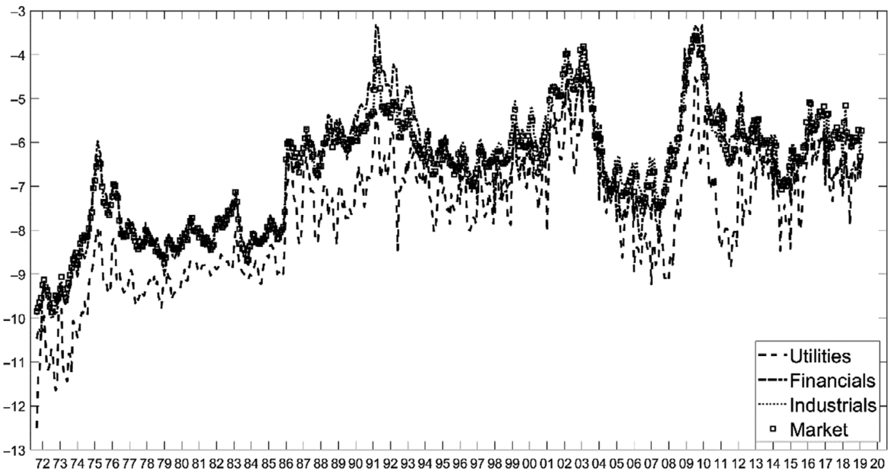

Figure 1 Monthly indices of market-wide and industry-wide idiosyncratic cash flow volatility. *Notes*. This figure plots the logarithm of aggregate idiosyncratic cash flow volatility computed at the industry group and market levels as: $IdioCFVol_{at} = \left(\frac{1}{3}\right)\left(\frac{1}{N}\right)\sum_{i=1}^{N}\left(\frac{\pi}{2}\right)\left(E2P_{it} - E2P_{at}\right)^2$, where $E2P_{it}$ is the firm-level price normalised cash flow shock for month t, $E2P_{at}$ is the industry average or market average price normalised cash flow shock, and N is the number of stocks that belong to the industry or market in that month. Cash flow shocks are in turn based on the residual from the following pooled regression estimated for the industry the stock belongs to, using quarterly cash flows: $E_{ik} - E_{ik-4} = \alpha + \beta_1(E_{ik-1} - E_{ik-5}) + \beta_2(E_{ik-2} - E_{ik-6}) + \beta_3(E_{ik-3} - E_{ik-7}) + e_{ik}$, with E_{ik} being the vector of firm-level earnings per share at quarter k. 'Utilities' corresponds to Fama–French's (1997) utilities industry. 'Financials' combines Fama–French's (1997) banks, real estate, insurance and trading industries. 'Industrials' comprises the remainder of Fama–French's (1997) 49 industries.

profitability is pervasive across disjoint portfolios of pairs and attribute it to an unidentified risk factor that has become 'dormant' in recent decades (p. 798). Our time-series evidence presents an alternative explanation in which aggregate idiosyncratic volatility represents a holding cost to relative value arbitragers. An increase in this holding cost in recent decades adversely affects the ex-post profits. This interpretation is consistent with Pontiff (2006)'s conclusion that idiosyncratic risk is a major holding cost for arbitrageurs when substitutes are close but imperfect.

Our study further highlights the contrasting effects coming from idiosyncratic cash flow volatility versus idiosyncratic return volatility. In our sample, pairwise idiosyncratic return volatility is not related to contemporaneous pairs trading performance, but *positively* predicts future pairs trading success. In the time-series test, market aggregate idiosyncratic return volatility is also positively associated with pair portfolio returns. Superficially, these contrasting effects seem at odds with some prior studies suggesting that idiosyncratic return volatility and cash flow volatility generally track each other (Irvine and Pontiff, 2009; Herskovic *et al.*, 2016). In our sample, the monthly time series of these two idiosyncratic risk measures has a high correlation of 0.56. Our interpretation of the differential effects is that high idiosyncratic return volatility is associated with regimes of high mispricing as it deters arbitrage (e.g. Stambaugh *et al.*, 2015). As cases of mispricing are eventually corrected, conditioning on high idiosyncratic return volatility, either at the pair level or aggregate level, results in stronger pairs trading performance. However, in contrast, we contend that idiosyncratic cash flow volatility captures firm-specific fundamental risk. Holding constant idiosyncratic return volatility/mispricing, high idiosyncratic cash flow volatility necessarily lowers the convergence probability, hence lowering pairs trading profits.

Our contribution to the literature is as follows. By demonstrating idiosyncratic cash flow volatility as a new and distinct determinant of pairs trading performance, we present explicit evidence supporting the notion that a large part of pairs trading profits accrues from the ability to identify fundamentally close substitutes, thereby reducing holding costs. While prior studies such as Engelberg *et al.* (2009) and Jacobs and Weber (2015) focus on the mispricing aspect of the anomaly, we show that at its heart, pairs trading is specifically about enforcing the law of one price among close substitutes. Further, by pointing to the increase in aggregate idiosyncratic cash flow volatility as an alternative explanation for the secular decline of the strategy's profitability, we add to the literature on anomaly attenuation (e.g. Chordia *et al.*, 2014; McLean and Pontiff, 2016).[3] Combined with the evidence in McLean and Pontiff (2016) that increased competition in the product market increases idiosyncratic cash flow risk, our results highlight that anomaly attenuation can be driven by developments outside the financial markets.[4]

The remainder of our paper is organised as follows. Section 2 develops our hypotheses. Sections 3 and 4 present the cross-sectional results. Section 5 provides time-series evidence and Section 6 concludes the paper.

[3]Chordia *et al.* (2014) find that the growth in hedge fund assets under management and increased liquidity and trading activity have led to a decline in the profitability of size, value, earnings, and short-term reversals, among others. McLean and Pontiff (2016) document a discovery effect whereby anomaly-based trading profits have declined following academic publication of the anomaly.

[4]It is noteworthy that pairs trading is not a microcap phenomenon. Like prior pairs trading studies, we require stocks to have traded every day in the 1-year formation period, and to have a price exceeding \$5. These screens lead to our stocks falling in the top quartile of market capitalisation based on NYSE breakpoints. Hou *et al.* (2020b) find that two-thirds of 452 anomalies fail to clear the single test hurdle of $|t| \geq 1.96$ when the microcap issue is mitigated by employing NYSE breakpoints and value weighting.

2. Hypothesis development

Conceptually, pairs trading is based on the presumption that the traded pair are close substitutes with similar valuation fundamentals during the trading period. Similar fundamentals ensure stock prices move together such that deviations are attributable to noise. Since noise has temporary impact on prices, noise-driven divergence represents mispricings that will be corrected subsequently. As such, pairs trading profits should be positively associated with the extent to which fundamentals are homogeneous. Appendix A in Appendix S1 (available online) describes a simple empirical model that illustrates this link explicitly. Essentially, the model allows random walk cash flows with common and firm-specific shocks to govern the dynamic of the 'efficient' price component of a stock, while adding a noise term to capture temporary mispricings, vital to pairs trading. Having observed two stock prices moving together then diverge, one can express the price spread from the divergence onwards as the cumulative sum of the differences in firm-specific cash flow shocks (scaled by the appropriate discount rate) plus the contemporaneous difference in the noise terms. It is then straightforward to verify that when the differences in cash flow shocks individually tend to zero, the price spread is predominantly driven by the dynamics of the noise differential. The transitory nature of the latter term is beneficial to pairs traders. As such, similar fundamental cash flows necessarily imply successful pairs trading. Perhaps less obvious is that in light of empirical evidence on the time-series behaviour of earnings and price reaction, cash flow similarity is also a sufficient condition for profitable pairs trades. For example, when the two firms produce divergent cash flow shocks that subsequently revert, that could induce reversals in the price spread. However, as pointed out in Appendix A in Appendix S1, such a scenario is at odds with the evidence of positive auto-correlation in firm earnings in adjacent quarters (e.g. Bernard and Thomas, 1990).

This analysis leads to our central hypothesis which predicts a negative relation between pairs trading performance and the extent to which firm-specific cash flow shocks differ pairwise over the trading period. Analogous to Irvine and Pontiff's (2009) calculation of market-wide idiosyncratic cash flow volatility, we measure this cash flow heterogeneity by the sum of squared differences in cash flow shocks and interpret it as within-pair idiosyncratic cash flow volatility (where a lower volatility implies a higher cash flow homogeneity).[5]

[5]The above line of argument pertains to a contemporaneous relation, whereby idiosyncratic cash flow risk is measured over the very trading horizon. Studying this synchronous relation is quite natural, as it allows us to shed light on the nature of pairs trading as a bet that the traded pair remain close substitutes. While the relation is contemporaneous, it is not plausibly mechanical as we link high-frequency price behaviours to lower-frequency accounting-based fundamentals. Moreover, our empirical execution will control for other price-based variables such as idiosyncratic return volatility that is also observed over the trading period.

Arguably, of more practical interest is the question whether fundamental homogeneity gives worthwhile power to predict future pairs trading performance. One can expect fundamental similarity to be a stable property in a pair of stocks: if two stocks have similar cash flow performance in the past, hence lower idiosyncratic cash flow volatility, they are expected to do so in the near future. This is because similar cash flows suggest that most of the variation in individual cash flows is caused by common economic forces, for example the firms enjoy similar competitive positions in the same addressable market. These attributes should be relatively stable over time, at least in the near term. Conversely, high idiosyncratic cash flow volatility implies a major source of variation in individual firm cash flows is firm-specific. This is suggestive of two firms that have differed fundamentally in a meaningful way, for example the markets they serve have little overlap. Again, these characteristics are not expected to change in the near future. This persistence in pairwise idiosyncratic cash flow volatility means past observations of the variable can predict future pairs trading performance. Accordingly, we conjecture that within-pair idiosyncratic cash flow volatility negatively predicts future pairs trading performance.

Finally, the argument that stocks with similar idiosyncratic cash flows are more attractive for pairs trading than stocks with dissimilar idiosyncratic cash flows – a cross-sectional statement – also has a time-series implication. We expect pairs trading to work well when the aggregate market experiences low idiosyncratic cash flow shocks. In such periods, close substitutes are more prevalent and are less likely to be ‘short-changed’ by unexpected idiosyncratic cash flow shocks. As such, we conjecture that there is a negative relation between the cross-sectional heterogeneity in firm-level cash flow shocks and monthly pairs trading returns.

3. Cross-sectional results

3.1. Data and pairs trading implementation

We obtain daily data on prices, returns and volumes from the Center for Research in Security Prices (CRSP) and earning data from the CRSP/Compustat Merged database. The sample comprises common stocks (share codes 10 and 11) trading on the NYSE, AMEX and NASDAQ, and covers the period from August 1970 to December 2016. The sample is determined by the availability of earnings reporting dates. Following the asset pricing literature, stocks with prices under $5 are excluded. To participate in the pair matching process, a stock must have a positive trading volume and a valid price each day for the entire pair matching period, taken to be one year. Since the strategies are implemented on a monthly basis, there are 540 cycles and 545 monthly portfolio returns, the first month being August 1971 and the last being December 2016.

Following Gatev *et al.* (2006) and subsequent studies in this research stream, we match pairs by minimising the sum of squared deviations (*SSD*) in the daily normalised total return indices over the prior 12 months. The pairs matching is performed within each of Fama and French's (1997) 49 industry groups. Trading, hypothetically carried out in the subsequent six months, involves taking long-short positions of $1 each whenever a pair's spread exceeds two historical standard deviations. A traded pair is closed when its spread crosses zero or at the end of the trading period, whichever occurs earlier. The strategy is repeated monthly, giving rise to overlapping portfolios that are staggered by one month.

The payoff per trade is computed as the sum of daily marked-to-market payoffs to all positions in the trade. Aggregating across all trades for a given pair gives the payoff per pair. We compute monthly portfolio returns by summing up marked-to-market payoffs across all pairs each month and dividing by the number of pairs committed for trading. In ignoring the ability to earn risk-free interest on the capital that is not deployed to non-traded pairs, this measure understates the return on committed capital. However, it means our analysis of the profitability trend is not contaminated by temporal variation in interest rates. Finally, following the literature, we delay the trades to the next day following the trigger to alleviate concerns related to bid-ask bounce.

Table 1 provides a snapshot of pairs trading performance over our sample period for the top 50 lowest *SSD* pairs and the next 50 pairs. Studying these non-overlapping portfolios allows us to understand common variables driving pairs trading. As shown in Table 1, the two reported portfolios display similar performance attributes with high Sharpe ratios and time series dynamics that are hardly explained by standard risk factors (Panel A). On the event-time performance (Panel B), the top 50 pairs report a convergence rate of 61.82 percent while pairs 51–100 experience 56.37 percent convergence. The latter portfolio offsets its lower convergence ratio by larger spreads (by design), thus it enjoys an average return that is of similar magnitude as that of the top 50 pairs.

In investigating the time trend in pairs trading profitability, for simplicity, we split our sample into two equal halves: August 1971–March 1994 and April 1994–December 2016. Table 1 shows that, consistent with prior studies, the average return as well as the convergence ratio for both portfolios deteriorate over these two sub-periods. As posited in Gatev *et al.* (2006), there appears to be a latent factor beyond the standard risk factors that causes the correlation in pairs trading performance. The remainder of our paper connects this latent factor to idiosyncratic cash flow volatility.

3.2. Cross-sectional evidence on pairs trading performance and pairwise idiosyncratic cash flow volatility

For pairs that experience similar firm-specific cash flow shocks during the trading period, their price spreads are driven by temporary forces that are

Table 1
Basic pairs trading performance statistics

	Top 50 pairs			Pairs 51–100		
	Aug71–Dec16	Aug71–Mar94	Apr94–Dec16	Aug71–Dec16	Aug71–Mar94	Apr94–Dec16
Panel A: Pairs trading performance in calendar time						
Raw return	0.0043***	0.0072***	0.0014***	0.0046***	0.0064***	0.0028***
	(8.67)	(11.42)	(3.53)	(13.08)	(14.13)	(7.86)
Annualised Sharpe ratio	1.99	3.55	0.72	2.35	3.42	1.48
Risk-adjusted return	0.0042***	0.0070***	0.0015***	0.0046***	0.0064***	0.0028***
	(8.79)	(11.27)	(3.57)	(13.02)	(13.74)	(7.50)
No. of months	545	272	273	545	272	273
Panel B: Pairs trading performance in event time						
Total number of trades	44,455	24,943	19,512	40,824	21,157	19,667
Proportion of converged trades	61.82%	69.53%	51.96%	56.37%	60.05%	52.42%
Mean payoff on all trades	0.0159	0.0238	0.0057	0.0184	0.0252	0.0112
Standard deviation of payoffs	0.0759	0.0594	0.0918	0.1027	0.0919	0.1127
Median payoff on all trades	0.0326	0.0349	0.0283	0.0442	0.0474	0.0398
Mean payoff on converged trades	0.0532	0.0492	0.0599	0.0746	0.0724	0.0773
Median payoff on converged trades	0.0482	0.0458	0.0523	0.0680	0.0679	0.0682
Mean payoff on non-converged trades	−0.0445	−0.0342	−0.0528	−0.0541	−0.0458	−0.0617
Median payoff on non-converged trades	−0.0325	−0.0251	−0.0399	−0.0368	−0.0294	−0.0442

This table reports key pairs trading performance statistics for two portfolios of pairs that are matched by minimising the sum of squared differences (*SSD*) in the normalised prices. Normalised prices are the total return index that is scaled to start at $1 at the beginning of the 12-month formation period. Over the six-month period subsequent to the formation, long–short positions of $1 each are taken whenever the absolute spread $|p_{1t} - p_{2t}|$ exceeds two historical standard deviations and unwound when the spread crosses zero or the end of the trading period is reached, whichever occurs first. 'Top 50 pairs' comprises the top 50 pairs with lowest *SSD*. 'Pairs 51–100' comprises the next 50 lowest *SSD* pairs. Monthly returns reported in Panel A are portfolio returns computed as the sum of marked-to-market payoffs for the month divided by 50 (the number of committed pairs, also the value of the committed capital on each long position). Risk-adjusted return is based on Fama and French's (2015) five-factor model augmented with momentum and short-term reversal factors. *t*-statistics are reported in parentheses and based on Newey–West (1987) standard errors with six lags. ***, **, * indicate statistical significance at 1 percent, 5 percent and 10 percent levels, respectively. Panel B reports performance statistics at the per-trade level.

expected to correct themselves following large divergences. Such pairs are expected to generate strong pairs trading performance compared to those that face dissimilar firm-specific cash flow shocks. We test this central hypothesis by estimating the following regression:

$$Performance = \alpha_0 + \alpha_1 logIdioCFVol + \sum \beta_j Controls_j + error \quad (1)$$

We measure performance using the payoff per trade and the payoff per pair, consistent with Jacobs and Weber (2015) and Engelberg *et al.* (2009), respectively. We also use the trade convergence status as a third performance metric, captured by a dummy variable that takes a value of 1 if the trade successfully converges and zero otherwise. For this third metric, the ordinary least squares (OLS) approach allows us to assign intuitive interpretation to the estimated coefficients. The explanatory variable of interest, *logIdioCFVol*, is the logarithm of within-pair idiosyncratic cash flow variance in which idiosyncratic cash flows are estimated using Irvine and Pontiff's (2009) method.

Specifically, for each of the Fama–French's (1997) 49 industries, we estimate the following pooled regression:

$$E_{ik} - E_{ik-4} = \alpha + \beta_1(E_{ik-1} - E_{ik-5}) + \beta_2(E_{ik-2} - E_{ik-6}) + \beta_3(E_{ik-3} - E_{ik-7}) + e_{ik} \quad (2)$$

with E_{ik} being the vector of firm-level earnings per share for quarter k.[6] The residual, e_{ik}, is then taken as firm i's cash flow shock for quarter k. As Irvine and Pontiff (2009) point out, with the model not requiring a firm's unexpected cash flow innovations to sum to zero, it allows the firm to underperform or overperform over time. Further, at any given time, the cross-sectional sum of cash flow residuals does not have to be zero, so the model allows all firms to overperform or underperform in accordance with the economic condition at that time. Firm-specific cash flow shocks defined this way are consistent with the innovation variable w in our model in Appendix A in Appendix S1.

Next, we scale these per-share shocks by the stock price at the beginning of the trading period so the cash flow measures, denoted *E2P*, are comparable across firms. We then map these quarterly values into monthly observations by assigning the quarterly value to the earnings announcing month, as well as the month before and the month after. For example, the cash flow shock computed from December 2010 quarterly results that are announced in February 2011 is assigned to January 2011, February 2011 and March 2011. This quarter-to-month mapping is consistent with Irvine and Pontiff's (2009) procedure and helps to address the non-synchronicity in cash flow reporting across firms. The look-ahead bias in the assignment is not a concern because we are examining a

[6]Our results based on Irvine and Pontiff's (2009) two other alternative cash flow measures – earnings plus depreciation, and sales – are qualitatively similar. Refer to Table B1 in the Appendix S1 for this supplementary analysis.

contemporaneous, not predictive effect. In any case, our results do not change qualitatively if quarterly earnings are mapped to the post-announcement months.

For each pair (i, j), we then compute the variance of intra-pair idiosyncratic cash flow shocks as:

$$IdioCFVol = \left(\frac{1}{3}\right)\left(\frac{1}{n}\right)\sum_{t=1}^{n}\left(\frac{\pi}{2}\right)\left(E2P_{it} - E2P_{jt}\right)^2 \tag{3}$$

where $t = 1$ to n reflects the trading months spanned by that particular trade, or the six-month period if the performance is measured at the per pair level. A trade is deemed to span a given month if it overlaps at least a third of the month. If a trade is closed out within a third of a month, such observation is removed. Assuming that the cash flow spread has a zero mean, multiplying the average squared deviations by $\left(\frac{\pi}{2}\right)$ gives an estimate of idiosyncratic volatility for period $(1, 2, \ldots, n)$. Multiplying by $\left(\frac{1}{3}\right)$ transforms quarterly variance into monthly variance. This procedure of computing within-pair idiosyncratic cash flow volatility is analogous to Irvine and Pontiff's (2009) calculation of market-wide idiosyncratic cash flow volatility.[7] The former defines idiosyncrasy pairwise, whereas the latter does so with reference to the market average. We apply a log transformation to the variance to correct for severe positive skewness.

For control variables, in the regressions at the trade level, we follow Engelberg *et al.* (2009) and include pairwise measures of market capitalisation (the average market value over the formation period); book to market (*BM*) (based on the latest quarterly book value and the average market value over the formation period); prior-month return (*Ret(−1)*) and return over the preceding 11 months (*Ret(−12,−2)*); Amihud's (2002) illiquidity (computed over the formation period); and change in Amihud illiquidity (measured in the previous five days leading to the event date minus the illiquidity ratio measured in the formation period). To control for the possibility that our cash flow variable measures capture the announcement effect identified in Engelberg *et al.* (2009) and Jacobs and Weber (2015), we also include a dummy variable for earning announcements that occur within one day of the initial divergence. Since we are investigating a contemporaneous relation, we also add the change in Amihud ratio and an earnings announcement dummy that are measured over the trading months. The contemporaneous change in Amihud ratio is the ratio over

[7]Specifically, Equation (3) is analogous to Irvine and Pontiff's (2009) equation (9), whereby they compute the market idiosyncratic volatility of cash flows using the deviations of individual firms' cash flow shocks from the market average, hence, a cross-sectional variation measure. Our measure is based on the deviations of monthly cash flow shocks produced by one firm in the pair relative to the other firm and, hence, is a time-series variation measure.

the trading window minus the ratio over the five-day window preceding the trading day. Finally, we control for the very metric that is used to rank pairs, the *SSD*, which is purported to capture the pairwise similarity but in the price space. There is a possibility that fundamental similarity is already reflected in this simple price metric.

For the regression at the pair level, apart from pairwise illiquidity level computed over the formation period and change in illiquidity over the trading period (versus the formation period); market capitalisation; *BM* and *SSD*; we also include the pairwise average of formation period returns. We take the natural log of market capitalisation, *BM* variables (with negative *BM* observations discarded), and *SSD*. To mitigate biases induced by extreme observations, we also winsorise payoffs and past returns to the top and bottom percentiles. The regressions are estimated with fixed industry and time effects, respectively identified by the 4-digit SIC code and the cycle in which the pair was traded. Inferences are based on standard errors, clustered by both industry and time effects (Thompson, 2011).

Table 2 presents the time-series average of the cross-sectional distribution for the regression variables. Idiosyncratic cash flow variance is heavily positively skewed, hence, our log transformation. The statistics on *Announce* show that, on average, about 9 percent of pairs trades occur around an earnings announcement event, similar to the percentage reported in Jacobs and Weber (2015). About two-thirds of pairs trades experience an earnings announcement event *during* the trade (*Announce_trading*). The average size of stocks in the two portfolios is about \$6–7 billion – at this size, the stocks belong to the top quartile of the market using NYSE size breakpoints. Apart from having a larger *SSD* value than the top 50 pairs portfolio by construction, the portfolio of pairs 51–100 has a greater average idiosyncratic cash flow volatility during both formation and trading periods. We confirm this via a *t*-test on a *51–100* dummy variable in a regression that includes fixed effects. As expected, pairs 51–100 are made up of less fundamentally similar stocks than the top 50 pairs.

Our main cross-sectional results are shown in Table 3, based on 36,635 trades from 22,462 pairs for the top 50 *SSD* pairs and 34,839 trades from 22,790 pairs for the 51–100 portfolio.[8] Consistent with our central hypothesis, pairwise idiosyncratic cash flow volatility is negatively associated with the probability of trade convergence, the payoff per trade and the total payoff per pair over the six-month trading period. The negative relation is highly significant across all specifications with *t*-statistics comfortably exceeding 10 for the trade-level regressions. The effect is also economically meaningful. For the top 50 pairs, a one standard deviation increase in the log idiosyncratic cash flow variance is associated with a 6 percentage point decrease in the convergence probability, 0.7 of a percentage point decrease in the payoff for the trade and a 0.5

[8]The slight difference in the number of observations is due to accounting data availability.

Table 2
Summary statistics of regression variables

	Top 50 pairs					Pairs 51–100				
	Mean	Std	p5	p50	p95	Mean	Std	p5	p50	p95
Trade-level variables										
IdioCFVol_trading	0.0001	0.0007	0.0000	0.0000	0.0004	0.0041	0.2899	0.0000	0.0000	0.0007
Amihud	0.0399	0.0746	0.0009	0.0155	0.1518	0.0401	0.1020	0.0007	0.0135	0.1591
ΔAmihud	−0.0007	0.0509	−0.0480	0.0000	0.0474	0.0000	0.0881	−0.0488	0.0000	0.0509
ΔAmihud_trading	0.0021	0.0498	−0.0382	0.0003	0.0473	0.0006	0.0769	−0.0415	0.0002	0.0458
Announce	0.0923	0.2889	0.0000	0.0000	1.0000	0.0947	0.2919	0.0000	0.0000	1.0000
Announce_trading	0.6159	0.4821	0.0000	1.0000	1.0000	0.6685	0.4701	0.0000	1.0000	1.0000
IdioRetVol_trading	0.0030	0.0039	0.0009	0.0020	0.0077	0.0040	0.0063	0.0012	0.0028	0.0100
Ret(−1)	0.0114	0.0496	−0.0686	0.0116	0.0866	0.0125	0.0569	−0.0765	0.0114	0.1029
Ret(−12,−2)	0.1240	0.1673	−0.1360	0.1110	0.3948	0.1327	0.1904	−0.1592	0.1187	0.4548
Pair-level variables										
IdioCFVol	0.0054	0.0284	0.0000	0.0000	0.0006	0.0223	0.1081	0.0000	0.0000	0.0252
IdioCFVol_trading	0.0001	0.0003	0.0000	0.0000	0.0006	0.0075	0.0357	0.0000	0.0000	0.0204
Amihud	0.0300	0.0307	0.0043	0.0208	0.0873	0.0342	0.0465	0.0016	0.0175	0.1244
ΔAmihud_trading	−0.0009	0.0147	−0.0192	−0.0010	0.0153	−0.0022	0.0263	−0.0290	−0.0013	0.0200
IdioRetVol	0.0024	0.0007	0.0015	0.0022	0.0037	0.0032	0.0012	0.0018	0.0030	0.0053
IdioRetVol_trading	0.0027	0.0014	0.0015	0.0024	0.0050	0.0037	0.0024	0.0017	0.0032	0.0071
FormationRet	0.1324	0.0872	0.0042	0.1273	0.2780	0.1387	0.1352	−0.0631	0.1299	0.3695

(continued)

Table 2 (continued)

	Top 50 pairs					Pairs 51–100				
	Mean	Std	p5	p50	p95	Mean	Std	p5	p50	p95
Size ($ billion)	5.89	9.90	0.51	2.79	23.85	6.82	13.01	0.33	2.26	31.97
BM	0.78	0.16	0.56	0.78	1.01	0.79	0.55	0.34	0.75	1.13
SSD	0.1413	0.0330	0.0835	0.1443	0.1875	0.2499	0.0351	0.1978	0.2494	0.3030

The main explanatory variable *IdioCFVol* is idiosyncratic cash flow volatility computed as $\left(\frac{1}{3}\right)\left(\frac{1}{n}\right)\sum_{t=1}^{n}\left(\frac{\pi}{2}\right)(E2P_{1t}-E2P_{2t})^2$ with *E2P* being monthly firm-specific earning shocks scaled by price. Firm-specific quarterly earning shocks are the residual from the following pooled regression estimated for each of the 49 Fama–French (1997) industry groups with E_{ik} being the vector of firm-level earnings at quarter k $E_{ik}-E_{ik-4}=\alpha+\beta_1(E_{ik-1}-E_{ik-5})+\beta_2(E_{ik-2}-E_{ik-6})+\beta_3(E_{ik-3}-E_{ik-7})+e_{ik}$. Quarterly shocks are scaled by the closing price in the prior quarter and assigned to monthly observations as follows: a shock for, for example, the December quarter cash flow that is announced in February, is assigned to January, February and March. *IdioRetVol* is idiosyncratic return volatility computed from daily return and based on Fama–French's (2015) five-factor model. With (without) suffix *trading*, *IdioCFVol* and *IdioRetVol* are measured over the trading (formation) period. When listed under "Trade-level variables" ("Pair-level variables"), *IdioCFVol_trading* and *IdioRetVol_trading* are measured over the period the trade takes place (over the entire six months the pair is traded). Trade-level *Amihud* is measured over the five days preceding the five days prior to the divergence; trade-level *ΔAmihud* is the change in the variable over these two windows and trade-level *ΔAmihud_change* is the change over the trading months versus the divergence window. Pair-level *Amihud* is measured over the formation period and pair-level *ΔAmihud_trading* is the change over the trading period versus the formation period. *Announce* is a dummy variable that takes a value of one if either firm in the pair makes a quarterly earnings announcement within one day of the trade opening, and zero otherwise. *Ret(−1)* is pairwise average of stock returns over the one month period prior to the trade opening. *Ret(−12,−2)* (*FormationRet*) is defined analogously but over the 11-month period that ends one month prior to the trade opening (over the formation period). *SSD* is the sum of squared differences in the normalised prices over the formation period.

Table 3
Idiosyncratic cash flow volatility and contemporaneous pairs trading performance

	Top 50 pairs			Pairs 51–100		
	(1)	(2)	(3)	(1)	(2)	(3)
Log *IdioCFVol_trading*	−0.0250***	−0.0028***	−0.0027***	−0.0254***	−0.0044***	−0.0045***
	(−15.89)	(−13.36)	(−3.52)	(−16.32)	(−11.96)	(−8.24)
Amihud	0.1435***	0.0088**	0.0521**	0.2435***	0.0361***	0.0686***
	(4.37)	(2.37)	(2.44)	(6.21)	(3.29)	(2.96)
ΔAmihud	0.1587***	0.0137***		0.2103***	0.0362***	
	(6.28)	(5.09)		(4.50)	(4.47)	
ΔAmihud_trading	0.0936***	−0.0400***	0.0649	0.1044	−0.0559***	0.0819***
	(3.37)	(−12.86)	(1.34)	(1.47)	(−16.18)	(2.89)
Announce	−0.0399***	−0.0016		−0.0745***	−0.0069**	
	(−5.16)	(−1.46)		(−4.39)	(−2.59)	
Announce_trading	−0.4271***	−0.0400***		−0.4458***	−0.0559***	
	(−62.83)	(−12.86)		(−43.15)	(−16.18)	
Ret(−1)	0.0983	−0.0108		0.0029	−0.0426	
	(0.62)	(−0.57)		(0.06)	(−3.58)	
Ret(−12,−2)	−0.0187	0.0069		−0.0188	−0.0044	
	(−0.40)	(1.21)		(−0.79)	(−0.80)	

(continued)

Table 3 (continued)

	Top 50 pairs			Pairs 51–100		
	(1)	(2)	(3)	(1)	(2)	(3)
Log *Size*	−0.0238***	−0.0017***	−0.0060***	−0.0187***	−0.0011	−0.0057**
	(−14.50)	(−16.49)	(−7.23)	(−3.19)	(−0.77)	(−2.49)
Log *BM*	−0.0499	0.0052***	−0.0021	−0.0153	0.0063**	0.0018
	(−1.27)	(3.06)	(−0.35)	(−0.54)	(2.21)	(0.30)
SSD	−0.0294***	0.0081***	0.0020	−0.0454***	0.0146***	0.0036
	(−7.47)	(6.04)	(1.26)	(−4.25)	(4.82)	(0.69)
Formation Ret			0.0168			−0.0005
			(1.65)			(−0.06)
R^2	24.1%	14.2%	10.6%	22.1%	12.6%	6.3%
Observations	36,635	36,635	22,462	34,839	34,839	22,790

This table presents the estimation results for three sets of panel regression of the form $Performance_i = \alpha_0 + \alpha_1 logIdioCFVol\_trading_i + \sum \beta_j Controls_j + error$. The regressions correspond to three measures of pairs trading performance: a dummy variable that is equal to one if the trade converges and zero otherwise (1); the trade-level payoff (2); and the pair-level payoff which aggregates payoffs from all trades executed for the pair in a given trading period (3). $logIdioCFVol\_trading_i$ is the logarithm of the idiosyncratic cash flow volatility measured over the months the trade spans for specifications (1) and (2) and is the logarithm of the same variable but measured over the entire six-month trading period for specification (3). The description of the control variables is provided in Table 2. "Top 50 pairs" comprises the top 50 pairs with lowest *SSD*. "Pairs 51–100" comprises the next 50 lowest *SSD* pairs. The regressions are estimated with fixed industry and time effects. The *t*-statistics, reported in parentheses, are based on standard errors that are clustered by both industry and time (Thompson, 2011), respectively identified by the 4-digit SIC code and the cycle in which the pair was traded. ***, **, * indicate statistical significance at 1 percent, 5 percent and 10 percent levels, respectively.

percentage point reduction in the payoff for the pair. Given the convergence probability is 61.82 percent and the mean payoff per trade is 1.59 percent per trade (Table 1), the effect is sizeable. For pairs 51–100, the statistics are 6.5 percent, 1.1 percent and 1.0 percent, respectively.

Consistent with Engelberg *et al.* (2009) and Jacobs and Weber (2015), the level of illiquidity and changes in illiquidity positively predict pairs trading performance, whereas earnings announcements around the divergence event negatively predict performance. Earnings announcements during the trade also have a highly significant effect on performance as expected. These findings apply for both pairs portfolios under investigation.

Next, we test whether past idiosyncratic cash flow volatility predicts pairs trading performance. We replace the contemporaneous cash flow volatility value in regression (1) by the corresponding measure that is computed over the formation period. We then use this latter variable, measured at the pair level, to predict future performance at both per trade and per pair levels. Other contemporaneously measured variables are also dropped from this predictive regression.

Panel A of Table 4 reveals that consistent with our conjecture, past idiosyncratic cash flow volatility negatively predicts future pairs trading performance. The coefficients are negative and significant for all measures of performance, and for both portfolios. Generally, *SSD* negatively predicts pairs performance. A notable exception is that among the top 50 lowest *SSD* pairs, high *SSD* values predict *greater* per trade payoffs. This is plausible because high *SSD* also mean larger mispricings all else equal, a point noted in Do and Faff (2012).

For a direct measure of the economic significance of the predictive relation, we combine the two portfolios together and sort them on formation-period idiosyncratic cash flow volatility. Panel B of Table 4 shows that portfolio returns decline monotonically with the sort, with the bottom quintile of the sort outperforming the top quintile by 11 bps per month. Since the unconditional average return is about 43 bps (see Panel A, Table 1), this spread is economically material. In an untabulated test, a similar sort on *SSD* results in no difference in portfolio performance.

3.3. Idiosyncratic cash flow risk versus idiosyncratic return volatility

Our analysis thus far shows a negative effect coming from idiosyncratic cash flow risk on pairs trading. On the face of it, our measure of cash flow (fundamental) volatility is very similar to idiosyncratic return volatility (*IdioRetVol*). As such, it is important to ask how does our main finding fit with the broader literature on *IdioRetVol*? There is an extensive literature that documents that *IdioRetVol* negatively predicts stock returns (e.g. Ang *et al.*, 2006; Stambaugh *et al.*, 2015; Gu *et al.*, 2018). On the other hand, McLean (2010) finds that long-term return reversals are more pronounced among high

Table 4
Idiosyncratic cash flow volatility and future pairs trading performance

Panel A: Multivariate predictive regression

	Top 50 pairs			Pairs 51–100		
	(1)	(2)	(3)	(1)	(2)	(3)
Log *IdioCFVol*	−0.0055***	−0.0010***	−0.0012***	−0.0060***	−0.0014***	−0.0018***
	(−3.15)	(−6.31)	(−3.09)	(−2.88)	(−3.52)	(−2.84)
Amihud	0.1427***	0.0040	0.0159	0.2107***	0.0228**	0.0464*
	(2.70)	(0.67)	(0.68)	(6.29)	(2.19)	(1.76)
ΔAmihud	0.1176***	0.0082*		0.1249***	0.0170***	
	(3.96)	(1.70)		(3.17)	(2.52)	
Announce	−0.0264***	−0.0013		−0.0318*	−0.0017	
	(−4.06)	(−1.09)		(−1.95)	(−0.68)	
Ret(−1)	0.2469	0.0016		0.1017*	−0.0312***	
	(1.26)	(0.08)		(1.69)	(−2.37)	
Ret(−12,−2)	0.0344	0.0117*		−0.0034	−0.0017	
	(0.73)	(1.82)		(−0.10)	(−0.35)	
Log *Size*	−0.0376***	−0.0028***	−0.0057***	−0.0364***	−0.0036**	−0.0063**
	(−12.94)	(−22.61)	(−7.04)	(−5.24)	(−2.71)	(−2.85)
Log *BM*	−0.1036	0.0005	−0.0038	−0.0619	−0.0001	−0.0010
	(−1.75)	(0.17)	(−0.65)	(−1.55)	(−0.03)	(−0.19)
SSD	−0.0746***	0.0045***	0.0019*	−0.1020***	0.0069**	0.0000
	(−10.12)	(5.17)	(1.85)	(−6.28)	(2.13)	(0.01)
Formation Ret			0.0200**			−0.0041
			(2.36)			(−0.54)
R^2	7.4%	5.8%	9.9%	5.2%	4.1%	5.9%

(continued)

Table 4 (continued)

Panel A: Multivariate predictive regression

	Top 50 pairs			Pairs 51–100		
	(1)	(2)	(3)	(1)	(2)	(3)
Observations	37,533	37,533	23,658	35,114	35,114	23,778

Panel B: Sorting by pairwise idiosyncratic cash flow volatility during the formation period

	1	2	3	4	5	5-1
No. of pairs	18	18	18	18	18	0
Raw return	0.0044***	0.0044***	0.0046***	0.0040***	0.0033***	0.0011**
	(9.55)	(8.52)	(8.99)	(8.16)	(5.70)	(2.20)
Annualised Sharpe ratio	1.61	1.58	1.68	1.39	1.02	0.34
Risk-adjusted return	0.0047***	0.0041***	0.0046***	0.0041***	0.0033***	0.0014**
	(9.72)	(8.04)	(9.46)	(8.31)	(5.98)	(2.51)
No. of months	545	545	545	545	545	545

Panel A presents the estimation results for three sets of predictive panel regression of the form $Performance_i = \alpha_0 + \alpha_1 logIdioCFVol_i + \sum \beta_j Controls_j + error$. The regressions correspond to three measures of pairs trading performance: a dummy variable that is equal to one if the trade converges and zero otherwise (1); the trade level payoff (2); and the pair-level payoff which aggregates payoffs from all trades executed for the pair in a given trading period (3). $logIdioCFVol_i$ is the logarithm of the idiosyncratic cash flow volatility measured over the 12-month formation period. The description of the control variables is provided in Table 2. Panel B presents portfolio returns from a quintile sort on formation-period *IdioCFVol*. "Top 50 pairs" comprises the top 50 pairs with lowest *SSD*. "Pairs 51–100" comprises the next 50 lowest *SSD* pairs. The regressions are estimated with fixed industry and time effects. In Panel A, the *t*-statistics, reported in parentheses, are based on standard errors that are clustered by both industry and time (Thompson, 2011), respectively identified by the 4-digit SIC code and the cycle in which the pair was traded. In Panel B, the *t*-statistics are computed using Newey–West (1987) standard errors with six lags. ***, **, * indicate statistical significance at 1 percent, 5 percent and 10 percent levels, respectively.

IdioRetVol, hence, implying a positive effect. Accordingly, these observations beg two related questions with respect to relative value arbitrage: To what extent is our result distinct from prior findings? And how does our new result reconcile with the existing evidence?

There are several considerations worthy of mention. First, our *cash flow risk* effect is a *pairwise* phenomenon specific to a relative value trade, whereas the traditional *return volatility* effect arises in the cross-section of *individual* stocks. Second, the economic mechanisms underlying each of these effects are distinctly different from each other. The negative *IdioCFVol* effect results from high idiosyncratic cash flow volatility representing poor substitutes, i.e. from the 'supply' side, and as such, relative-value arbitrage among these substitutes are likely to encounter high holding costs. In contrast, the negative *IdioRetVol*-return relation seems to be a result of arbitrage constraints coupled with arbitrage asymmetry, i.e. in a sense the role of *IdioRetVol* is coming from the 'demand' side, as investors searching for such relative arbitrage opportunities can see them but are thwarted. It is generally accepted that high *IdioRetVol* deters arbitrage and supports 'lingering' mispricings. Stambaugh *et al*. (2015) contend that since it is relatively easier to buy under-priced stocks than it is to go short in over-priced stocks, the negative *IdioRetVol*-return relation among over-priced stocks dominates the positive relation among under-priced stocks, giving rise to the overall negative effect.[9] Notably, the very argument that high *IdioRetVol* deters arbitrage also explains the positive effect of the idiosyncratic risk measure on long-term return reversals, as shown in Pontiff (2010).

To provide explicit evidence whether our effect is indeed distinct from the *IdioRetVol* effect, Table 5 reproduces the cross-sectional analysis, controlling for pairwise idiosyncratic return volatility. Here, we define pairwise *IdioRetVol* as the variance of the residual returns from the Fama–French (2015) five-factor model regression, averaged across the two stocks. To conserve space, we report only the estimated loadings on the two idiosyncratic volatility variables. Panel A relates to the estimation of Table 3 for the contemporaneous setting. It shows that while cash flow volatility retains its negative role, pairs trading performance metrics are not related to *IdioRetVol* (with just one exception, namely the probability of convergence for pairs 51–100). Panel B, relating to the estimation of Table 4 for the future setting, reveals again a negative cash flow risk effect, whereas the counterpart *return volatility* measured over the pair formation period positively predicts future performance of pairs trades. This predictive result, which is analogous to Pontiff's (2010) findings for long-term reversals, is consistent with idiosyncratic return risk deterring future arbitrage efforts and inducing mispricings.

The key thing is that in both panels of Table 5, the negative effect of *IdioCFVol* remains. For the predictive test, in untabulated analysis, we note a

[9] Gu *et al*. (2018) document essentially similar results for the Chinese equity market with the negative relation most pronounced among high limits-of-arbitrage stocks.

Table 5
Idiosyncratic cash flow volatility versus idiosyncratic return volatility

	Top 50 pairs			Pairs 51–100		
Panel A: Idiosyncratic volatility and contemporaneous pairs trading performance						
	(1)	(2)	(3)	(1)	(2)	(3)
Log *IdioCFVol_trading*	−0.0264***	−0.0030***	−0.0028***	−0.0274***	−0.0047***	−0.0049***
	(−14.43)	(−11.19)	(−4.12)	(−13.54)	(−10.45)	(−7.18)
Log *IdioRetVol_trading*	−0.0065	−0.0046	−0.0017	0.0502***	−0.0034	0.0017
	(−0.37)	(−1.42)	(−0.23)	(7.81)	(−1.09)	(0.25)
Control variables included	Yes	Yes	Yes	Yes	Yes	Yes
R^2	20.7%	13.3%	10.6%	19.5%	11.8%	6.3%
Observations	32,981	32,981	22,462	32,221	32,221	22,790
Panel B: Idiosyncratic volatility and future pairs trading performance						
	(1)	(2)	(3)	(1)	(2)	(3)
Log *IdioCFVol*	−0.0075***	−0.0012***	−0.0017***	−0.0081***	−0.0016***	−0.0024***
	(−4.50)	(−9.41)	(−4.81)	(−3.86)	(−4.11)	(−3.58)
Log *IdioRetVol*	0.0739***	0.0063***	0.0146***	0.0942***	0.0060***	0.0145***
	(7.22)	(2.89)	(5.80)	(4.47)	(3.06)	(3.83)
Control variables included	Yes	Yes	Yes	Yes	Yes	Yes
R^2	7.6%	5.9%	9.9%	5.8%	4.2%	6.1%
Observations	37,533	37,533	23,658	37,533	37,533	23,778

This table presents the effects of idiosyncratic cash flow volatility (*IdioCFVol*) and idiosyncratic return volatility (*IdioRetVol*) on different measures of pairs trading performance. Panel A reports key results for regression $Performance_i = \alpha_0 + \alpha_1 logIdioCFVol\_trading_i + \sum \beta_j Controls_j + error$ (analogous to Table 3), with log *IdioRetVol_trading* (measured over the trading period) added as additional control variable. Panel B presents key results for regression $Performance_i = \alpha_0 + \alpha_1 logIdioCFVol_i + \sum \beta_j Controls_j + error$ (analogous to Table 4), with log *IdioRetVol* (measured over the formation period) added as additional control variable. The description of these variables and other control variables is provided in Table 2. Three sets of results correspond to three measures of pairs trading performance: a dummy variable that is equal to one if the trade converges and zero otherwise (1); the trade-level payoff (2); and the pair-level payoff which aggregates payoffs from all trades executed for the pair in a given trading period (3). "Top 50 pairs" comprises the top 50 pairs with lowest *SSD*. "Pairs 51–100" comprises the next 50 lowest *SSD* pairs. The regressions are estimated with fixed industry and time effects. The *t*-statistics, reported in parentheses, are based on standard errors that are clustered by both industry and time (Thompson, 2011), respectively identified by the 4-digit SIC code and the cycle in which the pair was traded. ***, **, * indicate statistical significance at 1 percent, 5 percent and 10 percent levels, respectively.

broadly similar economic significance for both idiosyncratic risk measures. A one standard deviation increase in log *IdioRetVol* among the top 50 pairs is associated with a 2.96 percent increase in the probability of convergence, a 0.25 percent increase in per trade payoff and a 0.61 percent increase in the per pair payoff. The corresponding effect of a one standard deviation increase in log *IdioCFVol* is a reduction of 1.44 percent, 0.28 percent and 0.43 percent, respectively. Note that the cash flow measure is based on four quarterly observations of earnings whereas the return measure is constructed with one year's worth of daily observations and, hence, presumably is less noisy. As such, it is hard to draw a definitive conclusion on whether cash flow volatility or return volatility dominates in this particular test. What is clear is that these two effects are distinct and both are important.

4. Robustness tests and extended cross-sectional analysis

4.1. Sub-period results

As discussed earlier, pairs trading strategies have suffered a widespread decline in profitability since the 1990s. Since the dynamics of the strategy has apparently changed, it is possible that our core findings are not representative of the whole sample. As shown in Table 6, for both equally split sub-periods, the negative effect of idiosyncratic cash flow volatility holds with similar magnitude. This is particularly the case for the contemporaneous test. For the predictive test, the results are less pervasive, however, there is no evidence that the overall result hinges on any particular sub-period.[10]

4.2. Industry effects

As per Gatev *et al.* (2006), pairs portfolios are disproportionately represented by utilities stocks. The fixed industry effect incorporated in our panel regressions should somewhat alleviate the concern that our result is driven by a particular industry. To provide further assurance, we partition our top 100 *SSD* pairs into three industry groups: Utilities, Financials (comprising Fama–French's (1997) banking, insurance, real estate and trading), and Industrials (the remaining industries). Table 7 presents this sub-sample result. Consistent with the Gatev *et al.* (2006) sample, Utilities account for 61 percent of the top 100 pairs, while Financials comprise 26 percent and Industrials account for 13 percent. Across all these industry groups, the negative effect of idiosyncratic cash flow volatility holds for the contemporaneous test. Predictive tests yield negative and significant results for Utilities and Financials, while insignificant results show for Industrials. It is possible that Utilities and

[10]In all robustness tests, we control for pairwise idiosyncratic return volatility.

Table 6
Sub-period results

	Aug71–Mar94			Apr94–Dec16		
	(1)	(2)	(3)	(1)	(2)	(3)
Panel A: Idiosyncratic cash flow volatility and contemporaneous pairs trading performance						
Top 50 pairs						
Log *IdioCFVol_trading*	−0.0269***	−0.0031***	−0.0041***	−0.0251***	−0.0028***	−0.0017**
	(−16.57)	(−20.17)	(−12.56)	(−11.33)	(−6.73)	(−1.99)
Control variables included	Yes	Yes	Yes	Yes	Yes	Yes
R^2	22.0%	15.8%	14.0%	17.0%	10.8%	5.5%
Observations	16,654	16,654	10,368	16,327	16,327	12,094
Pairs 51–100						
Log *IdioCFVol_trading*	−0.0299***	−0.0047***	−0.0051***	−0.0259***	−0.0047***	−0.0045***
	(−8.89)	(−7.85)	(−4.29)	(−15.17)	(−10.42)	(−5.59)
Control variables included	Yes	Yes	Yes	Yes	Yes	Yes
R^2	22.3%	13.3%	8.0%	17.1%	10.8%	5.3%
Observations	15,759	15,759	10,600	16,462	16,462	12,190
Panel B: Idiosyncratic cash flow volatility and future pairs trading performance						
Top 50 pairs						
Log *IdioCFVol*	−0.0088***	−0.0013***	−0.0024***	−0.0039	−0.0010***	−0.0011**
	(−6.48)	(−9.82)	(−10.21)	(−1.41)	(−4.64)	(−2.11)
Control variables included	Yes	Yes	Yes	Yes	Yes	Yes
R^2	6.5%	7.2%	8.3%	4.6%	3.7%	5.1%
Observations	19,760	19,760	10,823	17,773	17,773	12,835
Pairs 51–100						
Log *IdioCFVol*	−0.0054*	−0.0006	−0.0011	−0.0102***	−0.0024***	−0.0033***
	(−1.74)	(−0.78)	(−0.98)	(−5.88)	(−6.37)	(−6.00)

(continued)

Table 6 (continued)

Panel B: Idiosyncratic cash flow volatility and future pairs trading performance

Control variables included	Yes	Yes	Yes	Yes	Yes	Yes
R^2	6.2%	4.7%	7.0%	5.4%	3.8%	5.2%
Observations	17,324	17,324	11,062	17,790	17,790	12,716

Panel C: Sorting by pairwise idiosyncratic cash flow volatility during the formation period

	1	2	3	4	5	5-1
Aug71–Mar94						
No. of pairs	16	16	16	16	16	0
Raw return	0.0062***	0.0062***	0.0062***	0.0064***	0.0061***	0.0001
	(10.69)	(7.81)	(7.46)	(9.78)	(7.81)	(0.21)
Annualised Sharpe ratio	2.35	2.14	2.18	2.25	2.03	0.04
No. of months	272	272	272	272	272	272
Apr94–Dec16						
No. of pairs	19	19	19	19	19	0
Raw return	0.0026***	0.0026***	0.0029***	0.0015***	0.0005	0.0021***
	(4.42)	(5.10)	(6.70)	(3.41)	(0.86)	(2.91)
Annualised Sharpe ratio	0.96	1.00	1.18	0.56	0.15	0.62
No. of months	273	273	273	273	273	273

This table reports results on the relation between monthly pairs trading performance and idiosyncratic cash flow volatility over two subperiods August 1971–March 1994 and April 1994–December 2016. Panel A reports key regression results based on idiosyncratic cash flow volatility measured over the trading period with control variables the same as those displayed in Table 3, plus log idiosyncratic return volatility. In Panel B, idiosyncratic cash flow volatility is measured over the formation period and control variables are the same as those displayed in Panel A of Table 4, plus log idiosyncratic return volatility. Panel C presents portfolio returns from a quintile sort on formation-period idiosyncratic cash flow volatility. "Top 50 pairs" comprises the top 50 pairs with lowest *SSD*. "Pairs 51–100" comprises the next 50 lowest *SSD* pairs. In Panel A and B, the *t*-statistics, reported in parentheses, are based on standard errors that are clustered by both industry and time (Thompson, 2011), respectively identified by the 4-digit SIC code and the cycle in which the pair was traded. In Panel C, the *t*-statistics are computed using Newey–West (1987) standard errors with six lags. ***, **, * indicate statistical significance at 1 percent, 5 percent and 10 percent levels, respectively.

Table 7
Results by industry groups

	Utilities			Financials			Industrials		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Panel A: Contemporaneous effect of idiosyncratic cash flow volatility									
Log *IdioCFVol_trading*	−0.0256***	−0.0031***	−0.0034***	−0.0266***	−0.0039***	−0.0040***	−0.0265***	−0.0049***	−0.0053***
	(−21.88)	(−17.76)	(−8.06)	(−6.92)	(−9.09)	(−5.42)	(−9.21)	(−6.30)	(−3.56)
Control variables included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	24.1%	14.0%	10.2%	21.8%	12.7%	7.4%	26.2%	17.7%	13.4%
Observations	43,490	43,490	26,643	18,453	18,453	12,083	9,531	9,531	6,526
Panel B: Past idiosyncratic cash flow volatility and pairs trading performance									
Log *IdioCFVol*	−0.0108***	−0.0015***	−0.0020***	−0.0073***	−0.0015***	−0.0019**	−0.0019	−0.0017	−0.0026
	(−5.66)	(−5.29)	(−4.31)	(−7.77)	(−3.84)	(−1.99)	(−0.46)	(−1.45)	(−1.61)
Control variables included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	7.3%	5.5%	9.0%	6.0%	2.9%	7.5%	9.5%	9.1%	12.8%
Observations	44,624	44,624	28,534	18,582	18,582	12,261	9,441	9,441	6,641

The top 100 pairs by *SSD* are sorted into three industry groups: Utilities (comprising pairs from Fama–French's (1997) utilities industry), Financials (Fama–French's (1997) banks, real estate, insurance and trading) and Industrials (the remaining industries). Panel A presents the results of regressing pairs trading performance on contemporaneous log idiosyncratic cash flow volatility, with control variables the same as those displayed in Table 3 plus log idiosyncratic return volatility. Panel B presents the results of regressing pairs trading performance on log idiosyncratic cash flow volatility measured over the formation period, with control variables the same as those displayed in Panel A of Table 4 plus log idiosyncratic return volatility. Three regression specifications correspond to three measures of pairs trading performance: a dummy variable that is equal to one if the trade converges and zero otherwise (1); the trade-level payoff (2); and the pair-level payoff which aggregates payoffs from all trades executed for the pair in a given trading period (3). In Panels A and B, the *t*-statistics, reported in parentheses, are based on standard errors that are clustered by both industry and time (Thompson, 2011), respectively identified by the 4-digit SIC code and the cycle in which the pair was traded. ***, **, * indicate statistical significance at 1 percent, 5 percent and 10 percent levels, respectively.

Financials have stronger predictability because they have a stability in fundamentals due to greater regulation, that is largely absent in Industrials.

4.3. Alternative measure of idiosyncratic cash flow volatility

Our baseline analysis defines idiosyncrasy within the pair. As such, the story so far points to the sensitivity of pairs trading to the ability to match up stocks that are sufficiently similar in terms of cash flow fundamentals. Can we generalise the result to say something about the idiosyncratic risk of the constituent stocks relative to the market and/or the industry to which it belongs? Specifically, do stocks that individually exhibit low idiosyncratic cash flow shocks with respect to the aggregate market or industry make for a better pairs trade than stocks that exhibit high idiosyncratic cash flow shocks? This notion of idiosyncrasy is more in line with how idiosyncratic risk is traditionally interpreted. Intuitively, close substitutes would be more available for stocks that display a low level of idiosyncratic behaviours than those that deviate greatly from the aggregate.

We test this conjecture by constructing, for each constituent stock i, its idiosyncratic cash flow volatility with respect to the market, and separately, to its industry. Specifically,

$$IdioCFVol_{i,a} = \left(\frac{1}{3}\right)\left(\frac{1}{n}\right)\sum_{t=1}^{n}\left(\frac{\pi}{2}\right)(E2P_{it} - E2P_{at})^2 \tag{4}$$

where $E2P_{at}$ is the market-wide/industry-wide cross-sectional average of cash flow shocks in month t. A pair's idiosyncratic cash flow volatility is then the pairwise average of the variances.

It turns out that these alternate measures of idiosyncratic cash flow volatility are strongly correlated with the baseline measure, with the time-series average of the correlation of about 0.8. We continue to document a negative and highly significant relation between pairs trading performance and these alternate measures. The magnitude of the effect is similar to the baseline result.[11]

4.4. Earnings announcement effect

Engelberg *et al*. (2009) and Jacobs and Weber (2015) find that divergence that is preceded by a firm-specific news event such as earnings announcements is associated with poorer pairs trading performance. Individual firm earnings announcements are predictable sources of (likely) idiosyncratic cash flow volatility; however in this paper, we examine a broader relation between fundamental cash flow similarity and pairs trading. To verify that our results are not subsumed by the news effect, we re-estimate regression (1) for the set of

[11]Details are available in Table B2 of the Appendix S1.

trades that are initiated around an earnings announcement, and separately for the trades that are not. We find statistically significant results for both subsamples, with the estimated coefficients very similar in magnitude to the unconditional results. This is particularly remarkable for the announcement subset which comprises only 3,652 trades for the top 50 pairs and 3,596 trades for pairs 51–100. The content of the announcement, not just the event itself, predicts subsequent pairs trading performance.[12]

5. Time-series evidence

5.1. Empirical tests

To this point, our evidence is cross-sectional: pairs with higher idiosyncratic cash flow risk tend to produce lower pairs trading returns, holding other cross-sectional characteristics constant. We now test the conjecture that poor pairs trading performance is associated with a high idiosyncratic cash flow volatility state, i.e. a time-series relation. In the first test, we regress monthly portfolio returns against common risk factors augmented with a measure of aggregate idiosyncratic cash flow volatility, defined as:

$$IdioCFVol_{mt} = \left(\frac{1}{3}\right)\left(\frac{1}{N}\right)\sum_{i=1}^{N}\left(\frac{\pi}{2}\right)(E2P_{it} - E2P_{mt})^2 \tag{5}$$

with N reflecting the number of stocks in month t. To ensure our estimate is not affected by extreme observations, we follow Irvine and Pontiff (2009) and winsorise monthly cash flow shocks at the top and bottom 5 percent percentile of the monthly firm-level sample before computing Equation (5). Whereas Equation (4) captures the idiosyncratic cash flow volatility of a given stock relative to the market over a certain period (hence a measure of time-series heterogeneity), Equation (5) reflects the cross-sectional heterogeneity in firm-level cash flow shocks experienced at each point in time. Low (high) values of $IdioCFVol_{mt}$ imply a market state in which close substitutes are more (less) likely to exist, and, hence, more (less) favourable to pairs trading. In the regression, we again apply the log transformation on this series.

As for common factors, we use Fama and French's (2015) five-factor model augmented with the momentum factor; the short-term reversal factor; and Pástor and Stambaugh's (2003) liquidity factor. The last factor is to control for the possibility that improved liquidity over time may affect the time-series variation of the strategy. Table 8 reports results for three sets of factors. Specification 1 comprises the eight common factors. Specification 2 adds the log aggregate idiosyncratic cash flow volatility. Finally, to ensure that our cash flow effect is indeed unique from a potential return-volatility effect,

[12] Details are reported in Table B3 of the Appendix S1.

Table 8
Pairs portfolio returns and market wide idiosyncratic cash flow volatility

	Top 50 pairs			Pairs 51–100		
	(1)	(2)	(3)	(1)	(2)	(3)
Raw return	0.0043***	0.0043***	0.0043***	0.0046***	0.0046***	0.0046***
	(8.64)	(8.64)	(8.64)	(13.06)	(13.06)	(13.06)
Intercept	0.0043***	−0.0072***	−0.0037	0.0046***	−0.0017	0.0030
	(8.91)	(−3.64)	(−1.54)	(13.15)	(−1.10)	(1.62)
Mkt-RF	0.0029	0.0085	0.0102	−0.0131*	−0.0100	−0.0077
	(0.36)	(1.13)	(1.38)	(−1.76)	(−1.38)	(−1.11)
SMB	0.0023	0.0090	0.0106	0.0189*	0.0226**	0.0246**
	(0.20)	(0.79)	(0.94)	(1.86)	(2.30)	(2.64)
HML	0.0100	−0.0036	−0.0011	0.0183	0.0109	0.0143
	(0.62)	(−0.23)	(−0.07)	(1.43)	(0.88)	(1.17)
RMW	−0.0067	0.0040	0.0045	−0.0122	−0.0064	−0.0057
	(−0.31)	(0.20)	(0.23)	(−1.05)	(−0.58)	(−0.52)
CMA	0.0320	0.0549**	0.0533**	0.0124	0.0249	0.0229
	(1.29)	(2.32)	(2.26)	(0.63)	(1.30)	(1.21)
Momentum	−0.0318***	−0.0395***	−0.0391***	−0.0322***	−0.0364***	−0.0358***
	(−3.73)	(−4.55)	(−4.78)	(−4.93)	(−5.04)	(−5.66)

(continued)

Table 8 (continued)

	Top 50 pairs			Pairs 51–100		
	(1)	(2)	(3)	(1)	(2)	(3)
St_Reversal	0.0256	0.0188	0.0168	0.0419***	0.0382***	0.0356***
	(1.64)	(1.35)	(1.31)	(3.76)	(3.54)	(3.54)
Liquidity	−0.0185*	−0.0196**	−0.0187**	−0.0062	−0.0068	−0.0057
	(−1.98)	(−2.18)	(−2.08)	(−0.67)	(−0.73)	(−0.63)
Log $IdioCFVol_m$		−0.0017***	−0.0023***		−0.0009***	−0.0018***
		(−5.59)	(−6.12)		(−4.06)	(−6.66)
Log $IdioRetVol_m$			0.0021**			0.0028***
			(2.59)			(4.84)
No. of cycles	544	544	544	544	544	544
R^2	7%	16%	17%	13%	16%	19%

Specification (1) regresses monthly pairs trading portfolio returns on Fama and French's (2015) five factors augmented with momentum, short-term reversals and Pástor and Stambaugh's (2003) liquidity factor. Specification (2) adds the logarithm of market-wide idiosyncratic cash flow volatility, computed as: $IdioCFVol_{mt} = \left(\frac{1}{3}\right)\left(\frac{1}{N}\right)\sum_{i=1}^{N}\left(\frac{\pi}{2}\right)\left(E2P_{it} - E2P_{mt}\right)^2$, where $E2P_{it}$ is the firm-level price normalised cash flow shock for month t, $E2P_{mt}$ is the market average price normalised cash flow shock, and N is the number of stocks in that month. Specification (3) further adds the logarithm of monthly market-wide idiosyncratic return volatility, computed as: $IdioRetVol_{mt} = \left(\frac{1}{N}\right)\left(\frac{n}{n-1}\right)\sum_{i=1}^{N}\sum_{j=1}^{n}\left(R_{ij} - R_{mj}\right)^2$, where R_i is the daily return for stock i, R_m is the daily return of the equally weighted market index and n is the number of days in month t. The t-statistics, reported in parentheses, are computed using Newey–West standard errors with six lags. ***, **, * indicate statistical significance at 1 percent, 5 percent and 10 percent levels, respectively.

Specification 3 further adds the log aggregate idiosyncratic return volatility. The latter variable is constructed using the cross-sectional average of stock-level variances of market-adjusted daily returns (following Irvine and Pontiff, 2009).

Table 8 shows that, without the market-level idiosyncratic cash flow volatility, the intercept from the regression, interpreted as alpha, is hardly different from the raw return, as previously documented. However, when the market idiosyncratic cash flow volatility is added to the regression (i.e. Specification 2): (i) the intercept is markedly lower than the raw return; (ii) R^2 increases appreciably; and (iii) both portfolios load negatively on this variable, with high statistical significance.

Adding aggregate idiosyncratic return volatility (Specification 3) further enhances the magnitude of the cash flow volatility effect. Notably, in this specification, pairs portfolios load positively on log aggregate idiosyncratic return volatility. However, we can reveal that either weakly *negative* or insignificant results are obtained for *IdioRetVol* when *IdioCFVol* is excluded from the regression. Further, the two measures of aggregate idiosyncratic risk are highly positively related with a correlation of 0.56. This suggests that although they share certain commonality, once we control for fundamental heterogeneity in the cross-section, *IdioRetVol* seems to capture the extent of mispricings in the market, which is favourable for pairs trading. In any case, the consistently negative effect both in the time series and the cross-section of idiosyncratic cash flow volatility leads us to conclude that idiosyncratic cash flow risk is, indeed, an important holding cost for pairs traders.[13]

Some might find it surprising that our within-industry matched pairs load on the market-wide idiosyncratic volatility. However, this is consistent with idiosyncratic volatility exhibiting a factor structure. Herskovic *et al.* (2016) find that idiosyncratic return, as well as cash flow volatilities obey a factor structure and that this factor is priced in the cross-section of stock returns. Christoffersen *et al.* (2019) also observe commonality in commodity futures return volatility. Consistent with these findings, we find strong co-movement among industry-wide idiosyncratic cash flow volatility series, computed using Equation (5) with observations within each industry. Indeed, the average pairwise correlation of log idiosyncratic cash flow variances of two industries is 0.61. The average log idiosyncratic cash flow variance across all the industries has a correlation of 0.99 with our market-wide series computed above. This means Equation (5) gives us the common idiosyncratic cash flow volatility factor. Figure 1 shows

[13]Several recently proposed factor models appear to better describe the cross-section of stock returns in the US market. Hou *et al.* (2015) develop an investment-based model which is subsequently extended to a five-factor model in Hou *et al.* (2020a). Stambaugh and Yuan (2017) construct mispricing factors by aggregating ranking from 11 anomalies. Our pair portfolios load on some of these alternative factors, however, as a whole, these models do not explain away the strategy's alpha nor capture its time series variation. Details are available in Tables B4 and B5 in the Appendix S1.

that the log monthly idiosyncratic cash flow volatility for Utilities, Financials and Industrials, as well as the market, are indeed strongly correlated.

Other factors might also contribute to the decline. For example, as pairs trading has been performed on Wall Street since the mid-1980s, large inflows of capital into this arbitrage strategy may attenuate its success. A similar mechanism is market learning from academic publication, which causes the 'anomaly' to be exploited away (McLean and Pontiff, 2016). Accordingly, we should be concerned that the increase in idiosyncratic cash flow volatility happens to run parallel to these trends giving rise to the results reported in Table 8.

To alleviate this concern, in a second test, we examine the convergence behaviour in the pairs portfolio as opposed to portfolio returns. If anything, the factors cited above should enhance the probability of convergence, thus biasing against us finding a negative relation. We construct the monthly convergence probability by computing, for each month t, the proportion of converged trades that are initiated in month t or $t-1$. Counting trades that open in the prior month accommodates the fact that the median duration of converged trades is about 30 days. We examine the link between this monthly convergence ratio with monthly market-wide idiosyncratic cash flow volatility by computing the rank correlation as well as regressing the log of 1 plus the ratio against log volatility for the same month. For the regression, we compute t-statistics using Newey–West standard errors with two lags. Again, we find a negative and significant relation for both portfolios of pairs. Clearly, there is a negative time-series effect of idiosyncratic volatility on pairs trading performance that is not simply a by-product of other trends that occur over the same horizon.[14]

5.2. Economic significance

For a sense of the economic significance of this time-series effect, we examine the extent to which it explains the decline in pairs trading profitability in the US market that is well-documented in prior literature and confirmed in this paper. The OLS regression of monthly portfolio returns against common risk factors and log market-wide idiosyncratic cash flow volatility (Specification 2 in Table 8) allows us to write:

$$\begin{aligned}\overline{Ret_2} - \overline{Ret_1} &= (\overline{e_2} - \overline{e_1}) + \sum_{i=1}^{7} \beta_i (\overline{f_{i,2}} - \overline{f_{i,1}}) \\ &\quad + \beta_8 \left(\overline{logIdioCFVol_{m,2}} - \overline{logIdioCFVol_{m,1}}\right)\end{aligned} \tag{6}$$

[14]The results of this analysis are reported in Table B6 in the Appendix S1.

Table 9
Portfolio performance attribution analysis based on time series regression results

	Sep71–Mar94 *Raw Return*	Apr94–Dec16 *Raw Return*	Diff	% Explained by standard factors	% Explained by Log Market *IdioRetVol*
Top 50 pairs	0.0071	0.0014	−0.0057	−1.1%	41.6%
Pairs 51−100	0.0063	0.0028	−0.0035	1.7%	36.7%
Average			−0.0046	0.3%	

Monthly pair portfolio returns are regressed against Fama and French's (2015) five factors augmented with momentum, short-term reversals, Pástor and Stambaugh's (2003) liquidity factor, and the logarithm of market-wide idiosyncratic cash flow volatility, the latter computed as: $IdioCFVol_{mt} = \left(\frac{1}{3}\right)\left(\frac{1}{N}\right)\sum_{i=1}^{N}\left(\frac{\pi}{2}\right)(E2P_{it} - E2P_{mt})^2$. This table presents an attribution analysis based on the following equality: $\overline{Ret_2} - \overline{Ret_1} = (\overline{e_2} - \overline{e_1}) + \sum_{i=1}^{7}\beta_i(\overline{f_{i,2}} - \overline{f_{i,1}}) + \beta_8(\overline{logIdioCFVol_{m,2}} - \overline{logIdioCFVol_{m,1}})$, where β_i are loadings and $\overline{e}$ is the mean residual return obtained from the above regression. For a given period, $\overline{Ret}$ is the mean raw portfolio return, $\overline{f_i}$ is the mean return and $\overline{logIdioCFVol_m}$ is the mean of log market idiosyncratic cash flow volatility. "% Explained by Standard Factors" and "% Explained by Log Market IdioCFVol" are respectively equal to the second and third term on the RHS divided by the LHS.

In this equality, $\overline{Ret}$ is the average raw return over a given sub-period;$\overline{f}$ corresponds to the average common factor return over the same sub-period; $\overline{logIdioCFVol_m}$ is defined analogously for the log market idiosyncratic cash flow volatility; $\overline{e}$ is the average residual return over the sub-period after accounting for the standard risk factors and the market idiosyncratic cash flow volatility; and β_i are the estimated coefficients. Dividing each of the three quantities on the right-hand side by the quantity on the left-hand side, we obtain, respectively, the proportion of the profit decline that is unexplained by the variables considered, the proportion that is collectively explained by variation in the standard factors and the portion that is explained by variation in market idiosyncratic cash flow volatility. Table 9 reports this attribution exercise over two sub-periods: August 1971–March 1994 and April 1994–December 2016.

Over these sub-periods, the two portfolios suffer a per-month profit decline of 46 bps or 68 percent, on average. The proportion of the raw return decline collectively accounted for by the eight standard risk factors is −1.1 percent for the top 50 pairs and +1.7 percent for pairs 51–100. The variation observed for these factors across the two sub-periods simply does not explain any of the profit decline by the pairs trading strategy. In contrast, the increase in the market-wide idiosyncratic cash flow variance (from −7.33 to −5.97 at the log level; or from 0.0015 to 0.0041 at the raw level; untabulated) is responsible for

41.6 percent of the drop in the profit of the top 50 distance-based pairs and 36.7 percent of the drop for the next 50 pairs. These statistics are substantial, pointing to an important role of aggregate idiosyncratic cash flow volatility in the decline of pairs trading profits.

Does *IdioRetVol* contribute to explaining the profit decline? We note that like *IdioCFVol*, *IdioRetVol* also increases over the sub-periods. However, as the pairs portfolios load positively on this variable (Specification 3 in Table 8), its time-series variation has helped to *dampen*, not contribute to, the decline in pairs trading profitability.

5.3. Discussion

The time-series evidence above points to the aggregate idiosyncratic cash flow volatility as a relevant state variable affecting the performance of pairs trading. This state variable explains a substantial portion of the profit decline over the two equal halves of our sample. Furthermore, this time-series effect corroborates with the cross-sectional evidence presented earlier. The negative nature of these effects means idiosyncratic cash flow volatility is *not* the source of profits for pairs trading. Rather, it represents a holding cost for investors engaging in this relative value arbitrage. This interpretation is consistent with Pontiff's (2006) view that idiosyncratic risk is an important holding cost for arbitrageurs.

Gatev *et al*. (2006) suggest a latent risk factor is responsible for the profit decline in pairs trading since the 1990s. They document a strong correlation in disjoint pairs portfolios, the top 20 lowest *SSD* pairs and pairs 101–120. They further note that the correlation drops in the later part of the sample, coinciding with the period of lower excess returns. These observations seem consistent with pairs trading driven by a latent risk factor that becomes dormant in recent decades. Our analysis presents an alternative story in which the profit decline in pairs trading is driven by increasing holding costs as idiosyncratic cash flow volatility increases. While we largely replicate Gatev *et al*.'s (2006) observation that the correlation between the top 20 pairs and pairs 101–120 drops over time, we continue to document negative and significant relations between the aggregate idiosyncratic cash flow volatility and the portfolios' monthly returns and convergence rate.[15]

6. Conclusion

Pairs trading provides a unique setting to understand the relative value arbitrage trade in equity markets. Since stocks are subject to idiosyncratic cash flow shocks, pairs trading is a bet that the traded pair exhibit similar fundamental cash flows over the trading period. We presented a simple model

[15]Details are available in Tables B6 and B7 in the Appendix S1.

that explicitly gives rise to the positive relation between pairs trading performance and fundamental similarity. This mechanism is largely ignored in the literature which tends to focus on frictions as the main source of pairs trading profits.

Consistent with this mechanism, we identified idiosyncratic cash flow volatility as a novel and dominant determinant of pairs trading profitability. We documented robust cross-sectional evidence in which pairs that experience high pairwise idiosyncratic cash flow volatility are associated with poor trading performance. We also documented a time-series result in which portfolio returns and convergence probability are negatively related to the market-wide idiosyncratic cash flow volatility. Our results hold for non-overlapping sets of pairs portfolios and across time and are distinct from the announcement effect, as well as from the idiosyncratic return-volatility effect previously documented in the literature. Armed with our time-series evidence, we were able to explain a substantial part of the continual decline in pairs trading profits since the 1990s.

Overall, our study provides compelling empirical support for the notion that idiosyncratic cash flow risk is a major holding cost for arbitrageurs when perfect substitutes do not exist. Our main theoretical contribution is to characterise pairs trading as necessarily a phenomenon among close economic substitutes whose fundamental cash flows are similar. From a practical perspective, our results suggest that pairs traders should expend considerable effort on identifying and exploiting pairs with strong cash flow similarity, instead of just relying on historical price closeness.

Future research on pairs trading should extend beyond the existing paradigm which traditionally focuses on the competitive link among fundamentally related firms that are captured via pairwise co-movement in the price space. As business linkages exist in various dimensions, for instance, an input–output connection, it would be interesting to examine relative pricing behaviours within these alternative networks identified outside the price space.

References

Amihud, Y., 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang, 2006, The cross-section of volatility and expected returns, *The Journal of Finance* 61, 259–299.

Bernard, V., and J. Thomas, 1990, Evidence that stock prices do not fully reflect the implication of current earnings for future earnings, *Journal of Accounting and Economics* 13, 305–340.

Chen, H., S. Chen, Z. Chen, and F. Li, 2019, Empirical investigation of an equity pairs trading strategy, *Management Science* 65, 370–389.

Chordia, T., A. Subrahmanyam, and Q. Tong, 2014, Have capital market anomalies attenuated in the recent era of high liquidity and trading activity?, *Journal of Accounting and Economics* 58, 41–58.

Christoffersen, P., A. Lunde, and K. V. Olesen, 2019, Factor structure in commodity futures return and volatility, *Journal of Quantitative and Financial Analysis* 54, 1083–1115.

Do, B., and R. Faff, 2010, Does simple pairs trading still work?, *Financial Analysts Journal* 66, 83–95.

Do, B., and R. Faff, 2012, Are pairs trading profits robust to trading costs?, *Journal of Financial Research* 35, 261–287.

Engelberg, J., P. Gao, and R. Jagannathan, 2009, *An Anatomy of Pairs Trading: the Role of Idiosyncratic News, Common Information and Liquidity*. Unpublished Paper (University of North Carolina, University of Notre Dame, Northwestern University).

Fama, E. F., and K. R. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153–193.

Fama, E., and K. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Gatev, E., W. N. Goetzmann, and K. G. Rouwenhorst, 2006, Pairs trading: performance of a relative-value arbitrage rule, *The Review of Financial Studies* 19, 797–827.

Gu, M., W. Kang, and B. Xu, 2018, Limits of arbitrage and idiosyncratic volatility: evidence from China stock market, *Journal of Banking and Finance* 86, 240–258.

Herskovic, B., B. Kelly, H. Lustig, and S. Van Nieuweburgh, 2016, The common factor in idiosyncratic volatility: quantitative asset pricing implications, *Journal of Financial Economics* 119, 249–283.

Hou, K., C. Xue, and L. Zhang, 2015, Digesting anomalies: an investment approach, The *Review of Financial Studies* 28, 650–705.

Hou, K., H. Mo, C. Xue, and L. Zhang, 2020a, An augmented q-factor model with expected growth, *Review of Finance*. https://doi.org/10.1093/rof/rfaa1004

Hou, K., C. Xue, and L. Zhang, 2020b, Replicating anomalies, *The Review of Financial Studies* 33, 2019–2133.

Irvine, P. J., and J. Pontiff, 2009, Idiosyncratic return volatility, cash flows, and product market competition, *The Review of Financial Studies* 22, 1149–1177.

Jacobs, H., and M. Weber, 2015, On the determinants of pairs trading profitability, *Journal of Financial Markets* 23, 75–97.

McLean, R. D., 2010, Idiosyncratic risk, long-term reversal and momentum, *Journal of Financial and Quantitative Analysis* 45, 883–906.

McLean, R. D., and J. Pontiff, 2016, Does academic research destroy stock return predictability?, *The Journal of Finance* 71, 5–32.

Newey, W. K., and K. D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Pástor, L., and R. F. Stambaugh, 2003, Liquidity risk and expected stock retums, *Journal of Political Economy* 111, 642–685.

Pontiff, J., 2006, Costly arbitrage and the myth of idiosyncratic risk, *Journal of Accounting and Economics* 42, 35–52.

Roll, R., 1988, R2, *The Journal of Finance* 43, 541–566.

Stambaugh, R. F., and Y. Yuan, 2017, Mispricing factors, The *Review of Financial Studies* 30, 1270–1315.

Stambaugh, R. F., J. Yu, and Y. Yuan, 2015, Arbitrage asymmetry and the idiosyncratic volatility puzzle, *The Journal of Finance* 70, 1903–1948.

Thompson, S. B., 2011, Simple formulas for standard errors that cluster by both firm and time, *Journal of Financial Economics* 99, 1–10.

Wurgler, J., and E. Zhuravskaya, 2002, Does arbitrage flatten demand curves for stocks?, *The Journal of Business* 75, 583–608.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix S1. Supplementary Materials.