# Understanding the Profitability of Pairs Trading


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This Version February 15, 2005*


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**Keywords:** Asset pricing, return predictability, limits of arbitrage

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# 1 Introduction

This paper studies the profitability of pair trading. Since the mid-1980s such strategies have constituted a rather secretive and lucrative part of Wall Street activity. Pairs trading is a type of relative value strategy that buys an overpriced security and simultaneously sells a similar, underpriced security. Traders typically track a pair of securities whose prices move together. When prices diverge, they buy the down stock and simultaneously sell the up stock. Traders profit if prices converge but lose money if prices diverge further. Pairs trading has generated hundreds of millions of dollars in profits for companies such as Morgan Stanley and D.E. Shaw.

Studying pairs trading broadens our understanding of financial markets. Because pairs trading entails risk taking, one can think of our paper as speaking to the limits of arbitrage in actual financial markets. Profits need not be thought of as coming from a narrow Wall St. strategy. Rather, readers can think of these arbitrageurs as playing a vital role in the relative pricing of securities. Profits are compensation for performing this service. Equivalently, readers can think of profits as compensation for providing liquidity during times of differential market stress (e.g., stresses that affect some stocks but not others.) A goal of this paper is to understand why prices of similar securities diverge. Since pairs trading strategies are currently being employed in stock markets around the world, we choose this framework for studying price divergence. Measuring pairs trading profits represents a succinct way to quantify the costs of liquidity provision (i.e., the costs of keeping relative prices in line.)

Surprisingly, relative value strategies have received little attention in the academic literature. The most notable paper is by Gatev, Goetzmann, and Rouwenhorst (2003) and offers a comprehensive analysis.[1] The authors use daily US data from 1962 to 2002. They show a simple pairs trading rule produces excess returns of 11% per annum. Returns have high risk-adjusted alphas, low exposure to known sources of systematic risk, cover reasonable transaction costs, and do not come from short-term return reversals as documented in Lehmann (1990). GGR (2003) interpret pairs trading profits as pointing towards a "systematic *dormant* factor" relating to "the agency costs of professional arbitrage."

We conjecture that uninformed trading shocks can explain the profitability of pairs trading. We would like to carry out our study with CRSP data. Unfortunately, one cannot identify aggregate uninformed shocks on the NYSE due to order routing decisions. For example, one might think that aggregate individual investor order flow is a good proxy for uninformed demand. However,

[1] As of 2-Feb-2005, the paper has been downloaded 7,533 times from SSRN. Hereafter we refer to it as GGR (2003). Other work on pairs trading includes Richards (1999) and Nath (2003).

brokers filter such orders so that uninformed orders are likely to go to regional exchanges while other orders get sent to the NYSE. Luckily, institutional features of the Taiwan Stock Exchange allow us to identify a large pool of uninformed buys and sells.

Our contribution to the literature is twofold. First, we provide an out-of-sample test of the pairs-trading strategy described in GGR (2003). Using daily Taiwanese data from 1994 to 2002, we find excess returns of 10.18% per annum. The returns are statistically significant at all conventional levels and annualized Sharpe ratios are greater than one. Furthermore, the returns cannot be explained by exposure to known sources of systematic risk. Therefore, our results provide additional support regarding the profitability of relative value strategies. Again, this profitability can be thought of as compensation for keeping prices in line.

Second, and much more importantly, we link uninformed trading shocks to the profitability of pairs-trading. Such a link is, to our knowledge, new. We show that uninformed net buying is significantly correlated with a pair's initial price divergence. Additionally, we show that uninformed trading is a significant "factor" in explaining the strategy's marked-to-market returns. These results suggest that pairs-trading strategies are profitable because they identify situations with temporary price pressure. The strategy has low risk because a position is effectively hedged by an offsetting position with similar factor loadings. Execution is simplified and costs kept to a minimum because the offsetting position is limited to a single stock.

## 2 Pairs Trading in Taiwan

We collect daily stock prices, returns, and share information at the individual stock level. Data contain all listed stocks on the Taiwan Stock Exchange. Data are available from a number of vendors including the Taiwan Economic Journal (the "TEJ".) The TEJ adjusts daily returns for capital changes. The full sample contains information on 647 different listed companies in Taiwan. Our sample period begins 5-Jan-1994 and ends 29-Aug-2002. Thus, the sample consists of 2,360 holding/trading days.

We follow the same pairs trading strategy described in GGR (2003). By doing so, our results remain free from data snooping biases, and constitute an out-of-sample test of their results. The strategy calls for observing stock price movements over a one year "formation period."[2] At the end of the formation period, pairs of stocks are ranked based on co-movement or "closeness" measures. The two stocks with the highest degree of co-movement are called the "first pair," the next two

[2]Throughout this paper, we define one year to be 250 trading days and half a year to be 125 trading days. These numbers remain constant during our entire study.

stocks are called the "second pair", and so on. In a market with 500 listed stocks, one must rank 124,750 different pair combinations. We refer to the two stocks in a pair as Stock A and Stock B. Designations "A" and "B" are arbitrary since the strategy can later buy or sell either stock.

After forming the twenty closest pairs, we engage in a six month "trading period." The trading strategy consists of three basic rules: 1) follow the a pair of stocks until prices diverge by a certain amount called the "trigger value"; 2) at the time prices diverge, sell the up stock in a pair and buy the down stock in the same pair; and 3) wait until prices re-converge to close-out a position. At the end of the six month trading period all open positions are closed out (possibly at a loss.) A detailed description of the methodology is given in Appendix A.

During the trading period a pair of stocks can be in one of three states: i) not open; ii) short A and long B; or iii) long A and short B. We define a tri-state indicator function to reflect these three possibilities:

$$I_t^{AB} \equiv \begin{array}{rc} 0 & \text{not open} \\ +1 & \text{short A; long B} \\ -1 & \text{long A; short B} \end{array} \tag{1}$$

The excess return to a given pair position (consisting of Stock A and Stock B) is:

$$r_t^{AB} = I_t^{AB} \cdot \left( r_t^B - r_t^A \right) \tag{2}$$

Note that a pair's excess return is zero whenever the position is closed since $I_t^{AB} = 0$ as indicated in Equations (1) and (2). Over one day the portfolio excess return to following twenty pairs is:

$$r_t^{port} = \frac{1}{20} \sum_{pair=1}^{20} r_t^{AB,pair} \tag{3}$$

We repeat the strategy every half year during our sample and end with a series of non-overlapping returns (returns only come from the six month trading periods.) Figure 1 shows the timing of the formation and trading periods. We have sixteen trading periods in our study for a total of 2,000 trading days. Table 1, Panel A gives descriptive statistics of the data and timing of our pairs trading strategy.

## 2.1 A pairs trading example

We provide an example of the pairs trading strategy. Figure 2 shows the normalized prices for two stocks during the formation period. Readers who are skeptical that we picked a particularly "nice" picture can rest assured. Figure 2 shows the "first pair" from the first formation period. The normalized price series tend to move together and both stocks lost approximately 10% during this particular formation period.

Over the trading period, the stocks continue to move together most of the time—see Figure 3, Panel A.[3] However, their normalized price series do diverge by more than the trigger value on four occasions—see Figure 3, Panel B. Notice that the first two times prices diverge, Stock B price is above Stock A price $\left(I_t^{AB} = -1\right)$. A pairs trading strategy calls for buying Stock A and selling Stock B. The second two times prices diverge, Stock A price is above Stock B price $\left(I_t^{AB} = +1\right)$. Therefore, the strategy takes the opposite positions. Finally, notice that the fourth position is not closed due to normalized prices re-converging, but rather by the trading period ending. Being left with an open position is a risk that finite-horizon arbitrageurs face.

Figure 3, Panel C shows the cumulative profit associated with this particular pair. There are flat (no profit) periods when the pair's position is not open (i.e., when $I_t^{AB} = 0$.) The strategy for this particular pair during this particular trading period earns an excess return of 22.29% over six-months.

## 2.2 Overview statistics

Table 1 gives overview statistics of our pairs trading strategy. In Panel B we see that positions are open 70.34% of the possible stock-days. We follow 20 pairs for 16 half-year periods, of which only five pairs never open. The average pair opens 2.29 times during its half-year trading period. Panel C shows a single pair earns 3.879 bp per day on average.[4] Since our portfolio is simply an equally weighted average of the twenty constituent pairs, 3.879 bp is the daily portfolio return as well. The Sharpe ratio of our strategy is much higher than the realized Sharpe ratio of the Taiwanese stock market over the same period.

## 2.3 Profitability and risk-adjusted returns

We show the pairs trading profits in Taiwan are not coming from exposure to known sources of systematic risk. We regress the time series of pairs trading profits on excess market returns, Fama-French factors, and a momentum factor.

$$r_t^{port} = \alpha + \beta_1 \left(r_t^{mkt} - r_t^f\right) + \beta_2 \left(SMB_t\right) + \beta_3 \left(HML_t\right) + \beta_4 \left(MOM_t\right) + \varepsilon_{p,t} \tag{4}$$

[3] This example continues to consider the first pair of stocks from the first trading period.

[4] Each day a position is actually open it earns 5.515bp on average ($3.879 \div 0.7034 = 5.515$).

Table 2, Regression 1 shows the pairs trading portfolio earns 3.876bp per day or 10.18% annualized returns. The risk adjusted returns in Regressions 2 and 3 range between 2.612bp (6.75% per annum) to 3.886bp (10.20% per annum). While the returns load significantly on the market and $HML_t$ in Regression 3, the magnitudes are economically insignificant. The insignificant loading on $MOM_t$ is comforting because one might worry that slow price adjustment in a market like Taiwan is driving our results. Regression 3 shows this is not the case.

Our results from Taiwan compare very favorably to results in GGR (2003) from the United States. We find annualized excess returns of 10.18% and they find 11.28% annualized excess returns. They report an average of 19.30 pairs traded (in the top 20.) We show that five pairs never open which equals an average of 19.69 pairs traded. They report an average of 1.96 round-trips per pair; we report 2.29 round-trips per pair.[5]

At this point, it is logical to address the numerous questions a reader might have regarding the returns to the pairs trading strategy. Given that our results are so similar to those in GGR (2003) we refer readers to the earlier work. GGR (2003) provides a very thorough investigation into possible explanations of pairs trading profits. The authors detail the value-at-risk of the trading strategy, the returns of randomly matched pairs, industry effects, a breakdown of long/short components, and the effect of short selling costs.[6]

Industry practitioners already engage in pairs trading in Taiwan. This fact provides additional support of the strategy's economic significance and viability. A Merrill Lynch report by Chang et. al. (2001) outlines a pairs trading strategy that is very similar to ours.[7] We now turn to explaining the returns to a pairs trading strategy with uninformed trading shocks.

[5]Slight differences when looking at loadings on the market and Fama-French factors can be attributed to studying different markets. GGR (2003) show a negative and insignificant market beta. Our market beta of 0.0287 to 0.0551 is economically small but statistically significant. Returns in GGR (2003) load negatively on a momentum factor while our returns do not.

[6]Following GGR (2003) we employ a bootstrap procedure to make sure our profits are not the result of short-term reversals studied in Lehmann (1990). Our bootstrap results are very close to those reported in GGR (2003) and available upon request.

[7]Their back testing strategy opens positions at a two standard deviation gap and closes them when prices re-converge to a one standard deviation gap. Transaction costs in our strategy would be even less than transaction costs in the Merrill Lynch strategy.

## 3 Uninformed demand shocks and pairs-trading

We hypothesize that uninformed trading shocks help explain the returns of relative value trading strategies. As in traditional asset pricing models, assume that stock returns are determined by loadings on risk factors plus an idiosyncratic component. Given a long enough observation period, two stocks that have historically moved together can be thought of as having similar factor loadings. Assuming factor loadings remain constant in the future, the two stock returns should continue to move together.

In reality, future stock returns may not always move together. Divergence in prices may come from idiosyncratic shocks.[8] Suppose we track a pair of mining companies. Further suppose that one firm receives positive information such as finding a new mineral deposit. We expect the stock price of the lucky firm to jump ahead of the stock price of the other firm. Returns in the future may continue to move together, but we expect the price difference to persist. On average, we expect idiosyncratic shocks based on firm-specific information to lead to persistent price differences.

A change in factor loadings can also cause prices to diverge. Suppose one of the mining companies invests heavily in an internet start-up company. Such a change may cause prices to diverge today. In contrast to the case of idiosyncratic shock discussed above, we do not expect the price differential to remain constant in the future (even if it is zero today). Future returns should cease moving together whenever factor loadings change.

Now consider a market with limited risk bearing capacity.[9] Uninformed traders place demands that are uncorrelated with asset fundamentals. Optimizing investors, who are risk averse, accommodate the demands but require compensation. Thus, uninformed buying is accompanied by a contemporaneous rise in prices. Following a demand shock, prices mean-revert back to pre-shock (fundamental) levels. Likewise, uninformed selling is accompanied by a contemporaneous fall in prices and similar mean-reversion.

In a world with limited risk-bearing capacity, a pairs trading strategy effectively matches stocks with similar (historical) factor loadings. When prices diverge, the strategy takes a risky position by "betting" the divergence stems from different uninformed trading shocks

[8] Stock prices are normalized at the start of all observation periods so that "divergence in prices" becomes a meaningful concept. We use the term "price" to mean "normalized price" throughout this paper. Appendix A gives a full overview of the pairs trading methodology.

[9] Examples include DeLong et. al (1990); Campbell, Grossman, and Wang (1993); Greenwood (2004).

and not different informational shocks.[10] In models such as Greenwood (2004), prices mean-revert back towards fundamentals in a linear fashion.

The divergence and subsequent mean-reversion leads to three testable hypotheses. The first is that differential demand shocks are correlated with initial price divergence (i.e., the opening of an arbitrageur's position) The second hypothesis is that, in the absence of any type of future shock, the future returns to a pair's trading strategy should be uncorrelated with all other factors in the economy. The zero correlation comes from the fact that the stocks are good hedges for each other and prices mean-revert smoothly back together. The third hypothesis applies to a world where future shocks may very well affect the underlying stocks. If this is the case, the marked-to-market returns of a pair's trading strategy should be correlated with the correctly signed shocks of the underlying stocks. Positive (negative) shocks to the higher (lower) priced stock cause prices to diverge farther apart than they already are. An increased divergence makes today's marked-to-market profits negative. Negative (positive) shocks to the higher (lower) priced stock cause prices to mean-revert more quickly than normal thus increasing today's marked-to-market profits.

### 3.1 Uninformed trading data

We use $F_t^A$ to denote the net uninformed trading in stock of Company "A" on day "t". Readers can think of $F_t^A$ as representing the flow of money from the uninformed traders into, or out of, Company A's stock. Uninformed traders are net buyers whenever $F_t^A$ is positive. Uninformed traders are net sellers whenever $F_t^A$ is negative.

To calculate $F_t^A$ we collect daily holdings data for each listed firm. The holdings data cover 608 listed stocks between 5-Jan-1994 and 29-Aug-2002. We follow Andrade, Chang, and Seasholes (2004) and define $F_t^A$ as the daily change in the aggregate net shares held long on margin divided by total shares outstanding. Normalizing by total shares outstanding provides a straightforward method to compare $F_t$ across stocks.

Support for the identification of uninformed shocks is given in Andrade, Chang, and Seasholes (2004). For example, the net trades come almost exclusively from individual investors. The trades under-perform the market, are noisy, have relatively low pairwise correlation

[10] Monitoring news stories can help an arbitrageur identify situations when prices diverge due an informational event. Thus, using news as well as prices should lead to higher returns than using prices alone. In this way, the pairs trading profits shown in this paper represent a lower bound of what Wall St. firms actually earn.

across stocks, and are directly tied to temporary price shocks. Andrade, Chang, and Seasholes (2004) provide three levels of analysis. All three are consistent with using $F_t$ as a proxy for uninformed trading. The paper also provides full statistics for $F_t$ which represents a sizable fraction of daily trading in Taiwan.[11]

### 3.2 Uninformed trading and initiating positions

We consider each of the 732 positions opened during our sample period and test if uninformed trading shocks are correlated with trading positions being opened. In other words, we ask if uninformed trading shocks are linked with initial divergence in prices? Figure 3, Panel B provides a nice reference point. We see that four positions are opened during this particular 125 day trading period. On these four days, we want to know if net trading is correlated with stock returns.

Table 3 displays the average return on the day positions open (i.e., when divergence reaches the trigger value.)[12]. We see on days positions open, stocks diverge by 4.15% on average. Such a result indicates the trigger value is not reached in a slow and smooth manner. Rather, large, differential shocks cause a pair to hit its trigger value.[13] The rising stock ("Up Stock") in a pair accounts for 71.08% of the divergence on average (i.e., 71.08% = 2.95% ÷ 4.15%), while the falling stock ("Down Stock") accounts for the remaining 28.92%.

Table 3 shows the uninformed buying differential is 11.15bp ("$Up - Down$"). There is clear and strong uninformed buying of the "Up Stock." Uninformed investors in our sample buy 11.36bp of total market capitalization on the day a position is opened. On average, there is neither buying nor selling of the stock that goes down (0.21bp is not significantly different from zero.) We see an average correlation of 0.3192 between returns and net uninformed trading in the "Up Stock." [14] Interestingly, the high correlation remains when looking at the "Down Stocks."

The results in Table 3 can be explained with straightforward economic intuition. If there is

[11]Readers who are not entirely comfortable with the identification are welcome to associate the pairs trading profits with shocks to long margin holdings rather than uninformed trading. We are careful to check that factors such as interest rate movements are not driving our results.

[12]After the position opens, the strategy calls for selling the "up" stock and buying the "down" stock.

[13]The value of 4.15% should not be greater than the average trigger value of 6.24% from Table 1 since 4.15% represents one day's divergence and 6.24% is a cumulative divergence needed to open a position.

[14]T-statistics are calculated using the following estimation of the standard error: $s.e. = \frac{\rho\sqrt{T-2}}{1-\rho^2}$ where $T$ is the number of observations.

large uninformed selling pressure, any outside investor can easily step in to buy the excess supply. However, large uninformed buying pressure creates a different situation. Not all investors own the stock so not all investor can step in to meet the excess demand. Arbitrageurs who do not currently own the stock must sell short. To the extent that short selling is only available to sophisticated investors, the ability of the market to provide liquidity appears limited.[15]

### 3.3 Survival analysis and initiating positions

A more precise way to gauge which factors affect position openings is through survival analysis. We measure the amount of time (in days) from the start of each trading period to the time a pair first opens. We concentrate on time until first opening because we know every pair of stocks starts the trading period with both prices normalized to one. There are 320 different trading period-pair combinations of which 315 open at least once before the end of the trading period. There are five pairs that never open and we keep these in the sample.

Figure 4 shows the distribution of a pair's time to first opening measured in days. A fitted gamma distribution is shown as well. The average time to first opening is 20.5 days. The figure clearly shows the five pairs that never open during their 125-day trading periods.

Table 4 presents the results of the hazard analysis and reports coefficients. Estimation is by maximum likelihood and the baseline hazard function is parameterized as a generalized gamma function. A negative coefficient indicates pairs open more quickly as the covariate (RHS variable) goes up.[16] In Regression 1, a negative coefficient for $F_t^{up}$ indicates pairs open more quickly when the covariate (RHS variable) is high. Shocks to $F_t^{down}$ have an insignificant effect.

Since normalized prices are the cumulative returns from the start of the trading period, we also include cumulative values of $F_t^{up}$ and $F_t^{down}$. Regression 2 shows that cumulative shocks are insignificant and only contemporaneous shocks matter. During periods of high market volatility pairs open more quickly as can be seen from the negative coefficient on

[15]Note the GGR (2003) are careful to check the pairs trading profits exceed all transaction costs including short selling costs.

[16]The coefficients may initially cause confusion. In these regression, the subjects status is "alive" as long as the pair remains closed. As soon as the trigger value is hit, the status switches to "dies." A negative coefficient can be thought of as a decrease in expected life. Notice that our specification includes time-varying co-variates.

$\left(r_t^{mkt} - r_t^f\right)^2$ in Regression 3 and Regression 4.

To assess the economic significance of the survival analysis we note that a two standard deviation shock to $F_t^{up}$ increases the probability of opening a position by approximately 50% from the baseline case.[17] A two standard deviation shock to market volatility (the only other significant covariate) increases the probability of a position being opened by 25% from the baseline case. We conclude that net uninformed buying has a statistically and economically significant impact on a pair becoming open.

### 3.4 Marked-to-market returns and uninformed trading

In an effort to explain the marked-to-market returns, we regress the returns of our pairs trading portfolio on excess market returns, Fama-French factors, a momentum factor, and measures of uninformed trading:

$$r_t^{port} = \alpha + \mathbf{X_t}\beta + \varepsilon_{p,t} \tag{5}$$

Since the pairs trading strategy can buy or sell Stock A (while doing the opposite with Stock B) at any time, there is no reason to think a measure of aggregate market buying or selling can explain returns. We test this by including a market-wide measure of uninformed trading on the right hand side of Equation (5):

$$F_t^{mkt} = \frac{1}{608} \sum_{stk=1}^{608} F_t^{stk} \tag{6}$$

We also calculate a measure of the uninformed trading that is specific to our portfolio called $F_t^{port}$ which we include on the right hand side of Equation (5). This is a signed measure that depends on whether positions are open and long Stock A, open and short Stock A, or not open at all:

$$F_t^{port} = \frac{1}{20} \sum_{pair=1}^{20} I_t^{AB,pair} \cdot \left(F_t^{B,pair} - F_t^{A,pair}\right) \tag{7}$$

Table 5, Regression 1 shows the market-wide measure of uninformed trading is significant when it's the only right-hand side variable. Regression 2 shows the portfolio-specific measure

[17] The increase in probability can be seen using $\sigma(F_t^{up}) = 0.0014965$ and the coefficient reported in Table 4. Results can also be obtained using approximate time ratios. A Probit analysis gives qualitatively similar results.

is far more significant. The coefficient on $F_t^{port}$ is 2.486 with a 8.66 t-statistic. In Regression 3, the portfolio measure remains highly significant when standard measures of risk are added to the regression. The market-wide measure ceases to matter. This result is not surprising as $F_t^{mkt}$ and $\left(r_t^{mkt} - r_t^f\right)$ have a 0.5263 correlation coefficient. It turns out the part of $F_t^{mkt}$ that is orthogonal to excess market returns is not significant either (results not shown.)

This high level of significance for $F_t^{port}$ remains when lags of itself and other risk factors are included in Regression 4. Interestingly, the negative coefficients on the lagged variables $\left(F_{t-1}^{port} \text{ and } F_{t-2}^{port}\right)$ also support our hypothesis that pairs trading profits are directly linked to uninformed trading. To see this, consider a portfolio that has only one open position. The portfolio is long Stock B and short Stock A (i.e., $I_t^{AB,pair} = +1$). In this case, a positive shock to $F_t^{port}$ indicates that either $F_t^B$ is positive or $F_t^A$ negative. Since uninformed trading shocks are positively correlated with returns, this means the relative prices converge and the marked-to-market profit is positive. Conversely, a negative shock to $F_t^{port}$ indicates a further widening of prices and a marked-to-market loss. When considering lagged shocks, the opposite situation applies. A negative shock yesterday widened prices. A widening of prices leads to higher average profits in the future (which includes today). The same can be said for negative shocks two days ago as well. The higher average profits in days following an adverse shock can be seen in the negative coefficients in Table 5, Regression 4.

We end with a final note on interpreting the results in Table 5. The $F_t^{port}$ variable is not a systematic risk factor therefore the constant cannot be interpreted as an alpha (i.e., a measure of abnormal returns.) This also implies that we do not necessarily expect the constant value to go to zero even if $F_t^{port}$ has large explanatory power (which it does.) The purpose of the regression is simply to show that the marked-to-market risk-adjusted returns are highly correlated with uninformed trading ($F_t^{port}$). It is, however, important to note that the adjusted $R^2$ in Table 5, Regression 4 is approximately three times higher than any of the adjusted $R^2$ in Table 2.

# 4 Conclusion

Our paper seeks to understand the profitability pairs trading (a type of relative value strategy.) We show that such strategies work in Taiwan as they do in the United States. Average profits and trading frequency are nearly identical across the two countries. The thrust of this paper is the conjecture that pairs trading profits are compensation for providing liquidity in markets with limited risk bearing capacity. Specifically, liquidity is demanded by uniformed traders and this demand is observed as temporary pressure in stock prices.

We find that initial price divergence (the opening of a pairs trading position) is highly correlated with uninformed shocks to the underlying stocks. A survival analysis shows that positions open more quickly when one of the stocks experiences large uniformed buying. The marked-to-market returns of a pairs strategy are highly correlated with the correctly signed shocks to the underlying stocks. These results holds for both raw and risk-adjusted returns. Taking into account uninformed trading increases adjusted $R^2$ by a factor of three.

Our results provide additional support for theoretical models with limits to arbitrage. In such models, markets have limited risk-bearing capacity arising from agency considerations and specialization. As a result, non-informational shocks have an economically and statistically significant impact on asset prices. The profits to the pair's trading strategy represent another way to quantify the economic impact of the limited risk-bearing capacity.

Related future research is almost limitless. One could correlate the magnitude of pairs trading profits with institutional details of markets around the world or in a single market over time. Markets in which the underlying securities are more difficult to price should give rise to greater pairs trading profits. Markets with more pervasive uninformed shocks should generate greater pairs trading profits (or similarly sized profits spread across more arbitrageurs.) Our paper studies the shocks that cause a pair's underlying stocks to diverge. An equally interesting paper could track the actual trades of arbitrageurs (liquidity providers) who take the other side of the transactions.

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## Appendix A
## Background on Forming Pairs

We follow the same pairs trading strategy described in Gatev, Goetzmann, and Rouwenhorst (2003). We begin by defining a one year formation period (or observation period) during which we observe *normalized stock prices.*[18] Consider the stock of company "A." Its normalized price begins the observation period with a value of one. Stock A's normalized price is then increased or decreased each day by its daily return (compounded.)

$$\widetilde{P}_t^A \equiv \prod_{\tau=1}^{t} \left(1 + r_\tau^A\right) \tag{8}$$

At the end of the one-year formation period, we calculate the time series of normalized stock price deviation for every pair of stocks. In a market with 500 listed stocks, this methodology entails calculating 124,750 series of deviations. We rank pairs of stocks from lowest to highest based on the sum of squared deviations. At the end of each formation period, we consider the twenty closest pairs based on our "$Closeness_{AB}$" measure. Here $A$ represents one stock in the pair and $B$ represents the other. Order is unimportant since we can later buy or sell either Stock A or Stock B:

$$Closeness^{AB} = \sum_{t=1}^{250} \left(\widetilde{P}_t^A - \widetilde{P}_t^B\right)^2 \tag{9}$$

Following the formation period, we track each of the twenty pairs for the next half year (125 trading days.) At the beginning of this so called "trading period" we again renormalize all prices to be one. We wait until prices have diverged sufficiently before initiating a position. The "trigger value" which prompts opening a position is based on two standard deviations of historical price divergence (historical in this case means measured over the formation period that immediately precedes the trading period.)

$$Trigger^{AB} = \pm 2 \cdot stdev\left(\widetilde{P}_t^A - \widetilde{P}_t^B\right) \tag{10}$$

[18] Throughout this paper, we define one year to be 250 trading days and half a year to be 125 trading days. These numbers remain constant during our entire study.

Once a position is opened, the strategy sells the higher priced stock (Up Stock) and buys the lower priced stock (Down Stock). We create a tri-state indicator variable to denote the pair's position during each day of the trading period:

$$I_t^{AB} \equiv \begin{array}{cc} 0 & \text{not open} \\ +1 & \text{short A; long B} \\ -1 & \text{long A; short B} \end{array}$$

The pair's normalized prices and returns are marked-to-market each day and the position is held open until prices re-converge. If a position is still open when the trading period ends, it is closed and a gain or loss is recorded.

$$r_t^{AB} = I_t^{AB} \cdot \left(r_t^B - r_t^A\right)$$

Over one trading period, the portfolio return to following twenty pairs is:

$$r_t^{port} = \frac{1}{20} \sum_{pair=1}^{20} r_t^{AB,pair}$$

**Figure 1**
**Timing of Formation and Trading Periods**

This figure shows the timing of formation and trading periods. We define one year to be 250 trading days and half a year to be 125 trading days. The sample period starts 05-Jan-1994 and ends 29-Aug-2002 (equals 2,360 days.) We have 16 non-overlapping trading periods, lose 250 days due to the first formation period, and have 110 days left over at the end. Note: 250+(16×125)+110 = 2,360. Data are from the Taiwan Economic Journal.

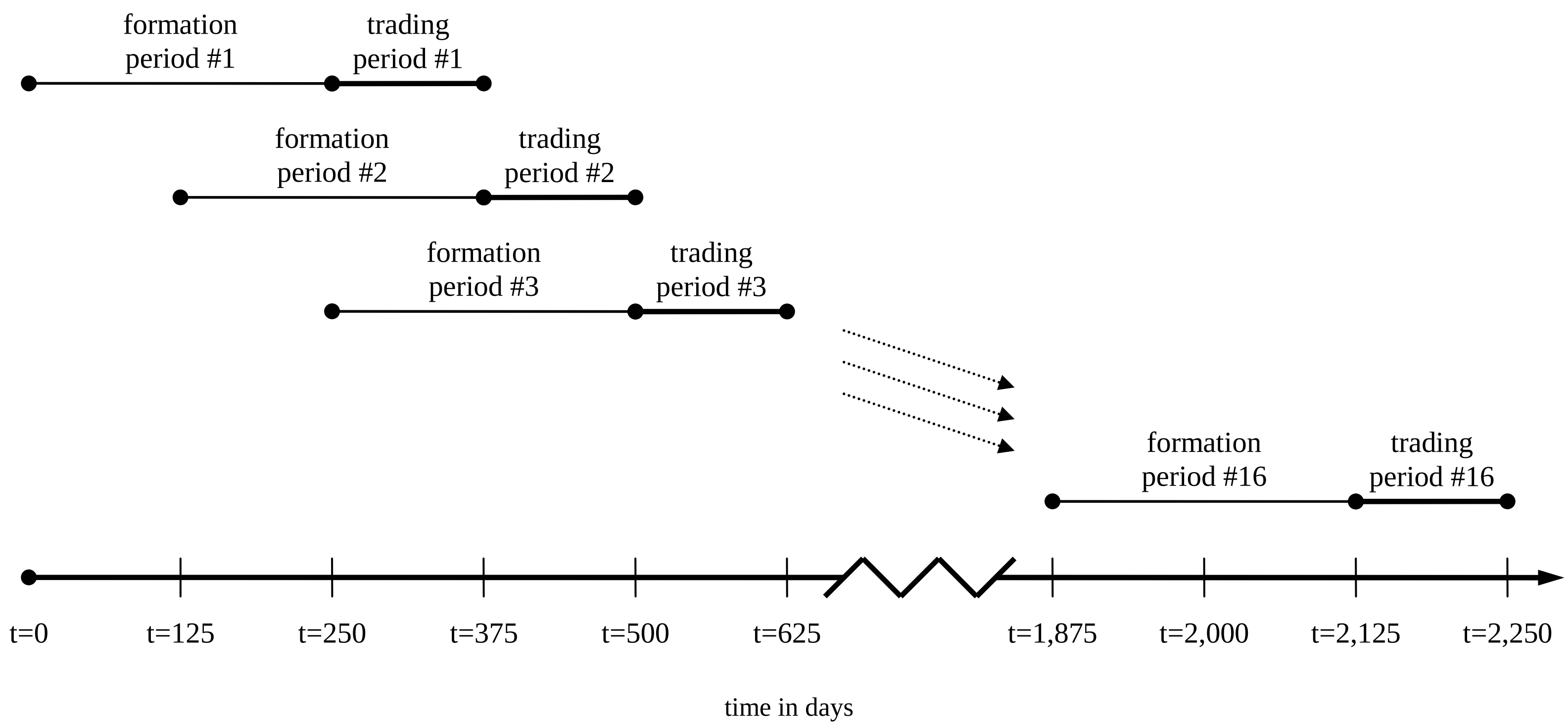
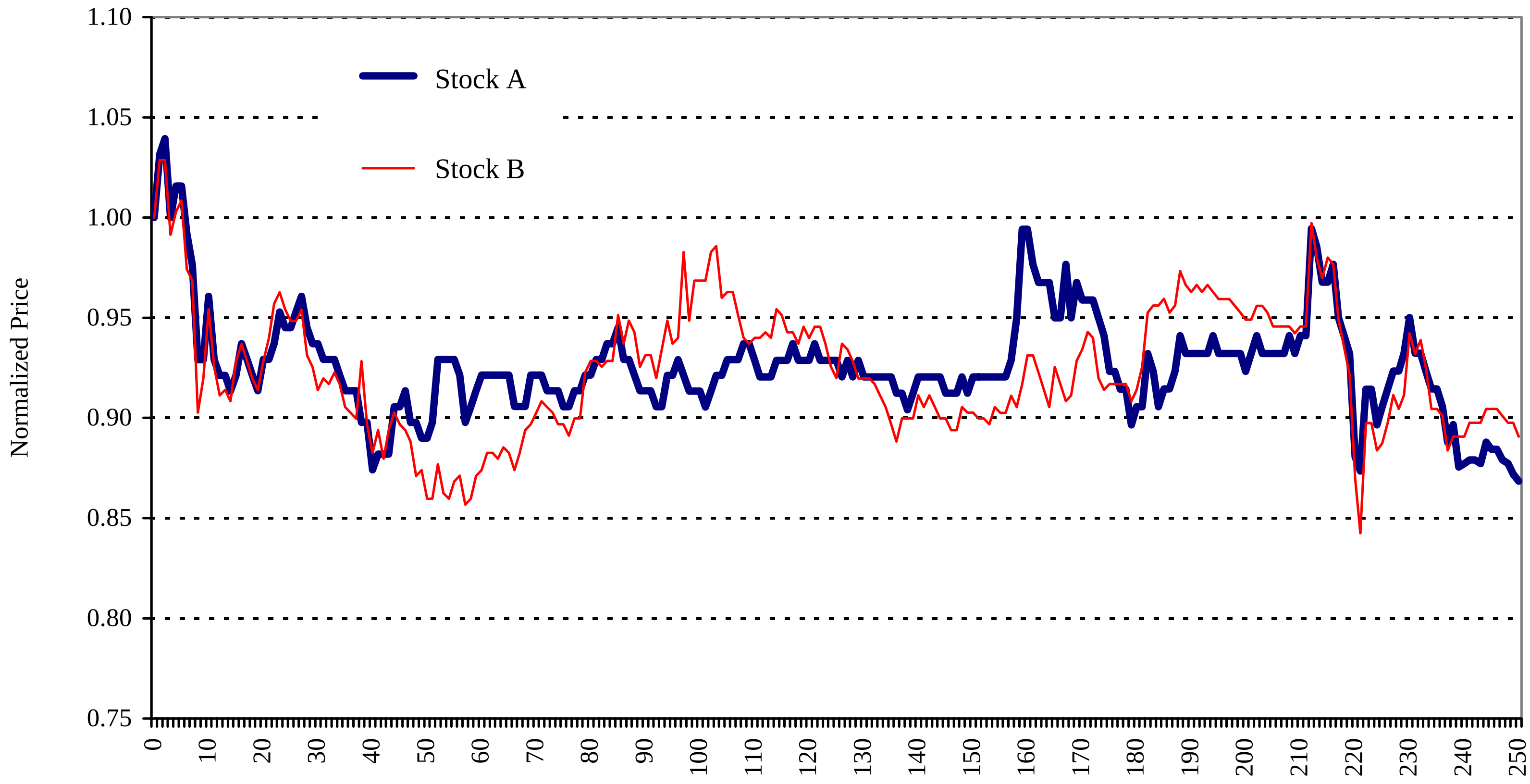


**Figure 2**
**Formation Period Example**

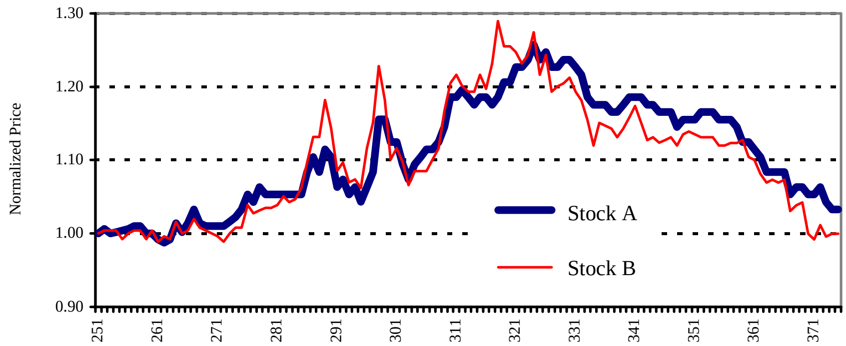
This figure shows the normalized price series of two stocks during a formation period. A normalized price series starts at 1.000 and increases (decreases) by the stock's gross return compounded daily. This particular graph shows the first matched pair from the first formation period in our sample. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.



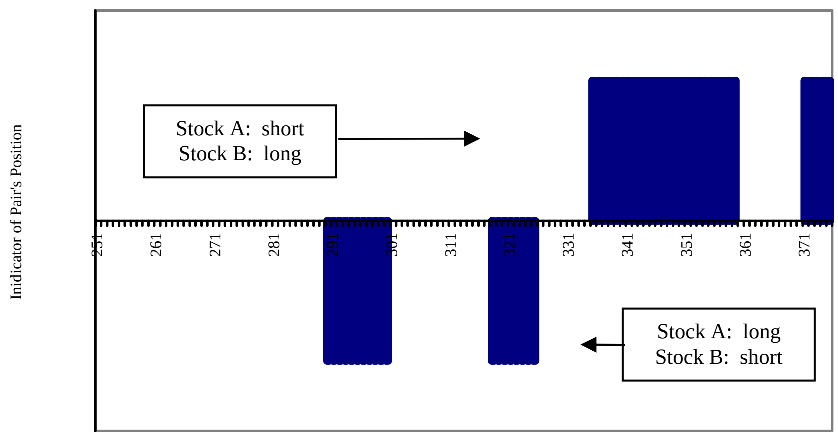
# Figure 3
# Trading Period Example

These figures detail the returns to a relative value trading strategy. Panel A shows the normalized price series of a single pair of stocks. A normalized price series starts at 1.000 and increases (decreases) by the stock's gross return compounded daily. Panel B shows when, and for how long, positions remain open. Panel C shows the cumulative return to this pairs trading strategy. All three figures are based on the first matched pair from the first formation period in our sample. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.

**Panel A: Normalized Price Series**




**Panel B: Position Series**




**Panel C: Cumulative Returns**

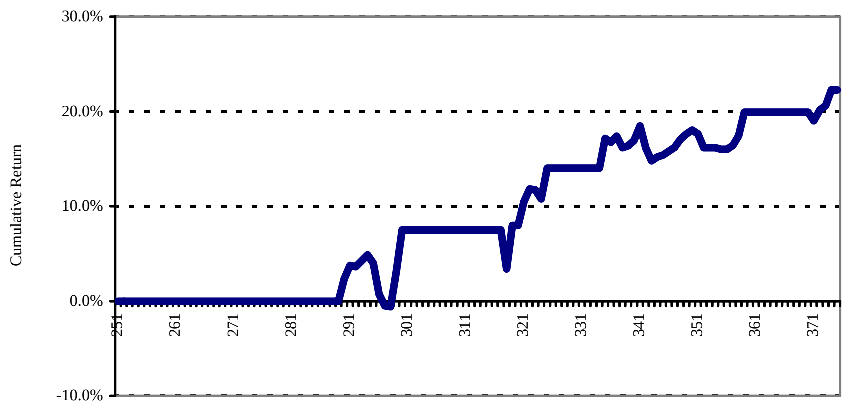
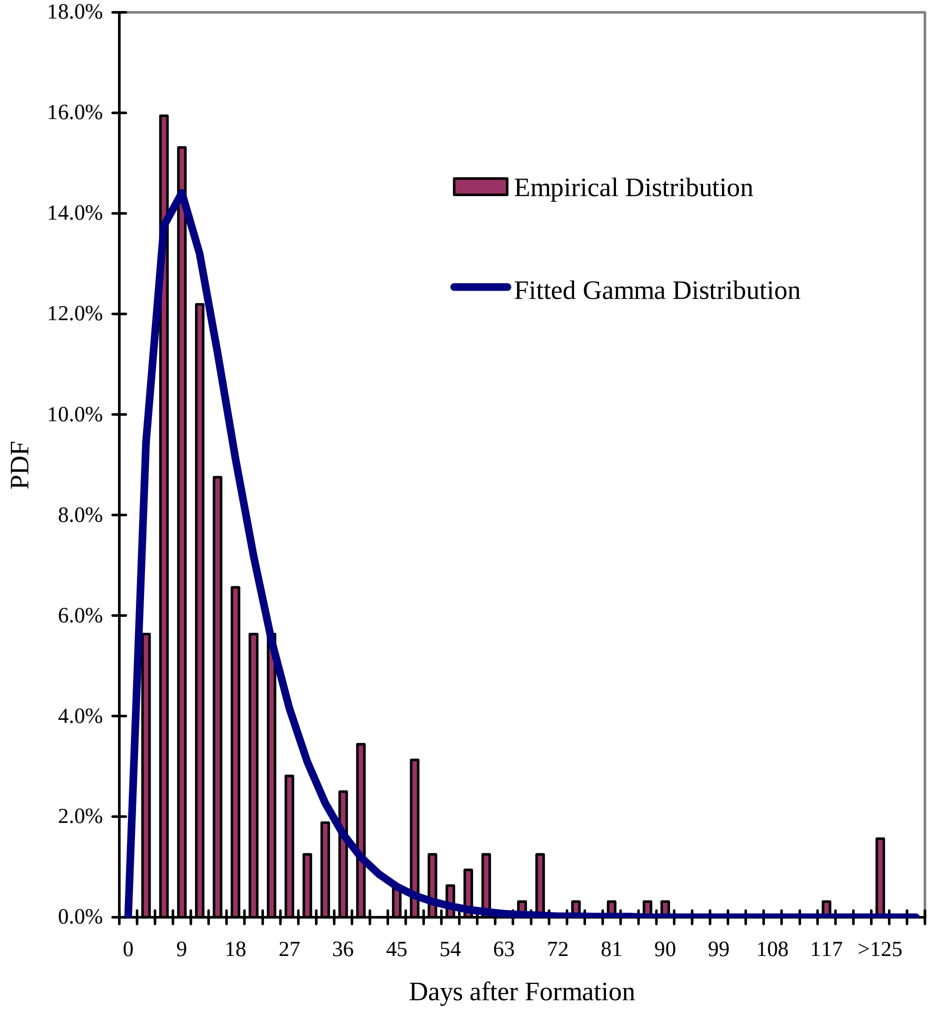


**Figure 4**
**Time to First Opening**

This figure shows how many days it takes a pair of stocks to first open after the start of a trading period. Equivalently, we can view the graph as the amount of time a pair remains closed. A pair opens when prices diverge by two or more historical standard deviations. Details relating to forming pairs are given in the text. A fitted gamma function is also shown along with the empirical distribution. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.



## Table 1
## Descriptive Statistics

This table gives descriptive statistics of our relative value (pairs trading) strategy. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.

### Panel A: Data Description

| | |
|---|---|
| Total days in sample | 2,360 |
| Days in each formation period | 250 |
| Days in each trading period | 125 |
| Number of trading periods in sample | 16 |
| Total trading days in sample (16*20=) | 2,000 |
| Days lost due to initial formation period | 250 |
| Days lost at end of sample (unused data) | 110 |
| Check of total days (250 + 16×125 + 110 = ) | 2,360 |

### Panel B: Description of Pairs Trading Strategy

| | |
|---|---|
| Number of pairs during one trading period | 20 |
| Max number of open pair-days (20 * 16 * 125 =) | 40,000 |
| Actual number of open pair-days | 28,135 |
| Fraction of time positions are open | 70.34% |
| | |
| Number of pair-positions opened during study (openings) | 732 |
| Number of pairs that never open | 5 |
| Average trigger value ( $2\sigma$ ) | 0.0624 |
| | |
| Average number of days a position is open (28,135 / 732) | 38.4 days |
| | |
| Average number of positions opened during one trading period (732 / 16=) | 45.75 |
| | |
| Average number of positions opened for one pair during one trading period (45.75 / 20 =) | 2.29 |

### Panel C: Overview of Pairs Trading Profits

| | |
|---|---|
| Average daily return of one pair during trading period | 3.879bp |
| | |
| Average daily return of pairs trading portfolio | 3.879bp |
| Stdev of daily returns | 57.893bp |
| Sharpe ratio of returns (daily) | 0.0670 |
| | |
| Average return of pairs trading portfolio | 10.18% |
| Stdev of return (annualized) | 9.15% |
| Sharpe ratio of returns (annualized) | 1.11 |

## Table 2
## Profitability and Pairs Trading

This table shows results from regressions of returns to a pairs trading portfolio on risk factors. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal. T-statistics (shown in parentheses) are based on standard errors that are robust to heteroskedasticity and autocorrelation. Adjusted R-squared values from a standard OLS regression shown at bottom.

Dependent Variable: The Return to the Pairs Trading Portfolio $\left(r_t^{port}\right)$

| | **Reg 1** | **Reg 2** | **Reg 3** |
|---|---|---|---|
| Constant | 3.876 bp<br>*(2.88)* | 3.886 bp<br>*(2.92)* | 2.612 bp<br>*(2.14)* |
| $r_t^{mkt} - r_t^f$ | | 0.0287<br>*(2.46)* | 0.0537<br>*(4.00)* |
| $SMB_t$ | | | 0.0146<br>*(1.83)* |
| $HML_t$ | | | 0.0238<br>*(4.56)* |
| $MOM_t$ | | | 0.0040<br>*(0.77)* |
| *Adj Rsq* | --- | *0.0060* | *0.0386* |
| *N (days)* | *2,000* | *2,000* | *2,000* |

## Table 3
## Opening Positions, Stock Returns, and Net Uninformed Trading

This table shows stock returns and net uninformed trading on days pairs positions are opened. A pair represents two stocks (labeled "A" and "B") that have historically moved together. Designating one stock as "A" and the other as "B" is not significant since the strategy can buy or sell either stock. A trading position is opened when the stock prices separate by more than two historical standard deviations (called the "trigger value" as defined in the text.) On the day a pair's position is opened, the "Up Stock" price is above the "Down Stock" price and the difference is labeled "Up - Down". Below, $r_t$ is the daily return differential or the return of one stock in the pair. $F_t$ is net uninformed trading differential or net uninformed trading in one stock. $F_t$ is measured as a fraction of shares outstanding. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal.

| | **Average $r_t$** | **Average $F_t$** | **corr ( $r_t$ , $F_t$ )** |
|---|---|---|---|
| Up - Down | 4.15% | 11.15bp | 0.1171 |
| *(t-stat)* | *(46.32)* | *(8.41)* | *(3.19)* |
| Up Stock | 2.95% | 11.36bp | 0.3192 |
| *(t-stat)* | *(28.01)* | *(9.06)* | *(9.10)* |
| Down Stock | -1.20% | 0.21bp | 0.2560 |
| *(t-stat)* | *(-12.96)* | *(0.33)* | *(7.15)* |
| *N* | *732* | *732* | *732* |

## Table 4
## Survival Analysis of Time to First Opening

This table reports coefficients from a survival analysis as they relate to a pair's time to first opening. $F_t$ is net uninformed trading in a pair's up or down stock. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal. T-statistics (shown in parentheses) are based on standard errors that are robust to heteroskedasticity and allow for clustering by pairs.

| | **Reg 1** | **Reg 2** | **Reg 3** | **Reg 4** |
|---|---|---|---|---|
| $F_t^{up}$ | -170.22<br>*(-4.24)* | -179.81<br>*(-3.67)* | -164.14<br>*(-4.35)* | -164.06<br>*(-4.40)* |
| $F_t^{down}$ | 12.94<br>*(0.42)* | 18.92<br>*(0.55)* | 8.24<br>*(0.27)* | 9.99<br>*(0.33)* |
| $\sum_{\tau=0}^{t-1} F_\tau^{up}$ | | -1.68<br>*(-0.15)* | | |
| $\sum_{\tau=0}^{t-1} F_\tau^{down}$ | | -14.56<br>*(-1.36)* | | |
| $\left(r_t^{mkt} - r_t^{f}\right)^2$ | | | -380.77<br>*(-3.89)* | -350.83<br>*(-3.46)* |
| $\left(F_t^{mkt}\right)^2$ *in bp* | | | | -8.50<br>*(-0.94)* |
| *Num. of Pairs.* | *320* | *320* | *320* | *320* |

# Table 5
## Uninformed Trading and Profitability

This table shows results from regressions of returns to a pairs trading portfolio on risk factors and a measure of net uninformed trading *( $F_t$ )*. Here, $F^{mkt}$ is an equally weighted measure of net trading across all firms. And, $F^{port}$ is a correctly signed measure of the net trading for stocks in the pairs trading portfolio. The sample period starts 05-Jan-1994 and ends 29-Aug-2002. Data are from the Taiwan Economic Journal. T-statistics (shown in parentheses) are based on standard errors that are robust to heteroskedasticity and autocorrelation. Adjusted R-squared values from a standard OLS regression shown at bottom.

Dependent Variable: The Return to the Pairs Trading Portfolio $\left(r_t^{port}\right)$

| | **Reg 1** | **Reg 2** | **Reg 3** | **Reg 4** |
|---|---|---|---|---|
| Constant | 3.379 bp<br>*(2.48)* | 3.520 bp<br>*(2.64)* | 3.044 bp<br>*(2.56)* | 2.917 bp<br>*(2.45)* |
| $F_t^{mkt}$ | 0.769<br>*(2.23)* | 0.918<br>*(2.80)* | -0.035<br>*(-0.09)* | |
| $F_t^{port}$ | | **2.486**<br>***(8.66)*** | **2.486**<br>***(9.16)*** | **2.558**<br>***(9.38)*** |
| $F_{t-1}^{port}$ | | | | **-0.365**<br>***(-1.55)*** |
| $F_{t-2}^{port}$ | | | | **-0.444**<br>***(-2.00)*** |
| $r_t^{mkt} - r_t^{f}$ | | | 0.0558<br>*(3.61)* | 0.0555<br>*(4.34)* |
| $SMB_t$ | | | 0.0177<br>*(2.15)* | 0.0180<br>*(2.37)* |
| $HML_t$ | | | 0.0233<br>*(4.51)* | 0.0234<br>*(4.54)* |
| $MOM_t$ | | | 0.0019<br>*(0.37)* | 0.0023<br>*(0.45)* |
| *Adj Rsq* | *0.0579* | *0.0563* | *0.0959* | *0.0960* |
| *N (days)* | *2,000* | *2,000* | *2,000* | *2,000* |