On the determinants of pairs trading profitability

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December 2014

We perform a large-scale empirical analysis of pairs trading, a popular relative-value arbitrage approach. We start with a cross-country study of 34 international stock markets and uncover that abnormal returns are a persistent phenomenon. We then construct a comprehensive U.S. data set to explore the sources behind the puzzling profitability in more depth. Our findings indicate that the type of news leading to pair divergence, the dynamics of investor attention as well as the dynamics of limits to arbitrage are important drivers of the strategy's time-varying performance.

Keywords: Pairs trading, relative-value arbitrage, return predictability, international stock markets, limited attention, limits to arbitrage *JEL classification:* G12, G14

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1 Introduction

The apparent profitability of pairs trading, which bets on the future relative performance of two assets with very similar past performance, constitutes an intriguing anomaly. It seems to violate even the weak form of market efficiency, and it is very popular among sophisticated practitioners, but it has largely been neglected in the academic literature so far. As a consequence, it is still an open question when, where, and why pairs trading is particularly successful. Our large-scale empirical analysis aims to shed new light on these questions.

The idea behind pairs trading is "disarmingly simple" (Gatev, Goetzmann, and Rouwenhorst, 2006, p. 797). It uses statistical methods to identify economically related firms, and then tries to exploit potential short-term relative mispricings between the constituents of a pair. More precisely, for each month and all possible pair combinations, one first computes the historical distance between normalized daily return paths. One then selects the pairs with minimum distance for trading, thereby building on the assumption that these stocks represent to some extent economic substitutes. Whenever the cumulative daily returns of any of these top pairs diverge by more than what would be expected based on historical price patterns, one shorts the relatively overpriced winner and buys the relatively underpriced loser. If the future resembles the past, prices are likely to finally converge again, thereby generating positive returns on zero-cost portfolios.

As a relative-value arbitrage approach, pairs trading is widely used by hedge funds and investment banks. For instance, in a practitioner's book, Vidyamurthy (2004, p. 74) concludes that pairs trading has "increased in popularity and has become a common trading strategy." Andrade, di Pietro, and Seasholes (2005, p. 2) estimate the realized profit from pairs trading for sophisticated investors at "hundreds of millions of dollars."

In the academic literature, pairs trading has nevertheless attracted much less attention, in particular when compared to the few other anomalies seemingly contradicting the weak form of the efficient markets (most notably momentum). Our contribution is twofold.

Little is known about pairs trading in international markets, even though only few trading strategies have survived the test of time and independent scrutiny. We first address this gap in the literature. To our knowledge, our paper provides the first cross-country study of pairs trading. By relying on more than 200 million stock pairs from 34 countries, we first establish that abnormal returns generated from pairs trading are a persistent phenomenon. For the average country and measured over the period from 2000 to 2013, both the annualized one-month event-time return and the annualized calendar-time Fama and French (1993) three-factor alpha are in the area of 8% to 9%.

Our large cross-section also allows us to determine in which country groups trading is particularly profitable. We find that abnormal returns are most pronounced in emerging markets on the one hand and in markets with a large number of eligible pairs on the other hand. Further analysis indicates that these patterns may be related to limits to arbitrage in the case of emerging markets and information overload in the case of large markets. For instance, abnormal returns to pairs trading are larger in countries with higher average idiosyncratic volatility, as well as in countries with large stock markets relative to their economic size.

Second, and in light of these results, we construct a comprehensive U.S. data set based on daily data over a 47-year period to explore the potential drivers of pairs trading profitability in more depth. Our insights are based on more than 100,000 round-trip trades of the monthly top 100 pairs constructed from large and liquid stocks only. Again, the findings show that pairs trading has generated average annualized excess returns of at least 12%. Nevertheless, there is also surprisingly large time-variation in the profitability, even within each single year of the sample period. Our three key insights are that the type of news on the day of the pair divergence, the dynamics of investor attention, and the dynamics of market-wide limits to arbitrage appear to be major forces behind these return patterns.

Broadly speaking, abnormal long-short profits can arise from two general sources. On the one hand, investors might overreact to firm-specific shocks. On the other hand, due to investor underreaction, shocks that affect both stocks of the pair to a similar degree might be impounded at differential speed. The small empirical literature on pairs trading lends more support to the idea of differential responses to common news shocks (e.g., Engelberg, Gao, and Jagannathan, 2009; Chen, Chen, and Li, 2013; Deaves, Liu, and Miu, 2013). Our analysis supports this view. We find that pairs which diverge on days with public firm-specific earnings news, firm-specific dividend news, or firm-specific coverage in newswires yield considerably lower returns than pairs on average. In contrast, on days with macroeconomic news the returns generated from pairs trading tend to be higher than usual.[1]

The two channels sketched above also have important and in fact opposing implications for the impact the dynamics of investor attention is likely to have on pairs trading profitability. On the one hand, increased attention could lead to more overreaction to public firm-specific shocks, thus leading to higher pairs trading profits. We refer to this mechanism as "excessive attention hypothesis." On the other hand, more attention could facilitate the incorporation of common shocks to both stocks in the pair, thereby reducing the profits. We refer to this mechanism as "limited attention hypothesis." Again, our tests support the second channel. Pairs trading profitability appears to be negatively related to investor attention, both in the cross-section and in the time series.

[1] Please note that we cannot definitively determine whether the underreaction-to-common-shocks channel is generally more important than the overreaction-to-idiosyncratic-shocks channel in driving pairs trading profits. The data are also consistent with the view that investors underreact to public news, but overreact to private news, in which case firm-specific announcements do not capture investor overreaction.

Imagine, for instance, that common news during times of high distraction is released, which clearly and directly affects the first firm in the pair, but has an only indirect and less clear impact on the second firm. If the news does not become fully incorporated into the price of the second stock, then prices will temporarily diverge and lead to the opening of the pair. When investors become fully aware of the link between both firms, relative prices should adjust gradually and the pair is likely to finally converge again. In other situations, however, the opening will be due to public news disproportionately affecting only one constituent. Our findings indicate that the relative price difference is likely to often remain unchanged or increase even further in these settings, thereby often generating losses. Figure 1 illustrates the pairs trading process in these two situations with examples.

Please insert figure 1

The key to the strategy's success under the limited attention hypothesis is thus to ex ante identify days in which the opening of the pair has a particularly high probability to have been caused by short-term attention constraints, which impede timely information spill-over. In line with this view, our findings uncover that pairs trading is generally more successful for pairs with sluggish cross-stock information transfer. Similarly, the delayed reaction to common news is particularly slow for pairs for which a differential response is particularly likely.

To investigate the role of attention in more depth, we construct a number of time-varying investor distraction proxies inspired by previous work. Collectively, our conceptually diverse set of proxies indicates that pairs trading is up to 60 bps per month more profitable if stocks initially diverged during phases of high distraction. Among others, proxies include the number of simultaneous events competing for investors' attention, absolute investor sentiment, and public holidays. Further in line with the limited attention hypothesis, the increase in profitability tends to be strongest for pairs that are difficult to arbitrage or in general less visible.

Relating the type of return predictability observable in pairs trading to time-varying limited investor attention appears plausible for several reasons. It is a short-term strategy whose profitability almost monotonically declines in event-time (see section 3), both of which are in line with the idea of slow information diffusion. Moreover, a related stream of literature documents that limited attention is an important determinant for the return predictability among stocks with economic linkages. More precisely, there appear to be lead-lag effects related to industry factors (e.g., Hong, Torous, and Valkanov, 2007; Hou, 2007) and lead-lag effects along the supply chain (Cohen and Frazzini, 2008; Menzly and Ozbaz, 2010). Recent work also uncovers cross-stock return predictability based on information about a firm's strategic alliance partners (Cao, Chordia, and Lin, 2014) or its foreign operations (Huang, 2013).

Pairs trading is related to the aforementioned papers in that it also aims to be predictive of the relative performance of assets deemed to be partial economic substitutes. Nevertheless, pairs trading is conceptually different in that it is solely based on information about historical prices. Moreover, and in contrast to most cited studies, in our setting there is typically no systematic leader. In fact, the pairs trading algorithm matches stocks that not only tend to be both relatively large and liquid but also are very similar in many other dimensions as well.

Behavioral finance research indicates that both cognitive biases and constraints (such as attention effects) and limits to arbitrage (such as idiosyncratic volatility in our cross-country analysis) are likely to contribute to the existence of anomalies (e.g., Barberis and Thaler, 2013). We thus run another event-time analysis for the U.S. market with several promising daily proxies for time-varying limits to arbitrage derived from the literature. Among others, our measures include average bid-ask spreads estimated as recently proposed by Corwin and Schultz (2012), the TED spread, or the trading cost measure as proposed by Hasbrouck (2009).

We find strong evidence that arbitrage constraints measured on the day of divergence are important drivers of abnormal returns to pairs trading. For instance, multivariate regressions, which control for other market-level variables, calendar and industry effects, firm variables as well as pair characteristics show that a one standard deviation change of the first principal component of all proxies for arbitrage constraints goes along with a 41 bps change in the average one-month event-time return.

Our setting is related to several other long-standing empirical puzzles, in which there are price discrepancies between similar assets.[2] In a broader sense, our in-depth analysis of pairs trading might thus help us to better understand how the interaction of news, limited attention, and limits to arbitrage affects the efficiency of fundamentally linked assets in practice.

[2] For instance, Lee, Shleifer, and Thaler (1991), Pontiff (1995), or Cherkes, Sagi, and Stanton (2009) focus on the relationship between the prices of closed-end fund shares and the per share market value of the assets held by the funds. Mitchell, Pulvino, and Stafford (2002) and Lamont and Thaler (2003) study situations in which a firm's market value is less than the value of its ownership stake in a publicly-traded subsidiary. Rosenthal and Young (1990), Froot and Dabora (1999), and Baker, Wurgler, and Yuan (2012) study the price parity deviations of dual-listed companies ("Siamese Twins"). Gagnon and Karolyi (2010) study discrepancies between the prices of US and home-market shares of companies with cross-listed stocks. Smith and Amoako-Adu (1995), Zingales (1995), and Schultz and Shive (2010) study dual class shares, which differ in voting rights but have equal cash flow rights.

2 Baseline empirical analysis

2.1 Pairs trading: international evidence

We start by gathering daily stock-level data from Datastream for all countries used in Chui, Titman, and Wei (2010). Both at the stock level and at the country level, we then apply a number of screens intended to exclude small and illiquid firms as well as to minimize the fraction of error-prone daily return and volume data.[3] Panel A of Table 1 lists the 34 countries that remain after all filter rules. For the vast majority of countries, the pairs trading evaluation period is January 2000 to December 2013. The beginning of the sample period is mostly determined by the availability of non-missing daily stock-level trading volume for many countries as well as reliable and comprehensive data for some of the emerging markets.

Please insert table 1

As the number of potential pairs grows quadratically with the number of available stocks, comprehensively investigating pairs trading can be computationally very costly. Potentially to mitigate this issue, previous work has partly concentrated on monthly

[3]The most important screens are the following: First, we exclude stocks with a lagged market capitalization that is less than 250 million U.S. dollars (absolute criterion) or which is below the median firm size in a given month and country (relative criterion). Second, we exclude stocks with a lagged share price of less than one U.S. dollar. Third, we discard stocks with missing market capitalization, missing daily returns, or missing or zero daily turnover during the pair formation period. Fourth, we eliminate outliers (for instance by winsorizing extreme returns). Fifth, for each country, we require at least 20 eligible stocks in each sample month. Sixth, we require a smooth, uninterrupted time series of sample months. Returns are denominated in U.S. dollars and account for corporate actions.

data (e.g., Chen, Chen, and Li, 2013) or on same industry pairs (e.g., Engelberg, Gao, and Jagannathan, 2009). In contrast, we build on daily data and consider all possible pair combinations. Our approach of constructing pairs closely follows the methodology of Gatev, Goetzmann, and Rouwenhorst (2006). Specifically, we use daily price data to compute a stock-specific cumulative total return index over the whole twelve-month estimation period. Let $R_{i,t}$ ($R_{j,t}$) be the normalized return series of stock i (j) in estimation period t, which is comprised of trading days 1 to n. The algorithm, intended to provide a parsimonious, intuitive framework to identify pairs with similar historical return pattern, is then defined as:

$$\frac{1}{n}\sum_{t=1}^{n}(R_{i,t} - R_{j,t})^2. \tag{1}$$

We compute the distance measure for all pairwise combinations of eligible firms. In total, our analysis of international stock markets is based on more than 200 million pairs and the comparison of more than 100 billion data points, as indicated by equation 1.

At the beginning of each month, we then choose the top 100 pairs with minimum distance. This number is motivated by previous empirical work on pairs trading (e.g., Gatev, Goetzmann, and Rouwenhorst, 2006; Engelberg, Gao, and Jagannathan, 2009) and meant to be a compromise between identifying close economic substitutes on the one hand and assuring a sufficient sample size on the other. In general, our findings are robust with respect to alternative cut-off points. In results unreported for brevity, we find that the stocks entering the country-level top pairs tend to belong to the largest size quintile and moreover tend to be well diversified across industries.

The monthly top 100 pairs are then eligible for trading in the immediately following six-month evaluation period. Prices are again set to equal unity. Following Gatev, Goetzmann, and Rouwenhorst (2006), if the spread between the cumulative return series of two substitutes exceeds two historical standard deviations, we form a long-short portfolio. The self-financing pair is then held for up to one month. If prices converge before this cut-off date, the trade is closed with a gain. If prices do not converge within a month, positions are offset. This results in a loss if prices have diverged even further.

A pair may trade several times during the evaluation period. In the mean time, we assume that the proceeds are held in cash with zero interest. The money invested in later trades differs depending on whether we report event-time results or calendar-time results. In event-time, we again go one dollar long (short) into the cheap (expensive) stock. In calendar-time, proceeds from previous trades are reinvested.

Throughout the paper, we rely on a conservative return computation scheme intended to account for microstructural effects. We skip one day after the divergence and, provided that the pair converges within a month, add one day following the crossing of the prices. Table 1 displays the main findings from in total about 642,000 round-trip trades.

For each country, we rely on three performance measures. First, we report the fraction of pairs that converges within one month after divergence. Second, we compute the average long-short one-month return in event-time. Third, we compute the alpha from calendar-time regressions of pairs trading returns on a Fama and French (1993) three-factor model. For this purpose, we compute the market factor, the size factor, and the value factor separately for each country.

As Panel A of Table 1 shows, the success of pairs trading is remarkably robust, even though we focus on large stocks, on a recent sample period, and on conservative return estimates. Averaged across all observations, the one-month event-time return is 72 bps, and the monthly Fama and French (1993) three-factor alpha is 63 bps. About 75% of the return estimates are significant at least at the 5% level, and not a single coefficient is reliably negative.

Nevertheless, there are also substantial cross-sectional differences in the magnitude of the abnormal returns. In Panel B of Table 1, we thus explore in which country groups pairs trading is particularly successful. The findings demonstrate that trading pairs in emerging markets (as determined by the MSCI classification) yields returns that are about a quarter higher than in developed markets, even though the likelihood of pair convergence within a month is comparable. In other words, all else equal, pairs in emerging markets tend to diverge by a larger extent, eventually leading to higher returns. This pattern appears to be in line with the notion of stronger limits to arbitrage in emerging markets induced by, for example, short-selling constraints or idiosyncratic risk (e.g., Gagnon and Karolyi, 2010).

However, Panel B of Table 1 also shows another interesting finding: trading pairs in large markets (i.e. countries with an above median number of stocks eligible for trading as outlined at the beginning of this section) is much more successful than trading pairs in small markets. The one month event-time return difference is 19 bps, the difference in the calendar-time alpha (based on a global three-factor model) even 45 bps.

There seem to be at least two plausible explanations for this phenomenon. First, as the number of pairs increases quadratically with the number of eligible stocks, the monthly top 100 pairs are more likely to be true economic substitutes in large markets. For instance, in markets such as Austria, Denmark, or Portugal, there are on average only a few hundred eligible pair combinations per month so that even the top 100 pairs often have a rather large distance between historical price paths. In contrast, in countries such as Japan or China, there are hundreds of thousands of pairs in each month. Second, the large number of pair combinations might also induce information overload and lead to limited visibility of individual pairs. In other words, the limited attention hypothesis might be particularly relevant for markets in which resources need to be allocated across many assets at the same time, after accounting for factors such as average firm size.

Both the explanation based on economic substitutes and the explanation based on limited attention indicate that the fraction of pairs that converge again within one month should be higher in large markets than in small markets. As Panel B of Table 1 shows and as the Online Appendix verifies in more depth, the data lend strong credibility to this hypothesis. The average fraction of converging pairs is 19.2% in smaller than median markets, but 28.6% in larger than median markets. As Panel B of Table 1 further shows, larger markets yield higher profits both in the subset of emerging markets and in the subset of developed markets.

To further investigate cross-country determinants of pairs trading profitability, we implement a Fama and MacBeth (1973) regression approach. For each country, we define monthly benchmark-adjusted abnormal returns as the sum of the alpha and the fitted value of the residual from regressions of pairs trading returns on a country-specific Fama and French (1993) three-factor model (as in Table 1). For each month between January 2000 and December 2013, we then pool the county-specific estimates and regress them on country-level variables. Statistical inference is based on the time series of the monthly coefficients. We rely on Newey and West (1987) standard errors with six lags. Table 2 shows the main findings.

Please insert table 2

The first specification of Table 2 again verifies that benchmark-adjusted abnormal returns are higher among emerging markets and markets with many stocks, respectively. In the second specification, we test the idea of information overload due to cognitive constraints. We compute the average industry market share (e.g., Hou, 2007) of the monthly top 100 pairs as well as the market capitalization of the stock market relative to country-level GDP. We expect pairs to be less visible if their constituents do not tend to be industry leaders. Similarly, we expect slower information diffusion if the stock market is large relative to a country's economic size. In both cases, the limited attention hypothesis (excessive attention hypothesis) predicts higher (lower) returns. Specification two of Table

2, which also controls for the average market capitalization of the top pairs, supports the limited attention view. The impact of both variables of interest is statistically significant and economically meaningful. A one standard deviation increase in stock market size relative to GDP is estimated to go along with a 15 bps increase in monthly abnormal returns. Similarly, a one standard deviation decrease in the average industry market share of top 100 pairs implies an 10 bps increase in pairs trading profits.

In specification three of Table 2, we test the idea that the emerging markets dummy proxies for cross-sectional differences in limits to arbitrage. We rely on country-level estimates of average Amihud (2002) illiquidity, idiosyncratic volatility (e.g., Pontiff, 2006), and a dummy that quantifies whether short-selling is allowed. While the coefficients of all variables go in the predicted direction, only the estimate for idiosyncratic volatility is reliably different from zero (t-stat=3.04). A one standard deviation change implies a 17 bps change in monthly abnormal returns.

Specifications four to six of Table 2 test more comprehensive models. Due to the partly high correlations between the explanatory variables, estimates should be interpreted with some care. However, the emerging markets dummy and the measure of relative stock market size remain reliably different from zero.

Specification six of Table 2 also establishes that pairs trading profitability is all else equal negatively related to the average R^2 obtained from rolling stock-level market-model regressions (using the most recent twelve months) and positively related to the degree of individualism, a cultural dimension explored in, for example, Chui, Titman, and Wei (2010). Both measures are related to low stock price comovement and high firm-specific return variations (e.g., Morck, Yeung, and Wu, 2000; Eun, Wang, and Xiao, 2014). Potentially, these factors might increase the number of trading signals a pairs trading investor has to process, which would be further in line with the idea of information overload. Nevertheless, even this comprehensive model can explain only a small fraction of variation in pairs trading returns. In the following section, we thus aim at identifying further drivers of pairs trading profitability using a detailed U.S. stock market data set.

2.2 Pairs trading: U.S. evidence

We obtain daily stock price data on all common shares traded on NYSE or AMEX at any time between January 1960 and December 2008. We discard all stocks with at least one missing return or zero trading volume on any day of the twelve-month period during which pairs are matched. Moreover, we only consider stocks with a market capitalization larger than the median of the NYSE/AMEX stock universe at that time.[4] The identification process of pairs is then performed analogously to our approach for international stock markets. The initial data set consists of more than 200 million stock pairs, and the final data set is based on 103,386 round trip trades of the monthly top 100 pairs. Table 3 shows descriptive statistics.

Please insert table 3

The major insights from Table 3 can be summarized as follows. First, firms in general are large and liquid (see Panel A). For instance, the median firm belongs to the second

[4] In the baseline analysis, we require firms to belong to one of the 49 Fama and French (1997) industries and restrict our focus again to different industry pairs. Firms from different industries are interesting candidates for our limited attention tests as industrial boundaries have been shown to go along with informational boundaries induced by specialization of analysts or fund managers (e.g., Hong, Torous, and Valkanov, 2007; Menzly and Ozbaz, 2010). The Online Appendix reveals that the monthly top pairs nevertheless have significantly correlated earnings surprises in the following quarters. Thus, the economic link between two firms in our empirical setting might be thought of as being potentially strong, but simultaneously often also less explicit and transparent, and thus likely to be neglected in phases of low attention.

largest NYSE/AMEX size decile and has an average daily turnover of 0.11%. About 54% of firms are members of the S&P 500. In close to a third of all pair observations, both firms belong to the S&P 500.

Second, there are typically only small differences in firm characteristics within pairs (see Panel B of Table 3). Moreover, both firms and top pairs are, in the overall picture, well diversified across industries. However, utility stocks make up close to 30% of all sample firms and are part of all top industry group combinations. We address this issue in later tests.

Third, the day of divergence is an interesting date. As Panel B of Table 3 shows, pairs on average are opened when cumulative standardized returns have diverged by 6.68%. More than 40% of this difference is attributable to the day of divergence itself. Thus, understanding the underlying drivers of stock price behavior on this day is essential.

Please insert table 4

Panel A of Table 4 shows return characteristics of the pooled pair trades from January 1962 to December 2008. The major insight is that pairs trading appears highly profitable with an unconditional monthly event-time return of close to 100 bps per month. The profitability is attributable to the on average 36.2% of pairs that converge within a month, thereby on average generating 6.38% return on a long-short position. In the remaining cases, pairs tend to diverge even further, thereby generating a loss of on average 2.09%. There are large differences in the profitability of individual pairs trades: the first (99th) percentile of the slightly negatively skewed distribution generates a return of -17.83% (15.19%).

In Panel B of Table 4, we transfer these event-time results to calendar-time. We construct a time series of monthly pairs trading profits and regress them on the Fama and

French (1993) factors in model 1 and additionally on the premiums for momentum, short-term reversal, and long-term reversal in model 2. Finally, model 3 also controls the traded liquidity factor of Pástor and Stambaugh (2003). In all cases, monthly alphas are about 130 bps and highly significant. Given the inability of standard risk factors to explain pairs trading profits (see also Gatev, Goetzmann, and Rouwenhorst, 2006) as well as our primary objective of understanding the importance of the day of divergence, we focus on event-time tests in the remainder of the paper.

2.3 Robustness checks and cross-sectional determinants

The main results from several sensitivity checks of our baseline analysis are reported in Panel A of Table 5. We repeat the baseline analysis for three consecutive subperiods of approximative equal length. Consistent with prior literature (e.g., Do and Faff, 2010, 2012), there seems to be a negative trend in pairs trading profitability, potentially due to the increased popularity among sophisticated traders. Nevertheless, the returns are significant in each subperiod.

We also modify the universe of stocks eligible for trading. First, we exclude utility stocks. Second, we identify the monthly top 100 pairs under the constraint that each firm is only considered once at maximum. This approach not only decreases the fraction of utility stocks from 30% to roughly 17%, but also changes the composition of the data set considerably. Finally, we only consider pairs of stocks belonging to the same industry. In all three cases, profits are large with monthly long-short returns exceeding 100 bps.

Please insert table 5

In Panel B of Table 5, we analyse cross-sectional determinants of pairs trading profitability, which has been the focus of previous work (e.g., Engelberg, Gao, and Jagannathan, 2009; Chen, Chen, and Li, 2013). Our tests are motivated by the insights from the international analysis. First, we explore the role of pair-level differences in limits to arbitrage. Proxies include the pre-event pair average of idiosyncratic volatility, average bid-ask spreads estimated as recently suggested by Corwin and Schultz (2012), average firm size, and average Amihud (2002) illiquidity. With respect to each variable and for each year separately, we determine the top and bottom quintile of traded pairs. We then analyze whether these pairs differ in their profitability.

The first three columns of Panel B of Table 5 show that pairs consisting of stocks with high idiosyncratic risk indeed generate considerably higher one-month event-time returns than pairs consisting of stocks with low idiosyncratic risk. The difference of more than 40 bps per month is highly significant. With respect to Amihud (2002) illiquidity, the difference is 19 bps and significant as well. The coefficients on the other two variables go in the predicted direction, but are less in magnitude and not significant. We conclude that cross-sectional limits to arbitrage often appear to be binding.

Second, we explore the idea that less visible pairs might be more profitable as timely cross-stock information flow could be hampered for neglected stocks. Proxies for pair visibility include average newswire coverage (e.g., Chan, 2003) and analysts coverage (e.g., Baker, Powell, and Weaveer, 1999), both orthogonalized with respect to firm size. We also consider average sales (e.g. Hong, Kubik, and Stein, 2008) and average industry market share as in the cross-country analysis.[5] Panel B of Table 5 shows that our predictions prove

[5]The orthogonalization procedure for analyst coverage follows Hong, Lim, and Stein (2000). For newswire coverage, we collect the logarithmized yearly number of news articles in the Dow Jones News Service (DJNS) database, "the best approximation of public news for traders" (Chan, 2003, p. 230). We use the top and bottom quintile of residuals to classify a stock as highly (lowly) covered by newswires or by analysts. Finally, we define a pair as being highly (lowly) covered if both of its components are firms with high (low) coverage. Industry market share is computed as a stock's relative market capitalization within one of the 49 Fama and French (1997) industries. A pair's industry market share or sale is com-

to be true. In all four cases, less visible pairs are always at least 30 bps more profitable than more visible pairs. The differences are persistently statistically significant.

3 Event-time analysis: why are some pairs more profitable than others?

In the following, we examine the mechanism behind pairs trading profitability by focusing on the day of divergence. Among others, this analysis is motivated by Figures 2 and 3.

Please insert figures 2 and 3

Figure 2 shows the distribution of one-month event-time returns on U.S. stock pairs averaged separately for each trading day. It shows that there is a large time variation in average returns. While this finding is based on our whole sample period, it can also be transferred to much shorter horizons. For instance, in each single year, the standard deviation of average profits for pairs opening on a given trading day is more than 200 bps. These results indicate that there are time-varying circumstances that make trading pairs more or less successful.

Figure 3 shows the probability of convergence and the average daily return by event day. As can be seen, by far the largest profits are typically made on the first few days following pair divergence. This is also the time when the likelihood of pair convergence is highest. Again, these findings indicate that the day of divergence is not a random day, but the key to understanding the strategy's success.

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puted as the average value of its two constituents. For each year separately, we finally determine the top and bottom quintile of pairs with respect to these variables.

3.1 Idiosyncratic vs. common news

We start by analyzing the link between different types of information shocks on the day of divergence and subsequent abnormal returns. As outlined in the introduction, such an analysis helps to discriminate between competing channels with respect to the sources of pairs trading profitability.

As proxies for firm-specific news, we gather earnings announcements and dividend announcements from CRSP. We also employ the data set of firm-specific articles in the Dow Jones Interactive Publications Library used by Chan (2003). As proxies for common news, which are likely to affect both pair constituents to a similar extent, we rely on the same macroeconomic news as Savor and Wilson (2013, 2014). More specifically, we consider inflation and unemployment announcements, consumer and producer price index announcements, and scheduled Federal Open Markets Committee interest rate decisions.

For each of the three types of firm specific news as well as for the combined macroeconomic news, we construct a dummy variable that is one (zero) if a news event does (does not) take place. We then analyze one-month event-time returns to pairs trading depending on the type of news identifiable on the day of pair divergence. Table 6 shows the main results.

Please insert table 6

We start with univariate results in Panel A of Table 6. A clear pattern emerges. All firm-specific news are negatively related to pairs trading profitability in a statistically significant and economically meaningful matter. Most notably, pairs opening on days where one constituent announces earnings generates a one-month return close to zero, whereas the average returns for pairs opening on any other trading day over the same sample period is 88 bps. Similarly, pairs opening on days with dividend announcements or news stories earn 26 and 36 bps lower returns than other pairs. In contrast, pairs diverging on days with macroeconomic news are, if anything, slightly more profitable.

Panel B of Table 6 focuses on the same variables, but presents main results from conservative multivariate regressions. We include three sets of control variables. The first set controls for calendar effects (indicator variables for year, month, and day of week). The second set controls for market-level conditions on the day of divergence (market return, squared market return, market turnover, factors for daily return premia on size, value, momentum, and short-term reversal). The third set includes the firm and pair characteristics as outlined in Table 3. For instance, controls include the return difference and the average bid-ask spread on the day of pair divergence, the average market capitalization decile and the idiosyncratic risk of the pair, as well as within-pair differences of the before mentioned variables. The findings are very similar to the insights from the univariate analysis. In the overall picture, public firm-specific news (public common news) are negatively (positively) related to pairs trading profitability.

The analysis in Panel C of Table 6 confirms this judgement. We concentrate on the subset of pairs for which there is a news event on the day of divergence. More precisely, the dummy is one (zero) if there is at least one macroeconomic shock but no firm-specific shock (at least one firm-specific shock but no macroeconomic shock). Both univariately and multivariately, the return difference turns out to be very large (65 and 45 bps, respectively) and statistically significant at the 1% level.

In Panel D of Table 6, we replicate the analysis performed to generate the results displayed in Panel C, but now additionally focus on the interaction between news and pair characteristics. The intuition is that, under the limited attention hypothesis, our findings should be particularly strong for pairs for which cross-stock information transfer is likely to be hampered. Empirically, we perform a median split for each of the following variables. First, we consider the extent of common analyst coverage (e.g., Engelberg, Gao, and Jagannathan, 2009). Findings should be weaker if there are more brokerage houses covering both pairs constituents at the same time. Second, we focus on idiosyncratic volatility as a proxy for limits to arbitrage and differences of opinion (e.g., Boehme et al., 2009). Third, we consider analyst forecast dispersion as a proxy for differences in beliefs (e.g., Diether, Malloy, and Scherbina, 2002). Low differences of opinion with respect to economically related stocks are likely to help keep relative prices in line. Panel D of Table 6 shows that our predictions prove to be true. Both univariately and multivariately, abnormal returns following common (as opposed to firm-specific) news are larger in pairs with low common analyst coverage, high idiosyncratic volatility, or high analyst forecast dispersion.

In sum, Table 6 shows that slow information diffusion following public common news (as opposed to overreaction to public firm-specific shocks) appears to be a major driver of pairs trading profitability. In sum, our findings also indicate that the limited (as opposed to the excessive) attention hypothesis is better supported by the data: at least with respect to public news, investor attention appears to be negatively (and not positively) related to the success of pairs trading. In the following, we explore this conjecture in more depth.

3.2 Time-varying investor attention

In the following, we analyze the role of seven investor distraction proxies inspired by previous work and measured on the day of pair divergence. The common theme is that all variables aim at identifying periods of high investor distraction. Nevertheless, investor attention has many facets, and considering all proxies simultaneously has the advantages of providing a more comprehensive picture of attention effects and of mitigating data mining concerns. Collectively, the proxies help to discriminate between the limited attention hypothesis and the excessive attention hypothesis as the former (latter) predicts higher (lower) returns if attention on the day of divergence is low.

In this context, several studies have tried to predict variations in the underreaction-driven post-earnings-announcement drift (PEAD). For instance, DellaVigna and Pollet (2009) simply use a Friday dummy based on the argument that investors are distracted by the upcoming weekend. Consistent with their hypothesis, they find PEAD to be stronger for announcements made on Fridays. Even though the interpretation of this result is not without controversy (Michaely, Rubin, and Vedrashko, 2013), we also employ a Friday dummy.

Hirshleifer, Lim, and Teoh (2009) use the number of same day earnings releases that compete for investors' attention. Similarly, Peress (2008) counts the number of firms featured in *The Wall Street Journal*. Again, these researchers find that the PEAD is stronger if attention is low. The idea that high distraction periods are represented by many events happening at the same time, which then leads to information overload for a market participant interested in these events, is also a defining characteristic of other limited attention studies (e.g., Corwin and Coughenour, 2008; Agarwal and Ma, 2012). We thus compute the number of pairs that start trading on a given day. The resulting time series has two attractive properties: there is considerable variation in each year, but no general time trend. The latter is not surprising, given that the number of pairs eligible for trading remains constant after the first six months of the sample period, which we exclude. Finally, we use the top and bottom quintile of the number of newly opened pairs to define a distraction dummy.

Again in the context of the PEAD, Hou, Peng, and Xiong (2009) use down market periods, during which investors are assumed to "put their heads in the sand" (see also Karlsson, Loewenstein, and Seppi, 2009). Following this idea, we create a dummy variable that takes the value of one if NBER classifies a month as recession and zero otherwise. An alternative dummy takes the value of one if the cumulative three-year value-weighted market return is negative and zero otherwise.

Our fifth dummy is constructed from the top and bottom quintile of a Google-based attention shift proxy. Recent work starting with Da, Engelberg, and Gao (2011) demonstrates that analyzing shocks in search terms entered into Google is a promising way of quantifying short-term investor attention allocation and information processing. We follow previous literature in measuring the interest in a sample of large individual firms by the search volume of ticker symbols. Interest in more aggregated information is quantified with search terms like "stock market," "market segments" or "stocks." This distinction between the demand for information at the individual stock level and at the market segment level or market level is motivated by recent attention allocation theories. For instance, Peng and Xiong (2006) argue that investors aim at optimally allocating their finite effort across several aggregation levels. The model implies that market-level information tends to be processed first. Remaining resources are then used to process firm-level information. A comparatively high demand for aggregate information thus indicates comparatively low attention to individual stocks (and thus pair constituents).

Our sixth attention dummy is one (zero) for the yearly top (bottom) quintile of VIX values. Building on Karlsson, Loewenstein, and Seppi (2009), Sicherman et al. (2013) show that the frequency of investors' financial account logins is negatively related to the VIX. Also the evidence in Deaves, Liu, and Miu (2013) provides support for the idea that the levels of the VIX might (to some extent) capture limited attention towards individual firms.

Finally, our seventh dummy is one for the top quintile of the absolute level of the orthogonalized monthly investor sentiment index of Baker and Wurgler (2007), and zero otherwise. Extreme sentiment, both positive and negative, has been shown to induce categorization bias (e.g., Cooper, Dimitrov, and Rau, 2001; Cooper, Gulen, and Rau, 2005), which in turn is linked to the allocation of attention across different aggregation levels (e.g., Barberis and Shleifer, 2003).

All seven distraction dummies are defined in a way that one (zero) signals low (high) investor attention. We start our empirical analysis by univariately regressing the pooled one-month event-time pairs trading returns separately on each of these limited attention dummies.

Please insert table 7

The main findings are presented in Panel A of Table 7. In line with the limited attention hypothesis, the coefficients are positive in all seven univariate regressions shown in Table 7. With the exception of the Friday dummy, the coefficients are moreover persistently statistically significant and economically meaningful. For instance, the findings indicate that returns are on average 38 bps larger on days where many pairs start trading as opposed to days when only a few pairs start trading. The return is even at least 90 bps larger in recessions as opposed to extensions and in times of high absolute sentiment as opposed to low absolute sentiment.

The main results from multivariate regressions are presented in Panel A of Table 7 as well. In these regressions, we use the same controls as in Table 6. The large number of observations additionally allows us to include dummies for pair industry group combinations. While the overall impact of the attention dummies becomes weaker, they all still obtain the predicted coefficient. Most notably, pairs trading is still estimated to be much more profitable (around 60 bps per month) if pairs diverge during NBER recessions, during times of high VIX, and during times of high absolute sentiment. These findings are both statistically significant and economically meaningful.

Given these insights, Panel B of Table 7 concentrates on the interaction effect between the attention dummies and average idiosyncratic volatility (as a proxy for limits to arbitrage) as well as average industry market share (as a proxy for pair visibility). The selection of these variables is motivated by the cross-country analysis (see Table 2) and the cross-sectional results for the U.S. market (see Table 5). For brevity, we report the findings from multivariate regressions only. Univariate results are similar.

For both characteristics, the limited attention hypothesis posits all else equal a higher sensitivity to the dynamics of attention shocks. Indeed, we find predominantly positive interaction effects which, for some attention dummies, are also statistically and economically significant. We conclude that cross-sectional pair characteristics interact with limited investor attention in a plausible fashion.

Finally, inspired by the literature on limited attention due to holiday effects (e.g., Frieder and and Subrahmanyam, 2004; Hong and Yu, 2009), in Panel C of Table 7 we examine whether pairs trading is particularly profitable immediately before the seven federal holidays for which the NYSE has been closed over the whole sample period. In contrast to the average firm, liquidity for opening pairs is not lower on these days. The stocks under consideration are likely to be affected by some type of news, which stipulates trading activity.

We compare returns on pairs that diverge on the last trading day before a holiday with returns on pairs that open on any other trading day of the year. The table shows the fraction of years in which pre-holiday pairs trading is more profitable. The fraction is larger than 50% in 11 out of 14 cases, and often statistically significant. Before Christmas Day and New Year's Day, pairs trading seems particularly successful. For instance, in about 70% of all sample years, mean and median returns from pairs opening on the last trading day of the year are higher than corresponding returns over the rest of the year. Collectively, these insights point to a link between investor inattention, price divergence, and subsequent pairs trading profitability.

3.3 Time-varying limits to arbitrage

Several of the findings presented so far are consistent with the idea that impediments to arbitrage may be related to the abnormal returns from pairs trading. First, the VIX is not only a proxy for limited attention, but it is also often used as a proxy for limits to arbitrage in the time series (e.g., Brunnermeier, Nagel, and Pedersen, 2008). Second, there seem to be interaction effects of measures of limited attention and common news with idiosyncratic risk, which is a popular proxy for limits to arbitrage in the cross-section. Third, also the cross-country evidence and the popularity of pairs trading among hedge funds point to the potential importance of limits to arbitrage. To delve further into this analysis, we consider several proxies for market-wide limits to arbitrage available at a daily frequency. Besides the VIX, we use the average bid-ask spread computed as in Corwin and Schultz (2012), the Moody's credit spread (e.g., Engelberg, Gao, and Jagannathan, 2009), the Libor, the TED spread (e.g., Bunnnermeier and Pedersen, 2009), the recently proposed market-wide liquidity measure of Hu, Pan, and Wang (2013) and the common factor of effective trading costs as proposed by Hasbrouck (2009).[6] Using all proxies simultaneously captures the different facets of limits to arbitrage and assures robustness. It also allows us to consider an aggregate measure of arbitrage constraints by computing the first principal component of the aforementioned seven individual measures. We regress the pooled one-month event-time returns individually on these proxies. To ease interpretation, all proxies for limits to arbitrage are standardized to have zero mean and unit variance.

Please insert table 8

[6]The credit spread is the difference between Moody's BAA corporate bond rate and Moody's AAA corporate bond rate. The eligible stock universe for our computation of the average daily bid-ask spread are all common stocks trading at NYSE/AMEX/NASDAQ with a lagged market capitalization larger than the first NYSE decile and a lagged stock price of at least 5 USD.

Panel A of Table 8 displays the main findings. In univariate regressions, a pervasive picture emerges. All proxies are positively related to pairs trading profitability in a statistically significant way. Most notably, a one standard deviation change in the average bid-ask spread, the Moody's spread, the TED spread, or the Hasbrouck (2009) measure on the day of pair divergence is estimated to go along with an about 30 bps change in pairs trading profitability.

To better isolate the effect of limits to arbitrage, we run multivariate regressions as in Table 7, thereby controlling for calendar effects, market conditions as well as pair and firm characteristics. In the overall picture, and as also shown in Panel A of Table 8, the impact of the proxies [with the Libor and the Hu, Pan, and Wang (2013) measure being the exceptions] is very strong. For instance, a one standard deviation change in the first principal component of the proxies implies a 41 bps change in pairs trading profitability.

In Panel B of Table 8, we focus on within year variation in the arbitrage constraints rather than on variation during the overall sample period. For each year separately, we sort the daily level of the six individual proxies into quintiles. We then compute a dummy variable that is one (zero) for the top (bottom) quintile and therefore quantifies days with high (low) limits to arbitrage. We also compute an aggregate measure defined as the sum of the dummy values divided by the number of available dummies on a given day.

The findings in panel Panel B of Table 8 show that our insights can largely be transferred to the within year perspective. Pairs trading yields substantially larger returns if pairs diverge on days in which arbitrage is likely to be limited. For instance, the aggregate measure indicates that the return for pairs opening on days with high arbitrage constraints is about 50 bps higher than the average one-month event-time return for pairs opening on days with low arbitrage constraints. Collectively, these insights point to a link between limits to arbitrage, price divergence, and subsequent pairs trading profitability.

4 Conclusion

Our large-scale analysis of the U.S. stock market as well as of 34 international markets reveals that trading pairs solely constructed from information about past prices turns out to be persistently profitable. Several diverse tests lend strong support to the notion that the relative efficiency of linked assets might not be not stable over time, but be affected by the dynamics and interaction of news, investor attention, and limits to arbitrage.

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Figure 1: Illustration of pairs trading process with two examples

At the beginning of the trading period, prices of pair constituents are set to equal unity. If the spread between the cumulative return series of the two stocks exceeds two historical standard deviations (as estimated during the pair formation period), we take a long position in the relatively underpriced stock, which is financed by short-selling the relatively overpriced stock. The self-financing pair is then held for up to one month.

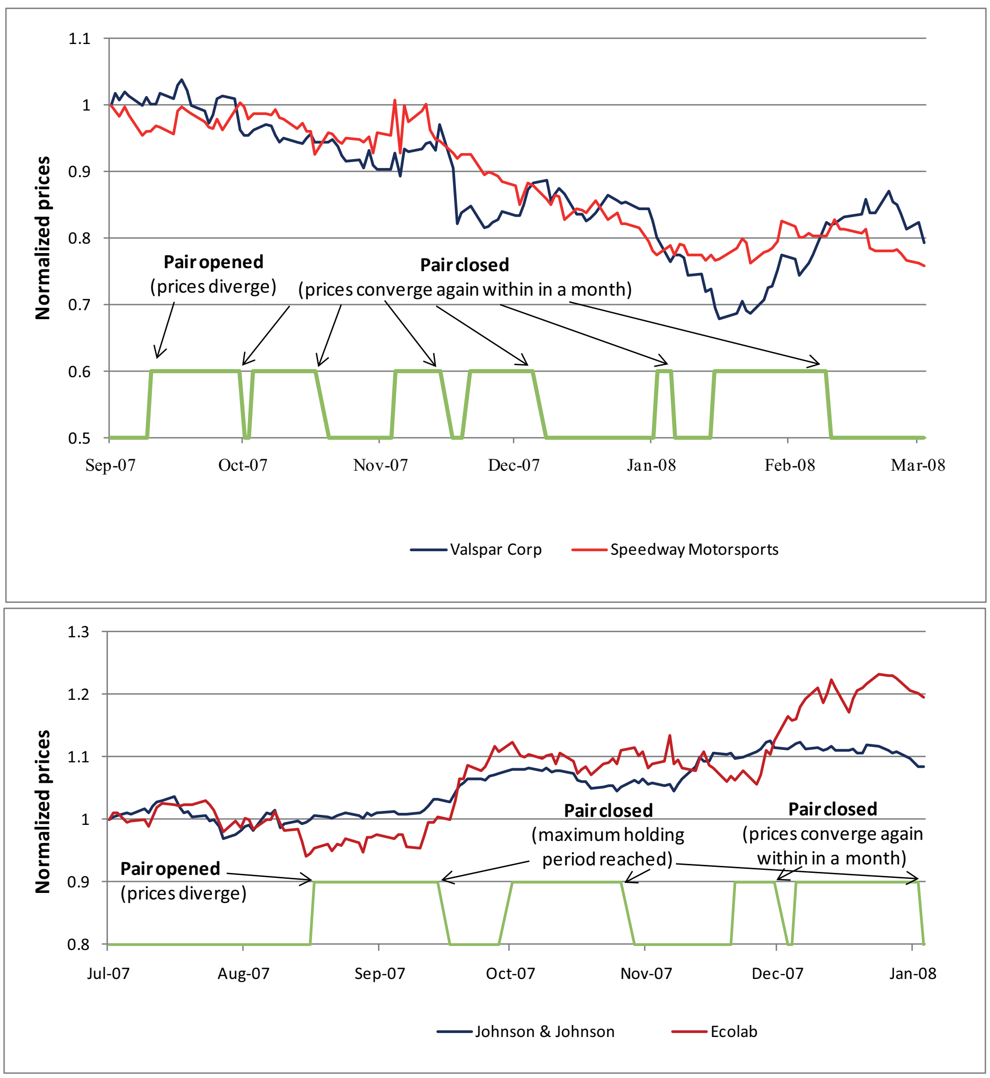

Figure 2: Distribution of event-time returns on U.S. stock pairs diverging on a given day

For each trading day between January 1962 and December 2008 during which at least one pair diverges, we compute the average one-month event-time return (in %). The graph shows the distribution of these average returns. A pair is opened if the spread between the cumulative return series of the pair constituents exceeds two historical standard deviations, as measured during the pair formation period. Trading positions in each pair are initiated on the day following the divergence and liquidated on the day following convergence or after one month has passed, respectively. The figure is based on 103,386 round-trip trades.

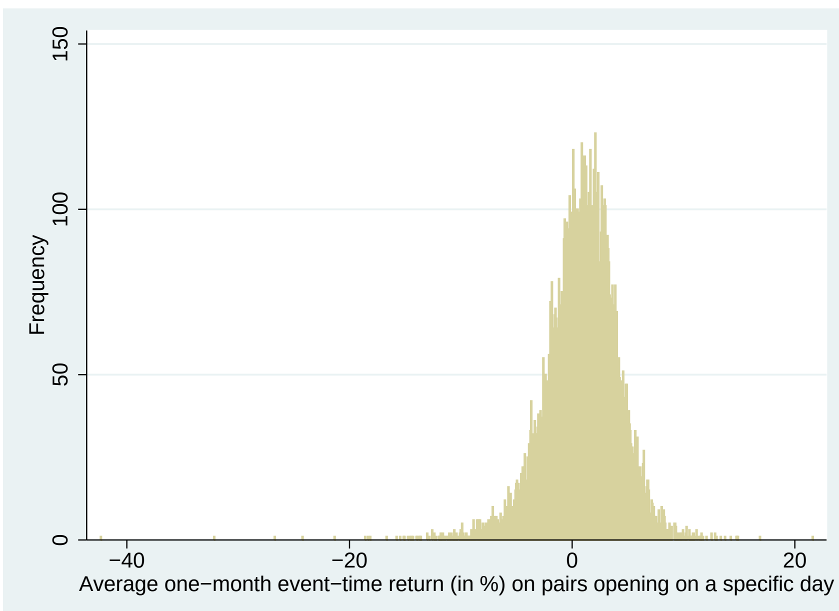

Figure 3: Probability of convergence and average daily return by event day

This graph shows the empirical probability of U.S. stock pairs converging on a given event day after divergence (marked in black) as well as the average daily return of open pairs in event time (marked in light grey). The figure is based on 103,386 round-trip trades between January 1962 and December 2008.

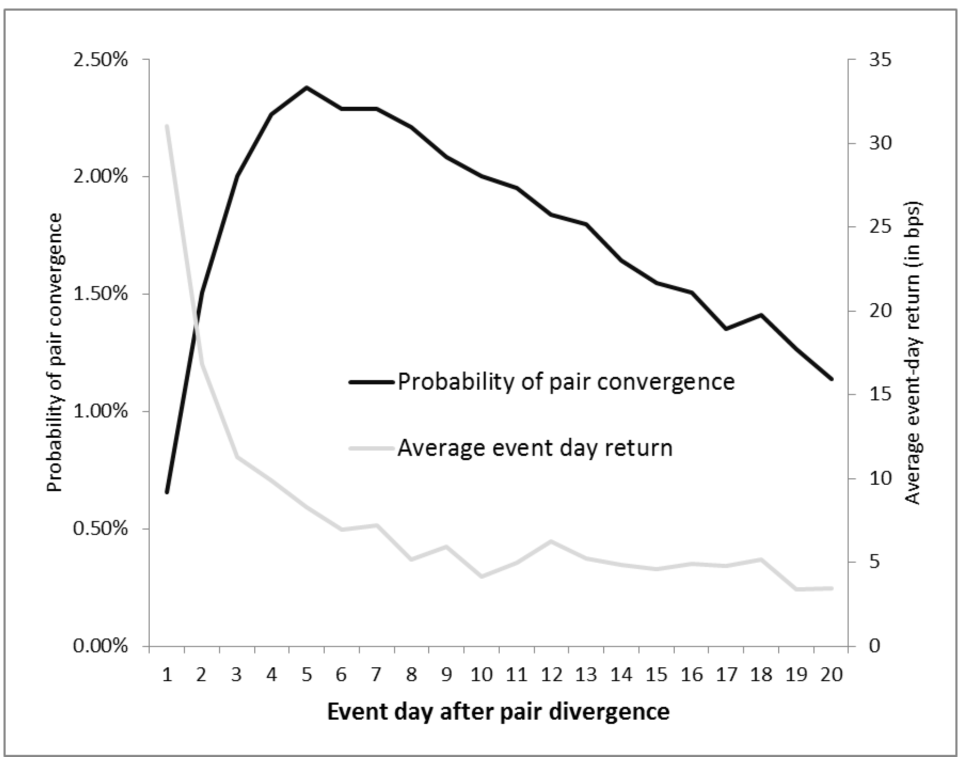

Table 1: Pairs trading: international evidence.

This table reports the main results from an analysis of pairs trading profitability in 34 international stock markets. A pair is opened if the spread between the cumulative return series of the pair constituents exceeds two historical standard deviations, as measured during the pair formation period. Trading positions in each pair are initiated on the day following the divergence and liquidated on the day following convergence or after one month has passed, respectively. In Panel A, the *emerging market dummy* is one if the country under consideration was at any point in time during the sample period a member of the MSCI Emerging Markets Index, and zero otherwise. The *large market dummy* is one (zero) for countries for which the average monthly number of eligible pairs, as indicated in Column (6), is above (below) the median. *% of convergence* refers to the percentage of trades of the monthly top 100 pairs which converge within one month after divergence. Country groups in Panel B are defined based on the classification displayed in Columns (2) and (3). In the case of event-time returns (Column (8)), t-statistics (in parentheses) are adjusted for heteroscedasticity and clustered by day of pair divergence. In the case of calendar-time returns (Column (10)), t-statistics (in parentheses) are based on Newey and West (1987) standard errors with six lags. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Analysis for individual countries										
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Country name	Emerging market dummy	Large market dummy	Sample period	Average monthly pairs in 1,000	Total trades (top 100 pairs)	% of convergence	One month long/short event-time return	T-stat	Three-factor alpha	T-stat
Australia	0	1	2000-2013	24.04	22,991	30.3%	1.100%***	(16.38)	1.356%***	(10.44)
Austria	0	0	2000-2013	0.51	15,057	14.0%	-0.168%	(-0.88)	-0.568%	(-1.39)
Belgium	0	0	2000-2013	1.41	18,252	21.0%	0.763%***	(7.80)	0.705%***	(4.01)
Brazil	1	1	2000-2013	3.61	12,016	24.5%	1.320%***	(9.19)	1.041%**	(2.03)
Canada	0	1	2000-2013	35.30	23,255	28.7%	1.205%***	(17.99)	1.530%***	(6.01)
Chile	1	0	2000-2013	1.24	18,354	19.7%	0.852%***	(8.66)	0.846%***	(4.19)
China	1	1	2000-2013	266.97	23,578	35.1%	0.665%***	(6.30)	0.261%	(1.28)
Denmark	0	0	2000-2013	0.98	15,458	14.7%	0.323%**	(2.36)	0.206%	(0.79)
Finland	0	0	2000-2013	1.19	17,667	17.8%	0.746%***	(6.83)	0.388%*	(1.76)
France	0	1	2000-2013	20.52	23,767	28.2%	0.785%***	(10.83)	0.903%***	(5.68)
Germany	0	1	2000-2013	12.19	21,929	26.2%	0.685%***	(7.60)	0.508%**	(2.17)

[continued overleaf]

(1) Country name	(2) Emerging market dummy	(3) Large market dummy	(4) Sample period	(5) Average monthly pairs in 1,000	(6) Total trades (top 100 pairs)	(7) % of convergence	(8) One month long/short event-time return	(9) T-stat	(10) Three-factor alpha	(11) T-stat
Greece	1	0	2000-2013	1.51	15,603	20.7%	0.566%***	(3.58)	0.608%*	(1.81)
Hongkong	0	0	2000-2013	3.58	20,613	23.2%	0.876%***	(8.43)	0.588%**	(2.24)
India	1	1	2000-2013	39.26	21,801	28.9%	0.837%***	(5.94)	0.828%***	(3.39)
Ireland	0	0	2005-2013	0.25	7,403	14.0%	1.163%**	(2.47)	0.792%	(1.40)
Israel	1	0	2000-2013	1.54	17,661	22.1%	1.655%***	(17.13)	1.561%***	(7.40)
Italy	0	1	2000-2013	7.83	22,108	26.6%	0.498%***	(5.92)	0.429%**	(2.44)
Japan	0	1	2000-2013	656.63	27,868	38.1%	0.514%***	(8.44)	0.707%***	(3.03)
Korea	1	1	2000-2013	20.60	22,851	31.9%	1.200%***	(7.46)	1.599%***	(3.40)
Malaysia	1	1	2000-2013	6.40	19,395	23.3%	0.475%***	(5.44)	0.447%**	(2.16)
Mexico	1	0	2000-2013	1.00	17,261	18.3%	0.822%***	(5.08)	0.851%**	(2.15)
Netherlanda	0	0	2000-2013	2.51	19,134	20.4%	0.656%***	(6.54)	0.587%**	(2.48)
Norway	0	0	2000-2013	1.22	15,603	17.4%	0.364%**	(2.47)	0.035%	(0.13)
Poland	1	0	2004-2013	1.32	11,637	18.2%	0.334%**	(2.23)	-0.178%	(-0.60)
Portugal	0	0	2000-2011	0.25	9,624	12.8%	0.394%**	(2.09)	-0.071%	(-0.18)
Singapore	0	1	2000-2013	5.05	20,054	23.1%	0.676%***	(5.64)	0.656%**	(2.42)
South Africa	1	1	2000-2013	5.19	22,300	31.4%	1.881%***	(23.57)	2.348%***	(10.82)
Spain	0	0	2000-2013	2.99	19,808	21.4%	0.173%*	(1.80)	-0.040%	(-0.17)
Sweden	0	1	2000-2013	4.26	20,179	22.9%	0.950%***	(10.56)	1.043%***	(5.11)
Switzerland	0	1	2000-2013	7.89	18,124	23.4%	0.336%***	(5.45)	0.416%***	(3.09)
Taiwan	1	1	2000-2013	36.83	21,740	26.6%	-0.058%	(-0.54)	-0.089%	(-0.32)
Thailand	1	0	2000-2013	2.92	17,024	19.2%	0.081%	(0.62)	-0.400%	(-1.53)
Turkey	1	0	2000-2013	2.77	17,885	23.3%	0.707%***	(4.09)	0.721%	(1.27)
UK	0	1	2000-2013	74.87	24,454	29.2%	0.669%***	(8.99)	0.703%***	(4.61)

Panel B: Analysis for country groups

(1) Country group	(2) Emerging market dummy	(3) Large market dummy	(4) Sample period	(5) Average monthly pairs in 1,000	(6) Total trades (top 100 pairs)	(7) % of convergence	(8) One month long/short event-time return	(9) T-stat	(10) Three-factor alpha	(11) T-stat
Large	0/1	1	2000-2013	72.20	368,410	28.6%	0.800%***	(27.65)	1.061%***	(9.43)
Small	0/1	0	2000-2013	1.60	274,044	19.2%	0.611%***	(13.54)	0.606%***	(5.36)
Diff						9.34%***	0.188%***	(4.28)	0.455%***	(3.99)
Emerging	0	0/1	2000-2013	27.94	259,106	25.3%	0.822%***	(19.70)	1.014%***	(8.34)
Developed	1	0/1	2000-2013	43.17	383,348	24.1%	0.650%***	(20.07)	0.746%***	(6.90)
Diff						1.18%***	0.172%***	(3.97)	0.268%**	(2.32)
Large/emerging	1	1	2000-2013	54.12	143,681	29.3%	0.885%***	(17.49)	1.192%***	(8.04)
Small/emerging	1	0	2000-2013	1.76	115,425	20.3%***	0.743%***	(12.60)	0.759%***	(4.27)
Large/developed	0	1	2000-2013	84.86	224,729	28.1%***	0.745%***	(24.88)	0.929%***	(7.55)
Small/developed	0	0	2000-2013	1.49	158,619	18.5%***	0.515%***	(9.43)	0.558%***	(4.28)

Table 2: Pairs trading: cross-country determinants of profitability.

This table reports the main results from cross-country Fama and MacBeth (1973) regressions. The dependent variable is the pooled benchmark-adjusted abnormal return in month t, which is defined as the sum of the alpha and the fitted value of the residual obtained from regressing pairs trading returns on a country-specific Fama and French (1993) three-factor model. The sample period is January 2000 to December 2013. The *emerging markets dummy* is based on the monthly MSCI classification. The *number of eligible stocks* refers to the number of stocks that survive all data screens as outlined in section 2.1. The data on *stock market capitalization/GDP* are taken from the World Bank. The *short selling dummy* is one (zero) if short-selling is (not) allowed. Data is taken from Charoenrook and Daouk (2005). Yearly data on *strength of auditing and reporting standards* are taken from the Global Competitiveness Report. T-statistics (in parentheses) are based on Newey and West (1987) standard errors with six lags. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Variable / Model specification	(1)	(2)	(3)	(4)	(5)	(6)
Emerging markets dummy in t	0.192*				0.237**	0.403***
	(1.85)				(2.01)	(2.99)
Ln (Number of eligible stocks in t)	0.150***				0.032	0.045
	(2.66)				(0.45)	(0.65)
Ln (Average market cap of top 100 pairs in t)		-0.208**	0.032	-0.135	-0.043	-0.202**
		(-2.36)	(0.32)	(-1.22)	(-0.38)	(-1.99)
Average industry market share of top 100 pairs in t		-0.684**		-0.411	-0.428	-0.376
		(-1.99)		(-1.14)	(-0.85)	(-0.74)
Stock market capitalization / GDP in a given year		0.195***		0.170***	0.178***	0.282***
		(2.86)		(2.62)	(2.86)	(4.04)
Ln (Average Amihud (2002) illiquidity in t)			0.001	0.014	0.010	-0.001
			(0.05)	(0.72)	(0.46)	(-0.05)
Short selling dummy			-0.169	-0.054	0.036	-0.29
			(-1.17)	(-0.36)	(0.23)	(-1.38)
Ln (Average idiosyncratic volatility in t)			0.595***	0.505**	0.246	0.683***
			(3.04)	(2.57)	(1.41)	(2.86)
Strength of auditing and reporting standards						-0.12
						(-0.83)
Individualism						0.010***
						(4.00)
Ln(Average market model R^2)						-0.510***
						(-2.96)
Average adjusted R^2	0.01	0.01	0.01	0.02	0.03	0.04
N	168	168	168	168	168	168

Table 3: Descriptive statistics for U.S. stock and pair characteristics.

In Panel A, the *Amihud illiquidity ratio* is computed as the average of a stock's absolute daily return divided by its total daily trading volume in millions of dollars. The estimation period for the illiquidity ratio, for average daily turnover as well as for idiosyncratic risk is the twelve-month period ending at the beginning of a pair's trading period. *Idiosyncratic risk* is computed as the standard deviation of the residual obtained from time series regressions of a stock's daily return on factors for the market premium, size, value and momentum. *Maximum industry weight* denotes the largest fraction of sample firms belonging to a specific industry group (out of the 49 Fama/French industries). *Industry concentration* is computed as the sum of squared industry weights. Panel B reports within-pair differences of stock characteristics.

Panel A: Firm characteristics		
NYSE/AMEX macap decile	Mean	8.86
	Median	9
Amihud illiquidity ratio	Mean	0.06
	Median	0.01
Average daily turnover	Mean	0.16%
	Median	0.11%
Idiosyncratic risk	Mean	1.12%
	Median	1.06%
Turnover on day of divergence	Mean	0.25%
	Median	0.08%
Bid-ask spread on day of divergence	Mean	0.44%
	Median	0.32%
No. industry groups		49
Maximum industry weight	Fraction	29.14%
	Industry	Utilities
Industry concentration		0.11
S&P 500 dummy		0.54
Panel B: Pair characteristics		
Macap decile difference	Mean	1.25
	Median	1
Amihud illiquidity ratio difference	Mean	0.06
	Median	0.01
Average daily turnover difference	Mean	0.072%
	Median	0.040%
Idiosyncratic risk difference	Mean	0.248%
	Median	0.20%
Turnover difference on day of divergence	Mean	0.23%
	Median	0.08%
Bid-ask spread difference on day of divergence	Mean	0.62%
	Median	0.43%
Cumulative price difference upon divergence	Mean	6.68%
	Median	6.28%
Return difference at day of divergence	Mean	2.84%
	Median	2.29%
No. industry group combinations		931
Maximum industry group weight	Fraction	15.89%
	Industries	Utilities/Communication
Industry group concentration		0.04
S&P 500 dummy difference		0.44
No. round-trip trades		103,386

Table 4: Pairs trading: U.S. evidence.

This table shows the profitability of pairs trading in the U.S. stock market. Panel A focuses on event-time one-month returns. A pair is opened if the spread between the cumulative return series of the pair constituents exceeds two historical standard deviations, as measured during the pair formation period. Trading positions in each pair are initiated on the day following the divergence and liquidated on the day following convergence or after one month has passed, respectively. Panel B focuses on calendar-time. In the case of event-time returns (Panel A), standard errors are adjusted for heteroscedasticity and clustered by day of pair divergence. In the case of calendar-time returns (Panel B), t-statistics (in parentheses) are based on Newey and West (1987) standard errors with six lags. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Pairs trading profitability in event-time (Jan 1962 to Dec 2008)			
N	103,386	% of convergence	36.2%
Mean return	0.97%***	$(Ret.\|convergence)$	6.38%***
	(30.41)	$(Ret.\|no\ convergence)$	-2.09%***
P1	-17.83%	P90	8.21%
P10	-7.04%	P99	15.19%
P25	-2.73%	SD	6.57%
P50	1.59%	Skewness	-0.78
P75	5.23%	Kurtosis	7.33

Panel B: Pairs trading profitability in calendar-time			
Specification	Model 1	Model 2	Model 3
Sample start	Jan 1962	Jan 1962	Jan 1968
Sample end	Dec 2008	Dec 2008	Dec 2008
N	564	564	492
Adjusted R^2	0.00	0.13	0.13
Market factor	0.03	-0.01	-0.00
	(1.18)	(-0.49)	(-0.06)
Size factor	0.03	-0.01	-0.00
	(0.91)	(-0.41)	(-0.04)
Value factor	0.04	-0.05	-0.03
	(0.84)	(-1.53)	(-0.73)
Momentum factor		-0.10***	-0.09***
		(-3.42)	(-3.22)
Short term reversal factor		0.16***	0.15***
		(3.64)	(3.39)
Long term reversal factor		0.11**	0.11**
		(2.31)	(2.18)
Liquidity factor			-0.05*
			(-1.81)
Alpha	1.29%***	1.31%***	1.32%***
	(9.75)	(10.28)	(9.52)

Table 5: Robustness checks and cross-sectional determinants of pairs trading profitability.

Panel A shows subperiod results of our baseline event-time analysis (see Panel A of Table 4). It also displays findings if we change the eligible firm universe in various ways. Panel B shows event-time results when conditioning on subsamples of pairs. The tests on newswire coverage (number of *articles*) and *analyst* coverage start in 1991. Both variables are orthogonalized with respect to firm size. All other tests in Panel A and B are based on daily data from January 1962 to December 2008. The computation of *bid-ask spreads* follows Corwin and Schultz (2012). *Liquidity* is estimated as in Amihud (2002). *(Industry) market share* is computed as a firm's relative market capitalization within the 49 Fama and French (1997) industry classification scheme. T-statistics (in parentheses) are adjusted for heteroscedasticity and clustered by day of pair divergence. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Robustness checks					
Subperiod 1962-1977	Subperiod 1978-1993	Subperiod 1994-2008	Excluding utilities	Only different firms	Only same industry
1.49%***	1.09%***	0.24%***	1.02%***	1.08%***	1.39%***
(29.16)	(20.64)	(4.01)	(32.87)	(37.24)	(48.76)

Panel B: Cross-sectional determinants of pairs trading profitability					
Limits to arbitrage			Pair visibility		
High idio vola	Low idio vola	Difference	Few articles	Many articles	Difference
1.17%***	0.74%***	0.43%***	0.73%***	0.06%	0.67%**
(18.22)	(12.82)	(5.12)	(5.32)	(0.23)	(2.36)
High bid-ask	Low bid-ask	Difference	Few analysts	Many analysts	Difference
1.09%***	1.05%***	0.04%	0.47%***	0.06%	0.41%*
(18.70)	(17.49)	(0.56)	(3.14)	(0.32)	(1.76)
Small firms	Large firms	Difference	Low sales	High sales	Difference
1.00%***	0.89%***	0.11%	1.04%***	0.73%***	0.31%***
(16.62)	(17.22)	(1.41)	(15.43)	(11.98)	(3.50)
Low liquidity	High liquidity	Difference	Low market share	High market share	Difference
1.06%***	0.87%***	0.19%**	1.16%***	0.82%***	0.34%***
(17.92)	(16.54)	(2.49)	(18.81)	(14.40)	(4.26)

Table 6: Firm-specific vs. common shocks and pairs trading profitability.

This table shows the profitability of pairs trading in the U.S. stock market depending on the type of news observable on the date of divergence. For each type of news, we construct a *news dummy* which is one (zero) if a news event does (does not) take place. In Panels B to D, the multivariate specifications control for calendar effects (indicator variables for year, month, and day of week), market-level conditions on the day of divergence (market return, squared market return, market turnover, factors for daily return premia on size, value, momentum and short-term reversal) as well as firm and pair characteristics as outlined in Table 3. In Panel C, the *common vs. individual new dummy* is one (zero) if there is at least one macroeconomic shock but no firm-specific shock (at least one firm-specific shock but no macroeconomic shock). In Panel D, we rerun the analysis from Panel C but additionally perform a median split based on pair characteristics. T-statistics (in parentheses) are adjusted for heteroscedasticity and clustered by day of pair divergence. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Different types of news and pairs trading profitability: univariate estimates				
Event type	Earnings news	Dividend news	Newswire articles	Macroeconomic news
Sample period	1971-2008	1962-2008	1980-2000	1964-2008
N	80,701	103,386	45,871	99,955
Adjusted R^2	0.00	0.00	0.00	0.00
Univariate: News dummy	-0.80%***	-0.26%*	-0.36%**	0.09%
	(-5.20)	(-1.80)	(-2.26)	(0.86)
Univariate: Constant	0.88%***	0.98%***	0.80%***	0.97%***
	(23.03)	(30.07)	(15.81)	(27.46)
Panel B: Different types of news and pairs trading profitability: multivariate estimates				
N	80,701	103,386	45,871	99,955
Adjusted R^2	0.02	0.02	0.02	0.02
Multivariate: News dummy	-0.53%***	-0.22%	-0.13%	0.19%*
	(-3.36)	(-1.52)	(-0.84)	(1.79)

Panel C: Common vs. firm-specific news (1964-2008)		
	Univariate	Multivariate
N	19,207	19,207
Adjusted R^2	0.00	0.02
Common vs. individual news dummy	0.65%***	0.45%***
	(4.61)	(2.81)

Panel D: Pair characteristics and common vs. firm-specific news				
	Low common analyst coverage (N=5,556)		High common analyst coverage (N=6,274)	
	Univariate	Multivariate	Univariate	Multivariate
Common vs. individual news dummy	0.61%**	0.63%*	0.23%	-0.15%
	(2.21)	(1.86)	(1.09)	(-0.61)
	High idiosyncratic volatility (N=9,397)		Low idiosyncratic volatility (N=9,810)	
	Univariate	Multivariate	Univariate	Multivariate
Common vs. individual news dummy	0.72%***	0.65%**	0.55%***	0.32%*
	(3.25)	(2.46)	(3.36)	(1.72)
	High analyst forecast dispersion (N=5,509)		Low analyst forecast dispersion (N=6,550)	
	Univariate	Multivariate	Univariate	Multivariate
Common vs. individual news dummy	0.72%***	0.69%**	0.57%***	0.35%
	(2.87)	(2.41)	(2.73)	(1.40)

Table 7: Time-varying investor attention and pairs trading profitability.

In Panel A, limited attention dummies are constructed in a way that they take on a value of 1 if investors are assumed to be distracted and 0 otherwise. The sample period for the test based on Google/Vix/Absolute sentiment is 2004-2008/1990-2008/1965-2008. The multivariate specifications control for calendar and industry effects, market-level conditions on the day of divergence (see Table 5) as well as firm and pair characteristics as indicated in Table 3. In all cases, standard errors are adjusted for heteroscedasticity and clustered by day of pair divergence. T-statistics are reported in parentheses. Panel B shows the interaction effect of the limited attention dummies with selected dummy-based cross-sectional pair characteristics (see Table 5). In Panel C, we compare mean and median returns of pairs opening on the last trading day before federal holidays with mean and median returns of pairs opening on any other trading day of the year. The table shows the fraction of years in which returns on pre-holiday pairs trading are higher. T-statistics (in parentheses) are adjusted for heteroscedasticity and clustered by day of pair divergence. In all panels, statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Impact of limited attention proxies inspired by previous work							
Model specification	Fridays	No. pairs opening	NBER recessions	3Y market return	Google	VIX	Abs. sentiment
N	103,386	53,274	103,386	103,386	4,067	16,507	96,315
Univariate	0.02	0.38***	0.90***	0.55***	0.52*	0.75***	0.97***
	(0.21)	(3.83)	(8.99)	(5.51)	(1.74)	(4.71)	(12.05)
Multivariate	0.03	0.11	0.59***	0.25	0.44	0.60***	0.60***
	(0.30)	(1.04)	(3.32)	(1.49)	(1.59)	(3.50)	(3.60)
Adjusted R^2	0.03	0.03	0.03	0.03	0.02	0.05	0.03
Panel B: Interaction terms with pair characteristics of Table 5 (multivariate regressions only)							
Model specification	Fridays	No. pairs opening	NBER recessions	3Y market return	Google	VIX	Abs. sentiment
Pairs with high idio vola	-0.21	0.09	0.68**	0.45*	0.58	-0.11	0.04
Pairs with low market share	-0.12	0.96***	0.67***	0.02	0.04	-0.10	0.57***
Panel C: Relative success of pre-holiday pairs trading							
	New Year's Day	Washington's Birthday	Memorial Day	Independence Day	Labor Day	Thanksgiving	Christmas Day
Mean	72%***	61%*	47%	51%	60%	61%*	70%***
Median	70%***	46%	45%	53%	60%	55%	63%
Excess probability of convergence	15.77%***	-0.48%	3.87%	5.61%	3.87%	0.42%	7.39%*
(Baseline: 36.15%-36.3%)	(3.67)	(-0.14)	(0.94)	(1.35)	(1.14)	(0.10)	(1.68)

Table 8: Pairs trading and time-varying limits to arbitrage.

This table explores the impact of arbitrage constraints (as measured on the day of divergence) on event-time one-month pairs trading returns. The multivariate specifications control for calendar and industry effects, market-level conditions on the day of divergence (see Table 5) as well as firm and pair characteristics as indicated in Table 3. To ease interpretation, all proxies in Panel A are standardized to have zero mean and unit variance. In Panel B, we focus on within year variation in the arbitrage constraints rather than on variation during the overall sample period. For each year separately, we sort the daily level of the six individual proxies into quintiles. We then compute a dummy variable which is one (zero) for the top (bottom) quintile and therefore quantifies days with high (low) limits to arbitrage. T-statistics (in parentheses) are adjusted for heteroscedasticity and clustered by day of pair divergence. Statistical significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel A: Raw level of proxies for time-varying arbitrage constraints								
	VIX	Bid-ask spread	Moody's spread	Libor	TED spread	Hu et al. (2013) measure	Hasbrouck (2009) measure	First principal component
Sample period	1990-2008	1962-2008	1986-2008	1986-2008	1986-2008	1987-2008	1962-2005	1990-2005
N	39,537	103,386	48,333	48,333	48,333	43,048	96,680	32,405
Univariate	0.24***	0.30***	0.31***	0.08*	0.27***	0.22***	0.33***	0.24***
	(3.49)	(4.51)	(4.88)	(1.72)	(4.13)	(3.32)	(5.86)	(3.95)
Multivariate	0.36***	0.66***	0.28**	0.23	0.47***	-0.00	0.22***	0.41***
	(3.44)	(4.51)	(2.39)	(1.15)	(4.55)	(-0.02)	(4.29)	(3.63)
Adjusted R^2	0.02	0.03	0.03	0.03	0.03	0.03	0.03	0.03
Panel B: Yearly quintile sorts of proxies for time-varying arbitrage constraints								
	VIX	Bid-ask spread	Moody's spread	Libor	TED spread	Hu et al. (2013) measure	Hasbrouck (2009) measure	Aggregate measure
Sample period	1990-2008	1962-2008	1986-2008	1986-2008	1986-2008	1987-2008	1962-2005	1962-2008
N	16,507	43,048	20,093	20,716	19,423	18,130	39,945	80,905
Univariate	0.75***	0.45***	0.51***	0.13	0.63***	0.20	0.62***	0.68***
	(4.71)	(4.37)	(3.45)	(0.87)	(4.23)	(1.29)	(5.88)	(7.89)
Multivariate	0.60***	0.36***	0.51***	0.23	0.43**	0.02	0.45***	0.52***
	(3.50)	(3.60)	(3.37)	(1.57)	(2.52)	(0.11)	(4.23)	(6.16)
Adjusted R^2	0.05	0.04	0.04	0.05	0.04	0.04	0.04	0.04