JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 45, No. 4, Aug. 2010, pp. 883–906

doi:10.1017/S0022109010000311

Idiosyncratic Risk, Long-Term Reversal, and Momentum

R. David McLean*

Abstract

This paper tests whether the persistence of the momentum and reversal effects is the result of idiosyncratic risk limiting arbitrage. Idiosyncratic risk deters arbitrage, regardless of the arbitrageur's diversification. Reversal is prevalent only in high idiosyncratic risk stocks, suggesting that idiosyncratic risk limits arbitrage in reversal mispricing. This finding is robust to controls for transaction costs, informed trading, and systematic relations between idiosyncratic risk and subsequent returns. Momentum is not related to idiosyncratic risk. Momentum generates a smaller aggregate return than reversal, so the findings along with those in related studies suggest that transaction costs are sufficient to prevent arbitrageurs from eliminating momentum mispricing.

I. Introduction

De Bondt and Thaler (1985), (1987) and Chopra, Lakonishok, and Ritter (1992) document long-term reversal (reversal) in cross-sectional stock returns over 2- to 5-year horizons. Jegadeesh and Titman (1993), (2001), Rouwenhorst (1998), (1999), and Chui, Titman, and Wei (2000) document cross-sectional momentum in both U.S. and non-U.S. stock markets over 3- to 12-month horizons. What causes these effects is still a matter of debate; several papers have argued that each effect is the result of mispricing.[1] In order for mispricing to persist,

*McLean, rdmclean@ualberta.ca, University of Alberta, School of Business, 4-20K Business Bldg., Edmonton, Alberta T6G 2R6, Canada. I am especially grateful to Hendrik Bessembinder (the editor), Wayne Ferson, Jeffrey Pontiff, and Michael Schill (the referee) for many valuable suggestions. I also thank Alon Brav, David Chapman, Tarun Chordia, Karl Diether, Richard Evans, Cliff Holderness, Gang Hu, Mark Huson, Randall Morck, Samuel Tibbs, and Mengxin Zhao; seminar participants at Boston College, University of Alberta, University of Virginia (Darden), University of Miami, Southern Methodist University, SUNY Buffalo, University of Cincinnati, and George Mason University; and conference participants at the Inquire-Europe Symposium on Portfolio Choice, the 2005 Financial Management Association International (FMA) Doctoral Consortium, and the 2005 FMA Special PhD Student Sessions for helpful comments. I acknowledge financial support from the Southam/Edmonton Journal Fellowship Award.

[1]De Bondt and Thaler (1985), (1987) contend that reversals are the result of mispricing. Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) contend that both momentum and reversal are the result of mispricing. Lee and Swaminathan (2000), Hong, Lim, and Stein (2000), and Cooper, Gutierrez, and Hameed (2004) provide empirical results that they interpret as consistent with mispricing explanations for momentum.

it must be that costs limit arbitrageurs in their efforts at keeping markets efficient (see Scholes (1972), Shiller (1984), De Long, Shleifer, Summers, and Waldmann (1990), Pontiff (1996), (2006), Shleifer and Vishny (1997), and Barberis and Thaler (2003)).[2] In this paper I study whether idiosyncratic risk, which can make holding an arbitrage position costly, can explain the persistence of reversal and momentum.

Arbitrage costs can be partitioned into 2 types: transaction costs and holding costs (Pontiff (1996)). I choose to focus on idiosyncratic risk because Shleifer and Vishny (1997) and Pontiff (2006) identify it as the primary arbitrage holding cost. Pontiff (1996), (2006) and Shleifer and Vishny (1997) assert that arbitrageurs will trade on a mispricing, but only to the point that the marginal benefit of a position is equal to its cost. In this framework high idiosyncratic risk stocks get fewer arbitrage resources. Therefore a sufficient (but not necessary) condition of limited arbitrage is that the largest mispricing will be found among the highest idiosyncratic risk stocks. This condition is not a necessary one, because in some cases transaction costs may be sufficient to limit arbitrage.

Financial economists have recognized that idiosyncratic risk limits arbitrage since at least Scholes (1972). While it may seem intuitive that idiosyncratic risk is only relevant if the arbitrageur is undiversified, in fact the diversification of the arbitrageur is irrelevant with respect to the effect that idiosyncratic risk has on a risk-averse arbitrageur's willingness to invest in a mispriced asset. This effect can be seen in Treynor and Black (1973) and Pontiff (2006), both of whom use a Markowitz (1952) mean-variance portfolio optimization framework to study the wealth allocation of an arbitrageur. The resulting portfolio weights show that a risk-averse arbitrageur will assign smaller portfolio weights to high idiosyncratic risk assets; this result is independent of the number of securities in the arbitrageur's portfolio. Hence, I study whether idiosyncratic risk can help to explain the persistence of momentum and reversal, 2 ubiquitous anomalies, both of which can be traded in fully diversified portfolios.

從公式可以看出，特有風險越高，風險趨避的套利者會持有更少該股(這也是為什麼高特有風險股票會獲得較少套利資源，以及特有風險為甚麼會是套利的成本)

I find a positive relation between α and idiosyncratic risk within the reversal portfolio; this is consistent with idiosyncratic risk limiting arbitrage. Weighting a reversal portfolio by idiosyncratic risk produces larger abnormal returns than does equal weighting; a reversal portfolio that is weighted by the inverse of idiosyncratic risk does not produce abnormal returns. Sorting the reversal portfolio into idiosyncratic risk quintiles yields similar inference; the difference in 3-factor αs between high and low idiosyncratic risk-reversal portfolios averages 1.11% per month (t-statistic = 3.77), and the portfolio's returns are monotonically increasing across the idiosyncratic risk quintiles. In regression tests I show that the findings are robust to controls for informed trading, transaction costs, and any systematic relation between idiosyncratic risk and returns.

Unlike the reversal effect, the momentum effect does not bear a relation to idiosyncratic risk, and it is strong among low idiosyncratic risk firms. The difference in 3-factor αs between high and low idiosyncratic risk-momentum portfolios is insignificant; it averages –0.021% per month (t-statistic = –0.29), so the

[2]Following Shleifer and Vishny (1990), the word arbitrage is used to describe "trading based on knowledge that the price of an asset is different from its fundamental value."

findings do not suggest that idiosyncratic risk is limiting arbitrage among momentum stocks. However, momentum may be the result of mispricing that persists due to limited arbitrage, but transaction costs may be the binding cost. This argument is consistent with the findings in Lesmond, Schill, and Zhou (2004), who find a cross-sectional relation between momentum profits and transaction costs, and show that momentum profits are within transaction costs.[3]

Why might transaction costs be the binding cost in momentum but not reversal? The results show that an arbitrageur with a horizon of 1 year or longer will receive a larger return from the reversal portfolio as compared to the momentum portfolio, and therefore has a better chance of recovering her transaction costs in a reversal portfolio. Hence, the findings suggest that transaction costs are likely to be the binding cost for smaller mispricing, while idiosyncratic risk plays an important role for larger mispricing, in which the αs are more likely to exceed transaction costs.

II. Empirical Predictions

The empirical predictions in this paper stem from a Markowitz (1952) portfolio optimization problem that is studied in both Treynor and Black (1973) and Pontiff (2006).[4] In this problem the arbitrageur decides how to optimally allocate her wealth among a market portfolio with expected return r_m, a risk-free asset with return r_f, and mispriced securities for which all systematic risk has been hedged, and with returns that are therefore equal to the sum of the mispricing α_i, and the risk-free rate. The market portfolio has variance of σ_m^2, and each mispriced asset has idiosyncratic variance of σ_{ie}^2. All of the assets can be shorted. The arbitrageur has risk aversion of λ and faces the following utility maximization problem:

$$(1) \qquad U = \sum_{i=1}^{N} w_i(\alpha_i + r_f) + w_m r_m + \left(1 - \sum_{i=1}^{N} w_i - w_m\right) r_f - \frac{1}{2}\lambda \sum_{i=1}^{N} w_{ie}^2 \sigma_{ie}^2 - \frac{1}{2}\lambda w_m^2 \sigma_m^2.$$

The arbitrageur chooses w_i, the weight in each mispriced asset, and w_m, the weight in the market portfolio, such that equation (1) is maximized. The resulting portfolio weights for the arbitrage positions are

$$(2) \qquad w_i = \frac{\alpha_i}{\lambda \sigma_{ie}^2}.$$

Equation (2) shows that the amount that an arbitrageur will dedicate to a particular asset is a function of the asset's α, its idiosyncratic risk, and the arbitrageur's risk aversion. Although it may seem intuitive that idiosyncratic risk

[3]There are also risk-based explanations for momentum (see Conrad and Kaul (1998), Berk, Green, and Naik (1999), and Johnson (2002)). Jegadeesh and Titman (2001) show that momentum reverses after 1 year, in that losers begin to have higher returns than winners. Jegadeesh and Titman claim that their finding makes a risk story less plausible, as it would have to be that risk reverses (high risk becomes low risk and vice versa).

[4]The model studied in this paper and in Pontiff (2006) is essentially the Treynor and Black (1973) model along with a risk-free asset that can be either invested in or shorted.

only deters arbitrage if the arbitrageur is undiversified, equation (2) shows that the amount invested in a mispriced asset does not depend on the arbitrageur's level of diversification, as it does not vary with N, the number of securities in the arbitrageur's portfolio. This result is sensible; the benefit of each position is its α, while each position's cost is the product of its idiosyncratic risk and the arbitrageur's level of risk aversion. Here, N does not affect any of these parameters, so it should not affect the arbitrageur's investment in the position.

Numerical Example: Comparison of 1- to 100-Asset Arbitrage Portfolios. Assume that an arbitrageur has $1M and the utility function described in equation (1). There is 1 mispriced stock; its α is 0.5% and its idiosyncratic variance is 2.0%. Assume the arbitrageur has a risk aversion of 4. Using the portfolio weights derived above, it can be shown that the arbitrageur invests $62,500 in the mispriced stock.

Now assume a scenario similar to the previous example, but with the 1 stock along with 99 other identical stocks. Using the portfolio weights derived above, the arbitrageur invests $62,500 in each mispriced stock, exactly the same amount that was invested in the 1 mispriced stock in the previous example. The arbitrage portfolio has 100 such stocks in it, so the total value of the portfolio is $6,250,000.

In this example the 1-stock arbitrage portfolio has variance of 2%, while the 100-stock arbitrage portfolio has variance of 0.02%.[5] The arbitrageur would choose to invest only $62,500 in the 1-stock portfolio and $6,250,000 in the 100-stock portfolio. These differences may lead some people to think that because the arbitrageur is willing to invest such a large amount in the 100-stock portfolio, that an anomaly with many mispriced stocks, such as long-term reversal, will be arbitraged away. However, the arbitrageur is investing the same amount in the mispriced stock in both the 1- and 100-stock portfolios, hence the price-corrective force of arbitrage on the stock's price is the same in both portfolios.

If the arbitrageur cannot borrow, then in the 100-stock portfolio the arbitrageur will spread out the $1M over the 100 mispriced assets and the market portfolio, resulting in investment that is less than $62,500 per mispriced asset, which is the amount invested in the mispriced asset in the 1-stock portfolio. Hence, in this restricted borrowing case, which more resembles the real world, one might expect to have greater mispricing in anomalies such as momentum and reversal, which affect a large number of assets.

The Assumption of Limited Arbitrage Capital. This framework does rely on the assumption that arbitrage capital is limited. If either 1 arbitrageur had a very large amount of resources or if there were a large enough number of arbitrageurs with small resources, then even for high idiosyncratic risk stocks the aggregate w_i would be very large, and all stocks may have 0 mispricing.[6] As an example, I will show that w_i of 0.59% is the weight estimated for a high idiosyncratic risk-reversal portfolio stock. Thus 1,000 arbitrageurs each with $1M choosing

[5]The idiosyncratic variance of the arbitrage portfolio is: $\sigma^2_{Ae} = \sum_{i=1}^{N} w_i^2 \times \sigma^2_{ie}$.

[6]One argument against the limited capital assumption is that if noise traders trade against arbitrageurs, then noise traders should lose all of their wealth, as arbitrageurs are better informed. De Long et al. (1990) show that it is possible for noise traders to earn even higher returns than arbitrageurs do. This is due both to the willingness of noise traders to hold risky assets and the aversion that the arbitrageurs have toward risk created by noise traders.

a w_i of 0.59% would make an aggregate investment of \$5.9M, and this would have a significant impact on the share prices of many stocks.

The Role of Transaction Costs. It can also be the case that transaction costs are sufficient to limit arbitrage. In such a scenario one may not observe a relation between idiosyncratic risk and α. Alternatively, if a stock's α is sufficiently greater than its transaction costs, then the arbitrageur needs to decide how much to invest in the stock. This decision should be affected by both transaction costs and idiosyncratic risk. As an example, consider a firm with an α of 0.02, transaction costs of 0.01, and idiosyncratic risk of 0.03. An arbitrageur has risk aversion equal to 3. The α net of transaction costs is 0.01, so per equation (2) in the paper the arbitrageur's position in this asset will be $0.01/(3 \times 0.03) = 0.11$. Hence, if mispricing is sufficiently large relative to transaction costs, then both idiosyncratic risk and transaction costs may affect the arbitrageur's position.

III. Sample and Preliminary Results

A. Sample

This study uses monthly data from the Center for Research in Security Prices (CRSP) and annual data from Compustat. The data obtained from CRSP are monthly returns, share price, shares outstanding, industry Standard Industrial Classification (SIC) code, and the monthly return of the Standard and Poor's (S&P) 500 Index. The only data item obtained from Compustat is book value of equity (data60). This study also uses transaction cost measures that were obtained from Joel Hasbrouck's Web site and the Fama-French-Carhart factors that were obtained from Ken French's Web site.[7] In order to be included in the sample, a firm must have at least 3 years of past return data and the Gibbs cost estimate that was obtained from Joel Hasbrouck's Web site. The sample begins in January of 1965 and ends in December of 2004. Variable descriptions are given in the Appendix, and summary statistics are reported in Panel A of Table 1.

B. Preliminary Results: Reversal, Momentum, and Idiosyncratic Risk Quintile Characteristics

Panels B, C, and D of Table 1 report average arbitrage costs measured within the reversal, momentum, and idiosyncratic risk quintiles. The reversal quintiles are formed each month by sorting stocks on past returns from month $t-36$ through $t-7$. The momentum quintiles are formed each month by sorting stocks on past returns from month $t-6$ through $t-1$. Idiosyncratic risk is monthly return variance that is orthogonal to the S&P 500, measured over the prior 36 months. The quintiles are constructed each month, and the monthly averages of the quintile characteristics are averaged over the sample period.[8]

[7] The author thanks both Ken French and Joel Hasbrouck for use of their data. Ken French's Web site can be found at http://mba.tuck.dartmouth.edu/pages/ken.french/. Joel Hasbrouck's Web site can be found at http://pages.stern.nyu.edu/~jhasbrou/.

[8] The results are robust to using alternative past return horizons for the momentum and reversal portfolios.

$t-7$ . . . . . $t-1$ t

TABLE 1
Summary Statistics and Portfolio Characteristics

Table 1 reports summary statistics for the arbitrage cost variables in this study. Panel A reports statistics for the entire sample, while Panels B, C, and D report mean values across long-term reversal, momentum, and idiosyncratic risk (IDIO_RISK) quintiles. The reversal (momentum) quintiles are formed each month by sorting stocks on past returns from $t-36$ through $t-7$ ($t-6$ through $t-1$). IDIO_RISK is monthly return variance that is orthogonal to the S&P 500 over the prior 36 months. The 5-factor IDIO_RISK is monthly return variance that is orthogonal to the Fama-French-Carhart 4-factor model and an industry factor, which is the excess return of the firm's equal-weighted 2-digit SIC code portfolio. The 5-factor IDIO_RISK is measured over the prior 36 months. Future IDIO_RISK is idiosyncratic risk measured over the subsequent 36 months. Variance is monthly return variance over the prior 36 months. SIZE is the natural logarithm of firm market value. ILLIQUIDITY is the Amihud (2002) illiquidity measure; it is the absolute value of daily returns divided by daily dollar volume. GIBBS is the Hasbrouck (2004) Bayesian estimation of Roll's (1984) spread model. ILLIQUIDITY and GIBBS are both measured annually; the other measures are updated each month. With the exception of SIZE and ILLIQUIDITY, each of the variables is reported in percentages. The sample is from January of 1965 through December of 2004.

Panel A. Sample Summary Statistics

複製這四個變數

Variable	*N*	Mean	Std. Dev.	25th Percentile	Median	75th Percentile
IDIO_RISK	1,416,365	2.195	9.007	0.471	1.023	2.237
5-factor IDIO_RISK	1,416,365	1.656	5.949	0.365	0.783	1.706
Future IDIO_RISK	1,141,140	1.969	8.638	0.425	0.905	1.991
Variance	1,416,365	2.488	9.222	0.621	1.279	2.609
SIZE	1,416,365	4.646	1.975	3.225	4.515	5.975
ILLIQUIDITY	1,416,222	6,653	64,887	34	284	2,111
GIBBS	1,416,365	1.286	1.683	0.357	0.688	1.551

Panel B. Reversal Portfolios' Characteristics: Mean Values

Past 36-Month Return	Loser	2	3	4	Winner
IDIO_RISK	3.005	1.539	1.114	1.206	2.381
5-factor IDIO_RISK	2.232	1.152	0.844	0.916	1.788
Future IDIO_RISK	3.547	1.713	1.124	1.079	1.548
Variance	3.417	1.829	1.355	1.453	2.744
SIZE	3.463	4.362	4.830	5.005	4.900
ILLIQUIDITY	16,562	5,652	3,178	2,437	2,372
GIBBS	2.045	1.174	0.864	0.782	0.834

Panel C. Momentum Portfolios' Characteristics: Mean Values

Past 6-Month Return	Loser	2	3	4	Winner
IDIO_RISK	2.870	1.483	1.144	1.240	2.386
5-factor IDIO_RISK	2.137	1.111	0.860	0.938	1.796
Future IDIO_RISK	3.224	1.577	1.152	1.181	1.822
Variance	3.265	1.762	1.389	1.499	2.746
SIZE	3.685	4.507	4.828	4.911	4.567
ILLIQUIDITY	9,268	4,732	3,612	4,012	8,690
GIBBS	1.492	1.053	0.907	0.938	1.338

Panel D. Idiosyncratic Risk Portfolios' Characteristics: Mean Values

IDIO_RISK	Low	2	3	4	High
IDIO_RISK	0.263	0.592	1.073	1.965	5.768
5-factor IDIO_RISK	0.206	0.464	0.832	1.494	4.250
Future IDIO_RISK	0.405	0.808	1.440	2.560	4.458
Variance	0.387	0.801	1.361	2.355	6.345
SIZE	5.888	5.222	4.394	3.700	2.957
ILLIQUIDITY	533	1,338	2,908	6,137	22,435
GIBBS	0.495	0.672	0.972	1.434	2.402

Panel B of Table 1 shows that both the winner (high past return) and loser (low past return) reversal quintiles have relatively high idiosyncratic risk. The idiosyncratic risk of the winner quintile is 2.38%, and for the loser quintile it is 3.01%. The idiosyncratic risk of the other 3 quintiles is 1.54% or less. Both 5-factor idiosyncratic risk and total variance are also highest in the winner and loser quintiles. Therefore, all 3 variance measures show that holding long-term reversal stocks requires holding highly volatile stocks.

The results show that reversal losers have high transaction costs, while reversal winners do not. The Gibbs cost estimate is 2.05% for the reversal losers, whereas it is only 0.83% for the winners and 0.86% for the middle quintile. Amihud's (2002) illiquidity measure also suggests that transaction costs are high for reversal losers, but not for reversal winners. Both transaction cost measures are inversely related to long-horizon past returns, as is firm size. These findings are consistent with Chopra et al. (1992) and Ball, Kothari, and Shanken (1995), both of which find that the reversal loser effect is concentrated in small and low-priced stocks.

Panel C of Table 1 shows that both the momentum winner and loser quintiles have higher idiosyncratic risk than do the other past return quintiles. The results also show that the momentum winner and loser quintiles have higher transaction costs than do the other quintiles. This finding is consistent with Lesmond et al. (2004), who argue that following a momentum strategy requires trading in stocks with high transaction costs.

Panel D of Table 1 shows that there is a good deal of variation in idiosyncratic risk across the firms in this sample. The average idiosyncratic risk in the low idiosyncratic risk quintile is 0.26%, while the average idiosyncratic risk in the high idiosyncratic risk quintile is 5.77%. From equation (2) one can show that if 2 firms have identical αs, then the relative amount that an arbitrageur will invest in each firm is equal to the inverse of the ratio of each firm's idiosyncratic risk. Hence, for a given level of α, a low idiosyncratic risk stock will get 5.77/0.26 = 22 times the amount of arbitrage resources as a high idiosyncratic risk stock. This suggests that in equilibrium, mispricing should be larger in high versus low idiosyncratic risk stocks.

Panel D of Table 1 suggests that idiosyncratic risk and transaction costs are correlated, which is consistent with the findings in Spiegel and Wang (2006). Both the Amihud (2002) and Gibbs cost measures are monotonically increasing in idiosyncratic risk, while firm size is monotonically decreasing in idiosyncratic risk. Hence, stocks in which it is costly to hold large positions because of idiosyncratic risk will also be costly to transact.

Panel D of Table 1 also shows that both total variance and 5-factor idiosyncratic risk are monotonically increasing in idiosyncratic risk. Although not reported in the table, the correlation between idiosyncratic risk and total variance is 0.99, and the correlation between idiosyncratic risk and 5-factor idiosyncratic risk is 0.94. These results are consistent with a number of studies that report that different measures of idiosyncratic risk are highly correlated, suggesting that choice of idiosyncratic risk measure is not important in studies such as this one (see Roll (1984), Pontiff (1996), (2006), Wurgler and Zhuravskaya (2002), Pontiff and Schill (2003), Brav, Heaton, and Li (2010), and Duan, Hu, and McLean (2010)).

In order to choose the portfolio weights described in equation (2), the arbitrageur must estimate each firm's idiosyncratic risk. In this paper idiosyncratic risk is estimated over the prior 36 months, so an assumption is that arbitrageurs use past idiosyncratic risk as a proxy for future idiosyncratic risk when deciding on portfolio weights. Panel D of Table 1 shows that the level of idiosyncratic risk is persistent. Future idiosyncratic risk is monotonically increasing across the idiosyncratic risk quintiles, and the future idiosyncratic risk values are similar to the idiosyncratic risk values.

The correlation between future and past idiosyncratic risk is only 0.07, however the correlation between past and future idiosyncratic risk ranks is 0.80, and the correlation between past and future idiosyncratic quintiles is 0.76. This shows that assuming that a high idiosyncratic risk stock will continue to be a high idiosyncratic risk stock in the future is a reasonable assumption, although estimating a precise value of idiosyncratic risk is difficult. The tests reported in the subsequent tables rely on the persistence in idiosyncratic risk quintiles, rather than the precise idiosyncratic risk value.

IV. Main Results

A. Portfolio Returns Measured via Different Weighting Schemes

This section makes use of different weighting schemes in an effort to study how arbitrage costs can affect the returns of the reversal and momentum portfolios. The portfolios' returns are computed using equal weights, value weights, idiosyncratic risk weights, and weighting by the inverse of idiosyncratic risk. A sufficient condition of limited arbitrage is that each effect will be strongest in the portfolios that give larger weights to positions that are more costly to transact and hold. Hence, a sufficient condition of limited arbitrage is that the equal-weighted and idiosyncratic risk-weighted portfolios should yield the highest returns.

投組形成後會持有6個月

The portfolios' returns are calculated over a 6-month holding period, via the methodology of Jegadeesh and Titman (1993), (2001). In this methodology the return for a time t portfolio is the equal-weighted average of the time t returns for each of the 6 portfolios that were formed over the last 6 months ($t-6, t-5, t-4, t-3, t-2$, and $t-1$). Therefore the portfolio at time t consists in equal amounts of the time $t-1$ portfolio plus the other 5 portfolios formed in the 5 months prior to $t-1$. Under this method simple t-statistics can be used, and the portfolio returns can be regressed on the time t Fama-French factor realizations.

The return for the reversal portfolio is the loser portfolio's return minus the winner portfolio's return. The return for the momentum portfolio is the winner portfolio's return minus the loser portfolio's return. The tables report raw returns as well as Fama-French 3-factor αs. The tables also report the idiosyncratic risk of each portfolio. Portfolio idiosyncratic risk is estimated twice; first as the portfolio variance, which is orthogonal to the S&P 500, and then as the portfolio variance, which is orthogonal to the Fama-French 3-factor model.

1. Long-Term Reversal Portfolio Results

Panel A of Table 2 reports the results for the reversal portfolio. The returns of the reversal portfolio are positive and significant when larger weights are placed on high-cost stocks, but insignificant when larger weights are place on low-cost stocks. These findings are consistent with limited arbitrage.

Consistent with idiosyncratic risk limiting arbitrage, the highest reversal portfolio returns come from the idiosyncratic risk weightings; the portfolio yields

https://doi.org/10.1017/S0022109010000311 Published online by Cambridge University Press

TABLE 2

Reversal and Momentum Portfolios via Alternative Weighting Schemes

Table 2 reports the average monthly returns and Fama-French 3-factor αs of momentum and long-term reversal portfolios via different weighting schemes. The returns are measured over a 6-month holding period and are reported in percentages. The weighting schemes include equal weights, value weights, idiosyncratic risk (IDIO_RISK) weights, and the inverse of IDIO_RISK weights. Firm IDIO_RISK is monthly return variance that is orthogonal to the S&P 500 over the prior 36 months. The reversal (momentum) quintiles are formed each month by sorting stocks on past returns from $t-36$ through $t-7$ ($t-6$ through $t-1$). The reversal portfolios' returns are calculated by buying the low past return quintile (losers) and selling the high past return quintile (winners). The momentum portfolios' returns are calculated by buying the high past return quintile (winner) and selling the low past return quintile (loser). Each portfolio's IDIO_RISK is measured twice: as return variance that is orthogonal to the S&P 500, and as return variance that is orthogonal to the Fama-French 3-factor model. The sample is from 1965 through 2004.

	Weighting			
Portfolio	Equal	Value	IDIO_RISK	1/IDIO_RISK
Panel A. Reversal Portfolios				
Loser	1.663	1.125	2.175	1.534
2	1.356	1.126	1.608	1.156
3	1.294	1.032	1.385	1.121
4	1.259	1.029	1.337	1.167
Winner	1.097	0.926	0.782	1.120
Winner – Loser	0.556	0.325	1.386	0.332
t-statistic	(3.04)	(1.43)	(4.19)	(1.42)
α	0.076	–0.226	0.901	–0.140
t-statistic	(0.37)	(–1.16)	(2.90)	(–0.69)
S&P 500 IDIO_RISK	0.247	0.247	0.485	0.239
3-factor IDIO_RISK	0.186	0.165	0.419	0.177
Panel B. Momentum Portfolios				
Loser	1.013	0.518	1.400	0.881
2	1.224	0.848	1.415	1.061
3	1.313	0.897	1.475	1.117
4	1.463	1.042	1.521	1.289
Winner	1.754	1.395	1.775	1.597
Loser – Winner	0.741	0.877	0.375	0.716
t-statistic	(3.39)	(3.95)	(1.42)	(3.38)
α	0.982	1.069	0.605	0.943
t-statistic	(4.47)	(4.66)	(2.25)	(4.46)
S&P 500 IDIO_RISK	0.204	0.234	0.315	0.199
3-factor IDIO_RISK	0.209	0.228	0.315	0.194

an average monthly return of 1.386% (t-statistic = 4.19). As a comparison, the equal-weighted portfolio yields returns of 0.556% per month (t-statistic = 3.04), and the inverse of idiosyncratic risk weighting produces an insignificant portfolio return of 0.332% per month (t-statistic = 1.42).

The 3-factor αs bear a similar pattern. The equal-weighted portfolio's α is positive but not significant, which is consistent with the findings in Fama and French (1996). The idiosyncratic risk-weighted portfolio has an α of 0.901% (t-statistic = 2.90), and the αs for the value-weighted and the inverse of idiosyncratic risk-weighted portfolios are not significant. The results show that the stocks within the reversal portfolio, which have the greatest idiosyncratic risk, also have the largest αs; this is consistent with idiosyncratic risk limiting arbitrage.

The idiosyncratic risk of the idiosyncratic risk-weighted portfolio is twice as large as the idiosyncratic risk of the equal-weighted portfolio. This shows that the idiosyncratic risk weighting causes the portfolio to become less diversified, as large weights are placed on high idiosyncratic risk stocks. This weighting scheme also results in a higher α, suggesting that arbitrageurs optimally trade off the benefit of α with the cost of risk.

2. Momentum Portfolio Results

Panel B of Table 2 displays the results for the momentum portfolio. The monthly return of the equal-weighted portfolio averages 74 basis points (bp) per month (t-statistic = 3.39), slightly smaller than what Jegadeesh and Titman (1993), (2001) find, although this paper uses quintiles, whereas they use deciles. The value-weighted portfolio's returns average 88 bp per month (t-statistic = 3.95), which is larger than that of the equal-weighted portfolio. These results are consistent with those in Korajczyk and Sadka (2004), who show that the momentum winner effect is similar in equal- and value-weighted portfolios, but that the momentum loser effect is stronger in value-weighted portfolios. Moreover, Hong et al. (2000) show that the momentum effect is weak in the 2 lowest New York Stock Exchange (NYSE) size deciles, and Lesmond et al. (2004) find that momentum is weak both in very small stocks and in stocks with the highest transaction costs (both Lesmond et al. and Hong et al. show that momentum increases in transaction costs and decreases with size once one moves past the smallest and highest cost stocks).

The idiosyncratic risk-weighted portfolio has a return of 0.375% per month (t-statistic = 1.42), whereas the inverse of the idiosyncratic risk-weighted portfolio has an average return of 0.716% per month (t-statistic = 3.38). Moreover, the idiosyncratic risk-weighted portfolio has the smallest α (0.605), whereas the value-weighted portfolio produces the largest α (1.069). These results are also inconsistent with idiosyncratic risk serving as an arbitrage deterrent within the momentum portfolio; if idiosyncratic risk were limiting arbitrage, then the idiosyncratic risk-weighted portfolio should have the higher return.

None of the results in Panel B of Table 3 are consistent with idiosyncratic risk explaining the persistence of the momentum effect. However, this does not mean that the persistence of the momentum effect cannot be explained by limited arbitrage, as transaction costs could prevent arbitrageurs from correcting momentum mispricing. This interpretation is consistent with Lesmond et al. (2004), who find that stocks with strong momentum also have high transaction costs.

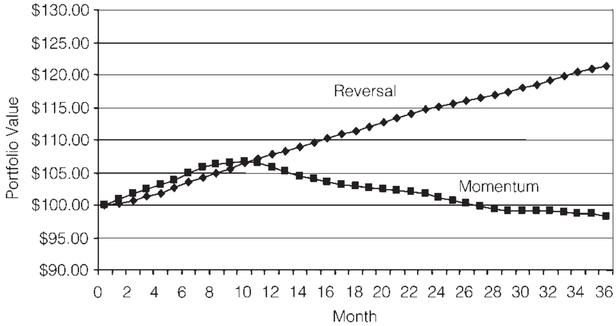
Table 1 shows that the momentum portfolio's average monthly returns are larger than those of the reversal portfolio over the 6-month holding period; so if transaction costs are preventing arbitrageurs from trading on momentum, then why do they not also prevent arbitrageurs from trading on reversal? Figure 1 plots the growth of $100 in the reversal and momentum portfolios over a 3-year holding period. Figure 1 shows that $100 invested in the momentum portfolio would grow to $105.00 after 6 months and $105.74 after 12 months. If the portfolio were held for 3 years, then the arbitrageur would be left with $98.28, as the portfolio's returns begin to reverse toward the end of the 1st year, which is consistent with the findings in Jegadeesh and Titman (1993), (2001).

Figure 1 also shows that $100 invested in the reversal portfolio would grow to $103.44 after 6 months, $107.73 after 12 months, and $121.32 at the end of 3 years. This is consistent with De Bondt and Thaler (1985), (1987) and Chopra et al. (1992), both of whom show that reversal can persist for as long as 5 years.

FIGURE 1

Growth of $100 Invested for 36 Months in the Reversal and Momentum Portfolios

Figure 1 displays the growth of $100 invested for 36 months in the reversal and momentum portfolios.



Hence an arbitrageur with a horizon of 1 year or longer has a better chance of recovering her transaction costs in a reversal portfolio than in a momentum portfolio.

TABLE 3

Cross-Sorted Reversal and Momentum Portfolios

Table 3 reports the equal-weighted average monthly returns and Fama-French 3-factor αs of momentum and reversal portfolios that are cross-sorted into idiosyncratic risk quintiles. The returns are measured over a 6-month holding period and are reported in percentages. The idiosyncratic risk and past return sortings are done independently. Firm idiosyncratic risk is monthly return variance that is orthogonal to the S&P 500 over the prior 36 months. The reversal (momentum) portfolios are formed each month by sorting stocks on past returns from $t-36$ through $t-7$ ($t-6$ through $t-1$). The reversal portfolios' returns are calculated by buying the low past return quintile (losers) and selling the high past return quintile (winners). The momentum portfolios' returns are calculated by buying the high past return quintile (winner) and selling the low past return quintile (loser). The *t*-statistics are reported in parentheses. The sample is from 1965 through 2004.

	Idiosyncratic Risk Quintile						
Portfolio	Low	2	3	4	High	H – L	*t*-Statistic
Panel A. Long-Term Reversal-Idiosyncratic Risk Portfolios: Monthly Equal-Weighted Returns							
Loser	1.318	1.531	1.734	2.078	2.130	0.812	(4.01)
Winner	1.372	1.542	1.448	1.333	0.943	–0.429	(–3.22)
L – W	–0.054	–0.011	0.286	0.745	1.187	1.241	
t-statistic	(–0.22)	(–0.59)	(1.53)	(3.29)	(4.57)	(4.23)	
α	–0.435	–0.419	0.189	0.184	0.675	1.111	
t-statistic	(–1.84)	(–2.42)	(1.10)	(1.87)	(2.69)	(3.77)	
Panel B. Momentum-Idiosyncratic Risk Portfolios: Monthly Equal-Weighted Returns							
Winner	1.511	1.645	1.810	1.909	1.793	0.282	(1.87)
Loser	0.810	0.744	0.733	1.015	1.157	0.347	(1.90)
W – L	0.701	0.901	1.077	0.894	0.636	–0.065	
t-statistic	(3.94)	(5.59)	(6.19)	(4.23)	(2.52)	(–0.26)	
α	0.845	1.121	1.352	1.138	0.824	–0.021	
t-statistic	(4.72)	(6.99)	(7.91)	(5.42)	(3.24)	(–0.29)	

B. Cross-Sorted Portfolios

In this section the reversal and momentum portfolios are cross-sorted into idiosyncratic risk quintiles. The past return and idiosyncratic risk sortings are done independently. Average monthly returns and 3-factor αs, both measured over a 6-month horizon, are displayed in the panels.

1. Long-Term Reversal-Idiosyncratic Risk Portfolios

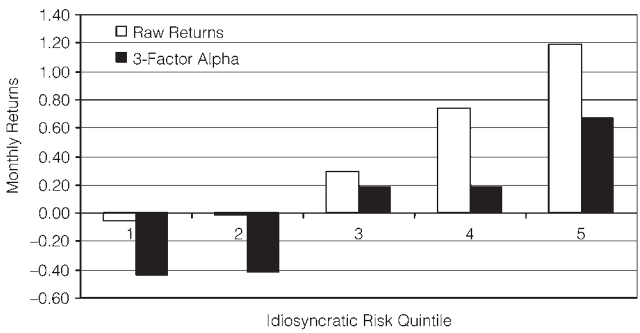
Panel A of Table 3 shows that reversals are greatest in high idiosyncratic risk firms (see Graph A of Figure 2), which is consistent with both the results in Panel A of Table 2 and with idiosyncratic risk limiting arbitrage. The reversal effect is significant only in the 2 highest idiosyncratic risk quintiles; the portfolio's returns are 0.745 (t-statistic = 3.29) and 1.187 (t-statistic = 4.57) in the 4th and 5th idiosyncratic risk quintiles, respectively. The reversal portfolio's returns are negative and insignificant in the 2 lowest idiosyncratic risk quintiles. The difference in monthly returns between the high and low idiosyncratic risk quintiles is 1.241 (t-statistic = 4.23).

FIGURE 2

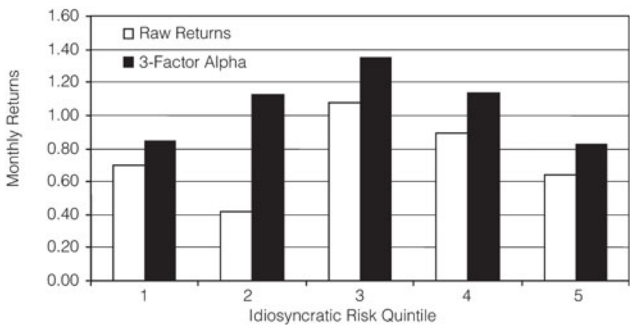
Momentum and Reversal Portfolios Sorted into Idiosyncratic Risk Quintiles

Figure 2 displays the average monthly returns of the reversal and momentum portfolios, each sorted into idiosyncratic risk quintiles. The returns are measured over a 6-month holding period as both raw returns and as Fama-French 3-factor αs. The returns are reported in percentages.

Graph A. Reversal Portfolio Average Monthly Returns by Idiosyncratic Risk Quintile



Graph B. Momentum Portfolio Average Monthly Returns by Idiosyncratic Risk Quintile



Like the raw returns, the 3-factor αs also produce a pattern that is consistent with idiosyncratic risk limiting arbitrage. The αs are only positive and significant in the 2 highest idiosyncratic risk quintiles, and they are negative and significant in the 2 lowest idiosyncratic risk quintiles. The difference between the high and low idiosyncratic risk quintiles' αs is 1.111 (t-statistic = 3.77).[9]

The effect of idiosyncratic risk on the reversal portfolios is prevalent in both the long and short positions of the portfolio. The high idiosyncratic risk-reversal losers have returns that are greater by 0.812 per month (t-statistic = 4.01) as compared to the low idiosyncratic risk-reversal losers, while the high idiosyncratic risk-reversal winners have returns that are lower by 0.429 per month (t-statistic = –3.22) as compared to the low idiosyncratic risk-reversal winners. These findings are consistent with the model in Section II, which predicts a relation between idiosyncratic risk and α across both long and short positions.

The effect of idiosyncratic risk on both long and short arbitrage positions is also consistent with the findings in studies by Duan, Hu, and McLean (2009), (2010). Duan et al. (2010) show that the low subsequent returns of highly shorted stocks arise only in stocks with high idiosyncratic risk, while Duan et al. (2009) show that the high subsequent returns of stocks that are bought by mutual funds arise only in stocks with high idiosyncratic risk.

The portfolio optimization problem studied in Treynor and Black (1973), Pontiff (2006), and Section II of this paper can help to put the results in perspective. The portfolio weights show that the amount that an arbitrageur will invest in an asset is a function of that asset's α, its idiosyncratic risk, and the arbitrageur's risk aversion. With respect to reversal, the average α of a stock in this portfolio is 0.34%. The idiosyncratic risk of the average high idiosyncratic risk firm is 5.77%. A recent paper Malloy, Moskowitz, and Vissing-Jørgensen (2009) shows that a risk aversion value of 10 can explain the equity premium and the premiums of several other test assets. If one plugs these numbers into the portfolio weight derived in Section II, then one finds that an arbitrageur would place only 0.59% of her wealth in a high idiosyncratic risk-reversal portfolio stock. Hence if arbitrage capital is limited, then it is not implausible that mispricing persists among high idiosyncratic risk firms in the reversal portfolio, as arbitrageurs' demands for these assets should be relatively small.

2. Momentum-Idiosyncratic Risk Portfolios

The results in Panel B of Table 3 are consistent with those in Panel B of Table 2, and show that momentum does not strengthen with idiosyncratic risk (see Figure 2). The difference between the high and low idiosyncratic risk quintiles in 3-factor αs is –0.021 (t-statistic = –0.29). The momentum portfolio's returns are significant in all 5 idiosyncratic risk quintiles, and the effect is weakest in the high idiosyncratic risk quintile. Spiegel and Wang (2006) show that idiosyncratic risk is correlated with size and transaction costs, so the findings here are consistent with Hong et al. (2000), who show that the momentum effect is weak in the 2 lowest NYSE size deciles, and Lesmond et al. (2004), who find that momentum is weak both in very small stocks and in stocks with the highest transaction costs.

[9]In untabulated tests, I did this analysis in January and non-January months separately and found that the results were robust to seasonality.

The average stock in the low idiosyncratic risk-momentum portfolio has an α of 0.42%, while the average idiosyncratic risk of a low idiosyncratic risk firm is only 0.26%. If one plugs these numbers, along with the Malloy et al. (2009) risk aversion value of 10, into the portfolio weight from Section II, then one finds that an arbitrageur would place 16.15% of her wealth in a low idiosyncratic risk-momentum portfolio stock, suggesting that idiosyncratic risk cannot be the only cost limiting arbitrage; if it were, then the momentum effect should have been arbitraged away. Moreover, it can be shown that the arbitrageur would place only 0.71% of her wealth in a high idiosyncratic risk-momentum portfolio stock. Hence, if arbitrageurs are deterred by idiosyncratic risk, then the low idiosyncratic risk-momentum stocks should get far greater arbitrage resources than the high idiosyncratic risk-momentum stocks, resulting in smaller mispricing, yet I find the same α in both the high and low idiosyncratic risk-momentum portfolios. These findings do not support the argument that idiosyncratic risk prevents arbitrage among momentum portfolio stocks.

3. Robustness: The Exclusion of Small and Low-Priced Stocks

This section studies how the results change after the exclusion of small and low-priced stocks. I consider 3 separate sample adjustments: i) the exclusion of stocks with prices under \$1, ii) the exclusion of stocks with prices under \$5, and iii) the exclusion of stocks with either prices under \$5 or with market capitalizations that place them in the smallest NYSE size decile.[10] The results from this section are not reported in the tables but are available from the author.

Table 1 shows that the total sample in this paper contains 1,416,365 firm-month observations. With exclusion i) I lose 46,959 observations, or 3% of the sample. Of these, 36,659 are from the highest idiosyncratic risk quintile. Each quintile contains 283,273 observations, so I lose 13% of the firms in the highest idiosyncratic risk quintile. Panel D of Table 1 shows that the average idiosyncratic risk of a firm in the high idiosyncratic risk quintile is 5.8%. If I reform the quintiles in this new sample, then the idiosyncratic risk of the highest quintile is 4.7%.

With exclusion ii) I lose 296,807 observations, or 21% of the sample. With exclusion iii) I lose 587,900 observations, or 41% of the sample. Exclusion ii) eliminates 56% of the firms in the highest idiosyncratic risk quintile, while exclusion iii) eliminates 80% of the firms in the highest idiosyncratic risk quintile. If I reform the quintiles in these new samples, then the idiosyncratic risk of the highest idiosyncratic risk quintile is 3.3% after exclusion ii) and 2.9% after exclusion iii).

Reversal. The full sample results in Panel A of Table 3 show that the reversal effect is only prevalent in the 2 highest idiosyncratic risk portfolios, suggesting that the effect is not limited to small and low-priced stocks. With each of the exclusions, only quintile 5 contains a positive α. The 5th quintile α is 0.468 (t-statistic = 2.25) with exclusion i), 0.612 (t-statistic = 3.15) with exclusion ii), and 0.542 (t-statistic = 2.34) with exclusion iii). As a comparison, Panel A of Table 3 shows that the 5th quintile bears an α of 0.675 (t-statistic = 2.69) in the

[10]The NYSE size deciles were obtained from Ken French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/).

https://doi.org/10.1017/S0022109010000311 Published online by Cambridge University Press

full sample. In all 3 of the altered samples the difference in α between the highest and lowest idiosyncratic quintiles remains significant.

Momentum. Hong et al. (2000) and Jegadeesh and Titman (2001) show that small and low-priced stocks have negative momentum effects. Spiegel and Wang (2006) show that idiosyncratic risk is negatively correlated to firm size. Hence, excluding small and low-priced stocks should create a stronger momentum effect in the highest idiosyncratic risk quintile.

With exclusion i) the momentum effect is still significant in all 5 idiosyncratic risk quintiles, the α is still largest in the 3rd quintile (as it is in the full sample), and the difference in α between the 1st and 5th quintiles is not significant. With exclusion ii) the α is largest in the 5th idiosyncratic risk quintile; however, the effect is still significant in all 5 quintiles. Moreover, the α in the 1st quintile also increases to 1% (as compared to 0.845% in the full sample), too large to be explained by idiosyncratic risk limiting arbitrage. Similar results are obtained with exclusion iii), although the α is largest in the 4th rather than the 5th idiosyncratic risk quintile.

Arena, Haggard, and Yan (2008) perform an analysis similar to the one reported here. Arena et al. use exclusion iii), excluding stocks in the lowest NYSE size decile and stocks with prices under $5, and then form idiosyncratic risk terciles. Arena et al. show that the momentum loser effect is strongest in the highest idiosyncratic risk tercile; however, their momentum winner effect is statistically indifferent between the high versus low idiosyncratic risk terciles. If I use exclusion iii) and form terciles, then I can get results that are similar to those of Arena et al.; however, this effect is documented after most of the high idiosyncratic risk firms are excluded from the sample.

Brav et al. (2010) sort firms into idiosyncratic risk quartiles and then value-weight their returns. They find that high idiosyncratic risk-momentum losers have especially low returns, but they do not find that high idiosyncratic winners have especially high returns, so their results are similar to those of Arena et al. (2008). Value weighting places smaller weights on high idiosyncratic risk firms. Hence, Brav et al.'s results may be similar to those of Arena et al., because like Arena et al., Brav et al.'s empirical design reduces the influence of high idiosyncratic risk-momentum firms that have either weak or negative momentum effects.

C. Regression Analysis: Alternative Interpretations of Idiosyncratic Risk

The results show that the reversal effect is greatest in high idiosyncratic risk stocks and that the momentum effect is not. With respect to reversal, the results are consistent with idiosyncratic risk limiting arbitrage. However different literatures have posited that idiosyncratic risk is related to other effects, and it could be that these other effects explain the results, rather than costly arbitrage. This section provides both discussions and tests of these alternative explanations.

Idiosyncratic Risk as a Systematic Predictor of Stock Returns. Ang, Hodrick, Xing, and Zhang (2006) show that high idiosyncratic risk stocks have low subsequent returns. However, it is unlikely that this effect can explain the reversal-idiosyncratic risk relation. The reversal portfolio is equally long reversal losers and short reversal winners. Hence, if only a systematic effect is present, then there should not be any difference in returns between the high and low idiosyncratic risk-reversal portfolios, as both the long and short high idiosyncratic risk positions would have lower expected returns, thereby canceling out any systematic effect.

Moreover, Panel A of Table 3 shows that high idiosyncratic risk-reversal losers have significantly higher returns than do low idiosyncratic risk-reversal losers, which is the opposite of what Ang et al.'s (2006) finding predicts. As a further robustness check, I reestimate the reversal-idiosyncratic risk relation in a multivariate framework that controls for the systematic relation between idiosyncratic risk and subsequent returns.

Transaction Costs. As with idiosyncratic risk, a sufficient condition of limited arbitrage is that mispricing should be greatest in stocks with high transaction costs (see Pontiff (1996), (2006), Shleifer and Vishny (1997)). To see why, think of the α in equation (1) as net of transaction costs; thus firms with high transaction costs will on average have smaller α, resulting in a smaller portfolio weight in equation (2). This shows that, as with high idiosyncratic risk firms, high transaction cost firms should get fewer arbitrage resources, resulting in larger equilibrium mispricing. Therefore, if the reversal-idiosyncratic risk relation documented in this study is the result of limited arbitrage, then one might also expect to observe a reversal-transaction cost relation.

Spiegel and Wang (2006) show that idiosyncratic risk is correlated with transaction costs. Hence, it could be that arbitrageurs are deterred only by transaction costs and not idiosyncratic risk. If the reversal-idiosyncratic risk relation is the result of a relation between reversal and transaction costs, then once the reversal-transaction cost relation is controlled for, the reversal-idiosyncratic risk relation should disappear. To separate the effects of transaction costs from those of idiosyncratic risk, I reestimate the reversal-idiosyncratic risk relation while controlling for the relation between reversal and transaction costs. I use firm size and the Gibbs cost estimate as proxies for transaction costs.[11]

Idiosyncratic Risk as a Measure of Market Efficiency. Morck, Yeung, and Yeu (2000) and Durnev, Morck, Yeung, and Zarowin (2003) propose that the percentage of a firm's variance that is idiosyncratic can be used as a measure of market efficiency. This "R^2" measure is different than idiosyncratic risk, in that idiosyncratic risk is the product of $1 - R^2$ and total variance. The correlation between idiosyncratic risk and $1 - R^2$ is 0.11, whereas the correlation between idiosyncratic risk and total variance is 0.99, so idiosyncratic risk is primarily a function of total variance.

In this paper idiosyncratic risk is measured over the 36 months prior to forming the portfolio. Hence, to the extent that idiosyncratic risk and $1 - R^2$ are correlated, the Morck et al. (2000) framework predicts that the reversal effect should be weaker among high idiosyncratic risk firms, as low R^2 firms are thought to have more efficient pricing.

Alternatively, Hou, Peng, and Xiong (2006) claim that R^2 is inversely related to investor overreaction and should decline as the overreaction of the marginal

[11]I also used Amihud's (2002) illiquidity measure. The results using this measure were similar to those with size and Gibbs, so for the sake of brevity these results are not reported in the tables.

investor increases. This framework predicts that the reversal effect should be stronger among low R^2 firms. To separate this effect from the limits to arbitrage effect of idiosyncratic risk, I reestimate the reversal-idiosyncratic risk relation while controlling for the relation between reversal and R^2.

Estimation. The methodology in this section is the Fama and MacBeth (1973) regression framework. The regressions include variables that measure firm size, market-to-book ratio, momentum, reversal, idiosyncratic risk, R^2, and the Gibbs estimate of spreads. Each of these variables is described in the Appendix.

Some of the regressions include interaction terms. To make the interactions, I first create a high idiosyncratic risk dummy variable that is equal to 1 if a firm is in the highest idiosyncratic risk quintile, and 0 otherwise. To test for limited arbitrage, I interact the momentum and reversal measures with the high idiosyncratic risk dummy variable. I create similar interaction terms with the HIGH_GIBBS, SMALL_SIZE, and low R^2 dummy variables.[12]

In an effort to keep my sample size as large as possible, I follow Pontiff and Woodgate (2008) and McLean, Pontiff, and Watanabe (2009) and create a market-to-book dummy variable, MB_DUM. If the book value of equity is either missing or negative, then I assign both market-to-book and MB_DUM values of 0. If book value of equity is positive, then MB_DUM is assigned a value of 1. MB_DUM allows for the inclusion of firms with either missing or negative book values of equity, without affecting inference of the market-to-book ratio's slope coefficient.

The dependent variable in each of the regressions is the average monthly return over the subsequent 6 months. There is overlap in returns, so the method of Newey and West (1987) is used to correct for autocorrelation that can bias the standard errors downward. All of the coefficients are reported in percentages.

1. Reversal Regression Results

Panel A of Table 4 confirms the results in Tables 2 and 3, and shows that reversals are stronger in high idiosyncratic risk firms. The results further show that the reversal-idiosyncratic relation is robust to controls for transaction costs, the systematic effects of idiosyncratic risk, and R^2. The results also show that reversals are stronger in high transaction cost firms, even after controlling for idiosyncratic risk, which is consistent with both idiosyncratic risk and transaction costs serving as limits to arbitrage.

Regression 1 establishes the base results. The coefficients for size and market-to-book ratio are both negative and significant, which is consistent with Fama and French (1992). The market-to-book dummy coefficient is 0.48 (t-statistic = 6.76). Pontiff and Woodgate (2008) and McLean et al. (2009) also find that the market-to-book dummy coefficient is positive and significant, and they report similar magnitudes in both economic and statistical significance. The reversal coefficient is –0.13 (t-statistic = –2.26). The standard deviation for this variable is 1.141; hence, a 1-standard-deviation increase in past 36-month return predicts a 0.15% decline in subsequent monthly return.

[12]I conducted the same tests with dummy variables made using Amihud's (2002) illiquidity measure, and the results were similar to those found with the Gibbs and size variables, so for the sake of brevity I do not report them.

Regression 2 shows that reversals are limited to high idiosyncratic risk firms, which is consistent with the results in Tables 2 and 3. In regression 2 the reversal coefficient is insignificant, but the high idiosyncratic risk-reversal interaction term (REV × HIGH_IDIO) is –0.28. This shows that across high idiosyncratic risk firms, a 1-standard-deviation increase in past 36-month return leads to a 0.32% decline in subsequent monthly return. This result is consistent with idiosyncratic risk limiting arbitrage, and therefore supports the limited arbitrage interpretation of the results in the previous tables.

Idiosyncratic risk is included as a control variable in the regression, hence the interaction term is not explained by a systematic relation between idiosyncratic

TABLE 4

Fama-MacBeth Regressions

Table 4 reports the results of Fama and MacBeth (1973) cross-sectional regressions. The regressions are estimated each month. The dependent variable is the average monthly return measured over a 6-month holding period. The independent variables include the natural logarithm of firm market value (SIZE), the natural logarithm of the market-to-book ratio (MB), the past 6-month stock return (MOM), and the past 36-month stock return (REV). The variable MB_DUM signals whether a firm has an MB value. If the book value of equity is either missing or negative, then both MB and MB_DUM are assigned values of 0. If book value of equity is positive, then MB_DUM is assigned a value of 1. MB_DUM allows the inclusion of firms with either missing or negative book values of equity without affecting inference of the log of the MB slope coefficient. IDIO_RISK is idiosyncratic risk measured with the market model. HIGH_IDIO is equal to 1 if a firm is in the highest idiosyncratic risk quintile, and 0 otherwise. SMALL_SIZE is equal to 1 if a firm is in the lowest SIZE quintile, and 0 otherwise. GIBBS is Hasbrouck's (2009) estimate of bid-ask spread. HIGH_GIBBS is equal to 1 if a firm is in the highest GIBBS quintile, and 0 otherwise. R^2 is the percentage of the stock's return variation that is explained by the return variation of the S&P 500. LOW_R^2 is equal to 1 if a firm is in the lowest R^2 quintile, and 0 otherwise. In Panel A REV is interacted with the IDIO_RISK, SIZE, GIBBS, and R^2 dummy variables. In Panel B MOM is interacted with the IDIO_RISK, SIZE, GIBBS, and R^2 dummy variables. The coefficients are reported in percentages. The standard errors are adjusted for overlap with the method of Newey and West (1987). The t-statistics are reported in parentheses. T is the number of monthly cross-sectional regressions. The sample ranges from 1965 through 2004.

Panel A. Reversal Interactions

Variable	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
INTERCEPT	1.61	1.63	1.54	1.13	1.63
	(4.30)	(5.23)	(4.77)	(3.92)	(5.21)
SIZE	–0.16	–0.17	–0.15	–0.10	–0.19
	(–3.62)	(–4.58)	(–3.97)	(–3.92)	(–4.20)
MB	–0.15	–0.14	–0.14	–0.16	–0.13
	(–2.65)	(–2.79)	(–2.65)	(–3.26)	(–2.50)
MB_DUM	0.48	0.47	0.47	0.46	0.48
	(6.76)	(6.91)	(6.70)	(6.82)	(6.74)
MOM	0.89	0.87	0.88	0.84	0.90
	(5.65)	(5.69)	(5.74)	(5.59)	(5.99)
REV	–0.13	–0.01	0.02	0.05	0.00
	(–2.26)	(–0.20)	(0.33)	(0.84)	(0.11)
IDIO_RISK		–0.49	–1.07	–4.06	–0.49
		(–0.12)	(–0.26)	(–1.12)	(–0.11)
REV × HIGH_IDIO		–0.28	–0.21	–0.22	–0.28
		(–5.71)	(–5.40)	(–5.12)	(–5.63)
REV × SMALL_SIZE			–0.61		
			(–4.40)		
GIBBS				18.07	
				(3.07)	
REV × HIGH_GIBBS				–0.25	
				(–2.87)	
R^2					0.59
					(2.24)
REV × LOW_R^2					–0.10
					(–2.29)
Average R^2	0.07	0.08	0.08	0.09	0.08
T	462	462	462	462	462

(continued on next page)

https://doi.org/10.1017/S0022109010000311 Published online by Cambridge University Press

TABLE 4 (continued)

Fama-MacBeth Regressions

Panel B. Momentum Interactions

Variable	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
INTERCEPT	1.61 (4.30)	1.65 (5.32)	1.60 (4.96)	1.12 (3.75)	1.66 (5.32)
SIZE	–0.16 (–3.62)	–0.17 (–4.56)	–0.16 (–4.15)	–0.10 (–2.91)	–0.19 (–5.69)
MB	–0.15 (–2.65)	–0.14 (–2.79)	–0.15 (–2.77)	–0.17 (–3.43)	–0.14 (–2.57)
MB_DUM	0.48 (6.76)	0.47 (6.87)	0.46 (6.64)	0.45 (6.78)	0.47 (6.73)
MOM	0.89 (5.65)	1.31 (7.89)	1.44 (8.14)	1.41 (8.16)	1.41 (8.13)
REV	–0.13 (–2.26)	–0.13 (–2.41)	–0.13 (–2.30)	–0.09 (–1.63)	–0.13 (–2.40)
IDIO_RISK		–0.93 (–0.23)	–0.93 (–0.22)	–4.61 (–1.31)	–0.69 (–0.15)
MOM × HIGH_IDIO		–0.90 (–6.60)	–0.69 (–5.03)	–0.63 (–4.72)	–0.84 (–5.13)
MOM × SMALL_SIZE			–1.01 (–5.66)		
GIBBS				21.17 (3.57)	
MOM × HIGH_GIBBS				–0.67 (–5.06)	
R^2					0.57 (2.19)
MOM × LOW_R^2					–0.29 (–2.39)
Average R^2	0.07	0.08	0.08	0.09	0.08
T	462	462	462	462	462

risk and subsequent returns (as in Ang et al. (2006)), as this is controlled for. The idiosyncratic risk coefficient is negative, which is consistent with the findings in Ang et al., although the coefficient's t-statistic is not significant.

Spiegel and Wang (2006) show that idiosyncratic risk and transaction costs are correlated, so the reversal-idiosyncratic risk interaction in regression 2 could just be a noisy proxy for a reversal-transaction cost interaction. Regressions 3 and 4 include the size and Gibbs interaction terms, and the results show that the reversal-idiosyncratic risk interaction is robust to controls for transaction costs. The REV × HIGH_IDIO coefficients are –0.21 and –0.22 in regressions 3 and 4, respectively, similar to the REV × HIGH_IDIO coefficient (–0.28) in regression 2, which did not include the transaction cost interaction terms. Moreover, the REV × HIGH_IDIO coefficients' t-statistics are greater than 5 in both regressions 3 and 4, similar to the t-statistic (–5.71) in regression 2. Hence, idiosyncratic risk's correlation with transaction costs does not explain the idiosyncratic risk-reversal interaction.

Regressions 3 and 4 also show that reversals are stronger in stocks with high transaction costs, which is consistent with these costs also limiting arbitrage in reversal stocks. The SMALL_SIZE interaction term is –0.61 (t-statistic = –4.60), while the HIGH_GIBBS interaction term is –0.25 (t-statistic = –2.87). Taken in their entirety, the results are consistent with the empirical predictions in Pontiff (1996), (2006) and Shleifer and Vishny (1997), and suggest that both transaction costs and idiosyncratic risk are important arbitrage deterrents with respect to long-term reversal.

Regression 5 shows that the idiosyncratic risk-reversal relation is not caused by idiosyncratic risk's correlation with $1 - R^2$. If this were so, then the inclusion of the low R^2 interaction term should reduce both the magnitude and significance of the REV × HIGH_IDIO coefficient. However, the REV × HIGH_IDIO coefficient is –0.28 (t-statistic = 5.63) in regression 5, identical to its value in regression 2.

The reversal-low R^2 interaction is –0.10 (t-statistic = –2.29), showing that the reversal effect is stronger among stocks with low R^2. This finding is not consistent with Morck et al.'s (2000) conjecture that $1 - R^2$ serves as a measure of price-informativeness. If R^2 measured price-informativeness, then, assuming reversals are the result of mispricing, the reversal effect should be weak among low R^2 stocks, as these stocks should have the most efficient pricing, yet here one finds the opposite. This finding is, however, consistent with the hypothesis of Hou et al. (2006), who contend that R^2 declines as investor overreaction increases. Hence, these findings are consistent with De Bondt and Thaler (1985), (1987), who propose that reversals are the result of investor overreaction.

Taken in their entirety, the results in this section show that the relation between reversal and idiosyncratic risk is not caused by a systematic relation between idiosyncratic risk and returns, and is robust to controls for both transaction costs and R^2. These findings strengthen the argument that the reversal-idiosyncratic risk relation is explained by the limits to arbitrage framework described in Section II.

2. Momentum Regression Results

Panel B of Table 4 confirms the findings in Tables 2 and 3 and shows that momentum is not stronger in high idiosyncratic risk firms. In regression 2, the high idiosyncratic risk-momentum interaction coefficient (MOM × HIGH_IDIO) is –0.90 (t-statistic = –6.60), while the momentum coefficient in regression 2 is 1.31 (t-statistic = 7.89). The MOM × HIGH_IDIO coefficient values and t-statistics in the other regressions are similar. Hence, as in the previous tables, the results here show that there is a strong momentum effect, but that it is weaker in high idiosyncratic risk firms as compared to other firms.

Regressions 3 and 4 show that momentum is weakest among small stocks and stocks with high Gibbs cost estimates. This is consistent with Hong et al. (2000), who find that momentum is negative in the smallest NYSE decile, and with Lesmond et al. (2004), who find that momentum is weak in their highest transaction cost and smallest size quintiles relative to the middle 3 quintiles for each measure, although these papers also show that once one moves past the highest cost and smallest size stocks, momentum is increasing in transaction costs and decreasing in size. In regression 5 the momentum low R^2 interaction coefficient is 0.57 (t-statistic = 2.19), showing that the momentum effect is weaker among the lowest R^2 firms as compared to the other 4 quintiles.

https://doi.org/10.1017/S0022109010000311 Published online by Cambridge University Press

V. Conclusions

The limits to arbitrage argument posits that mispricing can persist whenever the costs of arbitrage exceed the benefits. The arbitrage cost that I focus on is idiosyncratic risk, which is a holding cost to any risk-averse arbitrageur. I test to what extent idiosyncratic risk can explain the persistence of the momentum and reversal effects.

I find that reversals are stronger in high idiosyncratic risk firms. This is consistent with an equilibrium in which arbitrageurs attempt to correct mispricing, but only to the extent that the marginal benefit of each position is equal to its cost. The results, along with the model described in Section II, suggest that the amount that a risk-averse arbitrageur would invest in a high idiosyncratic risk-reversal portfolio stock is very small (0.59% of total wealth), so the persistence of a mispricing of this magnitude is not implausible, assuming that arbitrage capital is limited. The findings are therefore consistent with De Bondt and Thaler (1985), (1987), Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999), each of whom contends that reversal is the result of mispricing.

Momentum is not related to idiosyncratic risk. The results suggest that a risk-averse arbitrageur would invest 16% of her wealth in a single low idiosyncratic risk-momentum portfolio stock, making limited arbitrage due to idiosyncratic risk a less than plausible explanation for the persistence of the effect. However, momentum may still be the result of mispricing, but transaction costs may be the binding costs that limit arbitrage. This argument is supported by the findings of Lesmond et al. (2004), who show that there is cross-sectional relation between transaction costs and momentum profits.

Reversal represents a larger mispricing than momentum. Therefore, taken in their entirety, the results suggest that idiosyncratic risk plays an important role in preventing arbitrage in relatively large mispricing, in which the α is likely to exceed the transaction costs, whereas transaction costs are more important at limiting arbitrage in smaller mispricing.

Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999) contend that the momentum and reversal effects are part of the same phenomena, in that the momentum effect creates the subsequent reversal. The results in this paper show that momentum and reversal are each strongest in different types of stocks; reversal is strongest in the 2 highest idiosyncratic risk quintiles, and it does not arise in the other 3 quintiles. Momentum, on the other hand, arises in all 5 of the idiosyncratic risk quintiles, and it is strongest in the 2nd to lowest and middle idiosyncratic risk quintiles, in which there is no reversal effect. My findings are therefore not consistent with the single phenomenon argument put forth in the above studies and suggest that each effect is generated by a different underlying process.

Appendix. Variable Descriptions

Long-Term Reversal. The long-term reversal proxy is the buy and hold return measured from months $t-36$ through $t-7$. The measurement ends at month $t-7$ to avoid overlap with the momentum measure.

https://doi.org/10.1017/S0022109010000311 Published online by Cambridge University Press

Momentum. The momentum proxy is the buy and hold return measured from $t-6$ through $t-1$. Momentum is measured with a 1-month lag in order to avoid autocorrelation from bid-ask bounce.

Idiosyncratic Risk. Idiosyncratic risk is the variance of the residual from a regression of monthly firm returns on the monthly returns of the S&P 500 Index over the past 36 months.

Future Idiosyncratic Risk. Future idiosyncratic risk is idiosyncratic risk measured over the subsequent 36 months.

5-Factor Idiosyncratic Risk. 5-factor idiosyncratic risk is the variance of the residual from a regression of monthly firm returns on the Fama-French-Carhart 4-factor model and an equal-weighted 2-digit SIC code industry portfolio. This measure is estimated over the past 36 months.

R^2. The R^2 measure is obtained from the regression that is used to generate the idiosyncratic risk variable.

Size. The natural logarithm of market value of equity is used to proxy for firm size. Market value of equity is the product of the previous month-end's share price and the previous month-end's shares outstanding.

Market-to-Book Ratio. The market-to-book ratio is the ratio of market value of equity to book value of equity. Book value of equity is from the previous year's annual report.

Gibbs Cost Estimate. Hasbrouck (2004) developed the Gibbs transaction cost estimate. The Gibbs estimate is a Bayesian estimation of Roll's (1984) spread model. Hasbrouck (2009) finds that the correlation of the Gibbs estimate with actual bid-ask spreads (which are not widely available) is 0.944. This Gibbs measure is updated annually.

Amihud's Illiquidity Measure. The Amihud (2002) illiquidity measure is the absolute value of daily returns divided by daily dollar volume. This measure is update annually.

References

Amihud, A. "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." *Journal of Financial Markets*, 5 (2002), 31–56.

Ang, A.; R. Hodrick; Y. Xing; and X. Zhang. "The Cross-Section of Volatility and Expected Returns." *Journal of Finance*, 51 (2006), 259–299.

Arena, M. P.; K. S. Haggard; and X. S. Yan. "Price Momentum and Idiosyncratic Volatility." *Financial Review,* 43 (2008), 159–190.

Ball, R.; S. P. Kothari; and J. Shanken. "Problems in Measuring Portfolio Performance: An Application to Contrarian Investment Strategies." *Journal of Financial Economics,* 38 (1995), 79–107.

Barberis, N.; A. Shleifer; and R. Vishny. "A Model of Investor Sentiment." *Journal of Financial Economics,* 49 (1998), 307–343.

Barberis, N., and R. Thaler. "A Survey of Behavioral Finance." In *Handbook of the Economics of Finance,* Vol. 1B, G. Constantinides, M. Harris, and R. Stulz, eds. Amsterdam: Elsevier (2003), 1052–1090.

Berk, J. B.; R. C. Green; and V. Naik. "Optimal Investment, Growth Options, and Security Returns." *Journal of Finance,* 54 (1999), 1553–1607.

Brav, A.; J. B. Heaton; and S. Li. "The Limits of the Limits of Arbitrage." *Review of Finance*, 14 (2010), 157–187.

Chopra, N.; J. Lakonishok; and J. Ritter. "Measuring Abnormal Performance: Do Stocks Overreact?" *Journal of Financial Economics,* 31 (1992), 235–268.

Chui, A. C. W.; S. Titman; and K. C. J. Wei. "Momentum, Ownership Structure, and Financial Crises: An Analysis of Asian Stock Markets." Working Paper, University of Texas (2000).

Conrad, J., and G. Kaul. "An Anatomy of Trading Strategies." *Review of Financial Studies,* 3 (1998), 489–519.

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

Daniel, K.; D. Hirshleifer; and A. Subrahmanyam. "Investor Psychology and Security Market Underand Overreactions." *Journal of Finance,* 53 (1998), 1839–1886.

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

De Bondt, W. F. M., and R. H. Thaler. "Further Evidence on Investor Overreaction and Stock Market Seasonality." *Journal of Finance,* 42 (1987), 557–581.

De Long, J. B.; A. Shleifer; L. H. Summers; and R. J. Waldmann. "Noise Trader Risk in Financial Markets." *Journal of Political Economy,* 98 (1990), 703–738.

Duan, Y.; G. Hu; and R. D. McLean. "When Is Stock Picking Likely to Be Successful? Evidence from Mutual Funds." *Financial Analysts Journal*, 65 (2009), 55–66.

Duan, Y.; G. Hu; and R. D. McLean. "Costly Arbitrage and Idiosyncratic Risk: Evidence from Short Sellers." *Journal of Financial Intermediation*, forthcoming (2010).

Durnev, A.; R. Morck; B. Yeung; and P. Zarowin. "Does Greater Firm-Specific Return Variation Mean More or Less Informed Stock Pricing?" *Journal of Accounting Research,* 41 (2003), 797–836.

Fama, E. F., and K. R. French. "The Cross-Section of Expected Stock Returns." *Journal of Finance,* 47 (1992), 427–265.

Fama, E. F., and K. R. French. "Multifactor Explanations of Asset Pricing Anomalies." *Journal of Finance,* 51 (1996), 55–84.

Fama, E., and J. D. MacBeth. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy,* 81 (1973), 607–636.

Hasbrouck, J. "Liquidity in the Futures Pits: Inferring Market Dynamics from Incomplete Data." *Journal of Financial and Quantitative Analysis,* 39 (2004), 305–326.

Hasbrouck, J. "Trading Costs and Returns for U.S. Equities: Estimating Effective Costs from Daily Data." *Journal of Finance*, 64 (2009), 1445–1477.

Hong, H.; T. Lim; and J. C. Stein. "Bad News Travels Slowly: Size, Analyst Coverage and the Profitability of Momentum Strategies." *Journal of Finance,* 55 (2000), 265–295.

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

Hou, K.; L. Peng; and W. Xiong. "R^2 and Price Inefficiency." Working Paper, Ohio State University (2006).

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

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

Johnson, T. C. "Rational Momentum Effects." *Journal of Finance,* 57 (2002), 585–608.

Korajczyk, R. A., and R. Sadka. "Are Momentum Profits Robust to Trading Costs?" *Journal of Finance,* 59 (2004), 1039–1082.

Lee, C. M. C., and B. Swaminathan. "Price Momentum and Trading Volume." *Journal of Finance,* 55 (2000), 2017–2069.

Lesmond, D. A.; M. J. Schill; and C. Zhou. "The Illusory Nature of Momentum Profits." *Journal of Financial Economics,* 71 (2004), 349–380.

Malloy, C. J.; T. J. Moskowitz; and A. Vissing-Jørgensen. "Long-Run Stockholder Consumption Risk and Asset Returns." *Journal of Finance,* 64 (2009), 2427–2479.

Markowitz, H. "Portfolio Selection." *Journal of Finance,* 7 (1952), 99–91.

McLean, R. D.; J. Pontiff; and A. Watanabe. "Share Issuance and Cross-Sectional Returns: International Evidence." *Journal of Financial Economics*, 94 (2009), 1–17.

Morck, R.; B. Yeung; and W. Yu. "The Information Content of Stock Markets: Why Do Emerging Markets Have Synchronous Stock Price Movements?" *Journal of Financial Economics,* 58 (2000), 215–260.

Newey, W. K., and K. D. West. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica,* 55 (1987), 703–708.

Pontiff, J. "Costly Arbitrage: Evidence from Closed-End Funds." *Quarterly Journal of Economics,* 111 (1996), 1135–1151.

Pontiff, J. "Costly Arbitrage and the Myth of Idiosyncratic Risk." *Journal of Accounting and Economics,* 42 (2006), 35–52.

Pontiff, J., and M. J. Schill. "Long-Run Seasoned Equity Offering Returns: Data Snooping, Model Misspecification, or Mispricing? A Costly Arbitrage Approach." Working Paper, Boston College (2003).

Pontiff, J., and A. Woodgate. "Share Issuance and Cross-Sectional Returns." *Journal of Finance,* 63 (2008), 921–945.

Roll, R. "A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market." *Journal of Finance,* 39 (1984), 1127–1139.

Rouwenhorst, K. G. "International Momentum Strategies." *Journal of Finance,* 53 (1998), 267–284.

Rouwenhorst, K. G. "Local Return Factors and Turnover in Emerging Stock Markets." *Journal of Finance,* 54 (1999), 1439–1464.

Scholes, M. S. "The Market for Securities: Substitution versus Price Pressure and the Effects of Information on Share Prices." *Journal of Business*, 45 (1972), 179–211.

Shiller, R. J. "Stock Prices and Social Dynamics." *Brookings Papers on Economic Activity*, 2 (1984), 457–498.

Shleifer, A., and R. W. Vishny. "Equilibrium Short Horizons of Investors and Firms." *American Economic Review,* 80 (1990), 148–153.

Shleifer, A., and R. W. Vishny. "The Limits of Arbitrage." *Journal of Finance,* 52 (1997), 35–55.

Spiegel, M. I., and X. Wang. "Cross-Sectional Variation in Stock Returns: Liquidity and Idiosyncratic Risk." Working Paper, Yale University (2006).

Treynor, J. L., and F. Black. "How to Use Security Analysis to Improve Portfolio Selection." *Journal of Business,* 46 (1973), 66–86.

Wurgler, J., and E. Zhuravskaya. "Does Arbitrage Flatten Demand Curves for Stocks?" *Journal of Business,* 75 (2002), 583–608.