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Arbitrage Risk and Stock Mispricing

John A. Doukas, Chansog (Francis) Kim, and Christos Pantzalis*

Abstract

In this paper we examine the relation between equity mispricing and arbitrage risk and find that stocks with high arbitrage risk have higher estimated mispricing than stocks with low arbitrage risk. These results are not limited to high book-to-market or small capitalization stocks, and they are not sensitive to transaction and short-selling costs. In addition, they remain robust to alternative multifactor return generating specification models and mispricing measures. Overall, our empirical results are consistent with the conjecture that mispricing is a manifestation of the inability of arbitrageurs to hedge idiosyncratic risk, a major deterrent to arbitrage activity.

I. Introduction

Economic and financial theory conventionally assumes that securities prices do not systematically deviate from fundamental values, mainly because arbitrageurs have economic incentives to take positions against this pricing wedge. This view takes for granted the ability of arbitrageurs to restore equilibrium in securities prices. However, increasing empirical evidence supports the existence of pricing anomalies.[1]

*Doukas, jdoukas@odu.edu, Department of Finance, School of Business and Public Administration, Old Dominion University, Norfolk, VA 23529, and Judge Business School, University of Cambridge, Cambridge CB2 1AG, UK; Kim, acckim@cityu.edu.hk, Department of Accountancy, City University of Hong Kong, Tat Chee Ave., Kowloon, Hong Kong; and Pantzalis, cpantzal@coba.usf.edu, Department of Finance, College of Business Administration, University of South Florida, 4202 E. Fowler Ave., BSN 3403, Tampa, FL 33620. We acknowledge the contribution of IBES International Inc. for providing earnings per share forecast data, available through Institutional Brokers' Estimate System. The paper has benefited from the comments of Michael Brennan, Stephen Brown (the editor), David Hirshleifer, and Jeffrey Pontiff (associate editor and referee). We also thank PhD seminar participants at the 2004 European Financial Management Association (EFMA) meetings for helpful suggestions. All errors are our own.

[1]See Ball and Brown (1968), De Bondt and Thaler (1985), Jegadeesh and Titman (1993), and Chan, Jegadeesh, and Lakonishok (1996), among others. French and Roll (1986) argue that, on average, 4%–12% of the daily return variance of common stock returns is due to mispricing. De Long, Shleifer, Summers, and Waldman (1991), among others, claim that securities prices drift from fundamental values because arbitrageurs cannot undo mispricing caused by less rational traders. In recent studies, investor judgment biases (i.e., investor sentiment, overconfidence, and/or conservatism (Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998)) have been offered as possible explanations of securities mispricing.

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An important research question that emerges from these studies is why arbitrageurs do not exploit mispricing opportunities. The significance of this issue cannot be overstated: If true, persistent price deviations from fundamental values would imply arbitrage risk, suggesting that expected rates of return may depend not only on fundamental risk, as captured by a standard asset pricing model, but also on asset mispricing that varies with idiosyncratic risk. Whether arbitrage risk plays a systematic role in causing prices to deviate from fundamental values in the cross section of stocks has not been tested. While previous studies show that some anomalies (i.e., those associated with closed-end funds (Pontiff (1996)), momentum (Grundy and Martin (2001)), index inclusion (Wurgler and Zhuravskaya (2002)), book-to-market (BM) ratio (Ali, Hwang, and Trombley (2003)), post-earnings announcement drift (Mendenhall (2004)), and accrual anomaly (Mashruwala, Rajgopal, and Shevlin (2006))) are pronounced within the idiosyncratic component of stock returns, they do not investigate whether a systematic relation between mispricing and arbitrage risk exists in the cross section of stocks. In fact, these authors focus on certain specific groups of stocks or mutual fund returns. While the collective evidence attributes these price anomalies to arbitrage risk, inferences about the role of arbitrage risk on mispricing are primarily based on firms' BM ratios (e.g., Ali et al.). However, a host of other factors that affect mispricing are likely to contribute to this relationship (Rhodes-Kropf, Robinson, and Viswanathan (2005)). For example, firms with high growth opportunities, which typically have high market values relative to book assets and probably high idiosyncratic risk (i.e., firms with few substitutes) are more likely to elicit less arbitrage. Consequently, addressing the quantitative question about the impact of arbitrage risk on mispricing requires a mispricing measure that is not tied to the determinants of arbitrage risk. This study is also motivated by the mixed results of recent empirical studies on the relationship between idiosyncratic volatility (IVOL) and stock returns,[2] and the controversy associated with the BM ratio.[3]

First, we show that market price deviations from proxies of intrinsic value are consistent with mispricing. Second, we examine whether arbitrage risk plays a role in mispricing.[4] Then we address the research question of whether arbitrage risk is systematically related to mispricing proxies by conducting several empirical tests on the cross section of stocks. Specifically, we use time-series tests of arbitrage portfolio returns to test the arbitrage risk hypothesis. To perform these tests, we need a suitable measure that captures market price deviation from intrinsic values for individual stocks. Since intrinsic value is not directly observable,

[2]Ang, Hodrick, Xing, and Zhang (2006) show that stocks with high IVOL are systematically overpriced. Spiegel and Wang (2005), however, show that stock returns increase with the level of idiosyncratic risk. Duan, Hu, and McLean (2010) examine whether idiosyncratic risk, which makes arbitrage risk costly, deters arbitrage activity among short sellers and find that a negative relation exists only between high idiosyncratic risk stocks and subsequent returns.

[3]Beaver and Ryan (2000), in a different context, decompose the BM ratio into its bias and lag components, demonstrating that its ability to predict future returns stems from the bias component that results from the joint effects of accounting process (i.e., conservatism and historical costs) and economic environment (i.e., expected positive present value projections and inflation).

[4]Gromb and Vayanos (2002) and Chen, Hong, and Stein (2002) provide convincing theoretical explanations as to why arbitrageurs fail to close arbitrage opportunities, causing mispricing to persist.

we use 2 proxies: one based on information from sales and another based on Ohlson's (1995) valuation model. An advantage of our approach relative to previous studies is that our analysis proceeds after we empirically confirm the ability of the mispricing measures to predict future abnormal returns.[5] The power to predict market returns is important because it captures the responsiveness of the valuation model to economic forces that influence stock prices. Unlike past studies that use BM ratio as a market mispricing proxy, we show that the 2 proxies used in this study have superior cross-sectional abnormal stock return predictive power relative to the BM ratio.[6] Specifically, after controlling for several risks and transaction costs, our mispricing measures exhibit a significant and positive relation with future returns that is unlikely to be driven by omitted risk factors. Interestingly, when the BM ratio is included in the analysis along with our excess valuation measures, its predictive power vanishes, suggesting that our valuation-based approach has incremental value relative to the BM ratio.[7] Time-series tests also yield similar results. These findings oppose the notion that the BM ratio captures stock market mispricing, and they are consistent with Rhodes-Kropf et al. (2005), who show that the BM ratio consists of 2 components: i) mispricing and ii) growth or time-varying risk. This offers an explanation for the poor predictive power of the BM ratio relative to our measures, which resemble the Rhodes-Kropf et al. mispricing component.[8]

Furthermore, we check the robustness of our analysis with additional tests, using a relative valuation measure that is orthogonal to BM and size. These new tests produce supplementary evidence confirming our original findings. Finally, we inspect the adjusted R^2s from time-series regressions of the arbitrage return spreads between undervalued and overvalued portfolios, constructed using the relative valuation approach, on the well-known 3- or 4-factor models, to ensure that this valuation method yields a distinct mispricing measure. Indeed, our results show that the adjusted R^2s are significantly less than 100%, ranging between 54% and 57%, suggesting that stocks share incremental mispricing above and beyond the comovement implied from the 3- and 4-factor models. However, since we cannot observe either fundamental values or which stocks are mispriced, we recognize that the return predictability of our proxies may not necessarily imply

[5]We use the terms mispricing and deviation from fundamental (intrinsic) value interchangeably.

[6]Whether the BM ratio represents mispricing or risk remains unsettled (see, e.g., Subrahmanyam (2010)). Researchers who discovered the BM effect considered it market inefficiency. Behavioral finance offers an explanation based on investor overconfidence. That is, overconfident investors overestimate their own skill, especially when predicting future earnings growth for individual companies. Behavioral explanations look particularly appealing in helping us understand the extraordinary bubble in large capitalization high-technology growth stocks during 1999 and early 2000, and the suboptimal behavior of investors who held them. Fama and French (1993), among others, attribute the BM effect to risk and argue that a low price-to-book ratio is often a sign of financial distress and greater susceptibility to economic shocks. Lakonishok, Shleifer, and Vishny (1994), however, deny the assertion that value stocks are fundamentally riskier. Doukas, Kim, and Pantzalis (2002) provide empirical evidence refuting the claim of Lakonishok et al. (1994). Daniel and Titman (1997) argue that size and BM stand for firm characteristics.

[7]This result is consistent with Frankel and Lee (1998) and Lee, Myers, and Swaminathan (1999), who show that the value-to-price ratio can predict abnormal returns for up to 3 years.

[8]The Pearson correlation between the Rhodes-Kropf et al. (2005) mispricing component and the 2 mispricing measures used in this study is positive and significant at the 1% level.

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mispricing, but rather, a relationship that is consistent with an efficient capital market and a correct asset pricing model. To somewhat alleviate this latter concern, we employ alternative versions of the Fama and French (1993) model.[9]

In sum, this study contributes to the literature in 2 ways. First, it shows that our 2 relative valuation-based mispricing metrics tend to be more pronounced in highly idiosyncratic stocks. The second contribution relates to the return predictability of the 2 mispricing measures used in this study. Specifically, we present new evidence that the i) industry-adjusted price-to-sales ratio and ii) the residual income valuation-based mispricing measures each forecast cross-sectional returns, above and beyond those of BM and size, the common return predictors.

Our empirical tests show that price divergence from proxies of fundamental value is positively associated with arbitrage risk, as measured by idiosyncratic risk. We also find that this valuation difference spreads beyond small capitalization and high BM stocks, suggesting that arbitrage risk has pricing implications for a broad range of stocks. Because most risk-based rational asset pricing explanations require an extra unit of idiosyncratic risk across all securities having the same impact on expected returns, one might interpret our results as suggesting that asset prices can be explained by an unknown risk factor that is expressed through idiosyncratic risk. This interpretation, however, is inconsistent with our finding that abnormal returns are more negative for the group of apparently overpriced stocks with high idiosyncratic risk, and more positive for the group of apparently underpriced stocks with high idiosyncratic risk. Our results suggest that, when stock prices are subject to mispricing error, expected stock returns may depend not only on the fundamental risk factor captured by a standard asset pricing model, but also on the degree of mispricing caused by the inability of arbitrageurs to hedge idiosyncratic risk.

Consistent with the subsidiary prediction of the arbitrage risk hypothesis, which conjectures lower mispricing when sophisticated investors trade, our results show that valuation deviations from intrinsic values are mitigated in the presence of sophisticated investors only for low arbitrage risk stocks. An interesting implication of this result is that stock market price deviations from intrinsic values are not necessarily manifestations of economic irrationality among economic agents. Collectively, our results suggest that mispricing is driven by both arbitrage risk and scarcity of sophisticated trades.

This paper proceeds as follows. In Section II we describe the estimation of the mispricing measures used in the analysis. Section III contains a description of the data sources and sample selection process. Sections IV and V present and describe the empirical results of univariate and multivariate tests, respectively. Section VI concludes the paper.

II. Mispricing, Arbitrage Risk, and Stock Returns

Since we are interested in examining the relation between mispricing and stock returns, we need a meaningful mispricing measure that captures deviations

[9]Regression estimations based on the Ferguson and Shockley (2003) asset pricing model specification produced similar results. These results are not reported but are available from the authors.

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from intrinsic value. Because intrinsic values are not observable, we use 2 alternative mispricing measures to ensure that our results are not driven by the choice of valuation model.

In view of the fact that relative valuation is widely used by investors in making investment decisions, we rely on this valuation approach in constructing our first mispricing measure. Most equity research reports and many acquisition valuations are based on relative valuation. Relative performance affects prices at a given point in time through its impact on investor beliefs, as well as on the evolution of prices as investors learn more about other stocks and the economy. Moreover, relative valuation allows investors to categorize securities as "underpriced," "fairly valued," or "overpriced."[10] Relative valuation permits investors to make inferences about future growth prospects and to assess the quality of firm management. For instance, stocks trading at a premium (discount) relative to their industry peers may be perceived by investors as high (low) growth stocks. Therefore, if investors make decisions based on relative valuation inferences, they are likely to bid prices of overvalued (undervalued) stocks up (down), as they would consider them to have good (poor) prospects. If demand for such stocks remains relatively high, they will eventually realize lower (higher) future returns.

Categorization of stocks through relative valuation could generate a time-varying sentiment across classes of stocks. For example, when investor perceptions of overall growth opportunities are high, future returns will be relatively low. Thus, in this case, perceptions of growth opportunities, rather than risk tolerance, could be driving time variation. In addition, time-varying demand among stock categories may arise from "categorical inference" (see Mullainathan (2001)). Investors could, for example, react to information about a corporate decision differently depending on their categorical profile of the firm. Furthermore, managers may use relative valuation measures to identify potential acquisition targets. The above arguments provide several reasons why investors are likely to use the relative valuation approach as a way of classifying stocks into distinct valuation groups (i.e., overvalued or undervalued).

A. Excess Valuation Mispricing Measure (X_VALUE1)

We create an excess valuation measure (X_VALUE1) that relies on the relative valuation approach to determine whether a firm is underpriced or overpriced relative to its industry peers.[11] This measure relies on the assumption that investors have imperfect information about expected returns or cash flows and, therefore, learn about returns or cash flows using relative industry performance information. We measure the extent of mispricing by the natural logarithm of the

[10] Fund managers and investors often categorize securities as "small stocks," "large stocks," "value stocks," "growth stocks," "tech stocks," "utility stocks," and "junk bonds," among other categories. See also Barberis and Shleifer (2003).

[11] See Berger and Ofek (1995) for a similar measure that aggregates imputed values for all segments of a firm. Alternative measures of mispricing relying on "discretionary accruals" (Chan, Chan, Jegadeesh, and Lakonishok (2006)), "net equity issuance" (Daniel and Titman (2006)), and "momentum" (Jegadeesh and Titman (1993), (2001)) have been proposed in the literature.

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ratio of the firm's actual value relative to its primary Standard Industrial Classification (SIC) industry-based imputed value, using the Fama-French 48 industry sectors, rather than conventional SIC code industry classifications.[12] Actual value is measured by total firm capital. Imputed value is estimated as the ratio of firm sales, multiplied by its primary SIC industry median capital-to-sales ratio.[13] A positive excess market value indicates that a firm's stock trades at a premium, while a negative excess market value indicates that its stock trades at a discount.

B. Residual Income Mispricing Measure (X_VALUE2)

One problem with empirical studies that use simple market multiples in equity valuation is that they often rely on biased proxies as model inputs. Recent research suggests that the Ohlson (1995) valuation model is more robust than simple market multiples, because it leads to better predictions of cross-sectional stock returns (Frankel and Lee (1998)). Moreover, practical considerations, such as the availability of earnings forecasts, make this valuation model easier to implement for purposes of this study. Therefore, our second mispricing measure, X_VALUE2, is based on the Ohlson residual income valuation model. X_VALUE2 represents the difference between fundamental value, V, and market value, P. Specifically, it is measured as the natural logarithm of the ratio of a firm's actual to its imputed stock price. The imputed stock price, V, is derived from Ohlson's model, and serves as a proxy for the contemporaneous nonmarket measure of intrinsic (fundamental) value, using mean forecasts and a discount rate computed from the Fama-French (1993) 3-factor model, as in equation (3.2) of Frankel and Lee (1998).[14] The residual income valuation, V/P, filters out growth or time-varying risk factors (Rhodes-Kropf et al. (2005)) and has received strong support as an indicator of mispricing. Lee et al. (1999) report that V/P predicts 1-month-ahead returns on Dow 30 (Dow Jones Industrial Index (DJIA)) stocks better than aggregate BM. Frankel and Lee also show that residual income value is a better predictor than book value of the cross section of contemporaneous stock prices, and that V/P is a better predictor of the 1-year-ahead cross section of returns. D'Mello and Schroff (2000) apply V/P to measure mispricing of equity

[12] We obtain similar results with conventional industry classifications based on SIC codes. We also estimate the X_VALUE1 measure by relying on segment information as in Berger and Ofek (1995). Specifically, imputed value is computed as the sum of the imputed values of firm segments, which is an estimate of the firm's value if its segments were operated as stand-alone units (i.e., the firm's total imputed value). Results based on this alternative measure are similar to those reported and are available from the authors.

[13] We also repeated this procedure using asset multipliers, as in Berger and Ofek (1995). The results using excess market values based on asset-multipliers—not reported here, but available from the authors—are quantitatively and qualitatively similar to those based on the sales multipliers presented in this study.

[14] An alternative proxy of mispricing could be the BM ratio (i.e., book value as a proxy of fundamental value). However, since book value reflects historical costs rather than forward-looking prospects, the BM ratio (or any closely related variable such as the reciprocal of proxies for Tobin's q) is a proxy not just for mispricing, but for the ability of a firm to generate high returns on its investments. The BM ratio has been used in many studies as a proxy for various other firm characteristics (e.g., growth opportunities and the degree of managerial discipline).

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repurchases. Dong, Hirshleifer, Richardson, and Teoh (2006) use V/P to examine whether misvaluation is driving mergers and acquisitions.

As in Frankel and Lee (1998), we measure fundamental equity value, V_t, using a 2-period expansion of the following valuation model:

$$V_t = B_t + \frac{(\text{FROE}_t - r_e)}{(1+r_e)}B_t + \frac{(\text{FROE}_{t+1} - r_e)}{(1+r_e)r_e}B_{t+1},$$

where FROE_t is the forecasted return on equity (ROE) for the current year. The right-hand side of this equation consists of ex ante observable variables. FROE_t is estimated using analyst consensus 1-year-ahead Institutional Brokers' Estimate System (IBES) earnings forecasts (FY1) of ROE_t.[15] Hence, we require all sample firms to have 1-year-ahead (FY1) and 2-year-ahead (FY2) consensus earnings forecasts. Using analyst forecasts, the current and next-period forecast returns on equity are estimated as follows:

$$\text{FROE}_t = \text{FY1}/[(B_{t-1} + B_{t-2})/2] \quad \text{and} \quad \text{FROE}_{t+1} = \text{FY2}/[(B_t + B_{t-1})/2].$$

B_t is the estimated book value of common shareholder equity at the end of year t (i.e., $B_t = B_{t-1}[1 + \text{FROE}_t(1-k)]$, where k is the dividend payout ratio, computed by dividing common stock dividends paid in the most recent year (Compustat item 21) by net income before extraordinary items (Compustat item 237)), and r_e is the estimated cost of capital. Cost of capital is estimated using the Fama and French (1997) 3-factor model as an industry-specific rate based on the Fama and French 48-industry classification. Frankel and Lee (1998) show that the fundamental value-to-price ratio can predict abnormal returns for up to 3 years and argue that this is a more robust valuation method than conventional market multiples, implying that it is unlikely to be driven by omitted variables (i.e., size and BM).

We also employ a mispricing index (XV_INDEX), which combines X_VALUE1 and X_VALUE2. The XV_INDEX is constructed for each year and each observation $i = 1, \ldots, N$ as follows:

$$\text{XV_INDEX} = \frac{1}{N}\frac{1}{K}\sum_{k}^{K}\text{RANK}_k(\text{X_VALUE}_{ik}),$$

where $\text{RANK}_k(\text{X_VALUE}_{ik})$ is the rank function that assigns a rank for each observation from lowest (rank of 1) to highest value (rank of N). X_VALUE_{ik} is the kth measure of mispricing for firm i in our sample, and K represents the dimensions of mispricing measures. The denominator, K, averages the ranks by the number of mispricing values available for each firm in the sample in a particular year (i.e., K takes values from 1 to 2). Finally, dividing by N, we scale the XV_INDEX so that it takes values ranging from 0 (most undervalued) to 1 (most overvalued). Furthermore, to ensure that size and BM effects do not drive our results, we construct an XV_INDEX mispricing measure orthogonal to size and BM (RES_XV_INDEX).

[15] $\text{ROE}_t = \text{NI}_t/[(B_t + B_{t-1})/2]$, where NI is earnings to common shareholders in year t, net of extraordinary items, taxes, and preferred dividends (Compustat item 237).

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Finally, we estimate 2 arbitrage risk measures, AR1 and AR3. We follow Wurgler and Zhuravskaya (2002), who measure arbitrage risk as the variance/standard deviation of the residuals from a regression of a firm's stock returns on the returns of the market portfolio. A similar measure has been used in other studies (e.g., Ali et al. (2003), Pontiff and Schill (2003), Mendenhall (2004), and Mashruwala et al. (2006)). We proxy arbitrage risk (AR1 and AR3) with the standard deviation of the residuals in year $t - 1$. Specifically, we run a regression of weekly returns on a single-factor model (RMF). This regression is estimated over a 1-year period beginning 2 years prior to June of each year. The estimated coefficients are then used to compute expected returns in year $t - 1$. We also estimate arbitrage risk from a regression of weekly returns on the Fama-French (1993) 3 factors, AR3. We obtain similar results when we utilize arbitrage risk measures based on daily returns.

III. Data and Sample Selection

Our analysis is based on all firms covered in the Standard & Poor's Compustat Primary, Secondary, and Tertiary (PST), Full Coverage, Research, and Industry Segment databases over the 1960–2001 period. As in Berger and Ofek (1995), firms with total sales of less than $20 million are excluded in order to eliminate firms with distorted valuation multiples due to very low sales figures. We also exclude firms in the financial services industry. Firms included in the sample must have available information on total capital, measured by market value of common equity plus book value of debt, and their sum of segment sales should be within 1% of total sales reported for the firm in the Compustat database. For the construction of the X_VALUE2 measure, firms must have available analyst forecast data in the IBES database. We select analyst forecasts issued in June of each year for all stocks covered by securities analysts.

For our asset pricing tests, stocks are allocated to various portfolios at the end of June of each year (i.e., immediately after the mispricing measures are observed). These portfolios' equal-weighted returns are measured over the 12-month period starting at the beginning of July and ending at the end of June of the following year, when portfolios are rebalanced. Return data are from the Center for Research in Security Prices (CRSP). We use the Fama and French (1996) methodology in assigning stocks to size- and BM-ranked portfolios. Size rankings are based on firms' June market value of common equity. The BM ratio used to form portfolios in June of year t consists of the book value of common equity at the end of the fiscal year ending in calendar year $t - 1$, divided by the market value of equity at the end of December of year $t - 1$. Book value of equity is the Compustat book value of stockholder equity, plus balance sheet deferred taxes and investment tax credit, minus the book value of preferred stock. New York Stock Exchange (NYSE) breakpoints are used for portfolios of firms ranked on size and BM. Portfolios built based on rankings of excess value are based on excess values computed as of the end of December of year $t - 1$, while portfolios formed on the basis of excess analyst coverage rankings utilize information from analyst coverage in June of year t.

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IV. Empirical Results: Univariate Tests

In this section, we conduct univariate tests designed to examine the extent of mispricing in the context of the stock market, and using alternative mispricing measures.

Table 1 reports descriptive statistics for firms in our sample, sorted by the 2 mispricing measures and the mispricing index (i.e., X_VALUE1, X_VALUE2, and XV_INDEX, respectively). Before interpreting the results, it is important to check whether the mispricing measures have the desired characteristics with respect to BM, size, and return. Ideally, the relative valuation subsamples should contain stocks that display healthy BM, size, and return spread. Panel A shows that there is a strong (inverse) relation between BM and the X_VALUE1 measure. This is true as well with respect to size and excess analyst coverage, a surrogate for valuation ambiguity. Small (large) stocks have low (high) relative valuations. Similarly, excessively undercovered (overcovered) stocks have low (high) relative valuations, consistent with evidence from Doukas, Kim, and Pantzalis (2005). These characteristics are confirmed in Panels B and C when portfolios are sorted by the X_VALUE2 and XV_INDEX measures, respectively.

Another important observation is that the raw and market-adjusted monthly return difference between high and low X_VALUE1 stocks is –0.76% (with z-value of –16.96) and –0.83% (with z-value of –16.71), respectively. Similarly, the raw and market-adjusted monthly return difference between high and low X_VALUE2 stocks is –0.32% (with z-value of –4.55) and –0.31% (with z-value of –4.26), respectively. This confirms that the X_VALUE1 and X_VALUE2 measures depict overvaluation (undervaluation). The similarity of these results demonstrates that the relative valuation and residual income-based valuations yield comparable mispricing measures. As shown in Panel C of Table 1, a similar return difference pattern emerges when the XV_INDEX measure is used. In unreported results, we show that X_VALUE1 and X_VALUE2 capture deviations from fundamental value, even after controlling for several effects (e.g., BM, size, and excess analyst coverage).[16]

Finally, a remarkable pattern emerges from sorting on relative valuation: the relation between the 2 arbitrage risk measures, AR1 and AR3, and mispricing. The results reveal that the most mispriced stocks (Q1 and Q5) are associated with the highest levels of arbitrage risk. Specifically, as shown in Panel A of Table 1, for the highly undervalued (Q1) stocks, the AR1 (AR3) is 7.64 (7.83). For the highly overvalued stocks (Q5), the AR1 (AR3) is 8.47 (9.02). The AR1 (AR3) difference between Q5 and Q1 stock portfolios, adjusted for clustered observation standard errors using the generalized estimating equations (GEE) approach (Liang and Zeger (1986)), is generally positive and statistically significant across all 3 panels. Most importantly, the levels of arbitrage risk are lower for the 3 middle quintiles (Q2, Q3, and Q4) than for the extreme quintiles (Q1 and Q5), where mispricing is more likely.

[16]For the sake of brevity these results are not reported but are available from the authors.

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V. Empirical Results: Multivariate Tests

A. The Predictive Power of XV_INDEX Relative to Book-to-Market

Ali et al. (2003), among others, have used BM as a mispricing proxy despite the fact that Frankel and Lee (1998) and Lee et al. (1999) have made a strong case in favor of the value-to-price metric. In this section, we examine the incremental benefit of the XV_INDEX relative to the BM ratio in terms of predicting future stock returns. That is, we are interested in examining whether the XV_INDEX, as a mispricing measure, is a better predictor of future returns than the BM ratio, after controlling for risk and transaction cost effects. Therefore, we reestimate regression (1) from Ali et al. following the Fama and MacBeth (1973) procedure, for a larger sample of observations (133,650) over the period

TABLE 1

Summary Statistics for Stocks Sorted by Mispricing Measures

Table 1 reports mean values (and number of firm-years assigned to each quintile in parentheses) of book-to-market (BM), size, mean return (RET), mispricing, and arbitrage risk measures for the quintile portfolios of firms sorted annually on several mispricing measures. The mispricing measures are as follows: i) X_VALUE1 is measured as the natural logarithm of the ratio of a firm's actual value to its imputed value. A firm's imputed value is the ratio of the firm's sales, multiplied by its industry median capital-to-sales ratio (computed for single-industry firms in the industry. Industries are defined as the 48 Fama-French sectors. X_VALUE1 is available from 1960 to 2001. ii) X_VALUE2 is measured as the natural logarithm of the ratio of the firm's actual to imputed stock price. The imputed stock price is derived from Ohlson's (1995) model (residual income model) using mean forecasts, and a discount rate computed from Fama-French's 3-factor model, as in equation (3.2) of Frankel and Lee (1998). X_VALUE2 is available from 1976 to 2001. iii) XV_INDEX represents the excess value index created as the average, scaled cross-sectional ranking over the 2 aforementioned mispricing measures. Sorting by X_VALUE1, X_VALUE2, and XV_INDEX is done in Panels A, B, and C, respectively. BM ratios and size are computed as in Fama and French (1996). COVER is the number of analysts covering the stock. X_COVER represents excess analyst coverage, computed as the natural logarithm of the firm's actual-to-imputed analyst following ratio. The imputed analyst following is equal to firm sales, multiplied by the industry median analyst following-to-sales ratio computed for single-industry firms in the industry. Industries are defined with respect to the 48 Fama-French sectors. RET is the average monthly return for each quintile portfolio. X_RET represents excess return, computed as the difference between RET and the average expected return obtained from the market model. Arbitrage risk is defined in 2 ways: i) as the standard deviation of the residuals from the market model estimated over the 1-year period prior to June of each year using weekly returns, AR1; and ii) as the standard deviation of the residuals from the Fama-French 3-factor model estimated over the 1-year period prior to June of each year using weekly returns, AR3. Also reported are the differences in mean between the low (Q1) and high (Q5) mispricing quintiles and the corresponding *z*-statistics computed using the clustering GEE procedure (see Liang and Zeger (1986)) (in brackets). *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Using X_VALUE1 as Mispricing Measure

Variables	Q1 Low_ X_VALUE1	Q2	Q3	Q4	Q5 High_ X_VALUE1	All Stocks	Q5 – Q1 [*z*-statistic]
BM	1.15 (27,186)	1.07 (27,198)	0.92 (27,199)	0.74 (27,198)	0.49 (27,219)	0.88 (136,000)	–0.64*** [–13.11]
SIZE	500.53 (27,186)	594.75 (27,198)	902.84 (27,199)	1,148.54 (27,198)	1,266.16 (27,219)	882.66 (136,000)	141.15 [0.95]
X_COVER	–0.98 (7,511)	–0.39 (9,931)	–0.16 (11,616)	0.09 (12,250)	1.00 (9,671)	–0.04 (50,979)	1.68*** [24.43]
RET [%]	1.85 (24,059)	1.47 (24,353)	1.37 (24,595)	1.20 (24,608)	0.98 (24,330)	1.38 (121,945)	–0.76*** [–16.96]
X_RET [%]	0.76 (22,209)	0.38 (22,362)	0.24 (22,348)	0.09 (21,779)	–0.13 (18,985)	0.28 (107,683)	–0.83*** [–16.71]
X_VALUE1	–1.12 (27,186)	–0.38 (27,198)	0.00 (27,199)	0.40 (27,198)	1.57 (27,219)	0.09 (136,000)	2.57*** [178.91]
X_VALUE2	0.37 (7,239)	0.42 (9,804)	0.49 (11,531)	0.54 (12,062)	0.75 (7,840)	0.51 (48,476)	0.40*** [15.75]
AR1 [%]	7.64 (27,079)	6.62 (27,072)	6.23 (27,094)	6.33 (27,048)	8.47 (26,995)	7.06 (135,288)	–0.19** [–2.29]
AR3 [%]	7.83 (27,079)	6.82 (27,072)	6.40 (27,094)	6.55 (27,048)	9.02 (26,995)	7.32 (135,288)	0.56*** [6.17]

(continued on next page)

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TABLE 1 (continued)

Summary Statistics for Stocks Sorted by Mispricing Measures

Panel B. Using X_VALUE2 as Mispricing Measure

Variables	Q1 Low_ X_VALUE2	Q2	Q3	Q4	Q5 High_ X_VALUE2	All Stocks	Q5 – Q1 [*t*-statistic]
BM	0.82 (9,751)	0.82 (9,760)	0.77 (9,768)	0.68 (9,760)	0.66 (9,772)	0.75 (48,811)	–0.01*** [–7.97]
SIZE	1,254.97 (9,751)	1,596.66 (9,760)	2,101.24 (9,768)	2,552.53 (9,760)	2,678.19 (9,772)	2,073.03 (48,811)	1,688.69*** [4.80]
X_COVER	–0.16 (9,658)	–0.07 (9,716)	0.03 (9,701)	0.13 (9,690)	0.34 (9,711)	0.05 (48,476)	0.13*** [4.45]
RET [%]	1.45 (8,901)	1.39 (8,915)	1.31 (8,909)	1.16 (8,863)	1.08 (8,828)	1.28 (44,416)	–0.32*** [–4.55]
X_RET [%]	0.03 (8,557)	0.09 (8,648)	0.06 (8,697)	–0.16 (8,635)	–0.30 (8,520)	–0.05 (43,057)	–0.31*** [–4.26]
X_VALUE1	–0.16 (9,658)	–0.07 (9,716)	0.03 (9,701)	0.13 (9,690)	0.34 (9,711)	0.05 (48,476)	0.32*** [19.23]
X_VALUE2	–0.29 (9,751)	0.26 (9,760)	0.48 (9,768)	0.72 (9,760)	1.38 (9,772)	0.51 (48,811)	1.65*** [82.19]
AR1 [%]	5.49 (14,007)	5.07 (4,673)	5.02 (4,846)	4.90 (7,254)	5.88 (17,589)	5.46 (48,369)	0.26*** [7.23]
AR3 [%]	5.51 (14,007)	5.09 (4,673)	5.04 (4,846)	4.92 (7,254)	5.89 (17,589)	5.48 (48,369)	0.24*** [6.68]

Panel C. Using XV_INDEX as Mispricing Measure

Variables	Q1 Low_ XV_INDEX	Q2	Q3	Q4	Q5 High_ XV_INDEX	All Stocks	Q5 – Q1 [*t*-statistic]
BM	1.14 (27,241)	1.06 (27,273)	0.91 (27,258)	0.74 (27,278)	0.55 (27,285)	0.88 (136,335)	–0.56*** [–11.54]
SIZE	485.96 (27,241)	771.84 (27,273)	1,088.68 (27,258)	1,458.90 (27,278)	622.92 (27,285)	885.73 (136,335)	117.28 [1.49]
X_COVER	–0.93 (7,721)	–0.39 (11,879)	–0.11 (13,046)	0.23 (12,124)	1.23 (12,124)	–0.05 (51,227)	1.18*** [24.37]
RET [%]	1.86 (24,181)	1.45 (24,591)	1.31 (24,830)	1.19 (24,668)	1.07 (23,984)	1.38 (122,254)	–0.66*** [–14.26]
X_RET [%]	0.75 (22,333)	0.33 (22,912)	0.18 (23,067)	0.03 (22,011)	0.08 (17,659)	0.28 (107,982)	–0.60*** [–11.52]
X_VALUE1	–1.08 (27,082)	–0.37 (27,157)	0.06 (27,206)	0.44 (27,270)	1.41 (27,285)	0.09 (136,000)	2.30*** [167.14]
X_VALUE2	–0.01 (7,837)	0.38 (13,367)	0.49 (14,865)	0.90 (11,730)	1.98 (1,012)	0.51 (48,811)	1.99*** [55.12]
AR1 [%]	7.60 (26,980)	6.30 (27,034)	5.91 (27,103)	6.36 (27,109)	9.13 (27,062)	7.06 (135,288)	0.08 [1.05]
AR3 [%]	7.77 (26,980)	6.45 (27,034)	6.04 (27,103)	6.54 (27,109)	9.80 (27,062)	7.32 (135,288)	0.99*** [11.35]

1963–2001.[17] A significant negative coefficient on the interactive term BM $\times$ IVOL^{-1} would indicate that the BM effect increases with idiosyncratic risk, after controlling for beta risk, arbitrage cost, and investor sophistication variables. If XV_INDEX as a mispricing measure is superior to BM, it should enter the regression with a negative and significant coefficient; furthermore, its interaction with idiosyncratic risk, XV_INDEX $\times$ IVOL^{-1}, should have a positive and significant coefficient.

[17] Ali et al. (2003) use a sample with 63,855 observations spanning 1976–1997.

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Regression results are reported in Table 2. Regression (2) shows that the coefficient of the BM $\times$ IVOL^{-1} is statistically insignificant. A similar result is obtained in regression (3) even when we restrict the sample to NYSE and American Stock Exchange (AMEX) stocks over the 1976–1997 period and following the sample selection procedure described in Ali et al. (2003). Surprisingly, imposing these authors' restrictions produces a sample of 42,010 observations for the 1976–1997 period, about 34% less than the number of observations used in their regression analysis. The interesting conclusion that emerges from regressions (2) and (3) is that the insignificance of the interaction term, BM $\times$ IVOL^{-1}, is not driven by exchange listing or sample period considerations.

In regression (4), we control for other effects and obtain similar results. Interestingly, the explanatory power of the BM ratio in this regression drops dramatically, as shown by the magnitude of its coefficient. The BM effect is indistinguishable from 0 and does not increase with increases in idiosyncratic risk. This casts doubt on the ability of the BM ratio to predict future returns after controlling for other effects. These results contradict the findings of Ali et al. (2003), suggesting that the BM effect is unlikely to be caused by market mispricing arising from arbitrage risk. When we introduce our orthogonal XV_INDEX measure,[18] RES_XV_INDEX in regression (5), both BM and its interaction with IVOL retain their previous (insignificant) status, while RES_XV_INDEX enters the regression with a negative and significant coefficient, suggesting that this mispricing measure explains cross-sectional variation in future returns better than the BM ratio.

The same result is obtained when XV_INDEX replaces RES_XV_INDEX in regression (6). In regressions (7) and (8), we introduce the interactive term, XV_INDEX $\times$ IVOL^{-1}. Interestingly, the coefficients of XV_INDEX, in these regressions, and of RES_XV_INDEX in regression (5), are similar in terms of sign, magnitude, and statistical significance. The positive and statistically significant coefficient of XV_INDEX $\times$ IVOL^{-1} suggests that our excess valuation measure is a good predictor of future returns and that future returns increase with increases in idiosyncratic risk. Hence, the superior predictive power of XV_INDEX suggests that it is a more robust mispricing measure. Panel B of Table 5, Section V.D, presents similar results based on a time-series test.

B. Calendar-Time Arbitrage Portfolios

To examine the power of the univariate results presented thus far, we analyze returns on calendar-time portfolios of stocks, formed at the end of June of each year, and assigned to groups of stocks purchased and sold from our sample. The calendar-time portfolio method eliminates the problem of cross-sectional dependence among sample firms, because the returns on sample firms are aggregated into 2 portfolio returns. These intercept tests examine whether the difference in average subsequent returns to stocks purchased and stocks sold in our data set is significantly different from 0. Thus, the null hypothesis tested here is whether average returns to stocks bought are greater than or equal to those of stocks sold, before subtracting transactions costs.

[18] We thank the referee for this suggestion.

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TABLE 2

Regression Tests of the Incremental Role of Arbitrage Risk beyond Risk and Transaction Costs

Table 2 reports Fama-MacBeth (1973) coefficients and *t*-statistics (in parentheses) using Newey-West (1987) standard errors. The dependent variable is the size-adjusted 3-year buy-and-hold return, beginning in July of year *t*, computed as the raw buy-and-hold return, minus the size-decile return using NYSE and AMEX firm deciles. BETA is the systematic risk from a market model estimated over a maximum of 36 months using monthly returns beginning in July of year *t*. BM is book value at year $t-1$, divided by the market value of equity at the end of June of year *t*. XV_INDEX is estimated as described above in Table 1. RES_XV_INDEX is the residual from a fixed-effects regression, where XV_INDEX is regressed on size and book-to-market (BM) variables. IVOL, idiosyncratic volatility, is estimated by the variance of the residuals obtained from regressing daily returns on a value-weighted market index over a maximum of 250 days ending on June 30 of year *t*. PRICE is the closing price per share of common stock at the end of June of year *t*. VOLUME is the annual volume (in millions of dollars) of shares traded over the year ending in June of year *t*. ZERO_FREQ is the frequency of 0 daily returns over the year ending in June of year *t*. COVER is the number of earnings per share (EPS) estimates recorded in IBES in May of each year *t*. SIZE is the market value of equity (in millions of dollars) in May of year *t*. Model (3) is estimated using the 1976–1997 time period for NYSE and AMEX stocks, as in Ali et al. (2003). The other 7 models are estimated using all available observations during the period 1963–2001.

Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	–0.11***	–0.15***	–0.13***	–0.08*	–0.10**	0.07	0.00	0.09
	(–2.89)	(–4.38)	(–4.17)	(–1.71)	(–2.51)	(1.06)	(0.06)	(1.21)
BETA	0.10***	0.11***	0.12***	0.07**	0.07***	0.07***	0.11***	0.07***
	(2.66)	(3.09)	(3.38)	(2.53)	(2.64)	(2.75)	(3.25)	(2.74)
BM	0.02***	0.03***	0.02**	0.02	0.02	0.01		
	(2.93)	(3.23)	(3.15)	(1.44)	(1.52)	(0.66)		
BM × $(IVOL)^{-1}$		-0.80×10^{-6}	1.00×10^{-6}	3.00×10^{-6}	4.10×10^{-6}	2.20×10^{-6}		
		(–0.28)	(0.28)	(0.69)	(0.88)	(0.61)		
RES_XV_INDEX					–0.25***			
					(–4.84)			
XV_INDEX						–0.32***	–0.28***	–0.35***
						(–5.26)	(–4.22)	(–4.62)
XV_INDEX × $(IVOL)^{-1}$							0.16×10^{-4}*	0.24×10^{-4}**
							(1.87)	(1.96)
$(IVOL)^{-1}$		0.01×10^{-3}**	0.01×10^{-3}	0.25×10^{-3}***	0.24×10^{-3}***	0.23×10^{-3}***	0.00×10^{-3}	0.01×10^{-3}
		(2.13)	(1.18)	(3.14)	(3.07)	(3.01)	(0.14)	(1.59)
PRICE				0.00	0.00	0.00		0.00
				(1.26)	(1.34)	(1.41)		(1.41)
ln(VOLUME)				0.12***	0.12***	0.12***		0.12***
				(7.37)	(7.48)	(7.57)		(7.76)

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TABLE 2 (continued)

Regression Tests of the Incremental Role of Arbitrage Risk beyond Risk and Transaction Costs

Independent Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ZERO_FREQ				−1.65***	−1.77***	−1.59***		−1.52**
				(−2.62)	(−2.68)	(−2.47)		(−2.36)
COVER				0.00	−0.00	−0.00		−0.00
				(0.33)	(−0.17)	(−0.55)		(0.55)
ln(SIZE)				−0.10***	−0.09***	−0.09***		−0.09***
				(−6.72)	(−6.40)	(−7.05)		(−7.44)
No. of obs.	133,650	133,638	42,010	105,755	103,682	104,271	131,438	104,722
No. of years	39	39	22	26	26	26	39	26
R^2 [%]	0.14	0.15	0.08	0.92	1.08	1.24	0.29	1.23

Specifically, if undervalued (Low_X_VALUE1, X_VALUE2) stocks outperform overvalued (High_X_VALUE1, X_VALUE2) stocks on a risk-adjusted basis, time-series tests of arbitrage portfolios formed by going long Low_X_VALUE1 or X_VALUE2 stocks and short High_X_VALUE1 or X_VALUE2 stocks should consistently outperform relative to an explicit multifactor asset pricing model. We address this issue using alternative asset pricing models: the Fama-French (1993) 3-factor model, and a 4-factor model constructed by adding a momentum factor, following Carhart (1997), to the Fama-French 3-factor model. We include a momentum factor, up minus down (UMD), in the Fama-French 3-factor model, to capture the medium-term continuation in stock returns documented in Jegadeesh and Titman (1993). If Low_X_VALUE1 (X_VALUE2) stocks outperform High_X_VALUE1 (X_VALUE2) stocks, the α of the arbitrage portfolio should be positive and statistically significant. If the return difference between low and high valuation stocks is a manifestation of confounding effects (i.e., differences in market beta, size, BM, and momentum), the regression intercepts should be economically and statistically indistinguishable from 0. The arbitrage portfolios are constructed as the difference in returns between the top 30th and the bottom 30th percentile portfolios of stocks ranked on X_VALUE1 and X_VALUE2, respectively.

Table 3 presents the results. The 3- and 4-factor time-series arbitrage regression results, reported in the first 2 columns of Table 3, show that the return difference between low and high excess valuation stocks cannot be attributed to confounding effects (i.e., differences in market beta, size, BM, and momentum). The regression intercepts are different from 0 in economic and statistical terms. In fact, all intercepts are positive and statistically significant at conventional levels. The estimated intercepts suggest that both the 3- and 4-factor models leave unexplained a large fraction of the mispricing arbitrage portfolio returns. The intercept based on the 3-factor model is 0.56 (with t-statistic = 9.21), and the intercept for the 4-factor model is 0.47 (with t-statistic = 7.78). If our relative valuation approach does yield a fairly accurate and distinct mispricing measure, the adjusted R^2s from time-series regressions of the arbitrage return spread $(R_{\text{Low_X_VALUE1}} - R_{\text{High_X_VALUE1}})$ on the well-known 3 or 4 factors should be much less than 100%. Indeed, the adjusted R^2s are considerably lower than 100%

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(in the 16%–57% range), suggesting that stocks share incremental mispricing above and beyond the comovement implied from the 3- and 4-factor models. This additional evidence is consistent with the view that the arbitrage return differences $((R_{\text{Low_X_VALUE1}} - R_{\text{High_X_VALUE1}})$, $(R_{\text{Low_X_VALUE2}} - R_{\text{High_X_VALUE2}})$, and $(R_{\text{Low_XV_INDEX}} - R_{\text{High_XV_INDEX}}))$, constructed using our relative valuation approach, capture mispricing.[19] Since all 3 mispricing measures produce similar results, in Tables 4–8 we report results based on the XV_INDEX.

TABLE 3

Time-Series Tests for Mispricing Arbitrage Portfolios

Table 3 reports coefficients and *t*-statistics (in parentheses) for the Fama-French (1993) 3-factor model and for the 4-factor model that includes the 3 Fama-French factors and the momentum factor, UMD. The dependent variable is the equal-weighted return differential between undervalued and overvalued firm portfolios. The overvalued portfolio consists of firms with high (highest 30th percentile) X_VALUE1 (or X_VALUE2 or XV_INDEX), while the undervalued firm portfolio consists of firms with low (lowest 30th percentile) X_VALUE1 (or X_VALUE2 or XV_INDEX). Mispricing arbitrage portfolio returns are based on X_VALUE1, X_VALUE2, and XV_INDEX, respectively. $R_M - R_f$ is the value-weighted market return (R_M), minus the 1-month T-bill rate (R_f). SMB (small minus big) is the difference each month between the return on small and big firms, while HML (high minus low) is the monthly difference of the returns on a portfolio of high book-to-market (BM) and low BM firms. UMD (up minus down) is the momentum factor computed on a monthly basis as the return differential between a portfolio of winners and a portfolio of losers. $R_M - R_f$, HML, SMB, and UMD are extracted from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Mispricing Arbitrage Portfolios Created Using X_VALUE1 Rankings		Mispricing Arbitrage Portfolios Created Using X_VALUE2 Rankings		Mispricing Arbitrage Portfolios Created Using XV_INDEX Rankings	
Independent Variables	Dependent Variable: $R_{\text{Low_X_VALUE1}} - R_{\text{High_X_VALUE1}}$		Dependent Variable: $R_{\text{Low_X_VALUE2}} - R_{\text{High_X_VALUE2}}$		Dependent Variable: $R_{\text{Low_XV_INDEX}} - R_{\text{High_XV_INDEX}}$	
Intercept [%]	0.56***	0.47***	0.23**	0.26**	0.52***	0.47***
	(9.21)	(7.78)	(2.13)	(2.39)	(7.62)	(7.78)
$R_M - R_F$	–0.11***	–0.10***	–0.01	–0.01	–0.07***	–0.07***
	(–7.25)	(–6.95)	(–0.28)	(–0.28)	(–4.18)	(–3.97)
SMB	0.10***	0.10***	0.22***	0.23***	0.01	0.01
	(4.94)	(5.25)	(6.51)	(6.60)	(0.23)	(0.30)
HML	0.41***	0.43***	0.24***	0.23***	0.41***	0.43***
	(18.18)	(19.48)	(5.97)	(5.75)	(12.25)	(12.93)
UMD		0.08***		0.03		0.07***
		(5.60)		(–1.37)		(2.66)
N	474	474	306	306	474	474
Adjusted R^2 [%]	54.20	56.20	16.83	17.07	46.81	48.61

C. Arbitrage Risk

Taken as a whole, this evidence suggests that undervalued stocks systematically outperform overvalued stocks. The failure of the alternative multifactor asset pricing models to explain the return spread between undervalued and overvalued stocks supports the existence of a unique mispricing effect in stock returns.

[19] To ensure that our results are not driven by 1 particular asset pricing model, we check the robustness of our results by estimating the Ferguson and Shockley (2003) 3-factor model: $R(t) - Rf(t) = a + b\text{RMF}(t) + bD/E\ RD/E(t) + bZRZ(t) + e(t)$. The time series of the leverage, $RD/E(t)$, and distress, $RZ(t)$, factors are provided by Ferguson and Shockley and cover the period July 1983–December 2000. These regressions produced results similar to those reported here and are available from the authors.

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As discussed earlier, this stock market anomaly could stem from arbitrage risk. Elimination of mispricing assumes that arbitrageurs are able to purchase (sell) undervalued (overvalued) stocks. Hedging against fundamental risk, the arbitrageur should be able to take an opposite position in a stock that is a close substitute for the mispriced stock. However, if a mispriced stock has few close substitutes (i.e., is highly idiosyncratic), it will be difficult to elicit arbitrage activity that is free from fundamental risk and, therefore, arbitrage trading opportunity for such a stock will be limited. Hence, as long as arbitrageurs are risk averse and insufficiently diversified, their inability to perfectly hedge fundamental risk implies that arbitrage will be restricted, and stocks will remain mispriced.

Previous studies have shown that arbitrageurs are, in fact, averse to trading stocks with high idiosyncratic risk (Pontiff (2006)). That is, arbitrage activity is costly when idiosyncratic risk is high because arbitrageurs cannot absolutely hedge their positions. Therefore, in accordance with the arbitrage risk hypothesis, high arbitrage risk stocks should exhibit higher mispricing than low arbitrage risk stocks. In this section, we test this prediction by examining whether the risk-adjusted returns of the simple strategy, which involves buying undervalued stocks and selling overvalued stocks, are greater for stocks having higher idiosyncratic (arbitrage) risk than for stocks having lower idiosyncratic risk.

To perform this test, we classify stocks annually into high (top 30th percentile), medium (middle 40th percentile), and low (bottom 30th percentile) misvaluation portfolios, based on the misvaluation index measure (XV_INDEX). We also independently sort stocks on an annual basis into low, medium, and high arbitrage risk (AR1 and AR3) groups, depending on whether stock arbitrage risk falls into the bottom 30th, middle 40th, or top 30th percentiles, respectively. The arbitrage portfolio return is estimated as the difference between the top 30th and the bottom 30th percentile portfolios of stocks ranked on the XV_INDEX measure. Finally, we run 3- and 4-factor time-series arbitrage regressions on corresponding factors, separately, for the low, medium, and high arbitrage risk groups of stocks.

Panel A of Table 4 reports regression intercepts for portfolios of stocks sorted into 3 arbitrage risk groups. As expected, the pattern that emerges from these regressions shows that the intercepts increase monotonically with increases in arbitrage risk. Specifically, our evidence shows that high arbitrage risk stocks have almost 3 times higher intercepts than low arbitrage risk stocks. The intercept differences between high and low arbitrage risk stocks are statistically significant at the 1% level. This pattern holds for both the 3- and the 4-factor model specifications. When we classify firms into quintile arbitrage risk portfolios, as shown in Panel B, most of the intercepts retain their previous pattern. In addition, the difference in intercepts between high and low arbitrage risk portfolios (Q5 – Q1) is somewhat more dramatic. These results are consistent with the arbitrage risk hypothesis, which predicts that high idiosyncratic risk stocks will be more mispriced than low idiosyncratic risk stocks, since arbitrageurs are more constrained from hedging fundamental risk for high than for low idiosyncratic risk stocks. These findings are consistent with the empirical evidence of Pontiff (1996), who attributes the closed-end fund anomaly to arbitrage risk, and with the theoretical models of Shleifer and Vishny (1997), Gromb and Vayanos (2002), and Chen et al. (2002), which postulate that mispricing persists when arbitrageurs are unable

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TABLE 4

Time-Series Tests for Mispricing Arbitrage Portfolios at Different Levels of Arbitrage Risk

Table 4 reports intercepts (in percentage points) and *t*-statistics (in parentheses) obtained from estimating asset pricing models of mispricing arbitrage portfolio returns for different groups of firms sorted on arbitrage risk. The last column reports the differences in intercepts between the extreme arbitrage risk groups and the corresponding *t*-statistics. Mispricing arbitrage portfolio returns are based on XV_INDEX. The portfolios are formed after sorting independently on arbitrage risk and each of the 3 mispricing measures in June of each year. Panel A presents results for low, medium, and high arbitrage risk groups formed by classifying firms into the bottom 30th, middle 40th, and top 30th percentiles of arbitrage risk. Arbitrage risk is defined in 2 ways: i) as the standard deviation of the residuals from the market model estimated over a 1-year period prior to June of each year using weekly returns (AR1); and ii) as the standard deviation of the residuals from the Fama-French 3-factor model estimated over a 1-year period prior to June of each year using weekly returns (AR3). Panel B presents results for the AR1 and AR3 quintiles. The following 2 models are estimated:

$$\text{Model 1:}\quad [R_{\text{Low_XV_INDEX}} - R_{\text{High_XV_INDEX}}] = \alpha + \beta[R_M - R_F] + s[\text{SMB}] + h[\text{HML}],$$

$$\text{Model 2:}\quad [R_{\text{Low_XV_INDEX}} - R_{\text{High_XV_INDEX}}] = \alpha + \beta[R_M - R_F] + s[\text{SMB}] + h[\text{HML}] + u[\text{UMD}].$$

The dependent variable is the equal-weighted return differential between undervalued and overvalued firm portfolios. The overvalued portfolio consists of firms with high (highest 30th percentile) XV_INDEX, while the undervalued firm portfolio consists of firms with low (lowest 30th percentile) XV_INDEX. $R_M - R_f$ is the value-weighted market return (R_M), minus the 1-month T-bill rate (R_f). SMB (small minus big) is the difference, each month, between the return on small and big firms, while HML (high minus low) is the monthly difference of the returns on a portfolio of high book-to-market (BM) and low BM firms. UMD (up minus down) is the momentum factor computed on a monthly basis as the return differential between a portfolio of winners and a portfolio of losers. $R_M - R_f$, HML, SMB, and UMD are extracted from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Classifying Stocks into Low (bottom 30th percentile), Medium (middle 40th percentile), and High (top 30th percentile) Arbitrage Risk Groups

Arbitrage Risk Is the Standard Deviation of the Residuals from the Market Model (AR1)

	Low_AR1	Medium_AR1	High_AR1	High_AR1 – Low_AR1
Model 1	0.24***	0.50***	0.68***	0.44***
	(4.24)	(6.73)	(5.97)	(3.45)
Model 2	0.26***	0.52***	0.64***	0.38***
	(4.36)	(6.82)	(5.38)	(2.76)

Arbitrage Risk Is the Standard Deviation of the Residuals from the Fama-French 3-Factor Model (AR3)

	Low_AR3	Medium_AR3	High_AR3	High_AR3 – Low_AR3
Model 1	0.23***	0.51***	0.73***	0.50***
	(4.07)	(6.61)	(6.48)	(3.94)
Model 2	0.25***	0.52***	0.67***	0.42***
	(3.95)	(6.66)	(5.60)	(3.11)

Panel B. Classifying Stocks into Arbitrage Risk Quintiles

Arbitrage Risk Is the Standard Deviation of the Residuals from the Market Model (AR1)

	Low_AR1 Q1	Q2	Q3	Q4	High_AR1 Q5	High_AR1 – Low_AR1
Model 1	0.17***	0.33***	0.57***	0.51***	0.74***	0.57***
	(2.69)	(4.64)	(6.58)	(4.97)	(5.12)	(3.61)
Model 2	0.18***	0.35***	0.59***	0.52***	0.69***	0.51***
	(2.73)	(4.76)	(6.61)	(4.90)	(4.65)	(3.04)

Arbitrage Risk Is the Standard Deviation of the Residuals from the Fama-French 3-Factor Model (AR3)

	Low_AR3 Q1	Q2	Q3	Q4	High_AR3 Q5	High_AR3 – Low_AR3
Model 1	0.17***	0.33***	0.58***	0.57***	0.74***	0.56***
	(2.69)	(4.65)	(6.69)	(5.22)	(5.31)	(3.67)
Model 2	0.19***	0.33***	0.60***	0.58***	0.67***	0.48***
	(2.69)	(4.37)	(6.33)	(5.50)	(4.51)	(2.98)

to hedge fundamental risk. In general, these empirical results suggest that stocks with different arbitrage risk exposures realize significantly different returns after adjusting for risk, That is, expected rates of return depend not only on fundamental risk, captured by a standard asset pricing model, but also on the degree of asset mispricing associated with arbitrage risk.

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D. Limited Arbitrage Risk Absorption Capacity: Arbitrage Risk Premium

The previous significant αs are consistent with the notion that arbitrageurs are reluctant to place a large portfolio weight on a high idiosyncratic risk stock; this, in turn, decreases their influence on the stock's mispricing. If this is true, arbitrageurs would require a "premium" to establish positions in highly idiosyncratic stocks as compensation for loading their portfolios with unhedgeable risk.[20] To address this issue, we construct 2 alternative arbitrage risk premium measures, use them as additional independent variables, and replicate the previous regression analysis. The arbitrage risk premium measure ARP1 (ARP3) is estimated as the difference in AR1 (AR3) between the top and bottom arbitrage risk quintile portfolios of firm-year observations, sorted annually. If arbitrageurs indeed demand a premium to establish positions in highly idiosyncratic stocks (i.e., they exhibit low risk absorption capacity for such stocks), the ARP1 and ARP3 measures should enter the multifactor regressions with positive and significant coefficients, while the intercepts should turn out to be statistically insignificant. If the intercepts were found to be different from 0, this would imply that mispricing persists even if arbitrageurs are idiosyncratic-risk neutral.

Panel A of Table 5 reports these regression results. Two major findings emerge from these tests. First, with the inclusion of the ARP1 (or ARP3) variable in the regressions, all intercepts become statistically indistinguishable from 0, suggesting that if arbitrageurs could hedge idiosyncratic risk (or were offered a premium to establish such a risky position), stock mispricing would be eliminated. Hence, this evidence reinforces the view that arbitrage is not a risk-free activity. Second, these results corroborate the view that arbitrageurs have very low risk absorption capacity for highly idiosyncratic stocks. As expected, both ARP1 and ARP3 variables enter all regressions with a positive sign and statistically significant coefficients at conventional levels. These findings suggest that arbitrageurs are reluctant to remove mispricing in highly idiosyncratic risk stocks.

One concern with our evidence, based on the XV_INDEX, is that it does not negate the possibility that the BM ratio, as a mispricing proxy, could generate similar results. If this were the case, high minus low (HML) should have a strong and positive relation with ARP1 and ARP3. Panel B of Table 5, however, shows that this relationship is fairly weak, indicating that the BM ratio is not an appropriate mispricing measure. This result is in line with the findings reported in Table 3.

E. Robustness Tests

1. Orthogonal XV_INDEX

Although our previous analysis, reported in Table 2 and in accordance with that of Frankel and Lee (1998), shows that the predictive power of mispricing measures employed in this study are more robust and unlikely to be attributed to BM and size effects, an alternative explanation for the relation between mispricing and arbitrage risk is that the relative valuation measures used thus far may actually

[20]The arbitrage premium is not unidirectional, since arbitrageurs short stocks with negative αs and go long on stocks with positive αs.

TABLE 5

Time-Series Tests for Mispricing Arbitrage Portfolios Controlling for the Arbitrage Risk Premium

Table 5 reports coefficients and *t*-statistics (in parentheses) for the model that includes the 3 Fama-French factors; the momentum factor, UMD; and the arbitrage risk premium, ARP1 (or ARP3). We use a Newey-West (1987) estimator with a lag of 11. The dependent variable is the equal-weighted return differential between undervalued and overvalued firm portfolios. The overvalued portfolio consists of firms with high (highest 30th percentile) XV_INDEX, while the undervalued portfolio consists of firms with low (lowest 30th percentile) XV_INDEX. ARP1 (or ARP3) is computed as the difference in the arbitrage risk of the top and the bottom quintile portfolios of firms sorted annually on the absolute excess valuation index. AR1 is obtained using a single-factor (market) model, while AR3 is obtained from the Fama-French 3-factor model. $R_M - R_f$ is the value-weighted market return (R_M), minus the 1-month T-bill rate (R_f). SMB (small minus big) is the difference each month between the return on small and big firms, while HML (high minus low) is the monthly difference of the returns on a portfolio of high book-to-market (BM) and low BM firms. UMD (up minus down) is the momentum factor computed on a monthly basis as the return differential between a portfolio of winners and a portfolio of losers. $R_M - R_f$, HML, SMB, and UMD are extracted from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Panel A. Time-Series Tests for XV_INDEX Portfolios Controlling for Arbitrage Risk Premium Rankings		*Panel B. Time-Series Tests for BM (HML) Arbitrage Portfolios Controlling for Arbitrage Risk Premium Rankings*	
Independent Variables	Dependent Variable: $R_{Low_X_VALUE1} - R_{High_X_VALUE1}$		Dependent Variable: HML	
Intercept [%]	0.09 (0.68)	0.13 (0.92)	0.45 (1.53)	0.38 (1.26)
$R_M - R_F$	–0.07*** (–3.60)	–0.06*** (–3.44)	–0.25*** (–5.23)	–0.25*** (–5.29)
SMB	0.01 (0.20)	0.01 (0.20)	–0.16* (–1.74)	–0.16* (–1.70)
HML	0.43*** (8.00)	0.43*** (8.06)		
UMD	0.07 (1.57)	0.07 (1.60)	–0.12 (–1.44)	–0.12 (–1.44)
ARP1	0.15*** (3.10)		0.09 (1.53)	
ARP2		0.13*** (2.70)		0.10 (0.92)
N	482	450	462	450
Adjusted R^2 [%]	50.42	50.99	24.06	24.56

capture other effects. To confirm that these other effects do not drive our results, we construct a valuation measure (RES_XV_INDEX) that is orthogonal to both BM and size, and we use it to test for robustness. The RES_XV_INDEX is the residual from a fixed-effects regression, where XV_INDEX is regressed on size and BM variables. If the RES_XV_INDEX measure, purged from BM and size effects, is found to have a strong and positive association with arbitrage risk, this would further imply that the relation between our original valuation metrics and arbitrage risk is distinct and, therefore, cannot be attributed to BM and size factors.

In Table 6, we report results based on this orthogonal relative valuation measure. Panels A and B report the intercepts from 3- and 4-factor time-series arbitrage portfolio return regressions on their corresponding factors. The new evidence is consistent with our previous findings, reported in Table 4. Specifically, these results show that high arbitrage risk stocks have 2–3 times higher intercepts than low arbitrage risk stocks. Consistent with the arbitrage risk hypothesis, the intercept differences between high and low arbitrage risk stocks are statistically significant at the 1% level for almost all model specifications.

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Panel C of Table 6 reports regression coefficients for the 2 multifactor asset pricing models. In these regressions, we include the 2 alternative arbitrage risk premium variables (ARP1, ARP3) to determine whether arbitrageurs are averse to

TABLE 6

Robustness Tests: Time-Series Tests for Mispricing Arbitrage Portfolios Based on Residual XV_INDEX

Table 6 reports intercepts (in percentage points) and *t*-statistics (in parentheses) obtained from estimating asset pricing models of mispricing arbitrage portfolio returns for different groups of firms sorted on arbitrage risk. The last column reports the differences in intercepts between the extreme arbitrage risk groups and the corresponding *t*-statistics. Mispricing arbitrage portfolio returns are based on RES_XV_INDEX rankings. The portfolios are formed after sorting independently on arbitrage risk and each of the 3 mispricing measures in June of each year. Panel A presents results for low, medium, and high arbitrage risk groups formed by classifying firms into the bottom 30th, middle 40th, and top 30th percentiles of arbitrage risk. Arbitrage risk is defined in 2 ways: i) as the standard deviation of the residuals from the market model estimated over a 1-year period prior to June of each year using weekly returns (AR1); and ii) as the standard deviation of the residuals from the Fama-French 3-factor model estimated over a 1-year period prior to June of each year using weekly returns (AR3). Panel B presents results for AR1 and AR3 quintiles. The following 2 models are estimated:

$$\text{Model 1:} \quad [R_{\text{Low_XV_INDEX}} - R_{\text{High_XV_INDEX}}] = \alpha + \beta[R_M - R_F] + s[\text{SMB}] + h[\text{HML}]$$

$$\text{Model 2:} \quad [R_{\text{Low_XV_INDEX}} - R_{\text{High_XV_INDEX}}] = \alpha + \beta[R_M - R_F] + s[\text{SMB}] + h[\text{HML}] + u[\text{UMD}]$$

Panel C presents time-series tests for the models that include the 3 Fama-French factors; the momentum factor, UMD; and the arbitrage risk premium, ARP1 (or ARP3). The dependent variable is the equal-weighted return differential between undervalued and overvalued firm portfolios. The overvalued portfolio consists of firms with high (highest 30th percentile) XV_INDEX, while the undervalued portfolio consists of firms with low (lowest 30th percentile) XV_INDEX. $R_M - R_f$ is the value-weighted market return (R_M), minus the 1-month T-bill rate (R_f). SMB (small minus big) is the difference each month between the return on small and big firms, while HML (high minus low) is the monthly difference of returns on a portfolio of high book-to-market (BM) and low BM firms. UMD (up minus down) is the momentum factor computed on a monthly basis as the return differential between a portfolio of winners and a portfolio of losers. $R_M - R_f$, HML, SMB, and UMD are extracted from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/). ARP1 (or ARP3) is computed as the difference in the arbitrage risk of the top and the bottom quintile portfolios of firms sorted annually on the absolute excess valuation index. AR1 is obtained using a single-factor (market) model, while AR3 is obtained from the Fama-French 3-factor model. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Classifying Stocks into Low (bottom 30th percentile), Medium (middle 40th percentile), and High (top 30th percentile) Arbitrage Risk Groups

Arbitrage Risk Is the Standard Deviation of the Residuals from the Market Model (AR1)

	Low_AR1	Medium_ AR1	High_AR1	High_AR1 – Low_AR1
Model 1	0.27***	0.48***	0.62***	0.30***
	(4.76)	(6.95)	(5.77)	(2.80)
Model 2	0.29***	0.50***	0.58***	0.29**
	(4.62)	(6.53)	(5.04)	(2.23)

Arbitrage Risk Is the Standard Deviation of the Residuals from the Fama-French 3-Factor Model (AR3)

	Low_AR3	Medium_ AR3	High_AR3	High_AR3 – Low_AR3
Model 1	0.27***	0.50***	0.64***	0.37***
	(4.45)	(7.08)	(5.93)	(3.04)
Model 2	0.28***	0.52***	0.59***	0.31**
	(4.31)	(6.66)	(5.14)	(2.37)

Panel B. Classifying Stocks into Arbitrage Risk Quintiles

Arbitrage Risk Is the Standard Deviation of the Residuals from the Market Model (AR1)

	Low_AR1 Q1	Q2	Q3	Q4	High_AR1 Q5	High_AR1 – Low_AR1
Model 1	0.21***	0.38***	0.57***	0.48***	0.65***	0.44***
	(3.17)	(5.17)	(6.64)	(4.72)	(4.83)	(2.96)
Model 2	0.21***	0.40***	0.59***	0.46***	0.62***	0.40**
	(3.07)	(4.74)	(6.48)	(4.58)	(4.08)	(2.44)

Arbitrage Risk Is the Standard Deviation of the Residuals from the Fama-French 3-Factor Model (AR3)

	Low_AR3 Q1	Q2	Q3	Q4	High_AR3 Q5	High_AR3 – Low_AR3
Model 1	0.21***	0.36***	0.58***	0.50***	0.64***	0.43***
	(3.16)	(4.94)	(6.88)	(4.73)	(4.71)	(2.84)
Model 2	0.22***	0.36***	0.59***	0.50***	0.59***	0.37**
	(3.11)	(4.46)	(6.52)	(4.73)	(3.81)	(2.14)

(continued on next page)

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TABLE 6 (continued)

Robustness Tests: Time-Series Tests for Mispricing Arbitrage Portfolios Based on Residual XV_INDEX

Panel C. Time-Series Tests for Mispricing Portfolios Based on RES_XV_INDEX

Independent Variables	*Dependent Variable:* $R_{Low_RES_XV_INDEX} - R_{High_RES_XV_INDEX}$					
Intercept [%]	0.49*** (8.23)	0.12 (1.07)	0.15 (1.20)	0.46*** (7.26)	0.10 (0.77)	0.12 (0.92)
$R_M - R_F$	–0.08*** (–5.32)	–0.08*** (–4.49)	–0.08*** (–4.36)	–0.08*** (–5.32)	–0.08*** (–4.69)	–0.08*** (–4.56)
SMB	0.18*** (6.76)	0.19*** (5.79)	0.19*** (5.80)	0.18*** (6.61)	0.19*** (5.59)	0.19*** (5.60)
HML	0.22*** (7.45)	0.21*** (7.09)	0.21*** (7.14)	0.22*** (7.68)	0.22*** (7.29)	0.22*** (7.34)
UMD				0.03 (1.41)	0.03 (1.14)	0.03 (1.15)
ARP1		0.15*** (3.73)			0.15*** (3.61)	
ARP3			0.13*** (3.43)			0.12*** (3.30)
N	462	462	462	462	462	462
Adj. R^2 [%]	30.29	33.35	33.38	31.43	34.01	34.06

including in their portfolios high idiosyncratic risk stocks. In line with our previous results, reported in Table 5, the intercepts turn out to be statistically indistinguishable from 0 only when the ARP1 or ARP3 variables are included in the 2 different asset pricing specifications. Hence, the new evidence, based on a valuation measure that is orthogonal to BM and size effects, confirms the existence of a reliable relation between arbitrage risk and mispricing. Further, this new evidence suggests that BM and size effects did not drive our earlier results obtained from nonorthogonal valuation measures.

2. Transaction Costs and Investor Sophistication

The finance literature suggests that mispricing is more likely to occur in stocks with higher direct and indirect transaction costs (Bhardwaj and Brooks (1992), Blume and Goldstein (1992), and Lakonishok et al. (1994)), such as short-selling constraints. Short-selling costs contribute to the cost of arbitrage (e.g., Dechow, Hutton, Meulbroek, and Sloan (2001), Asquith, Pathak, and Ritter (2005), among others).

To examine whether our results are sensitive to these factors, we conduct additional tests in which we control for transaction costs and short-selling constraints. Previous studies suggest that, for thinly traded stocks, transactions are less likely to be completed quickly and therefore are more likely to cause adverse price effects. Hence, we use firm size as a broad proxy of transaction cost. In addition, we use the percentage of institutional ownership (IO) as a proxy for short-selling costs.[21] Because high short-selling costs tend to discourage the

[21] Duan et al. (2010), show that idiosyncratic risk is the most robust predictor of low returns across high short-interest stocks. They also provide evidence suggesting that idiosyncratic risk is the greatest deterrent to arbitrage among short sellers. They argue that idiosyncratic risk is not a short-sale constraint, as it also deters long arbitrage positions. Furthermore, they argue that their results imply

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participation of sophisticated traders, we also interpret IO as a proxy for trader sophistication.

If transactions and short-selling costs (trader sophistication) are the main drivers of our previously reported results, then the prediction of the arbitrage risk hypothesis should find support only in small capitalization stocks and stocks with high short-selling costs.

In Table 7, we present intercepts obtained from estimating 2 asset pricing models of mispricing arbitrage portfolio returns for firms sorted independently on

TABLE 7

Robustness Tests: Time-Series Tests for Mispricing Arbitrage Portfolios across Groups of Stocks Formed after Sorting on Arbitrage Risk and Size

Table 7 presents intercepts (in percentage points) and *t*-statistics (in parentheses) obtained from estimating asset pricing models of mispricing arbitrage portfolio returns for different groups of firms sorted independently on arbitrage risk, AR1 or AR3, and on market capitalization, SIZE. Mispricing arbitrage portfolio returns are based on XV_INDEX. The portfolios are formed after sorting independently on arbitrage risk, SIZE, and each of the 3 mispricing measures in June of each year. We form 4 groups of firms each year based on whether a firm is ranked in the top or bottom 50th percentiles after sorting on arbitrage risk and SIZE, respectively. Arbitrage risk is defined in 2 ways: i) as the standard deviation of the residuals from the market model, estimated over a 1-year period prior to June of each year using weekly returns (AR1); and ii) as the standard deviation of the residuals from the Fama-French 3-factor model estimated over a 1-year period prior to June of each year using weekly returns (AR3). The following 2 models are estimated:

$$\text{Model 1:} \quad [R_{\text{Low_XV_INDEX}} - R_{\text{High_XV_INDEX}}] = \alpha + \beta[R_M - R_F] + s[\text{SMB}] + h[\text{HML}]$$

$$\text{Model 2:} \quad [R_{\text{Low_XV_INDEX}} - R_{\text{High_XV_INDEX}}] = \alpha + \beta[R_M - R_F] + s[\text{SMB}] + h[\text{HML}] + u[\text{UMD}]$$

The dependent variable is the equal-weighted return differential between the undervalued and the overvalued firm portfolios. The overvalued portfolio consists of firms with high (highest 30th percentile) XV_INDEX, while the undervalued firm portfolio consists of firms with low (lowest 30th percentile) XV_INDEX. $R_M - R_f$ is the value-weighted market return (R_M), minus the 1-month T-bill rate (R_f). SMB (small minus big) is the difference each month between the return on small and big firms, while HML (high minus low) is the monthly difference in returns on a portfolio of high book-to-market (BM) and low BM firms. UMD (up minus down) is the momentum factor computed on a monthly basis as the return differential between a portfolio of winners and a portfolio of losers. $R_M - R_f$, HML, SMB, and UMD are extracted from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Arbitrage Risk Is the Standard Deviation of the Residuals from the Market Model (AR1)

	(1)	(2)		(3)	(4)	
	Low_AR1 and Small SIZE	Low_AR1 and Large SIZE	Low_AR1 Large – Small	High_AR1 and Small SIZE	High_AR1 and Large SIZE	High_AR1 Large – Small
Model 1	0.38***	0.14*	–0.24**	0.62***	0.53**	–0.09
	(5.26)	(1.89)	(–2.37)	(6.64)	(2.12)	(–0.33)
Model 2	0.39***	0.14*	–0.25**	0.55***	0.55*	–0.00
	(4.76)	(1.81)	(–2.31)	(5.18)	(1.92)	(–0.02)

Panel B. Arbitrage Risk Is the Standard Deviation of the Residuals from the Fama-French 3-Factor Model (AR3)

	(1)	(2)		(3)	(4)	
	Low_AR3 and Small SIZE	Low_AR3 and Large SIZE	Low_AR3 Large – Small	High_AR3 and Small SIZE	High_AR3 and Large SIZE	High_AR3 Large – Small
Model 1	0.36***	0.14**	–0.22**	0.64***	0.42*	–0.22
	(5.76)	(1.98)	(–2.27)	(6.82)	(1.73)	(–0.81)
Model 2	0.37***	0.13*	–0.24**	0.57***	0.45*	–0.12
	(5.04)	(1.77)	(–2.26)	(5.37)	(1.66)	(–0.41)

that the effects of idiosyncratic risk, as described in Pontiff (1996) and Shleifer and Vishny (1997), are a greater obstacle to market efficiency than are the short-sale constraints described in Miller (1977). Boehme, Kumar, Danielson, and Sorescu (2006), argue that the relation between idiosyncratic risk and future stock returns is positive (negative) in the absence (presence) of short-selling constraints.

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arbitrage risk, AR1 or AR3, and on market capitalization, SIZE. In Table 8, we report intercepts obtained from estimating 4 asset pricing models of mispricing arbitrage portfolio returns for firms sorted independently on arbitrage risk, AR1 or AR3, and IO. Consistent with our previous evidence, the results in Tables 7 and 8 show that the intercepts increase monotonically with increases in arbitrage risk, regardless of size and IO. This evidence suggests that the positive relation between arbitrage risk and mispricing is general, and is not rooted in small capitalization and/or high short-selling-cost stocks. For stocks of the same size, arbitrage risk is substantially greater for stocks with high rather than low idiosyncratic risk. For example, looking at Model 1, we notice that large stocks with high arbitrage risk (0.53, with a t-value of 2.12) have higher intercepts than large stocks with low arbitrage risk (0.14, with a t-value of 1.89). Similarly, small stocks with high arbitrage risk (0.62, with a t-value of 6.64) have higher intercepts than small

TABLE 8

Robustness Tests: Time-Series Tests for Mispricing Arbitrage Portfolios across Groups of Stocks Formed after Sorting on Arbitrage Risk and Institutional Ownership

Table 8 presents intercepts (in percentage points) and t-statistics (in parentheses) obtained from estimating asset pricing models of mispricing arbitrage portfolio returns for different groups of firms sorted independently on arbitrage risk, AR1 or AR3, and on the percent of common shares owned by institutional investors, IO. Mispricing arbitrage portfolio returns are based on XV_INDEX. The portfolios are formed after sorting independently on arbitrage risk, IO, and each of the 3 mispricing measures in June of each year. We form 4 groups of firms each year based on whether a firm is ranked in the top or bottom 50th percentiles after sorting on arbitrage risk and IO, respectively. Arbitrage risk is defined in 2 ways: i) as the standard deviation of the residuals from the market model estimated over a 1-year period prior to June of each year using weekly returns (AR1); and ii) as the standard deviation of the residuals from the Fama-French 3-factor model estimated over a 1-year period prior to June of each year using weekly returns (AR3). The following 2 models are estimated:

$$\text{Model 1:}\quad [R_{\text{Low_XV_INDEX}} - R_{\text{High_XV_INDEX}}] = \alpha + \beta[R_M - R_F] + s[\text{SMB}] + h[\text{HML}]$$

$$\text{Model 2:}\quad [R_{\text{Low_XV_INDEX}} - R_{\text{High_XV_INDEX}}] = \alpha + \beta[R_M - R_F] + s[\text{SMB}] + h[\text{HML}] + u[\text{UMD}]$$

The dependent variable is the equal-weighted return differential between undervalued and overvalued firm portfolios. The overvalued portfolio consists of firms with high (highest 30th percentile) XV_INDEX, while the undervalued firm portfolio consists of firms with low (lowest 30th percentile) XV_INDEX. $R_M - R_f$ is the value-weighted market return (R_M), minus the 1-month T-bill rate (R_f). SMB (small minus big) is the difference each month between the return on small and big firms, while HML (high minus low) is the monthly difference in returns on a portfolio of high book-to-market (BM) and low BM firms. UMD (up minus down) is the momentum factor computed on a monthly basis as the return differential between a portfolio of winners and a portfolio of losers. $R_M - R_f$, HML, SMB, and UMD are extracted from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Arbitrage Risk Is the Standard Deviation of the Residuals from the Market Model (AR1)

	(1)	(2)		(3)	(4)	
	Low_AR1 and Low_IO	Low_AR1 and High_IO	Low_AR1 High_IO – Low_IO	High_AR1 and Low_IO	High_AR1 and High_IO	High_AR1 High_IO – Low_IO
Model 1	0.54***	0.21*	–0.34*	0.74***	0.54	–0.20
	(3.68)	(1.73)	(–1.76)	(3.20)	(1.53)	(–0.50)
Model 2	0.64***	0.29**	–0.34*	0.56**	0.61	0.05
	(3.84)	(2.21)	(–1.65)	(2.43)	(1.62)	(0.11)

Panel B. Arbitrage Risk Is the Standard Deviation of the Residuals from the Fama-French 3-Factor Model (AR3)

	(1)	(2)		(3)	(4)	
	Low_AR3 and Low_IO	Low_AR3 and High_IO	Low_AR3 High_IO – Low_IO	High_AR3 and Low_IO	High_AR3 and High_IO	High_AR3 High_IO – Low_IO
Model 1	0.55***	0.23*	–0.31*	0.73***	0.65	–0.18
	(3.88)	(1.90)	(–1.71)	(3.16)	(1.55)	(–0.45)
Model 2	0.62***	0.30**	–0.33	0.57**	0.63*	0.06
	(3.93)	(2.15)	(–1.55)	(2.43)	(1.69)	(0.14)

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stocks with low arbitrage risk (0.38, with a *t*-value of 5.26). The same intercept pattern emerges from the other asset pricing model (Model 2). The difference in intercepts between large and small stocks with high arbitrage risk is statistically insignificant (e.g., for Model 1, it is –0.09, with a *t*-value of –0.33), suggesting that size does not drive the results. Size, however, appears to play a role in low arbitrage risk stocks. As shown in the second half of Table 7, the aforementioned patterns are retained even when we proxy arbitrage risk with the standard deviation of the residuals from the Fama-French (1993) 3-factor model.

A similar result is reported in Table 8 when we control for IO. For stocks with the same IO, the intercepts are larger in stocks with high rather than low idiosyncratic risk. For instance, intercepts from Model 1 show that high IO stocks with high arbitrage risk (0.54, with a *t*-value of 1.53) have higher intercepts than high IO stocks with low arbitrage risk (0.21, with a *t*-value of 1.73). Likewise, low IO stocks with high arbitrage risk (0.74, with a *t*-value of 3.20) have higher intercepts than low IO stocks with low arbitrage risk (0.54, with a *t*-value of 3.68). Another interesting result reported in Table 8 is that the intercepts in low arbitrage risk stocks are lower when IO is high, suggesting that mispricing tends to be lower in the presence of sophisticated traders.

The difference in intercepts between high and low IO stocks with low arbitrage risk is statistically significant in both models when AR1 and AR3 are used, implying that in the absence of arbitrage risk, IO tends to have a mild mitigating impact on mispricing. The difference in intercepts between high and low IO stocks with high arbitrage risk is statistically insignificant across all models, suggesting that IO does not appear to reduce mispricing in high arbitrage risk stocks.

In sum, our results suggest that idiosyncratic risk, an important arbitrage cost, deters arbitrage activity because arbitrage positions cannot be perfectly hedged, resulting in persistent mispricing. That is, for a given α, arbitrageurs are unlikely to place great portfolio weight on a high idiosyncratic risk stock. This, in turn, lessens the impact of arbitrage on mispricing.

VI. Conclusion

The finance literature suggests that stocks tend to trade at market prices regardless of fundamental values because arbitrageurs fail to close arbitrage opportunities, allowing mispricing to persist (Pontiff (1996), Shleifer and Vishny (1997), Gromb and Vayanos (2002), Chen, Hong, and Stein (2002), and Hirshleifer and Teoh (2003)). Specifically, it is argued that for highly idiosyncratic stocks, it is difficult to elicit arbitrage activity that is free from idiosyncratic risk and that such stocks are more likely to trade at market prices far from fair value. Therefore, arbitrage trading in highly idiosyncratic stocks will be limited. Hence, to the extent that arbitrageurs are risk averse and inadequately diversified, their inability to perfectly hedge fundamental risk suggests that arbitrage will be restricted and that stocks will remain mispriced. This paper examines the relation between mispricing and arbitrage risk.

Using 2 alternative relative valuation metrics (based on benchmarks from i) primary industry imputed value, and ii) residual income valuation (Ohlson

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(1995))), we construct mispricing measures with superior cross-sectional predictive power for future abnormal returns relative to book-to-market (BM) ratio and find that high idiosyncratic risk stocks (i.e., stocks with high arbitrage risk) are more mispriced than low idiosyncratic risk stocks. In addition, we find that mispricing is not limited to small capitalization and high BM stocks. Our results are consistent with the arbitrage risk hypothesis, which predicts that mispricing is positively associated with idiosyncratic risk, a major deterrent to arbitrage activity. Further, our evidence indicates that sophisticated trades tend to mitigate mispricing when arbitrage risk is low, implying that the deviation of market prices from fundamental value may not necessarily be rooted in economic irrationality. These results derive support from the data, even after controlling for transaction and short-selling costs. These findings remain robust after testing with alternative multifactor return generating specification models and mispricing measures. Overall, our tests provide new evidence in support of the conjecture that mispricing stems from the failure of arbitrageurs to hedge idiosyncratic risk and from a lack of sophisticated trader participation.

A caveat with studies such as ours is that because neither fundamental value nor mispricing are observable, the return predictability of our proxies may not necessarily imply mispricing, but rather, a relationship that is consistent with an efficient capital market and a correct asset pricing model. While we employ alternative measures of arbitrage risk to make inferences about the impact of arbitrage risk on asset prices, we acknowledge that the power of our tests may be driven by limitations associated with the specification of the asset pricing model used. To partly alleviate this concern, we use alternative versions of the Fama and French (1993) model.

The findings of this study have implications for liquidity studies in general, which tend to find a return differential between high and low liquidity portfolios of about 7% (Pastor and Stambaugh (2003)).[22] This high return spread associated with illiquidity is surprising, since theoretical work on transaction costs (Constantinides (1986), Vayanos (1998)) implies that while transactions costs affect trading frequency, they have only a small impact on prices.[23] Our evidence suggests that this result may be attributed to mispricing return biases due to cross-sectional correlation between arbitrage risk and liquidity. Furthermore, if high information uncertainty is most prevalent among high idiosyncratic volatility (IVOL) stocks, our findings also suggest that the return differential between high and low analyst dispersion stocks (Diether, Malloy, and Scherbina (2002)) could result from arbitrage risk. Generally, our analysis indicates that the high return premiums associated with other stock return anomalies that have been documented in previous studies may be the result of mispricing caused by the failure of arbitrageurs to hedge idiosyncratic risk. Finally, our results suggest that the argument

[22] See Amihud, Mendelson, and Pedersen (2005) for a survey of the research on liquidity and asset pricing.

[23] Novy-Marx (2004) argues that illiquidity is likely to be associated with high expected returns, not because the expected returns are a compensation for bearing illiquidity, but because both high returns and illiquidity are likely to be driven by risk factors that may be omitted from the standard asset pricing models. Equally, Johnson (2006) shows that liquidity and expected returns could comove without liquidity causing expected returns, because they are jointly determined in equilibrium.

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of Campbell and Cochrane (1999), that stock return predictability may reflect a time-varying risk premium, could be rooted in idiosyncratic risk that cannot be arbitraged away.

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